The Investment Value of Mutual Fund Portfolio Disclosure

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Abstract

This paper uses disclosed mutual fund portfolio holdings to develop stock selection models. Our models aggregate portfolio holdings across mutual funds, weighted by their past performance, to predict future stock returns – an overweighting by successful managers, or an underweighting by unsuccessful managers is considered to be a signal that a stock is currently underpriced. We find that investment strategies based on our stock signals generate returns exceeding seven percent during the following year, adjusted for the size, book-to-market, and momentum characteristics of the stocks. This evidence suggests that some managers have superior stock-selection skills, and that these skills strongly persist. Further, returns generated from our mutual fund holding-based strategies have a low correlation with those of 12 quantitative investment signals that are based on prior-documented market anomalies. Thus, our stock selection signals are unique, and indicate that some fund managers possess private skills that are unrelated to known anomalies.

I. Introduction

A rich history of research has analyzed whether mutual fund managers possess private information about the valuation of stocks. While the original work by Jensen (1968, 1969) finds no evidence of fund outperformance, a recent bootstrap-based study of fund returns by Kosowski, Timmermann, Wermers, and White (2006) indicates that roughly 10% of U.S. domestic-equity funds deliver persistent superior risk-adjusted returns to investors. However, it is likely that, even for this subset, superior performance is fleeting, as outperforming funds quickly grow to an uneconomic scale (as demonstrated by the model of Berk and Green (2004)).

Another approach to determining whether fund managers have private information on stock values is made possible through a close examination of the periodic disclosures of fund portfolio holdings. This approach has become increasingly relevant by the recent SEC regulation that requires all U.S. mutual funds to increase the frequency of public disclosure of security holdings from semiannually to quarterly, effective May 2004.[1] While these periodic portfolio "snapshots" do not perfectly capture manager trading activity, they do appear to reveal information that has investment value. For example, Wermers (2003) shows that stocks purchased by the best-performing funds continue to outperform over the following year. Further, Frank, Poterba, Shackelford, and Shoven (2004) demonstrate that the performance of "copycat" portfolios that mimic the disclosed positions of mutual funds (with a time lag) is indistinguishable from the after-expense performance of actual funds.

While a positive correlation exists between stockholdings- and net return-level performance (as shown by Wermers (2000)), investing in funds based on the past performance of their stock picks does not appear to lead to substantial net return performance, perhaps because outperforming funds either incur higher trading costs and expenses as they grow larger, or capture a greater share of the economic rents their talents produce, as indicated by the prior-mentioned model of Berk and Green (2004). In addition, many funds charge load fees and short-term trading fees, and strategies that invest in funds cannot take short

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[1] According to the SEC, the purpose of increasing the frequency of disclosure is "...to provide better information to investors about fund costs, investments, and performance" (see http://sec.gov/rules/final/33-8393.pdf).

positions in underperformers, thus limiting any profit opportunities.

In this study, we implement a new approach to uncovering private information possessed by mutual fund managers about stock values by examining the aggregate holdings and trades of successful managers. The intuition behind our approach is simple: stocks picked by skilled fund managers should outperform those picked by unskilled managers if stock-picking skills persist over time. Our approach aggregates the private information of fund managers through a statistical model that predicts the future performance of stocks based on how heavily they are held or purchased by fund managers with varying past track records in selecting stocks. Further, we determine whether private information possessed by fund managers lasts long enough to overcome the delay in the public release of portfolio holdings information, as well as the limited release frequency of that information.

Since the number of U.S. stocks is larger than the number of actively-managed domestic-equity mutual funds, estimating stock alphas from the model poses a challenge. To address this issue, we develop three robust estimators to extract information about the future alphas of a large number of stocks from portfolio data for a relatively small cross-section of funds. Our first stock alpha estimator is simple and intuitive – the forecasted alpha for a given stock is the weighted average of past fund alphas, where weights are proportional to current fund portfolio weights on the stock. Thus, a manager with half the past alpha, but twice the current portfolio weight on a stock, relative to another manager, will provide the same signal as the second manager about the future alpha of that stock. Simply put, the size of the portfolio "bet" conveys the magnitude of the manager's information, while the past alpha of the manager is a measure of the precision of that information. The other two stock alpha estimators follow the same intuition, but are more technical. The second estimator is based on a generalized inverse approach developed in the statistical literature to solve ill-posed regression problems. The third estimator is based on a Bayesian approach. We further decompose each estimator into three components, using information about recent purchases, recent sells, and lagged positions held by mutual funds.

It should be noted that past research by Chen, Jegadeesh, and Wermers (2000) uses aggregate mutual fund trades of individual stocks as a signal of value, which implies that mutual funds, as a group, possess valuable information relative to other investors. By contrast, our approach develops signals of stock value based on persistent differences in stock-picking skills *across* fund managers. For instance, a successful manager overweighting a stock is considered a positive signal, while an unsuccessful manager overweighting is considered a negative signal. This distinction from the approach of Chen et al. results in a much more successful stock selection model.

Specifically, we use the net returns and portfolio holdings of the universe of actively managed U.S. domestic equity funds from 1980 to 2002 to show that our three stock alpha estimators all exhibit significant and consistent power in predicting cross-sectional stock returns. For instance, under our first (weighted-average) stock alpha estimator, we find that the difference in returns between the equal-weighted decile portfolios of stocks with the highest and lowest forecasted alphas is about three percent during the quarter immediately following portfolio formation. Further, the second quarter spread between these two portfolios is about 2.5 percent,[2] and full-year compounded spreads exceed 8 percent. It is noteworthy that these return spreads are similar when adjusting for the size, book-to-market, and momentum characteristics of the stocks (using the Daniel, Grinblatt, Titman, and Wermers (1997) benchmarks), while exhibiting lower volatility and, therefore, higher levels of statistical precision than the unadjusted return spreads.

We also explore the use of trades (trade-based portfolio weight changes) rather than static portfolio weights in our predictive models of stock alphas. We find that stock alphas estimated using fund buys work well in predicting stock returns, but that alphas estimated using fund sales are much less informative, which is likely due to the effect of short-sale constraints that are self-imposed by most mutual funds.

Further, we show that the performance of our stock alpha estimators is not particularly related to the aforementioned forecasting model using aggregate fund trading of Chen, Jegadeesh, and Wermers (2000), or to the effect of changes in the breadth of mutual fund ownership documented by Chen, Hong, and Stein (2002). Our forecasting model generates return spreads that are much higher than those of either paper, and the correlation of our stock rankings with those of either paper are very low. Our model also generates returns

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[2] The significant return-predictive power of forecasted alphas during the second quarter is valuable to investors in light of the time lag of portfolio disclosure. Under current SEC rules, mutual funds have sixty days after the fiscal quarter-end to file portfolio holdings through the EDGAR system.

that far exceed those of the prior-mentioned “copycat” portfolio approach of Frank, Poterba, Shackelford, and Shoven (2004). Thus, our models generate unique forecasts of stock alphas that are previously undocumented by the mutual fund literature.

It is also interesting to relate our approach to selecting stocks to the Cohen, Coval, and Pastor (2005) approach to picking mutual funds. Our model is related to theirs, in that we weight portfolio holdings by past alphas to improve investment selection. However, while Cohen, Coval, and Pastor (2005) show that this procedure improves the precision of picking funds, our results show that even greater gains can be made by applying the model to select individual stocks.

While investors may view our models as valuable stock-selection signals, an alternative interpretation of our results is that they provide stock-level evidence for the persistence of mutual fund manager skills. That is, by examining the returns of individual stocks chosen in common by skilled fund managers, we provide new evidence on the value of active management, beyond that of analysis at the fund level (e.g., Wermers (2003)). We add further insight in finding that the private information possessed by fund managers about future stock returns is relatively short-lived, lasting roughly one year, which implies that a typical skilled manager must trade frequently to deliver performance. This is consistent with the finding by Wermers (2000) that stocks held by funds with higher turnover tend to outperform their benchmarks.

We further examine the source of the remarkable success of our fund holding-based stock-picking signals. Since the existing literature documents a prominent role for stock return momentum in explaining fund performance persistence (e.g., Carhart 1997), we examine the relation between our stock alpha estimators and momentum signals. We find that the forecasted alphas from our models are indeed positively correlated with price momentum; however, we continue to find significant return-predictive power from our models after jointly controlling for 12 quantitative investment signals, including momentum. These 12 signals are based on several market anomalies documented in academic studies–constructed using information about stock characteristics (such as size, book-to-market, and momentum), accounting information, and analyst forecasts. Therefore, the performance of our stock alpha estimators reflect private skills possessed by active mutual fund managers that are unexplained by known anomalies–these skills can be attributed to superior fundamental analysis by active managers. As such, our study is the first to distinguish between mutual fund performance based on two different types of stock selection processes–fundamental and quantitative research.

We also find that the market apparently partially reacts to the information contained in the disclosure of fund portfolio holdings. That is, stocks that our models rank highly exhibit returns that are much higher than low-ranked stocks during weeks 6 through 9 following the portfolio snapshot date, which likely reflects that funds may delay the disclosure of this snapshot for a maximum of 8 weeks.

Finally, we analyze the performance of stock alphas conditional on fund characteristics and stock characteristics. Our analysis suggests that smaller and older funds, and funds with lower expense ratios, higher turnover, and higher industry concentration of portfolio holdings are more likely to exhibit persistent skills. Further, fund managers with persistent skills exhibit slightly better skills when selecting smaller stocks, and exhibit significantly better skills at picking stocks with higher breadth of mutual fund ownership and lower return volatility. However, managers pick value and growth stocks equally well. In an out-of-sample setting, our conditional models that incorporate information about stock characteristics generate alpha forecasts that outperform those of our unconditional models.

The remainder of the paper proceeds as follows. Section II introduces model assumptions and develops three stock alpha estimators. In Section III, we describe the data and empirical methodology of this paper. Section IV presents empirical results. Section V concludes.

II. Stock Alpha Estimators

II.A. Assumptions

Suppose there are M mutual funds that jointly hold N unique stocks. Our stock alpha estimators are based on the following three assumptions.

First, we assume that the alpha of a fund is the weighted average alpha of stocks held by the fund. That is,

$$\alpha^f_{jt+1} = \sum_{i=1}^{N} \omega_{ijt}\alpha^s_{it+1} \tag{1}$$

where ω_{ijt} is the portfolio weight of fund j on stock i at time t, while α^f_{jt+1} is the *pre-expense* fund alpha and α^s_{it+1} is the stock alpha for the period from t to t+1. The above equation holds exactly when a fund employs a buy-and-hold strategy during the period. If the fund trades, (1) holds in approximation due to the effect of interim trading and transaction costs.

The second assumption is that pre-expense fund alphas persist. That is, funds with higher alphas in the past tend to have higher alphas in the future. We model such persistence by assuming an AR(1) process for fund alphas:

$$\alpha^f_{jt+1} = \alpha_0 + \rho\alpha^f_{jt} + \xi_{jt+1} \tag{2}$$

where α_0 is a constant, which is innocuously set to zero, and ρ is a constant between 0 and 1; for simplicity of illustration below, we assume it is the same across all funds. In a later section of this paper, we will relax this assumption to allow ρ to be a function of fund characteristics. In addition, ξ_{jt+1} is an error term that is independent of α^f_{jt}.

Finally, we assume that past fund alphas are observed with noise:

$$\hat{\alpha}^f_{jt} = \alpha^f_{jt} + \epsilon_{jt} \tag{3}$$

where α^f_{jt} is the true, but unobserved fund alpha, $\hat{\alpha}^f_{jt}$ is the observed or estimated fund alpha, and ϵ_{jt} is the estimation error. Fund alphas can be estimated, for example, from past fund returns using the CAPM, the Fama-French three-factor model, or the Carhart four-factor model, or from past fund portfolio holdings using the stock selectivity measure of Daniel, Grinblatt, Titman, and Wermers (1997).

Combining (1), (2), and (3), we have

$$\sum_{i=1}^{N} \omega_{ijt}\alpha^s_{it+1} = \rho(\hat{\alpha}^f_{jt} - \epsilon_{jt}) + \xi_{jt+1} \tag{4}$$

Let $e_{jt+1} = \rho\epsilon_{jt} - \xi_{jt+1}$; note that e_{jt+1} has zero autocorrelation, as long as the error in alpha estimation (ϵ_{jt}) and shocks to true alphas (ξ_{jt}) are uncorrelated white noise. The above can be further expressed as

$$\rho\hat{\alpha}^f_{jt} = \sum_{i=1}^{N} \omega_{ijt}\alpha^s_{it+1} + e_{jt+1} \tag{5}$$

Now let $\hat{\boldsymbol{\alpha}}^f = (\hat{\alpha}^f_{1t} \quad \hat{\alpha}^f_{2t} \quad ... \quad \hat{\alpha}^f_{Mt})'$, $\boldsymbol{\alpha} = (\alpha^s_{1t+1} \quad \alpha^s_{2t+1} \quad ... \quad \alpha^s_{Nt+1})'$, and let $\boldsymbol{e} = (e_{1t+1} \quad e_{2t+1} \quad ... \quad e_{Mt+1})'$. Further, let W be the M by N matrix of portfolio weights:

$$W = \begin{pmatrix} \omega_{11t} & \omega_{21t} & \cdots & \omega_{N1t} \\ \omega_{12t} & \omega_{22t} & \cdots & \omega_{N2t} \\ \cdots & \cdots & \cdots & \cdots \\ \omega_{1Mt} & \omega_{2Mt} & \cdots & \omega_{NMt} \end{pmatrix}$$

Then (5) can be written in matrix form as

$$\rho\hat{\boldsymbol{\alpha}}^f = W\boldsymbol{\alpha} + \boldsymbol{e} \tag{6}$$

Here we have dropped the time subscript for notational convenience. The error terms in $\boldsymbol{e}$ are assumed to be white noise with zero mean and covariance Ω.

II.B. Solutions

Equation (6) describes the relation of stock alphas, $\boldsymbol{\alpha}$, with observed fund alphas, observed portfolio weights, and random error terms from the data generating processes (2) and (3). Our goal is to obtain the expected value of future stock alphas, conditional on observed fund alphas and portfolio weights, $E_t(\boldsymbol{\alpha}|\hat{\boldsymbol{\alpha}}^f, W)$, which we refer to as a "stock alpha estimator." In the following, we describe several stock alpha estimators under both frequentist and Bayesian approaches.

II.B.1. OLS and GLS Estimators

First, consider two standard frequentist stock alpha estimators. The frequentist approach treats $\boldsymbol{\alpha}$ as a nonrandom vector in (6). In addition, we assume that ρ is a known positive constant, and $W'W$ is invertible. Then, the OLS estimator for $\boldsymbol{\alpha}$ is

$$\hat{\boldsymbol{\alpha}}_{OLS} = \rho(W'W)^{-1}W'\hat{\boldsymbol{\alpha}}^f \tag{7}$$

The GLS estimator takes into account the covariance structure of the error term $\boldsymbol{e}$ in (6):

$$\hat{\boldsymbol{\alpha}}_{GLS} = \rho(W'\Omega^{-1}W)^{-1}W'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f \tag{8}$$

Note that ρ affects the magnitude of stock alphas proportionally. Therefore, as long as $\rho > 0$, it does not affect the cross-sectional ranking of the forecasted stock alphas. On the other hand, if there is no performance persistence, $\rho = 0$, and both $\hat{\boldsymbol{\alpha}}_{OLS}$ and $\hat{\boldsymbol{\alpha}}_{GLS}$ are zero. In this case, the stock alpha estimators have no power in predicting future stock returns.

In empirical implementation, several problems render the OLS and GLS estimators impractical. First, the number of stocks (N) is usually larger than the number of funds (M). Therefore $W'W$ and $W'\Omega^{-1}W$, both N×N matrices, are singular and not invertible. Second, even if M $\geq$ N (e.g., if we were to examine a subgroup of stocks), $W'W$ and $W'\Omega^{-1}W$ would generally be of very large dimension, and numerical inversion of such large matrices is often inaccurate. Finally, for the GLS estimator, the estimation and inversion of Ω may cause additional problems.

II.B.2. Three Feasible Estimators

To overcome these problems, we consider three feasible stock alpha estimators. The first two are based on frequentist approaches, while the third is based on a Bayesian approach.

1. The Weighted-Average Alpha

First, consider a variation of the OLS estimator (7). Since the inversion of $W'W$ is often infeasible or highly inaccurate, we replace it with a diagonal matrix. Essentially, this is equivalent to assuming that information about future stock returns is mainly contained in the term $W'\hat{\boldsymbol{\alpha}}^f$, which leads to an estimator of the form:

$$\hat{\boldsymbol{\alpha}} \propto \rho W'\hat{\boldsymbol{\alpha}}^f \tag{9}$$

Based on this general form, we develop a weighted-average alpha estimator:

$$\hat{\boldsymbol{\alpha}}_{WAA} = \rho[W'\hat{\boldsymbol{\alpha}}^f]./[W'\iota] \tag{10}$$

where ./ is the element-by-element division operator, and ι is a unit vector. This means that each element of $\hat{\boldsymbol{\alpha}}_{WAA}$ is

$$\hat{\alpha}^s_{it+1} = \frac{\rho \sum_{j=1}^{M} \omega_{ijt}\hat{\alpha}^f_{jt}}{\sum_{j=1}^{M} \omega_{ijt}} \tag{11}$$

In (11), the alpha of a stock is the weighted average of fund alphas, where the weights are proportional to portfolio weights, ω_{ijt}. Intuitively, the portfolio weight, ω_{ijt}, measures the size of the "bet" by a fund manager (i.e., the level of information that the manager has about stock i at time t), whereas the past fund alpha, $\hat{\alpha}^f_{jt+1}$, measures the precision of the manager's private information. Computation of the weighted-average alphas does not involve numerical inversion of large matrices, and therefore is fast and potentially robust.

2. The Generalized-Inverse Alpha

The second feasible stock alpha estimator is based on generalized inversion, a statistical approach that deals with singularity or near-singularity problems in matrix inversion (Moor (1920) and Penrose (1955)). Let V be the N×N matrix consisting of all N eigenvectors for $W'W$, and D be the N×N diagonal matrix of eigenvalues. By definition $W'W = VDV'$. When $W'W$ is non-singular, it is known that $(W'W)^{-1} = VD^{-1}V'$. When $W'W$ is singular, some diagonal elements of D are zero, and D is not invertible. Now, let d_{ii} be the i-th diagonal element of D, and define D^+ as a diagonal matrix with the i-th diagonal element d^+_{ii}, where $d^+_{ii} = d^{-1}_{ii}$ if $d_{ii} > 0$ and $d^+_{ii} = 0$ if $d_{ii} = 0$. The generalized inverse of $W'W$ is then VD^+V', and the generalized-inverse estimator for the stock alpha vector is

$$\hat{\boldsymbol{\alpha}}_{GIV} = \rho(VD^+V')W'\hat{\boldsymbol{\alpha}}^f \tag{12}$$

There are N eigenvalues for the matrix $W'W$. In empirical implementation, we keep the first M/2 eigenvalues of $W'W$ and treating the remaining (N-M/2) eigenvalues as zero, where M is the number of funds.

3. The Bayesian Alpha

Under the Bayesian approach, stock alphas, $\boldsymbol{\alpha}$, are recognized as random variables, and our objective is to obtain their posterior means.

Let the prior distribution for the stock alpha vector be $\boldsymbol{\alpha} \sim N(\mu, \Sigma)$. Combining this prior with (6), together with the assumption $\boldsymbol{e} \sim N(0, \Omega)$, it is easy to show that

$$\hat{\boldsymbol{\alpha}}_{BYS} = E_t(\boldsymbol{\alpha}|\hat{\boldsymbol{\alpha}}^f, W) = \rho(W'\Omega^{-1}W + \Sigma^{-1})^{-1}(W'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f + \Sigma^{-1}\mu) \tag{13}$$

Under the reasonable prior that $\mu = 0$ and $\Sigma = \sigma^2 I$ (I is the identity matrix), the Bayesian estimator reduces to

$$\hat{\boldsymbol{\alpha}}_{BYS} = \rho(W'\Omega^{-1}W + \sigma^{-2}I)^{-1}W'\Omega^{-1}\hat{\boldsymbol{\alpha}}^{f} \tag{14}$$

Since $W'\Omega^{-1}W + \sigma^{-2}I$ is the sum of a semi-positive definite matrix and a diagonal matrix, it is always positive definite and invertible.

In the above, for illustration purposes, we have treated the estimated fund alpha vector, $\hat{\boldsymbol{\alpha}}^{f}$, as observed with normal errors. In empirical implementation, we use the Bayesian approach to estimate both fund alphas and stock alphas, taking into account the fact that the posterior distribution of fund alphas is typically non-normal. Without complicating the discussion here, we leave the details of the procedures to Appendix A.

Interestingly, (14) can also be derived under the frequentist approach as a *ridge*-regression estimator. See, for example, Hoerl and Kennard (1970).

II.B.3. Relation with Fund Performance Measure of Cohen et al. (2005)

Based on the intuition that skilled fund managers tend to make similar investment decisions, Cohen, Coval, and Pastor (2005) develop a measure of fund performance as the weighted average of alphas of all funds in the sample, with the weights related to the similarity of portfolio holdings among funds. In empirical analysis they show that this measure does better in predicting future fund performance than do fund alphas estimated solely from past fund returns.

There is an interesting link between the fund performance measure of Cohen et al. and the weighted-average stock alpha in our study. To see this, note that their fund performance measure, $\bar{\delta}^{*}_{m}$, can be expressed as (in their Equation (4)):

$$\bar{\delta}^{*}_{m} = \sum_{i=1}^{N} \omega_{m,n} \bar{\bar{\delta}}_{n} \tag{15}$$

where $\omega_{m,n}$ is the observed portfolio weight of fund m on stock n, and $\bar{\bar{\delta}}_{n}$ is their measure of stock quality. The weighted-average stock alpha estimator, $\hat{\boldsymbol{\alpha}}_{WAA}$, turns out to be the same as their stock quality measure, $\bar{\bar{\delta}}_{n}$ (defined in their Equation (1)). That is, the weighted-average stock alpha is an input to their fund performance measure.

Given the equivalence between the weighted-average stock alpha estimator and $\bar{\bar{\delta}}_n$, our assumption (1) is equivalent to (15). Since $\bar{\bar{\delta}}_n = \hat{\alpha}_{WAA}$ is a predictor of future stock alpha, naturally $\bar{\delta}^*_m$ can be interpreted as a predictor of future fund alpha. This provides an intuitive interpretation of their fund performance measure.

II.C. Trade-based Alphas

The stock alpha estimators in (10), (12), and (14) are all based on portfolio weights. We can also develop stock alpha estimators based on mutual fund trades, i.e., portfolio weight changes. To start with, we decompose portfolio weights into:

$$W_t = W_{t-1} + \Delta W^+ + \Delta W^- \tag{16}$$

where W_t is the portfolio weight matrix at time t, W_{t-1} is the lagged portfolio weight matrix, ΔW^+ is the positive part of portfolio weight changes from t-1 to t, i.e, weight changes due to recent mutual fund buys, and ΔW^- is the negative part of portfolio weight changes from t-1 to t, i.e., weight changes due to recent fund sells.

Based on the above, the weighted-average estimator of stock alpha (10) can be decomposed into:

$$\hat{\boldsymbol{\alpha}}^L_{WAA} = \rho[W'_{t-1}\hat{\boldsymbol{\alpha}}^f]./[W'_t\iota] \tag{17}$$

$$\hat{\boldsymbol{\alpha}}^B_{WAA} = \rho[(\Delta W^+)'\hat{\boldsymbol{\alpha}}^f]./[W'_t\iota] \tag{18}$$

$$\hat{\boldsymbol{\alpha}}^S_{WAA} = \rho[(\Delta W^-)'\hat{\boldsymbol{\alpha}}^f]./[W'_t\iota] \tag{19}$$

It is easy to see that $\hat{\boldsymbol{\alpha}}_{WAA} = \hat{\boldsymbol{\alpha}}^L_{WAA} + \hat{\boldsymbol{\alpha}}^B_{WAA} + \hat{\boldsymbol{\alpha}}^S_{WAA}$.

Similarly, we can decompose the generalized-inverse estimator (12) and the Bayesian estimator (14) into:

$$\hat{\boldsymbol{\alpha}}^L_{GIV} = \rho V D^+ V' W'_{t-1}\hat{\boldsymbol{\alpha}}^f \tag{20}$$

$$\hat{\boldsymbol{\alpha}}^B_{GIV} = \rho V D^+ V'(\Delta W^+)'\hat{\boldsymbol{\alpha}}^f \tag{21}$$

$$\hat{\boldsymbol{\alpha}}^S_{GIV} = \rho V D^+ V'(\Delta W^-)'\hat{\boldsymbol{\alpha}}^f \tag{22}$$

and

$$\hat{\boldsymbol{\alpha}}^L_{BYS} = \rho(W'_t\Omega^{-1}W_t + \sigma^{-2}I)^{-1}W'_{t-1}\Omega^{-1}\hat{\boldsymbol{\alpha}}^f \tag{23}$$

$$\hat{\boldsymbol{\alpha}}^B_{BYS} = \rho(W_t'\Omega^{-1}W_t + \sigma^{-2}I)^{-1}(\Delta W^+)'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f \tag{24}$$

$$\hat{\boldsymbol{\alpha}}^S_{BYS} = \rho(W_t'\Omega^{-1}W_t + \sigma^{-2}I)^{-1}(\Delta W^-)'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f \tag{25}$$

Note that, in all stock alpha estimators, the role of ρ is a constant multiplier. In empirical implementation, we assume that $\rho = 1$. Since we use sorted portfolios and cross-sectional regressions to evaluate the performance of stock alpha estimators, our conclusions are not affected by the specific value of ρ, as long as it is positive (i.e., there is persistence in skills, and not reversals).

III. Data and Empirical Methodology

III.A. Data

Mutual fund data are from two sources. First, the CDA/Spectrum data from Thomson Financial provide information on mutual fund portfolio holdings and self-declared investment objectives at either quarterly or semi-annual frequency. Second, the CRSP survivor-bias free mutual fund database provides information on monthly fund returns as well as fund characteristics such as total net assets, load, turnover, expense ratio, etc. Funds in these two databases are matched together using the MFLINKS dataset (available from Wharton Research Data Services, WRDS). The sample period for our study is from the first quarter of 1980 to the last quarter of 2002. Since our focus is on actively managed US equity funds, we only include funds with the investment objectives of aggressive growth, growth, or growth and income in the CDA dataset. We take an additional step to manually screen all funds to exclude index funds, foreign-based funds, US-based international funds, fixed-income funds, real estate funds, precious metal funds, balanced funds, closed-end funds, and variable annuities that have reported investment objectives among one of the above three. For the CRSP fund data, we treat different share classes of the same fund as a single fund–funds returns are computed as the weighted average returns across share classes, with weights proportional to the total net assets of each class. In addition, we obtain stock return data from CRSP, corporate accounting information from Compustat, and analyst earnings forecasts from IBES.

Table I provides summary statistics for the mutual fund sample. We report the number of funds in our sample, and the number of stocks they hold, at the end of each year from 1980 to 2002. In our sample, there are 247 actively-managed, domestic equity funds that report portfolio holdings for December 1980. They collectively hold 2,030 unique common stocks, and the market value of their aggregate equity holdings is \$30.89 billion. By comparison, there are 4,877 unique common stocks in the entire CRSP universe, with a total market capitalization of \$1,320.32 billion. The number of funds, the number of unique stocks held by these funds, and the market value of their equity holdings increase quickly during the sample period, except during the last several years. There are 935 actively-managed, domestic equity funds reporting portfolio holdings for December 2002, which collectively hold 3,889 unique common stocks. The market value of their equity holdings reaches \$945.88 billion. At the same time, there are 5,263 unique common stocks in the CRSP universe, with a total market value of \$9,940.55 billion. Note that the number of funds is always lower than the number of stocks in the sample.

III.B. Calculating Portfolio Weights and Weight Changes

Since our interest is in the persistent stock selection ability of mutual funds, we focus on the equity portion of a fund portfolio with the assumption that investments in non-equity securities do not contribute to fund alphas. Therefore, we compute fund portfolio weights as:

$$\omega_{ijt} = \frac{s_{ijt} p_{it}}{\sum_{i=1}^{N} s_{ijt} p_{it}} \tag{26}$$

where s_{ijt} is the number of shares of stock i held by fund j at the end of quarter t, and p_{it} is the price of stock i at the end of quarter t. Similarly, we compute fund portfolio weight change as:

$$\Delta\omega_{ijt} = \frac{(s_{ijt} - s_{ijt-1}) p_{it}}{\sum_{i=1}^{N} s_{ijt} p_{it}} \tag{27}$$

where, for funds disclosing holdings quarterly, s_{ijt-1} is the number of shares of stock i held by the fund at the end of quarter t-1. If a fund discloses holdings semiannually, s_{ijt-1} refers to the fund's position in stock i two quarters ago. For any $\Delta\omega_{ijt}$ to be included in our sample, we require that the two consecutive reporting dates be no more than two quarters apart. To control for the effect of stock splits, we adjust the lagged holding, s_{jit-1}, using the share adjustment factor from CRSP to an equivalent shareholding at the end of quarter t.

Some funds report portfolios held at dates other than quarter-ends. In these cases, we assume that all holdings reported within a calendar quarter are valid at the quarter-end (adjusting for splits).

III.C. Measuring Fund Alphas and Stock Portfolio Performance

We use two measures of fund performance and stock portfolio performance in this paper – the returns-based four-factor model of Carhart (1997), and its analogue using portfolio holdings, i.e., the characteristic-based performance measure of Daniel, Grinblatt, Titman, and Wermers (DGTW; 1997). We prefer the returns-based measure of fund performance, as unobserved actions of fund managers may impact performance measured using infrequent portfolio holding snapshots (see Kacperczyk, Sialm, and Zheng (2006)). On the other hand, we use the DGTW characteristic-based approach to measure the future buy-and-hold performance of stocks chosen by our models (where there are no unobserved actions), since this measure has more power in detecting abnormal returns (see DGTW for a discussion of this issue). Nonetheless, in untabulated results, we also apply the DGTW approach to measure fund performance – these results are discussed in Section IV.A.1.

III.C.1. Measuring Fund Alphas

To measure lagged mutual fund performance, we use the four-factor model of Carhart (1997):

$$r_t - r_{ft} = \alpha + \beta_1(r_{mt} - r_{ft}) + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \beta_4 \text{UMD}_t + e_t \tag{28}$$

where r_t is the *pre-expense* monthly fund return, computed as the net fund return plus 1/12 the annual expense ratio. The riskfree rate, r_{ft}, is the yield on treasury bills with one-month maturity, obtained from CRSP. The market return, r_{mt}, is the CRSP value-weighted NYSE/AMEX/Nasdaq index return, while SMB_t, HML_t, and UMD_t are monthly size, book-to-market, and momentum factor returns, obtained from Ken French's website.

The regression is performed at the end of each quarter from 1980 to 2002, on a rolling basis, using the prior 12 months of data.

III.C.2. Measuring Stock Portfolio Performance

To evaluate the buy-and-hold performance of stock portfolios that result from applying our proposed stock alpha estimators, we compute the characteristic-adjusted return of each stock during each month with the characteristic benchmarks developed by DGTW and modified by Wermers (2003).[3] Specifically, in June of each year, we identify a benchmark portfolio for each common stock in the CRSP universe with a sequential triple-sorting procedure. First, we rank all common stocks on their market capitalization at the end of June, using NYSE size breakpoints, and cut into quintiles. Then, within each size quintile, we rank stocks on their industry-adjusted book-to-market ratio (BTM), where fiscal year-end book value is measured during the calendar year prior to that June, and market value is measured on December 31 of that prior calendar year (see Wermers (2003) for details about calculating industry-adjusted book-to-market ratios). Finally, within each of the 25 size-and-BTM ranked groups, we further rank stocks into quintiles based on their returns during the prior June 1 to May 31 period. Sometimes, a stock may have missing characteristics and therefore cannot be assigned to any of the above 125 groups. An additional group is created for these stocks.[4] The characteristic group designation for each stock is fixed during the following 12 months. Within each of the 126 stock groups, we form quarterly-rebalanced, equal-weighted, benchmark portfolios. Since we exclude stocks with a beginning-of-quarter price below $5 when evaluating our stock alpha estimators (see Section IV.A), we similarly exclude these stocks from benchmark portfolios. We then compute quarterly buy-and-hold returns for these 126 portfolios. Finally, characteristic-adjusted stock returns are quarterly buy-and-hold individual stock returns, in excess of their respective benchmark portfolio returns.

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[3] These benchmark portfolio assignments are available at:
http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[4] All results that we report in later sections are very similar when we exclude portfolio holdings that fall within this 126^{th} group.

IV. Empirical Evidence

IV.A. Performance of Forecasted Stock Alphas

At the end of each quarter (referred to as the portfolio formation quarter, or Q0) during the period from 1980 to 2002, we estimate stock alphas using various estimators developed in Section II. Then, we sort stocks into decile portfolios according to the forecasted stock alphas, and examine their equal-weighted returns during the following four quarters (denoted as Q1 to Q4, the performance evaluation quarters). We impose the following two restrictions to ensure that the portfolio strategies can be realistically implemented. First, we only rebalance the portfolios quarterly, so that they have equal weights at the beginning of each evaluation quarter. Second, to avoid biases due to microstructure issues as well as to limit the impact of transaction costs (which are not included in our analysis), we require a stock to have a minimum price of \$5 at the beginning of an evaluation quarter to be included in any decile portfolio for that quarter.

We calculate quarterly net returns and characteristic-adjusted returns of the decile portfolios during Q1, Q2, Q3, and Q4, then compute their time-series averages. For instance, the average Q1 return that we report is computed as the time-series average return of a rolling strategy. The first Q1 return of this strategy is that accruing during April 1, 1980 to June 30, 1980 to equal-weighted portfolios of stocks selected on March 31, 1980. The second is that accruing during July 1, 1980 to September 30, 1980 to portfolios selected on June 30, 1980, and so on. If a stock becomes delisted during an evaluation quarter, we assume that the return of this stock during the remainder of the quarter is the CRSP delisting return. Following Shumway (1997), when the delisting return is missing, we replace it with -30% if the delisting is performance related, and zero otherwise. Naturally, delisted stocks are excluded from the portfolios for subsequent evaluation quarters.

IV.A.1. Stock Alphas Based on Fund Holdings

The performance of stock alphas estimated using fund holdings is reported in Table II. In Panel A, stock alphas are based on the weighted average alpha approach. For stocks in the bottom decile (D1) of forecasted alphas, the time-series average return during Q1 is 2.21%.

As the portfolio rank increases (from D1 to D10), the average portfolio return increases monotonically. For stocks in the top decile of forecasted alphas (D10), the average return is 5.25%; the return spread between top and bottom deciles is a statistically significant 3.05%. During the three subsequent evaluation periods (Q2, Q3, and Q4), returns across stock deciles exhibit a similar increasing trend. During Q2, the spread between D10 and D1 portfolios is 2.53%, while in Q3 and Q4, they are 1.17% and 1.09%, respectively–however, the Q4 spread is statistically insignificant. Compounding from Q1 to Q4, the return spread totals 8.06% per year–economically, a very large spread.

The results for characteristic-adjusted returns are similar. In Q1, the average characteristic-adjusted return to the D1 portfolio is -1.12%, versus 1.51% for the D10 portfolio. The return spread between these two portfolios is 2.63%, slightly lower than the net return spread, but with a slightly higher t-statistic (4.18 vs. 3.96). For Q2, Q3, and Q4, the characteristic-adjusted spreads are 2.20%, 1.06%, and 1.06%, respectively–slightly lower than the net return spreads, but all are now statistically significant (at the 10% level). Compounding over the four quarters, the characteristic-adjusted return spread between top and bottom deciles is 7.12% per year–a very large return, adjusted for size, book-to-market, and momentum.[5]

In Panel B, stock alphas are based on the generalized inverse approach. From Q1 to Q4, the net return spreads between top and bottom deciles are 2.24%, 1.66%, 0.80%, and 0.58%, respectively, with the first three quarterly spreads being statistically significant. The characteristic-adjusted return spreads during the four quarters are 2.09%, 1,57%, 0.85%, and 0.66%, respectively, all of which are significant. Note that the net return and characteristic-adjusted spreads are slightly lower than those under the weighted average approach in Panel A. However, t-statistics are higher (except for Q4), suggesting that the generalized inverse

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[5] The pattern of decreasing return spreads as we progress from Q1 to Q4 suggests that return-predictive information possessed by fund managers with persistent skills is relatively short-lived. This provides a perspective to why mutual funds trade so frequently, with an average turnover ratio of around 100% per year. It is also consistent with the finding in the literature that stocks held by funds with higher turnover tend to have better performance (Wermers (2003)). Indeed, perhaps it is the disclosure itself that leads to quickly dissipating fund manager skills–their best ideas are quickly revealed to the market. We will provide some evidence supportive of this idea when we examine weekly returns surrounding disclosure in a later section.

approach produces more accurate return-predictive signals. Therefore, if the objective is to maximize the Sharpe ratio (or information ratio) instead of merely the abnormal return of the investment strategy, the generalized inverse approach may be preferable.

In Panel C, we estimate stock alphas using the Bayesian approach, with detailed procedures described in Appendix A. From Q1 to Q4, the net return spreads between top and bottom deciles of stocks are 3.01%, 2.10%, 0.81%, 0.63%, with Q1 through Q3 exhibiting statistical significance. Characteristic-adjusted spreads are 2.60%, 1.97%, 1.04%, and 0.60% (again, only Q4 is insignificant). Again, spreads are slightly lower in magnitude than those under the weighted average approach, but t-statistics are higher for Q1, Q2, and Q3.

The last three rows of the table report time-series correlations between return spreads obtained using the three different approaches. All correlations between net return spreads exceed 0.80. Correlations between characteristic-adjusted return spreads are only slightly lower, with the lowest exceeding 0.50. Simply put, returns generated by the three alpha-estimation strategies are highly correlated, and appear to capture similar private information from portfolio holdings.

For robustness, we examine (in untabulated results) value-weighted net returns and characteristic-adjusted returns for the spread portfolios. We find results that are similar to those of the equal-weighted portfolios described above, except that value-weighted spreads during Q3 are insignificant. For instance, value-weighted characteristic-adjusted return spreads (between portfolios D10 and D1) for the holding-based weighted average alpha model are 2.3% and 2.1% during Q1 and Q2, respectively, and both are statistically significant. These spreads are similar to the equal-weighted spreads described above. We further examine (in untabulated results) alpha-weighting the portfolios, where each stock is weighted (within a given decile portfolio) by its forecasted alpha. Here, results are slightly stronger compared to the equal-weighted spreads. Specifically, characteristic-adjusted spreads for the holding-based weighted average alpha model during the four quarters are 3.1%, 2.5%, 1.2%, and 1.2%, respectively, and all are statistically significant.

As an alternative approach to measuring the past performance of fund managers, we use portfolio holdings (instead of the Carhart four-factor returns-based model) to compute the characteristic-adjusted performance of each fund. In untabulated results, we find that this holding-based approach to measuring past fund performance, and, thus, to ranking stocks performs much worse than the returns-based approach. For instance, the (equally-weighted) characteristic-adjusted returns of the spread portfolio (D10 minus D1) for the holding-based weighted average alpha model are only significant (marginally) during Q1 when we measure past performance of funds using their holdings. This reinforces the idea that we must use returns to measure fund performance, due to performance-affecting hidden manager actions that are not revealed though infrequent portfolio holdings disclosures.

At this point, we may wonder whether, for example, an overweighting by an outperforming manager or an underweighting by an underperforming manager contributes more to the success of buying highly ranked stocks from our model. To explore this issue, we generate our holding-based weighted average alpha model separately for managers with positive and negative past alphas. Thus, for example, the version of the model that is constrained to use holdings only for positive alpha funds generates a positive signal for a stock that is heavily held in common among these skilled managers, without regard to whether unskilled managers are underweighting or overweighting that stock. Results using either the subsample of outperformers or underperformers are weaker than the full sample, which indicates that information obtained from both skilled and unskilled managers is important to the return-forecasting success of our model.

In sum, stock alphas estimated using fund holdings have significant power in predicting stock returns. Such predictive power is not explained by stock characteristics including size, book-to-market, and momentum; after characteristic adjustment, return spreads between top and bottom decile portfolios remain economically large and exhibit even stronger statistical significance than unadjusted return spreads. The high correlations among return spreads obtained under the three different approaches indicates that the private information that we are capturing is strong enough to be robust to our different approaches of capturing it.

It is also worth noting that our forecasted stock alphas can predict returns beyond the first quarter after portfolio formation, making it feasible to exploit such stock return predictability after fund portfolio disclosure. According to current SEC regulations, funds are required to report their holdings within 60 days after their fiscal quarter ends. This means that by the time an investor obtains information on fund holdings, a large part of Q1 has passed. Nonetheless, return predictability during Q2 to Q4 could still be exploited. For example, under the weighted average approach, the average characteristic-adjusted return spread during Q2 is 2.20% per quarter, which compounds to over 9% per year. In a later section of this paper, we will explore higher frequency stock returns (e.g., weekly) to further explore the patterns in returns following disclosure.

IV.A.2. Stock Alphas Based on Fund Trades

Next, we examine the performance of stock alphas based on recent fund buys and sells. In Table III, stock alphas are based on fund buys, estimated under the weighted average approach, the generalized inverse approach, and the Bayesian approach. When fund alphas are estimated with the weighted average approach, the characteristic-adjusted return spreads between the top and bottom alpha decile portfolios are significantly positive during Q1 and Q2, at 2.26% and 1.33%. However, during Q3 and Q4, the spreads are statistically insignificant. Results for analogous value-weighted or alpha weighted portfolios are qualitatively similar.

The patterns are similar for generalized-inverse alphas and Bayesian alphas. Again, relative to weighted-average alphas, both generalized-inverse alphas and Bayesian alphas produce smaller spreads in Q1 and Q2, but higher t statistics.

The high correlations between return spreads among the three approaches, as reported in the last three rows of the table, indicate robustness of the results. In addition (not reported in the table), we find high correlations between return spreads derived from buy-based alphas and spreads from holding-based alphas.

The stock alphas based on recent fund sells, as reported in Table IV, fare worse in predicting returns. Here, the return spread represents a strategy of buying an equal-weighted portfolio of stocks most heavily sold by underperforming funds (and lightly sold by outperformers), and selling stocks most heavily sold by outperforming funds (and lightly sold by underperfomers). Under all three approaches to stock alpha estimation, return spreads between top and bottom alpha deciles tend to be negative–during the first two evaluation quarters, Q1 and Q2, such spreads are often significantly negative. For example, under the weighted average approach, the characteristic-adjusted return spread is a significant -1.17%

for Q1. Under the generalized inverse and Bayesian approaches, characteristic-adjusted spreads during Q1 and Q2 are statistically significant (and negative). Again, value-weighting or alpha-weighting portfolios D1 and D10 gives qualitatively similar results.

The correlations of return spreads between the three sell-based approaches are positive. However (not tabulated), we find negative correlations between return spreads for sell-based alphas and return spreads for holding-based and buy-based alphas, indicating (in addition to the poor returns of the sell-based strategies) that information revealed by fund selling is different. Since buy-based alphas and sell-based alphas are two components of holding-based stock alphas, the results here suggest that stock alphas based on recent fund purchases positively contribute to the overall return-predictive power of holding-based alphas, while the contribution by sell-based alphas tends to be negative. There are two potential reasons why our sell-based strategies perform poorly. First, most mutual funds have a self-imposed constraint on short-selling that effectively eliminates it as a strategy. This constraint may limit the information revealed by selling of stocks. And, second, outperforming funds may sell stocks that are still potentially promising, in pursuit of stocks with an even better outlook; if true, then we cannot look to their sales as a signal of stocks being overpriced.

Although not tabulated in our paper, we find that stock alphas based on *lagged* portfolio holdings also contribute positively to the overall predictive power of holding-based alphas. In fact, the performance of alphas constructed using lagged holdings can be inferred from Table II. For example, the performance of holding-based stock alphas during Q2 and Q3 can be interpreted as the performance of alphas based on fund holdings with lags of one to two quarters.[6]

In further untabulated results, we examine the implied turnover of the top- and bottom-decile portfolios of stocks, as well as their concentration among industry groups. We find that top decile stocks, according to the ranking of one quarter, remain as top decile stocks

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[6] It is also interesting that our holding-based alpha signals outperform both the buy- and sell-based signals. Since current holdings are simply lagged holdings plus buys minus sells, this finding reinforces the notion that the market does not fully and immediately adjust to the information revealed by portfolio holdings– again, this leads to a significant Q2-Q4 return spread for our models. In untabulated tests, we combine the forecasts generated by the holding-based and buy-based versions of the weighted average alpha model. We find little improvement over forecasts generated solely by the holding-based model.

for the following-quarter's ranking about 35% of the time. Further, 52% of top decile stocks remain in the top two deciles, while 63% remain in the top three deciles of the following ranking quarter. Among bottom decile stocks, 37%, 55%, and 65% remain in the bottom decile, bottom two deciles, or bottom three deciles, respectively, during the following ranking quarter. When we examine the concentration of top- and bottom-decile portfolios within certain industry sectors, we find no particular difference between these two portfolios, on average over time.

IV.A.3. Comparison with Other Holding-Based Stock Signals

A few previous studies have also used information on mutual fund portfolio holdings or fund trades to predict stock returns. For example, Chen, Jegadeesh, and Wermers (2000) document that aggregate mutual fund trades have significant power to predict stock returns. They argue that this is because mutual funds, on average, are better stock pickers than unsophisticated individual investors. In addition, Chen, Hong, and Stein (2002) find that a decrease in the number of mutual funds holding a stock (lower breadth of ownership) is associated with lower future returns for that stock, as the negative outlook of many funds is not fully expressed through their portfolio holdings (due to the self-imposed short-sale constraint of most funds). In this section, we examine whether our forecasted stock alphas have return-predictive information beyond that already captured by aggregate mutual fund trades and changes in the breadth of ownership.

We follow Chen, Jegadeesh, and Wermers (2000) in defining the aggregate fractional mutual fund holding as the total number of shares of a stock held by all mutual funds divided by the total number of shares outstanding of that stock. The aggregate trading (TRADE) is the change in quarterly aggregate fractional holding. Following Chen, Hong, and Stein (2002), we define the breadth of ownership of a stock as the number of mutual funds who have a long position in the stock divided by the total number of mutual funds that exist during a given quarter. The change in the breadth of ownership is then defined as the difference in breadth of ownership (ΔBREADTH) between two consecutive quarters. Also following Chen, Hong, and Stein (2002), when calculating the change variable ΔBREADTH, we include only funds that report holdings for both of the two consecutive quarters.

In each quarter, we sort stocks into decile portfolios based on TRADE or ΔBREADTH, then examine portfolio returns during the next four quarters. Results for these sorted portfolios, reported in Panel A of Table V, confirm the prior-documented effects of aggregating trading and breadth of ownership. For TRADE, the net return spreads during Q1 and Q2 between top and bottom deciles are 1.07% and 0.84%, both of which are statistically significant. Characteristic-adjusted spreads are qualitatively similar. For ΔBREADTH, characteristic-adjusted spreads are a statistically significant 2.3%, 0.9%, and 1.1% during the first three quarters (Q1 to Q3).

To see whether TRADE and ΔBREADTH are related to our stock alpha estimators, we compute their cross-sectional Spearman rank correlations with our forecasted stock alphas during each quarter, then average these correlations over time. Our stock alphas are based on the weighted average approach, using fund holdings, buys, and sells, respectively. The results, reported in Panel B, suggest that the correlations are almost zero.

We further perform Fama-MacBeth regressions to compare the return-predictive power of Trades and ΔBreadth with that of our weighted-average stock alpha estimator. The (successive) dependent variables in the four cross-sectional regressions are the characteristic-adjusted stock returns during Q1, Q2, Q3, and Q4. The regressors include TRADE, ΔBREADTH, and the weighted-average alphas based on fund holdings, buys, and sells, respectively (in three sets of four cross-sectional regressions). The time-series average coefficients (except for the intercept) and their time-series t-statistics are reported in Panel C of Table V (using the Newey-West procedure with 2 lags).

Note that, even in the presence of TRADE and ΔBREADTH, the average coefficient for the holding-based alpha is significantly positive during each of the four evaluation periods (Q1 through Q4). In fact, coefficients for the holding- and buy-based weighted-average alpha signals exhibit higher significance levels than either TRADE or ΔBREADTH. However, ΔBREADTH captures information better than our sell-based weighted-average alpha signal, which reinforces the idea that the short-sale constraint results in sell activity of mutual funds not being particularly informative.

Overall, however, we conclude that our stock alpha estimator captures an aspect of stock return predictability different from that captured by aggregate fund trading or changes in the breadth of ownership.

IV.A.4. Further Extensions of the Basic Model

We investigate several extensions to the weighted average alpha stock selection model. For all extensions described here, decile portfolios are formed at the end of each calendar quarter (where stocks are ranked based on the weighted-average alpha model), then we examine the difference in following-year returns between the equal-weighted top and bottom deciles of stocks. Although these results are not tabulated, we describe them here.

First, we apply the weighted average alpha model only using holdings of the subgroups of funds having the most extreme inflows or outflows (the top or bottom 5% of funds, ranked by formation quarter flows as a percentage of lagged assets). We find that the buy-based weighted average alpha signal derived from heavy inflow funds outperforms that derived from heavy outflow funds during Q1 through Q3 (e.g., characteristic-adjusted return spreads during Q1 of 2.8% vs. 1.2% for inflow vs. outflow funds, respectively) – consistent with flows generating persistent stock returns, as documented by Wermers (2003). However, among funds with more moderate flows, the model does not generate substantially different signals between inflow and outflow subgroups.

We next divide funds into self-declared investment objective groups, each quarter, then compute return spreads based on the weighted average alpha signal derived from the holdings of each group alone. This approach might improve the forecasting power of our models, if funds within a certain group (e.g., aggressive growth) have no persistence in skills, and add only noise to our alpha model. The results from this exercise suggest that some differences in skill persistence exist among funds – e.g., growth-and-income funds produce a less precise holding-based weighted average alpha forecast than either aggressive growth or growth funds (i.e., the spread portfolio performs worse for growth-and-income funds). However, even growth-and-income funds produce a positive return spread during Q1. Further, we find that no subgroup generates a signal as good as the overall fund universe, which indicates that the increased estimation error from the reduced number of funds overwhelms any benefits that may arise from focusing on subgroups with higher average skill persistence.

We next implement the model using only portfolio holdings from funds that report quarter-end snapshots – ignoring the information contained in funds that report portfolios at other dates within the quarter. This approach allows us to synchronize fund holdings information, rather than using holdings data that is stale for some of the funds. We find little difference in return spreads for the quarter-end subsample of funds, relative to the full sample, which indicates that the higher noise in the signal (because of the smaller sample of funds with quarter-end reporting) offsets any increases in signal precision due to the fresher portfolio holdings.

We also investigate whether calendar effects are present by separately examining weighted average alphas generated from March, June, September, and December quarter-end portfolio holdings. For example, we average (across all years) the returns for the top minus bottom decile portfolio formed based on March 31 holdings, then held for one year. Similar average returns are computed for the other three quarter-end portfolios. The results show little variation in the success of our strategy over the four calendar quarters.

Initiating buys or terminating sales by mutual funds may carry a stronger signal of stock value than other trades, due to the short-sale constraint that is self-imposed by most funds. Alexander et al. (2005) find that initiating buys outperform terminating sales by 1.8year. Following this logic, we recompute our buy-based weighted-average alpha signal, using only initiating buys, and compare the resulting portfolio returns with our baseline strategy based on all fund buys (shown in Table III). The characteristic-adjusted D10 minus D1 portfolio return for the initiating buy weighted-average alpha is only about 1.5% during the following year, while our baseline buy model generates an adjusted return of 4.1%. We attribute the failure of the initiating buy strategy to two potential reasons. First, using the vastly reduced subsample of initiating buys likely adds substantial noise to our model. And, second, initiating buys are likely at least partly motivated by inflows, and not superior manager information about a stock. Results for the weighted-average alpha based only on terminating sales slightly outperforms the baseline sell model of Table IV – roughly 0.25% vs. -2.2% during the following year. Thus, terminating sales do add some forecasting power to our model.

Finally, we examine whether fund managers with better skills both trade more frequently and choose to disclose less often in an attempt to hide their strategies. We find only partial support for this idea. That is, higher turnover funds generate a better signal, but so do high disclosure frequency funds. However, the weighted-average alpha signal based on these subgroups do not generated substantially different returns from the signals based on the full sample of mutual funds.

IV.A.5. A Closer Look at Stock Returns Surrounding Portfolio Disclosure

Does the market react to the disclosure of portfolio holdings of informed money managers? If so, we should observe changes in stock prices during the weeks following the public disclosure of portfolio holdings. For stocks most widely held by top performing funds (and least widely held by underperformers), we should observe price increases, while for stocks most widely held by underperformers (least widely held by outperformers), we should observe price decreases. Although our results of the prior sections support this story, a closer look at higher frequency returns may add further insight.

Accordingly, we compute weekly returns, equal-weighted, for the top- and bottom-decile portfolios of stocks chosen by the weighted-average alpha model. These portfolios are formed at the end of each quarter Q0, and returns are computed during the weeks surrounding this portfolio holdings date. The results of this higher-frequency analysis are shown in Table VI. Note that the weekly returns are, in some cases, higher during the portfolio formation quarter (which ends at the date for which portfolio holdings are reported for most funds in our sample). For instance, for the holding-based model, weeks -3 and -2 exhibit return differences (between top- and bottom-decile portfolios) of 0.5 and 0.6%, respectively, which are higher than any single-week return during the first month following portfolio formation (weeks 1 through 4). While this result may partially reflect superior manager information that is uncovered with our weighted-average alpha model, it also reflects the greater use of momentum investing strategies of outperforming managers relative to underperformers (as documented by Grinblatt, Titman, and Wermers (1995)).

When we examine the returns of the spread portfolio for the holding-based weighted-average alpha model during weeks 1 through 12, an interesting pattern emerges. These returns appear to reach a peak during weeks 6 through 10; this result is notable, in light of the delay in the public release of fund holdings of up to 60 days following the end of the fiscal quarter. For most funds (those reporting a snapshot taken at the end of a calendar quarter), public disclosure likely occurs during weeks 5-8, as funds probably delay disclosure to maintain secrecy, especially when implementing their strategies through prolonged trade packages.

Similar results obtain for the buy-based weighted average alpha model, as shown in Panel B. A Wald test strongly rejects that the weekly means of D10-D1 return spreads are equal across weeks 1 through 12 using either holding-based or buy-based weighted average alphas (Panels A and B), but not for the sell-based model (Panel C). Again, disclosure of fund sales does not seem to be very informative about future stock values, and the market seems to know this. However, the market appears to react to public disclosure of fund holdings and to information about fund purchases that are implied by such holdings disclosure.

IV.B. Relation with Quantitative Investment Signals

One might question whether we have identified stocks for which managers truly possess private information on valuations. For instance, if top performing managers, measured with the four-factor model of Equation (28), are simply using prior-documented strategies that can beat this model (such as an accruals-based strategy documented by Sloan (1996)), then we might not conclude that our approach is truly uncovering private information about stocks. To further test our strategies, we next examine the relation of our forecasted stock alphas with several prior-documented stock return anomalies.

IV.B.1. Quantitative Investment Signals

Academic studies have found that cross-sectional stock returns are predictable based on several firm-specific financial and accounting variables, which are sometimes referred to as “quantitative characteristics" or “quantitative investment signals" (e.g., Jegadeesh, Kim, Krische, and Lee 2004). There is evidence that mutual funds trade on at least some of these variables, such as price momentum (e.g., Carhart 1997 and Grinblatt, Titman, and Wermers 1995).

We consider 12 quantitative investment signals documented in the prior literature. These signals are used by Jegadeesh et al. (2004) to determine the value of analyst stock recommendations. We follow their definition of these variables, and provide a detailed description of the construction of each variable in Appendix B. The quantitative investment signals are measured at the end of each quarter, from 1980Q1 to 2002Q4.

The first four variables are momentum signals. RETP and RET2P measure price momentum as stock returns during months -6 through -1 and months -12 through -7, respectively, before the last month of Q0. FREV measures earnings momentum of stocks as the sum of monthly analyst earnings forecast revisions scaled by stock price over the six months prior to the last month of Q0, while SUE measures earnings momentum as the standardized unexpected actual earnings, computed as the earnings increase from four quarters ago scaled by the standard deviation of such earnings increases during the previous eight quarters. Both price momentum and earnings momentum have been extensively analyzed in the literature. See, for example, Jegadeesh and Titman (1993), Bernard and Thomas (1989), and Chan, Jegadeesh, and Lakonishok (1996).

The next seven variables are contrarian signals. TURN is the exchange-specific percentile ranking of stock trading turnover during the past 6 months – Lee and Swaminathan (2000) show that high turnover stocks subsequently have lower returns. EP is the average earnings-to-price ratio during the past four quarters, while BP is the log book-to-market ratio at the end of Q0. A number of studies, including Basu (1977) and Fama and French (1992), show that high EP (BP) stocks subsequently outperform low EP (BP) stocks. LTG is the average analyst forecast, during the last month of Q0, of a firm's long-term earnings growth rate. SG is the one-year sales growth rate, averaged over the past four quarters. Lakonishok, Shleifer, and Vishny (1994) and La Porta (1996) show that investors tend to overvalue stocks with higher past sales growth or higher long-term growth expectations. Further, TA is the total accounting accruals during the past four quarters divided by total assets, averaged over the most recent quarter and four quarters ago. CAPEX is capital expenditures during the past four quarters divided by this same average total assets. Sloan (1996) shows that firms with high accruals tend to have low future returns, while Titman, Wei, and Xie (2004) report that firms with high capital expenditure have low future stock returns.

Finally, we include the log of stock market capitalization (SIZE) as a predictive signal. Small firms are shown to have better returns by a large number of studies (e.g., Banz (1981) and Reinganum (1981)).

We first perform univariate and multivariate Fama-MacBeth regressions to confirm the ability of these quantitative signals to predict stock returns, with results reported in Table VII. The dependent variables are stock returns during each of the next four quarters (Q1 to Q4). In the univariate regressions, the explanatory variable is each quantitative signal. In multivariate regressions, we use all 12 signals as joint regressors.[7] The regressions are performed each quarter, from 1980Q1 to 2002Q4. We report time-series averages of the quarterly regression coefficients (except for the intercepts) and their time-series t-statistics, which are computed using the Newey-West procedure with 2 lags. For multivariate regressions, we also report time-series averages of adjusted R-squares.

In univariate and multivariate regressions, most variables exhibit a significant ability to predict returns during at least one of the four evaluation quarters (Q1 to Q4), and the signs of the estimated coefficients are consistent with those documented in previous studies. There are a few exceptions. First, LTG has insignificant coefficients in both univariate and multivariate regressions. Second, the coefficients for a few variables – including FREV, TURN, EP, and SIZE, become insignificant or change sign when switching from univariate to multivariate regressions.

IV.B.2. Forecasted Stock Alphas and Quantitative Signals

We now examine the relation between the forecasted stock alphas of our weighted average alpha model and these 12 quantitative signals. Table VIII reports results for a series of Fama-MacBeth regressions. The dependent variable is the estimated stock alpha using the weighted-average approach, based on fund holdings, buys, and sells, respectively. In univariate regressions, the explanatory variable is one of the 12 signals. In multivariate regressions, all 12 signals are used as joint regressors. Cross-sectional regressions are performed during

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[7] During any given quarter, especially for early sample periods, a significant number stocks have missing signals. To avoid a substantial reduction in the sample size in multivariate regressions, we replace missing observations with the quarterly cross-sectional means of respective signals. A further issue is that LTG is not available before 1982. When performing univariate regressions with LTG as the explanatory variable, we start the sample period from 1982. For multivariate regressions, we do not include LTG during the sample period from 1980 to 1982. We use the same approaches for Tables VIII and IX, too.

each quarter, and we report time-series averages for coefficients, as well as the corresponding time-series t-statistics (computed using the Newey-West procedure with 2 lags). We also report time-series averages of adjusted R-squares for the multivariate regressions.

First, note the results for stock alphas estimated using fund holdings. These stock alphas have a strong momentum bent. For example, in both univariate and multivariate regressions, holding-based alphas have significant (and positive) loadings on three of the four momentum variables – RETP, RET2P, and FREV. However, with the exception of SG and SIZE (only in multivariate regressions), remaining coefficients are insignificant.

For stock alphas based on fund buys, similar weak patterns of correlation emerge. While FREV is no longer significant, BP is significant (in multivariate regressions). Stock alphas based on fund sells, on the other hand, tend to have very weak relations with quantitative signals. No loading is statistically significant.

Overall, the evidence suggests that our stock alphas based on fund manager holdings have very weak correlations with prior-documented strategies, with the exception of momentum. This finding appears to be consistent with previous literature, in that momentum trading is an important factor in explaining performance persistence; see, e.g., Carhart (1997).

IV.B.3. Forecasted Alphas, Quantitative Signals, and Stock Returns

To further confirm that our weighted average alpha signal contains unique information not previously documented, in Table IX, we run a “horserace" between forecasted stock alphas and quantitative signals to predict returns. Specifically, we generate quarterly Fama-MacBeth regressions, where the dependent variable is the stock return during one the four evaluation quarters (Q1 through Q4), and the explanatory variables include all 12 quantitative signals and one of the weighted-average stock alpha estimators (based on fund holdings, fund buys, or fund sells). We report time-series average estimated coefficients (except for the intercepts), the corresponding time-series t-statistics (computed with Newey-West consistent standard errors, using 2 lags), and time-series average adjusted R-squares for the regressions. Notably, loadings on the holding-based weighted average stock alpha are significantly positive for all four evaluation quarters, after controlling for the 12 quantitative signals. Loadings on the buy-based stock alpha are significantly positive for Q1 and Q2, while coefficients for the sell-based alpha are insignificant for all four quarters. It is also notable that regressing future stock returns on the 12 quantitative signals alone (Table VII) results in coefficients that are similar to those when adding the weighted average alpha as a 13^{th} signal (Table IX). This finding indicates a low correlation between the weighted average alpha signal and the signals provided by the 12 quantitative strategies.

Overall, the performance of holding-based and buy-based stock alphas remains significant after controlling for quantitative signals. That is, fund trading on momentum and other market anomalies does not explain the persistent skills of mutual fund managers in selecting stocks–the weighted average alpha model uncovers a significant level of persistence after controlling for the quantitative strategies.

What, then, is the source of the return-predictive power of our weighted average alpha and other models? We note that most fund managers make stock selection decisions based on fundamental analysis, a process that may enable fund managers to obtain private information about stock values. If this is the case, then fundamental analysis may be quite different from quantitative stock selection, which is based on publicly available investment signals. Therefore, our findings provide an interesting perspective for understanding the value of fundamental analysis vs. quantitative research. The results presented here suggest that fundamental and quantitative analyses capture different aspects of stock return predictability, and they are both useful in stock selection decisions.

IV.C. Further Analysis: Conditioning on Fund and Stock Characteristics

Our analysis so far assumes that 1) persistent stock selection skills are equally likely to exist across funds (by assuming a constant ρ in equation (2)), and 2) fund managers with persistent skills are equally skillful in selecting stocks with different characteristics. In this section, we relax these two assumptions to examine the effect of differential fund and stock characteristics on the performance of our forecasted stock alphas. Such an analysis may further expose factors that affect fund performance persistence, and may lead to an improved return-predictive performance of our stock alpha estimators.

IV.C.1. Effect of Fund Characteristics

First, we relax the assumption that the persistence parameter, ρ, in (2) is the same across all funds. To accomplish this, we model ρ as a function of several fund characteristics:

$$\rho_{jt} = d_0 + \sum_{p=1}^{P} d_p H_{jpt} \tag{29}$$

where H_{jpt} is the p^{th} characteristic measure (to be detailed later) of fund j at time t, and d_p is a constant parameter, for $p = 1, ..., P$. For ease of computation, we incorporate the above conditional persistence parameter into the weighted average alpha approach to obtain a stock alpha estimator conditional on fund characteristics,

$$\hat{\alpha}^H_{it+1} = \frac{\sum_{j=1}^{M} \omega_{ijt} \rho_{jt} \hat{\alpha}^f_{jt}}{\sum_{j=1}^{M} \omega_{ijt}} = d_0 \hat{\alpha}_{it+1} + \sum_{p=1}^{P} d_p \hat{\alpha}^H_{ipt+1}, \tag{30}$$

where $\hat{\alpha}_{it+1} = \sum_{j=1}^{M} \omega_{ijt} \hat{\alpha}^f_{jt} / \sum_{j=1}^{M} \omega_{ijt}$ is the unconditional holding-based weighted-average alpha, and

$$\hat{\alpha}^H_{ipt+1} = \sum_{j=1}^{M} \omega_{ijt} \hat{\alpha}^f_{jt} H_{jpt} / \sum_{j=1}^{M} \omega_{ijt} \tag{31}$$

is a characteristic-scaled stock alpha, in which the fund alpha, $\hat{\alpha}^f_{jt}$, is scaled by a fund characteristic measure, H_{jpt}, to calculate the stock alpha, $\hat{\alpha}^H_{ipt+1}$. In essence, the conditional alpha estimator amplifies the signal from certain types of funds which are likely to have a higher level of persistence.

We perform Fama-MacBeth regressions to estimate parameters d_0 and d_p. Specifically, in each formation quarter (Q0), we cross-sectionally regress characteristic-adjusted individual stock returns during each of the four evaluation quarters (Q1 to Q4) onto $\hat{\alpha}_{it+1}$ and $\hat{\alpha}^H_{ipt+1}$, $p = 1, ..., P$. A set of five ($P = 5$) characteristic-scaled alphas, $\hat{\alpha}^H_{ipt+1}$, are included, together with $\hat{\alpha}_{it+1}$, as regressors. The five fund characteristic measures we consider include fund size (TNA), turnover (TURN), expense ratio (EXP), age (AGE), and industry concentration (ICON). TNA is the cross-sectional percentile rank of the total net assets of a fund at the end of Q0. TURN is the cross-sectional percentile rank of fund turnover, while EXP is the rank of expense ratio, both measured over the most-recent calendar year. AGE is the cross-sectional *quintile* rank of the duration of a fund's existence, as of Q0, while ICON is the cross-sectional percentile rank of a fund's market-weight adjusted Herfindahl index measure of industry concentration, based on portfolio weights at the end of Q0, and following the definition of Kacperczyk, Sialm, and Zheng (2005). We use quarterly cross-sectional ranks rather than fund characteristics per se, in order to control for nonstationarity or time trend in these characteristics.

Time-series average estimated coefficients (except for intercepts) and corresponding time-series t-statistics are reported in Table X. The coefficient for the TNA-scaled alpha is negative throughout the four evaluation quarters, and significantly negative during Q3 and Q4, suggesting less persistent stock-selection abilities for larger funds. The coefficient for TURN-scaled alpha is positive and significant only for Q1, suggesting that higher turnover managers have more persistent skills, but that this advantage is short-lived (perhaps necessitating the higher turnover). Further, the coefficient for EXP-scaled alpha is significantly negative for Q3 and Q4, whereas the coefficient for AGE-scaled alpha is significantly positive for Q3 and Q4, suggesting that low-expense and older funds have managers with more persistent stock selection skills. In addition, the coefficient for ICON-scaled alpha is positive and significant for Q1, but insignificant otherwise, suggesting that performance for funds with higher industry concentration in their portfolio holdings is more likely to persist, but that this advantage is quite short-lived.

To check for the robustness of these fund-characteristic tests, we also tried an alternative approach that applied the unconditional holding-based weighted average alpha to the holdings of subgroups of funds. For instance, the weighted-average alpha signal that is based only on the holdings of the largest half of mutual funds, each quarter, generates a characteristic-adjusted return spread of 1.7% and 1.3% during Q1 and Q2, respectively, while the signal based only on holdings of the smallest half of funds generates spreads of 2.9% and 2.1%, respectively. In general, this approach results in findings similar to those of the augmented regressions described above: small funds, older funds, and higher-turnover funds generated better stock-selection signals than their counterparts. However, we find little difference in forecasts generated using holdings of high vs. low expense ratio funds or high vs. low industry concentration funds. These results, however, may be affected by the lack of power that arises when aggregating portfolio weights from a reduced sample of funds, as well as interactions among the fund characteristics. The augmented conditional alpha regressions, by jointly including all characteristics of all funds, appear to be more powerful in capturing differences in the persistence of skills between different fund types.

Overall, the results indicate that mutual funds are heterogeneous in terms of the persistence of their stock selection abilities. Smaller and older funds, and funds with higher turnover, lower expense, and higher industry concentration in their portfolio holdings are more likely to exhibit persistent skills. It is important to note that these findings do not imply that such funds necessarily have higher average skills, but simply that whatever skills they possess (either good or bad) are more persistent.

IV.C.2. Effect of Stock Characteristics

To examine whether mutual fund managers have more persistent skills in selecting stocks with certain characteristics, we construct stock alphas scaled by stock characteristics in the following way:

$$\hat{\alpha}_{it+1}^{C} = g_0 \hat{\alpha}_{it+1} + \sum_{k=1}^{K} g_k C_{ikt} \hat{\alpha}_{it+1} \tag{32}$$

where $\hat{\alpha}_{it+1}^{C}$ is the stock alpha conditional on stock characteristics, $\hat{\alpha}_{it+1}$ is the holding-based, unconditional weighted-average stock alpha, and C_{ikt} is a stock characteristic measure detailed below. Essentially, $C_{ikt}\hat{\alpha}_{it+1}$ is the unconditional stock alpha scaled by a stock characteristic measure, meaning that we amplify the signal provided by mutual funds for stocks with certain characteristics to capture differential persistence in fund skills in selecting such stocks.

We perform quarterly Fama-MacBeth cross-sectional regressions to estimate the coefficients g_0 and g_k. The dependent variable is the characteristic-adjusted stock return during one of the four evaluation quarters, Q1 to Q4, while explanatory variables include the unconditional stock alpha, as well as a set of five ($K = 5$) scaled alphas. The stock characteristic measures used for scaled alphas include firm size (SIZE), book-to-market ratio (BTM), trading volume (VOL), breadth of mutual fund ownership (BRD), and return volatility (STDR). SIZE is the cross-sectional percentile rank of market capitalization at the end of Q0, while BTM is the cross-sectional rank of the ratio of book value of equity at fiscal year-end (during the prior calendar year) to the market capitalization at the end of Q0. VOL is the cross-sectional percentile rank of monthly trading volume divided by total shares outstanding, averaged over the three months in Q0. Since the trading volume is defined differently at NASDAQ than at NYSE/AMEX, we rank stocks traded on NASDAQ separately from those traded on NYSE/AMEX. Breadth of ownership is the cross-sectional *quintile* rank of the number of funds holding a stock divided by the total number of funds during Q0 in our mutual fund sample. Finally, STDR is the cross-sectional percentile rank of standard deviation of daily returns during Q0. Again, we use cross-sectional ranks, rather than stock characteristics per se, to control for the effect of nonstationarity or time trends in these characteristics.

The time-series average coefficients (except for the intercept) as well as corresponding t-statistics are reported in Table XI. The coefficient for SIZE-scaled alpha is significantly negative for Q3 and Q4, suggesting that persistence in fund manager skills is slightly stronger when picking smaller stocks. The coefficient for BTM-scaled alpha is not statistically significant throughout the four quarters, suggesting that fund managers with persistent skills are equally good at picking growth and value stocks. The coefficient for VOL-scaled alpha is also insignificant throughout the four quarters, an indication of similar persistence in skills in less vs. more liquid stocks. The coefficient for BRD-scaled alphas is positive and significant for the first three quarters (Q1 to Q3). Interestingly, although breadth of mutual fund ownership is positively correlated with firm size, the coefficients for SIZE-scaled and BRD-scaled alphas have opposite signs, suggesting very different effects for firm size and breadth of ownership.[8] Our finding that stock alphas are more accurately estimated with a greater number of funds holding a stock makes sense, since we would expect a larger fund sample to provide a clearer signal of private information (a better signal-to-noise ratio). Finally, STDR-scaled alphas have significantly negative coefficients for Q3 and Q4, suggesting that persistently-skilled fund managers are better at selecting stocks with lower volatility.

In sum, fund managers with persistent skills are slightly better at picking smaller stocks, less volatile stocks, and substantially better at picking stocks with higher breadth of mutual

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[8] The opposite signs for the coefficients of SIZE- and BRD-scaled alphas are not due to a multicollinearity problem. When SIZE- and BRD-scaled alphas are separately included in regressions, their coefficients have the same signs as reported here.

fund ownership (although this latter effect may simply be due to the noise-reducing power of an increased number of funds). They are equally good at selecting growth and value stocks, or liquid and illiquid stocks.

IV.C.3. Predictive Performance of Conditional Stock Alphas

Through the above in-sample analysis, we have identified factors (i.e., fund and stock characteristics) affecting the persistence of stock selection skills among mutual fund managers. Yet, it remains an open question of whether, in an out-of-sample setting, conditioning stock alphas on these characteristics leads to significantly improved stock return forecasts. For this purpose, we perform the following out-of-sample predictive analysis. During each quarter, we estimate the coefficients for the following models:

$$\tilde{r}_{i\tau+q} = a_q + d_{0q}\hat{\alpha}_{i\tau+1} + \sum_{p=1}^{P} d_{pq}\hat{\alpha}^{H}_{ip\tau+1} + e_{i\tau+q} \tag{33}$$

$$\tilde{r}_{i\tau+q} = a_q + g_{0q}\hat{\alpha}_{i\tau+1} + \sum_{k=1}^{K} g_{kq}C_{ik\tau}\hat{\alpha}_{i\tau+1} + e_{i\tau+q} \tag{34}$$

$$\tilde{r}_{i\tau+q} = a_q + h_{0q}\hat{\alpha}_{i\tau+1} + \sum_{p=1}^{P} d_{pq}\hat{\alpha}^{H}_{ip\tau+1} + \sum_{k=1}^{K} g_{kq}C_{ik\tau}\hat{\alpha}_{i\tau+1} + e_{i\tau+q} \tag{35}$$

where $\tilde{r}_{i\tau+q}$ is the characteristic-adjusted stock return during quarter $\tau + q$, and q=1, 2, 3, or 4. We estimate the above models using cross-sectional regressions that are conducted for each formation quarter (each Q0), and for each $q = 1$ to 4. Then, for a given portfolio formation quarter, τ, we average the estimated coefficients over all formation quarters from 1980Q1 until quarter τ. That is, the coefficients for quarter τ are estimated using all data available at the end of that quarter. We apply these estimated coefficients to fund and stock characteristics that are measured as of the end of quarter τ to construct conditional stock alphas, then we evaluate their performance in forecasting actual stock returns during quarter $\tau + q$. Note that estimated parameters are q-specific. Therefore, conditional alphas based on these parameters are also q-specific. That is, for any given portfolio-formation quarter, a stock will have four conditional alphas, one corresponding to each value of q. To test the out-of-sample performance of the estimated models, at each portfolio-formation quarter, we form decile portfolios based on conditional alphas for q=1, and examine their performance during the first evaluation quarter, Q1. This process is repeated for $q = 2, 3$, and 4, where performance is evaluated during Q2, Q3, and Q4, respectively.

For robustness, we require a minimum of 20 quarters of past data to be available to estimate the coefficients and construct conditional stock alphas. Therefore, the first portfolio formation quarter is 1985Q1 and the last is 2002Q4. To avoid data-snooping biases, we include all five fund characteristic measures and all five stock characteristic measures, despite the fact that some of them are not statistically significant in Tables X and XI.

In Table XII, we report net return spreads and characteristic-adjusted return spreads between equal-weighted top and bottom decile portfolios (D10 and D1, respectively) for the conditional holding-based weighted-average alphas. For comparison, we also report results for unconditional holding-based weighted-average alphas during the same period (1985Q2 to 2002Q4). Although the sample period is shorter here than in our first application of the (unconditional) weighted-average alpha, the performance is similar to that reported in Table II, with characteristic-adjusted return spreads of 2.62%, 2.16%, 1.61%, and 1.04% for the four evaluation quarters, respectively.

We next include all five fund characteristics, but no stock characteristics, in constructing conditional alphas (based on parameters from (33)). The resulting characteristic-adjusted spreads between top and bottom deciles are 2.84%, 1.94%, 1.40%, and 0.94% from Q1 to Q4. Note that these spreads are comparable to those for unconditional alphas, with similar t-statistics. Therefore, incorporating fund characteristics into conditional stock alphas does not improve the (out-of-sample) return-predictive performance in an economically significant way.

We also construct stock alphas conditional on all five stock characteristics, but ignoring fund characteristics (based on parameters from (34)). The resulting characteristic-adjusted return spreads are 2.90%, 2.31%, 1.75%, and 1.14% from Q1 to Q4. Both the spreads and the t-statistics are slightly higher than those derived from using unconditional alphas.

Finally, we condition stock alphas on all fund characteristics and stock characteristics jointly (based on parameters from (35)). The resulting characteristic-adjusted spreads are 2.93%, 2.19%, 1.62%, and 1.12% from Q1 to Q4. Relative to unconditional alphas, the predictive performance is slightly improved, but there is no clear improvement relative to alphas conditional on stock characteristics only.

To sum up, conditional stock alphas produce a slight improvement in predicting returns, and the improvement can be mainly attributed to conditioning on stock characteristics.

V. Conclusions

The empirical results of this paper strongly suggest that disclosed information about mutual fund portfolio compositions is valuable to stock investors. Combining such information with past fund performance, we develop stock alpha estimators that strongly predict cross-sectional stock returns. The predictive performance of forecasted stock alphas beyond the first quarter after portfolio disclosure suggests that an investment strategy based on forecasted alphas is feasible, even after taking into account the maximum time lag of fund portfolio disclosure, which is 60 days following the fiscal quarter-end. Interestingly, information about future stock returns contained in our stock alpha estimators cannot be explained by existing quantitative investment models. Further, we develop conditional stock alphas by taking into account stock characteristics and fund characteristics. The conditional alphas deliver further improved performance in predicting returns.

Our analysis also uncovers useful information about the stock selection ability of mutual funds. Since the stock alpha estimators are built on the assumption of performance persistence, the findings in this study suggest that there exist persistent stock picking skills among fund managers, and such skills vary widely across managers. We can also infer that fund managers' private information about future stock returns tends to be correlated with momentum signals, but not with other prior-documented stock market anomalies. We interpret this finding as meaning that the private information possessed by skilled fund managers that is captured by our models is a result of fundamental research. Finally, our analysis on conditional stock alphas shows that manager stock selection skills are more likely to persist among smaller funds and older funds, funds with higher turnover, lower expense ratio, and higher industry concentration in their portfolio holdings. In addition, fund managers with persistent skills are slightly better at selecting smaller stocks, and significantly better at selecting stocks with lower return volatility and higher breadth of mutual fund ownership.

APPENDIX

A. Bayesian Stock Alpha Estimator

We make the following assumptions on the data generating processes. First, from time t-K+1 to t (K=12), the fund return process is:

$$r_{j\tau} = \alpha^f_{jt} + \boldsymbol{f}'_\tau \boldsymbol{b}_{jt} + \epsilon_{j\tau}, \text{ for } \tau \in \text{[t-K, t]} \tag{36}$$

where $r_{j\tau}$ is fund j's return in excess of the riskfree rate at time τ, α^f_{jt} is the fund alpha, $\boldsymbol{f}_\tau$ is a vector of four factors (e.g., Carhart (1997) four factors), and $\boldsymbol{b}_{jt}$ is a vector of four factor loadings. α^f_{jt} and $\boldsymbol{b}_{jt}$ are time-invariant during the period from t-K+1 to t. Further, $\epsilon_{j\tau} \sim N(0, \sigma^2_{jt})$. $\epsilon_{j\tau}$ is i.i.d. over time and independent across funds.

Second, let α^f_{jt+1} be the fund alpha for the period from time t+1 to t+K, and

$$\alpha^f_{jt+1} = \alpha^f_{jt} + e_{jt+1} \tag{37}$$

which is consistent with our frequentist assumption (2) with $\alpha_0 = 0$ and $\rho = 1$ in Section II. Further, e_t is normally distributed and i.i.d. across funds: $e_{jt+1} \sim N(0, \sigma^2_e)$.

Third, let α^s_{it+1} denote the alpha of stock i for the period from t+1 to t+K. We have:

$$\alpha^f_{jt+1} = \sum_{i=1}^{N} w_{ijt} \alpha^s_{it+1} \tag{38}$$

where w_{ijt} is the portfolio weight of fund j on stock i at time t.

We now follow the Bayesian literature (e.g., Pastor and Stambaugh (1999; 2002)) to specify the priors for parameters in the fund return process. First, the prior distribution for σ^2_{jt}, the variance of $\epsilon_{j\tau}$, is inverted Gamma:

$$\sigma^{-2}_{jt} \sim \Gamma(h, v) \tag{39}$$

where h is the precision parameter and v is the degree of freedom. We set v=p+1, where p=4 is the number of factors, so that the prior is quite uninformative about σ^2_{jt}. Given (39), $E(\sigma^{-2}_{jt}) = v/h$. Following the "empirical Bayes" approach, we set h such that $E(\sigma^{-2}_{jt})$ equals the cross-fund average of OLS estimates (from (36)) of σ^{-2}_{jt}.

Second, define $\boldsymbol{\theta}_j$=$(\alpha_{jt} \quad b'_{jt})'$. Conditional on σ^2_{jt}, the prior for $\boldsymbol{\theta}_j$ is normal:

$$\boldsymbol{\theta}_j \sim N(\underline{\boldsymbol{\theta}}_j, \sigma^2_{jt}\underline{\Phi}) \tag{40}$$

where $\underline{\boldsymbol{\theta}}_j$ is the prior mean for $\boldsymbol{\theta}_j$ and $\sigma^2_{jt}\underline{\Phi}$ is the prior variance for $\boldsymbol{\theta}_j$. We assume a diffuse prior for $\boldsymbol{\theta}_j$ by setting $\underline{\Phi} = \infty$. Therefore, the exact value of $\underline{\boldsymbol{\theta}}_j$ is irrelevant for the posterior. In addition, the priors for σ^2_{jt} and $\boldsymbol{\theta}_j$ are independent of $\boldsymbol{f}_\tau$.

Given the above, the posterior distribution for $\boldsymbol{\theta}_j$, conditional on σ^2_{jt}, is,

$$\boldsymbol{\theta}_j | \sigma^2_{jt} \sim N(\tilde{\boldsymbol{\theta}}_j, \tilde{V}_{\theta j}) \tag{41}$$

where $\tilde{V}_{\theta j} = (F'F)^{-1}\sigma_{jt}^2$ and $\tilde{\boldsymbol{\theta}}_j = (F'F)^{-1}F'R_j$. F is the matrix of factor realizations augmented by a vector of ones as the first column. R_j is the vector of realized returns for fund j. Given the diffuse priors on $\boldsymbol{\theta}_j$, the conditional posterior mean and variance coincide with those from OLS. It also turns out that under diffuse priors, $\tilde{\boldsymbol{\theta}}_j$ does not depend on σ_{jt}^2.

The posterior distribution for σ_{jt}^2 is still inverted Gamma,

$$\sigma_{jt}^{-2} \sim \Gamma(\tilde{h}_j, \tilde{v}) \tag{42}$$

where $\tilde{v} = v + K$ and $\tilde{h}_j = h + (R_j - F\tilde{\boldsymbol{\theta}}_j)'(R_j - F\tilde{\boldsymbol{\theta}}_j)$. Note that the marginal posterior distribution for $\boldsymbol{\theta}_j$, after integrating out σ_{jt}^2, is a (p+1)-dimensional student t distribution.

Now let $\boldsymbol{\alpha}_t^f$ be the M-vector of fund alphas and $\boldsymbol{\varphi}$ be the M-vector whose j-th element is σ_{jt}^{-2}. The conditional posterior for $\boldsymbol{\alpha}_t^f$ is,

$$\boldsymbol{\alpha}_t^f | \boldsymbol{\varphi} \sim N(\tilde{\boldsymbol{\alpha}}_f, \tilde{V}_f) \tag{43}$$

where $\tilde{\boldsymbol{\alpha}}_f$ is a M-vector of posterior means of fund alphas, with its j-th element being the first element of $\tilde{\boldsymbol{\theta}}_j$, $\tilde{V}_f$ is an M×M diagonal matrix of posterior covariances of fund alphas, with its (j, j) element being the first element of $\tilde{V}_{\theta j}$. The posterior covariance matrix of fund alphas, $\tilde{V}_f$, is diagonal because of the assumption that the disturbance term ϵ_{jt} is independent across funds, and the assumption that the prior distribution of $\boldsymbol{\theta}_{jt}$ is independent across funds. For the same reason the posterior of σ_{jt}^{-2} is also independent across funds. As such, the "learnings across funds" effect of Jones and Shanken (2005) is not present here.

We now turn to stock alphas. Given (37) and (38), we have,

$$W'\boldsymbol{\alpha}_{t+1} = \boldsymbol{\alpha}_t^f + \boldsymbol{e}_{t+1} \tag{44}$$

where $\boldsymbol{\alpha}_{t+1}$ is the N-vector of stock alphas. $\boldsymbol{e}_{t+1}$ is vector of e_{it+1}. Our prior for $\boldsymbol{\alpha}_{t+1}$ is,

$$\boldsymbol{\alpha}_{t+1} \sim N(0, \underline{\sigma}_s^2 I_N) \tag{45}$$

where I_N is an N×N identity matrix. The setup here introduces additional parameters $\underline{\sigma}_s^2$ and σ_e^2, the values of which are part of our priors. We set $\underline{\sigma}_s^2$ to the average of the diagonal terms of $\tilde{V}_f$. That is, our prior uncertainty about stock alphas is at the same magnitude of our uncertainty about fund alphas. Further, we set $\sigma_e^2 = 0$, which means that we impose an extremely strong belief about the relation between α_{t+1}^f and α_t^f.

Given (44), (45), and conditional posterior of $\boldsymbol{\alpha}_t^f$ in (43), the conditional posterior for $\boldsymbol{\alpha}_{t+1}$ is:

$$\boldsymbol{\alpha}_{\boldsymbol{t+1}} | \boldsymbol{\varphi} \sim N(\tilde{\boldsymbol{\alpha}}, \tilde{\Sigma}) \tag{46}$$

where $\tilde{\boldsymbol{\alpha}} = \left(W'\tilde{V}_f^{-1}W + \underline{\sigma}_s^{-2}I_N\right)^{-1} W'\tilde{V}_f^{-1}\tilde{\boldsymbol{\alpha}}_t^f$ and $\tilde{\Sigma} = (W'\tilde{V}_f^{-1}W + \underline{\sigma}_s^{-2}I_N)^{-1}$.

We can further express $\tilde{\boldsymbol{\alpha}}$ into components based on fund buys, fund sells, and lagged holdings:

$$\tilde{\boldsymbol{\alpha}}^B = \tilde{\Sigma}(\Delta W^+)'\tilde{V}_f^{-1}\tilde{\alpha}_t^f, \quad \tilde{\boldsymbol{\alpha}}^S = \tilde{\Sigma}(\Delta W^-)'\tilde{V}_f^{-1}\tilde{\alpha}_t^f, \quad \text{and } \tilde{\boldsymbol{\alpha}}^L = \tilde{\Sigma}W_{t-1}'\tilde{V}_f^{-1}\tilde{\alpha}_t^f \tag{47}$$

Unfortunately $\tilde{\boldsymbol{\alpha}}$ (as well as its components based on fund buys, sells, and lagged holdings) is a nonlinear function of σ_{jt}^2 and there is no close-form expression for the marginal posterior mean of $\boldsymbol{\alpha}_{t+1}$ after integrating out $\boldsymbol{\varphi}$. Monte carlo integration (by simulating $\boldsymbol{\varphi}$ from its posterior distribution) is computational intensive and highly time consuming. Instead, we take an approximation approach. Consider the Taylor expansion for $\tilde{\boldsymbol{\alpha}}$ around the posterior mean of σ_{jt}^{-2}:

$$\tilde{\boldsymbol{\alpha}} \approx \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}}) + \sum_{j=1}^{M} \frac{\partial \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}})}{\partial \sigma_{jt}^{-2}} (\sigma_{jt}^{-2} - \bar{\sigma}_{jt}^{-2}) + \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{M} \frac{\partial^2 \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}})}{\partial \sigma_{it}^{-2} \partial \sigma_{jt}^{-2}} (\sigma_{it}^{-2} - \bar{\sigma}_{it}^{-2})(\sigma_{jt}^{-2} - \bar{\sigma}_{jt}^{-2}) \tag{48}$$

where $\bar{\sigma}_{jt}^{-2} = \tilde{v}/\tilde{h}_j$ is the posterior mean of σ_{jt}^{-2} and $\bar{\boldsymbol{\varphi}}$ is an M-vector of $\bar{\sigma}_{jt}^{-2}$. Based on that the posterior of σ_{jt}^{-2} is independent across funds, the marginal posterior mean of $\boldsymbol{\alpha}_{t+1}$ is,

$$\bar{\boldsymbol{\alpha}} \approx \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}}) + \frac{1}{4} \sum_{j=1}^{M} \left(\frac{\partial^2 \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}})}{\partial (\sigma_{jt}^2)^2} \right) \cdot\times \left(\frac{\partial^2 \tilde{\boldsymbol{\alpha}}(\bar{\boldsymbol{\varphi}})}{\partial (\sigma_{jt}^2)^2} \right) \mathrm{VAR}(\sigma_{jt}^{-2}) \tag{49}$$

where $\cdot\times$ is a dot multiplication operator, $\mathrm{VAR}(\sigma_{jt}^{-2})$=$2\tilde{v}/\tilde{h}_j^2$ is the posterior variance of σ_{jt}^{-2}, and

$$\frac{\partial^2 \boldsymbol{\alpha}}{\partial (\sigma_{jt}^{-2})^2} = 2 \frac{\partial \tilde{\Sigma}}{\partial \sigma_{jt}^{-2}} W' \frac{\partial \tilde{V}_f^{-1}}{\partial \sigma_{jt}^{-2}} (W \tilde{\Sigma} W' \tilde{V}_f^{-1} + I_M) \tilde{\boldsymbol{\alpha}}_t^f \tag{50}$$

where $\partial \tilde{\Sigma} / \partial \sigma_{jt}^{-2} = -\tilde{\Sigma} W' (\partial \tilde{V}_f^{-1} / \partial \sigma_{jt}^{-2}) W \tilde{\Sigma}$ and $\partial \tilde{V}_f^{-1} / \partial \sigma_{jt}^{-2}$ is a diagonal matrix with the j-th diagonal element being $1/z$ and the remaining diagonal elements being zeros. z is the (1,1) element of $(F'F)^{-1}$. Note that (49) also applies to stock alphas based on fund buys, sells, and lagged holdings, with the following expressions for the corresponding partial derivatives:

$$\begin{aligned}
\frac{\partial^2 \boldsymbol{\alpha}^B}{\partial (\sigma_{jt}^{-2})^2} &= 2 \frac{\partial \tilde{\Sigma}}{\partial \sigma_{jt}^{-2}} W' \frac{\partial \tilde{V}_f^{-1}}{\partial \sigma_{jt}^{-2}} (W \tilde{\Sigma} (\Delta W^+)' \tilde{V}_f^{-1} + I_M) \tilde{\boldsymbol{\alpha}}_t^f && (51) \\
\frac{\partial^2 \boldsymbol{\alpha}^S}{\partial (\sigma_{jt}^{-2})^2} &= 2 \frac{\partial \tilde{\Sigma}}{\partial \sigma_{jt}^{-2}} W' \frac{\partial \tilde{V}_f^{-1}}{\partial \sigma_{jt}^{-2}} (W \tilde{\Sigma} (\Delta W^-)' \tilde{V}_f^{-1} + I_M) \tilde{\boldsymbol{\alpha}}_t^f && (52) \\
\frac{\partial^2 \boldsymbol{\alpha}^L}{\partial (\sigma_{jt}^{-2})^2} &= 2 \frac{\partial \tilde{\Sigma}}{\partial \sigma_{jt}^{-2}} W' \frac{\partial \tilde{V}_f^{-1}}{\partial \sigma_{jt}^{-2}} (W \tilde{\Sigma} W'_{t-1} \tilde{V}_f^{-1} + I_M) \tilde{\boldsymbol{\alpha}}_t^f && (53)
\end{aligned}$$

B. Quantitative Investment Signals

This appendix describes the twelve quantitative signals. All these variables are winsorized at the 1 and 99 percentiles within each quarter. [text] refers to the data source, where D# is the item number from Quarterly Compustat. t refers to the portfolio formation quarter Q0. m is the last month of Q0. q refers to the most recently reported fiscal quarter prior at the end of Q0, assuming a two-month reporting lag.

Variable	Description	Computation Details
1. RETP	Cumulative market adjusted return for the preceding six months (months -6 through -1)	$[\Pi_{i=m-6}^{m-1}(1+\text{monthly return}_i)]-1$ -$[\Pi_{i=m-6}^{m-1}(1+\text{value-weighted market monthly return}_i]-1$, where m=month-end of quarter t [CRSP]
2. RET2P	Cumulative market-adjusted return for the second preceding six months (months -12 through -7)	$[\Pi_{i=m-12}^{m-7}(1+\text{monthly return}_i)]-1$ -$[\Pi_{i=m-12}^{m-7}(1+\text{value-weighted market monthly return}_i]-1$, where m=month-end of quarter t [CRSP]

3. FREV	Analyst forecast revisions to price	$\sum_{i=0}^{5}(\frac{f_{m-i}-f_{m-1-i}}{P_{m-1-i}})$, where f_m = mean consensus analyst FY1 forecast at month m, the month-end of quarter t [IBES] P_{m-1} = price at the end of month m-1, relative to the month-end of quarter t [CRSP]. Thus, $\sum_{i=0}^{5}(\frac{f_{m-i}-f_{m-1-i}}{P_{m-1-i}})$=rolling sum of preceding six months revisions to price ratios
4. SUE	Standardized unexpected earnings	$\frac{(\text{EPS}_q-\text{EPS}_{q-4})}{s_q}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ $\text{EPS}_q-\text{EPS}_{q-4}$= unexpected earnings for quarter q, with EPS defined as earnings per share (diluted) excluding extraordinary items [D9], adjusted for stock distributions [D17] σ_q = standard deviation of unexpected earnings over eight preceding quarters (quarters q-7 though q)
5. TURN	Average daily volume turnover	Percentile rank $\frac{\sum_{i=1}^{n}\text{Daily Volume/Shares Outstanding}}{n}$ by exchange, where n = number of days available for 6 months preceding the end of quarter t (months m-6 though m-1) [CRSP]
6. EP	Earnings to price	$\frac{\sum_{i=0}^{3}\text{EPS}_{q-i}}{P_t}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ EPS_q= earnings per share before extraordinary items for quarter q[D19] P_t = price at the end of the quarter t [D14] Thus, $\frac{\sum_{i=0}^{3}\text{EPS}_{q-i}}{P_t}$=rolling sum of EPS for preceding four quarters, deflated by price
7. BP	Natural log of book to price ratio	LOG($\frac{\text{Book value of common equity}}{\text{Mktcap}}$), where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ Book value of common equity$_q$ = book value of total common equity at the end of quarter q [D59] Mktcap$_t$ = P_t * Shares Outstanding$_t$ = price at the end of the quarter t [D14], multiplied by common shares outstanding at the end of quarter t [D61]
8. LTG	Long-term growth forecast	Mean consensus long-term growth forecast at end of quarter t [IBES]
9. SG	Sales growth	$\frac{\sum_{i=0}^{3}\text{Sales}_{q-i[D2]}}{\sum_{i=0}^{3}\text{Sales}_{q-4-i[D2]}}$ where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ Thus, $\sum_{i=0}^{3}\text{Sales}_{q-i}$=rolling sum of sales for preceding four quarters and $\sum_{i=0}^{3}\text{sales}_{q-4-i}$=rolling sum of sales for second preceding set of four quarters
10. TA	Total accruals to total assets	($\triangle$Current Assets$_q$ [D40] -$\triangle$Cash$_q$[D36])(based on balance sheet accounts) -($\triangle$Current Liabilities$_q$ [D49] -$\triangle$Current LTD$_q$ [D45]) -$\triangle$Deferred Taxes$_q$ [D35] $-$Depreciation and Amortization$_q$[D5] $\overline{(TA_q+TA_{q-4})/2}$ [D44] q = most recent quarter for which an earnings announcement was made a minimum of two months prior to the end of quarter t, with $q \geq t-4$ $\triangle X_q = X_q - X_{q-4}$, e.g., $\triangle$Current Assets$_{t-1}$ = Current Assets$_{t-1}$ $-$Current Assets$_{t-5}$
11. CAPEX	Capital expenditures to total assets	$\frac{\text{CAPEX}_q}{(TA_q+TA_{q-4})/2[D44]}$ q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ CAPEX$_q$ = rolling sum of four quarters (quarters q-3 through q) of Capital Expenditures [D90] (As D90 is fiscal-year-to-date, adjustments are made as needed to calculate the rolling sum of the preceding four quarters.)
12. SIZE	Natural log of market capitalization	Size$_t$ = LOG (P_t * Shares Outstanding$_t$) = LOG (price at the end of the quarter t [D14], multiplied by common shares outstanding at the end of quarter t [D61])

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Table I. Summary Statistics

Table I provides summary statistics on the sample of mutual funds and their stock holdings at the end of each year, from 1980 to 2002. To obtain the sample, we merge the CDA/Spectrum mutual fund holdings data with CRSP mutual fund returns data. We include only actively-managed, domestic equity mutual funds with a self-declared investment objective of aggressive growth, growth, or growth-and-income, and that report portfolio holdings sometime during the final calendar quarter of a given year. The first two columns present the total number of sample funds as well as the number of distinct common stocks held by sample funds. The next column presents the aggregate market value of equity holdings by sample funds. For comparison purpose we also report the total number of distinct stocks in the CRSP common stock universe and their total market capitalization, along with the proportion of these totals represented by the mutual fund sample.

	Mutual Fund Sample			CRSP Universe		Proportion	
Year	Number of Funds	Number of Distinct Stocks	Market Value of Stocks Held ($B)	Number of Distinct Stocks	Total Market Capitalization ($B)	Number of Stocks (%)	Value of Stocks (%)
1980	247	2,030	30.89	4,877	1,320.32	41.62	2.34
1981	209	2,081	22.49	5,242	1,231.09	39.70	1.83
1982	196	2,188	31.60	5,188	1,411.27	42.17	2.39
1983	248	3,050	50.28	5,770	1,743.06	52.86	2.89
1984	278	3,124	51.55	5,896	1,683.62	52.99	3.06
1985	310	3,409	72.00	5,882	2,098.43	57.96	3.43
1986	348	3,611	81.53	6,166	2,360.99	58.56	3.45
1987	413	3,529	97.13	6,451	2,320.18	54.70	4.19
1988	442	3,642	93.05	6,183	2,519.71	58.90	3.69
1989	482	3,600	122.73	5,981	3,067.00	60.19	3.99
1990	513	3,330	115.63	5,831	2,753.52	57.11	4.20
1991	563	3,541	172.65	5,870	3,721.61	60.32	4.64
1992	649	3,740	255.69	6,000	4,120.74	62.33	6.21
1993	740	5,022	290.93	6,532	4,681.56	76.88	6.21
1994	804	5,257	309.80	6,843	4,634.57	76.82	6.69
1995	821	5,671	464.34	7,066	6,327.48	80.26	7.34
1996	1,091	6,100	646.78	7,508	7,717.25	81.25	8.38
1997	1,125	6,110	903.79	7,497	10,055.79	81.50	8.99
1998	1,162	5,746	1,188.31	7,071	12,427.34	81.26	9.56
1999	1,185	4,880	1,364.79	6,730	15,913.33	72.51	8.58
2000	1,088	5,369	1,428.72	6,402	14,446.42	83.86	9.89
2001	918	4,769	1,007.12	5,693	12,815.61	83.77	7.86
2002	935	3,889	945.88	5,263	9,940.55	73.89	9.52

Table II. Performance of Stock Alphas Estimated Using Fund Holdings

From 1980 to 2002, in each quarter we use fund portfolio holdings to estimate stock alphas under the weighted average approach (WAA), the generalized inverse approach (GIV), and the Bayesian approach (BYS) respectively. Stocks are then ranked by forecasted alphas to form equal-weighted decile portfolios. We report the average buy-and-hold quarterly net returns and characteristic-adjusted returns during the next four quarters (Q1 to Q4), as well as the return spreads between the top and bottom deciles and the time-series t-statistics. The last three rows are correlations of return spreads among the three approaches.

	Net Return				Characteristic-adjusted Return			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A: Weighted Average Alphas								
D1 (Bottom)	2.21	2.33	2.74	2.77	-1.12	-1.10	-0.65	-0.76
D2	2.49	2.96	3.15	3.45	-0.89	-0.56	-0.37	-0.27
D3	3.02	3.13	3.40	3.65	-0.42	-0.49	-0.18	0.01
D4	3.43	3.52	3.51	3.90	-0.16	-0.13	-0.09	0.12
D5	3.79	3.51	3.52	3.50	0.12	-0.06	-0.02	-0.18
D6	3.93	3.73	3.60	3.53	0.18	0.17	0.03	-0.15
D7	4.02	3.79	3.45	3.61	0.33	0.20	-0.08	0.15
D8	4.10	4.06	3.49	3.38	0.47	0.45	0.05	-0.07
D9	4.69	4.01	3.76	3.66	1.00	0.37	0.36	0.20
D10 (Top)	5.25	4.86	3.91	3.86	1.51	1.11	0.41	0.30
D10-D1	3.05	2.53	1.17	1.09	2.63	2.20	1.06	1.06
t	(3.96)	(3.29)	(1.67)	(1.46)	(4.18)	(3.52)	(1.98)	(1.87)
Panel B: Generalized Inverse Alphas								
D1 (Bottom)	2.70	2.84	2.95	2.97	-0.73	-0.59	-0.43	-0.51
D2	2.99	3.22	3.04	3.39	-0.53	-0.28	-0.42	-0.20
D3	3.12	3.26	3.30	3.41	-0.35	-0.25	-0.16	-0.21
D4	3.25	3.41	3.30	3.65	-0.26	-0.23	-0.18	-0.04
D5	3.39	3.69	3.54	3.81	-0.35	-0.05	-0.11	-0.05
D6	3.92	3.61	3.64	3.81	0.21	-0.18	-0.07	0.05
D7	3.84	3.70	3.49	3.93	0.14	0.07	0.14	0.18
D8	4.12	3.64	3.64	3.57	0.54	0.08	0.15	0.03
D9	4.40	3.99	3.63	3.60	0.80	0.40	0.22	0.14
D10 (Top)	4.94	4.50	3.75	3.55	1.36	0.98	0.42	0.15
D10-D1	2.24	1.66	0.80	0.58	2.09	1.57	0.85	0.66
t	(4.74)	(3.90)	(1.95)	(0.90)	(5.36)	(4.42)	(2.64)	(1.84)
Panel C: Bayesian Alphas								
D1 (Bottom)	2.37	2.50	2.94	2.95	-0.93	-0.92	-0.49	-0.58
D2	2.81	3.11	3.05	3.48	-0.60	-0.33	-0.45	-0.18
D3	2.95	3.10	3.34	3.39	-0.46	-0.46	-0.27	-0.07
D4	2.91	3.15	3.36	3.59	-0.62	-0.45	-0.22	-0.16
D5	3.24	3.68	3.62	3.95	-0.41	0.01	0.08	0.14
D6	3.81	3.61	3.64	3.67	0.13	-0.09	0.01	-0.01
D7	4.04	3.86	3.63	3.75	0.29	0.21	0.04	0.13
D8	4.43	3.89	3.55	3.21	0.67	0.30	0.02	0.02
D9	4.97	4.25	3.65	3.89	1.29	0.65	0.25	0.09
D10 (Top)	5.38	4.61	3.75	3.58	1.67	1.05	0.55	0.03
D10-D1	3.01	2.10	0.81	0.63	2.60	1.97	1.04	0.60
t	(4.27)	(3.56)	(1.85)	(1.21)	(4.83)	(3.91)	(2.24)	(1.66)
Corr(WAA, GIV)	0.85	0.87	0.81	0.90	0.82	0.82	0.83	0.81
Corr(WAA, BYE)	0.86	0.85	0.86	0.91	0.84	0.83	0.56	0.78
Corr(GIV,BYS)	0.93	0.85	0.85	0.88	0.84	0.84	0.66	0.75

Table III. Performance of Stock Alphas Estimated Using Fund Buys

From 1980 to 2002, in each quarter we use recent fund buys to estimate stock alphas under the weighted average approach (WAA), the generalized inverse approach (GIV), and the Bayesian approach (BYS) respectively. Stocks are then ranked by forecasted alphas to form equal-weighted decile portfolios. We report the average buy-and-hold quarterly net returns and characteristic-adjusted returns during the next four quarters (Q1 to Q4), as well as the return spreads between the top and bottom deciles and the time-series t-statistics. The last three rows are correlations of return spreads among the three approaches.

	Net Return				Characteristic-adjusted Return			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A: Weighted Average Alphas								
D1 (Bottom)	2.86	2.81	2.87	3.21	-0.34	-0.56	-0.41	-0.11
D2	2.89	3.06	3.13	3.54	-0.38	-0.34	-0.20	-0.06
D3	2.97	3.07	3.13	3.55	-0.40	-0.32	-0.32	-0.14
D4	2.96	3.29	3.43	3.51	-0.28	-0.12	-0.05	-0.07
D5	3.41	3.27	3.43	3.66	-0.03	-0.06	0.00	0.12
D6	3.65	3.54	3.34	3.31	0.23	0.08	-0.14	-0.16
D7	3.80	3.35	3.39	3.19	0.37	0.02	0.03	-0.26
D8	4.04	3.35	3.52	3.01	0.54	0.03	0.06	-0.34
D9	4.44	3.81	3.33	3.00	0.91	0.40	0.04	-0.32
D10 (Top)	5.40	4.22	3.37	3.23	1.92	0.77	0.10	-0.08
D10-D1	2.54	1.41	0.50	0.02	2.26	1.33	0.51	0.03
t	(2.77)	(1.89)	(0.87)	(0.03)	(2.85)	(2.14)	(1.38)	(0.05)
Panel B: Generalized Inverse Alphas								
D1 (Bottom)	3.40	3.08	3.33	3.20	0.02	-0.24	0.04	-0.12
D2	3.21	3.30	3.08	3.52	-0.10	-0.09	-0.28	0.07
D3	2.93	3.27	3.29	3.36	-0.41	-0.10	-0.11	-0.17
D4	3.39	3.16	3.28	3.33	0.02	-0.24	-0.21	-0.28
D5	3.22	3.13	3.57	3.67	-0.24	-0.41	0.01	0.07
D6	3.78	3.48	3.12	3.30	0.29	0.02	-0.38	-0.30
D7	3.62	3.30	3.30	3.49	0.16	-0.13	-0.18	-0.04
D8	3.91	3.57	3.42	3.34	0.47	0.23	0.01	-0.18
D9	4.13	3.47	3.23	3.29	0.80	0.15	-0.07	-0.10
D10 (Top)	4.61	4.10	3.33	3.00	1.30	0.73	0.16	-0.28
D10-D1	1.21	1.02	0.00	-0.20	1.28	0.97	0.12	-0.16
t	(3.01)	(3.09)	(0.01)	(-0.58)	(3.51)	(3.36)	(0.46)	(-0.57)
Panel C: Bayesian Alphas								
D1 (Bottom)	2.82	2.94	3.20	3.23	-0.36	-0.42	-0.20	-0.26
D2	3.31	3.06	3.32	3.41	-0.03	-0.27	-0.09	-0.13
D3	2.70	3.08	3.48	3.76	-0.54	-0.32	-0.14	0.12
D4	2.84	3.25	3.59	3.75	-0.50	-0.18	0.06	0.08
D5	3.15	3.30	3.41	3.60	-0.25	-0.22	-0.06	0.00
D6	3.57	3.51	3.30	3.24	0.10	0.06	-0.09	-0.28
D7	4.01	3.41	3.23	3.48	0.49	0.05	-0.21	0.01
D8	4.10	3.41	3.27	3.28	0.70	0.09	-0.12	-0.07
D9	4.61	3.60	2.93	2.84	1.15	0.22	-0.32	-0.52
D10 (Top)	5.08	4.30	3.35	2.92	1.54	0.88	0.26	-0.24
D10-D1	2.26	1.36	0.15	-0.31	1.89	1.30	0.45	0.01
t	(2.88)	(1.91)	(0.25)	(-0.47)	(3.05)	(2.37)	(1.07)	(0.03)
Corr(WAA, GIV)	0.82	0.83	0.65	0.77	0.81	0.82	0.60	0.73
Corr(WAA, BYE)	0.91	0.81	0.82	0.90	0.79	0.86	0.77	0.87
Corr(GIV,BYS)	0.77	0.88	0.70	0.77	0.89	0.79	0.66	0.72

Table IV. Performance of Stock Alphas Estimated Using Fund Sells

From 1980 to 2002, in each quarter we use recent fund sells to estimate stock alphas under the weighted average approach (WAA), the generalized inverse approach (GIV), and the Bayesian approach (BYS) respectively. Stocks are then ranked by forecasted alphas to form equal-weighted decile portfolios. We report the average buy-and-hold quarterly net returns and characteristic-adjusted returns during the next four quarters (Q1 to Q4), as well as the return spreads between the top and bottom deciles and the time-series t-statistics. The last three rows are correlations of return spreads among the three approaches.

	Net Return				Characteristic-adjusted Return			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A: Weighted Average Alphas								
D1 (Bottom)	3.29	3.43	3.26	3.05	-0.01	0.03	-0.06	-0.27
D2	3.67	3.46	2.73	3.11	0.33	0.07	-0.49	-0.20
D3	3.58	3.20	2.92	3.59	0.25	-0.17	-0.31	0.24
D4	3.75	3.48	3.50	3.42	0.31	0.12	0.07	-0.07
D5	3.39	3.47	3.50	3.50	-0.01	0.12	0.09	-0.03
D6	3.31	3.26	3.51	3.52	-0.03	-0.14	0.05	-0.09
D7	3.36	3.37	3.20	3.47	0.04	-0.01	-0.21	-0.15
D8	3.17	3.01	3.53	3.63	-0.14	-0.37	-0.06	0.01
D9	2.79	3.03	3.05	3.12	-0.48	-0.37	-0.39	-0.39
D10 (Top)	2.04	2.70	2.99	3.01	-1.18	-0.58	-0.36	-0.40
D10-D1	-1.25	-0.74	-0.27	-0.04	-1.17	-0.62	-0.31	-0.13
t	(-1.85)	(-1.16)	(-0.49)	(-0.07)	(-2.24)	(-1.27)	(-0.77)	(-0.30)
Panel B: Generalized Inverse Alphas								
D1 (Bottom)	3.87	3.95	3.05	3.24	0.65	0.63	-0.18	-0.12
D2	3.74	3.48	3.45	3.28	0.39	0.05	0.07	-0.12
D3	3.49	3.42	3.17	3.00	0.11	0.06	-0.21	-0.48
D4	3.08	3.22	3.45	3.64	-0.28	-0.15	0.03	0.14
D5	2.85	3.12	3.49	3.49	-0.52	-0.33	-0.06	-0.15
D6	2.89	3.10	3.01	3.59	-0.49	-0.35	-0.56	-0.03
D7	3.35	3.19	3.28	3.35	0.00	-0.25	-0.21	-0.19
D8	3.06	3.12	3.28	3.46	-0.25	-0.22	-0.12	-0.06
D9	3.26	2.93	3.26	3.58	-0.09	-0.44	-0.12	0.06
D10 (Top)	3.11	3.15	3.25	3.13	-0.20	-0.10	0.03	-0.23
D10-D1	-0.77	-0.80	0.20	-0.11	-0.85	-0.74	0.21	-0.11
t	(-2.95)	(-3.03)	(0.82)	(-0.45)	(-3.71)	(-2.96)	(0.97)	(-0.53)
Panel C: Bayesian Alphas								
D1 (Bottom)	4.10	3.91	3.33	3.27	0.71	0.43	0.15	-0.04
D2	3.57	3.64	3.59	3.69	0.23	0.24	0.15	0.10
D3	3.27	3.18	3.62	3.53	-0.13	-0.17	0.05	0.02
D4	2.69	3.25	3.84	3.49	-0.63	-0.15	0.27	-0.04
D5	2.83	3.05	3.11	3.43	-0.49	-0.40	-0.42	-0.06
D6	3.14	3.31	2.99	3.58	-0.36	-0.23	-0.36	0.03
D7	3.36	3.26	3.07	3.54	-0.06	-0.11	-0.30	-0.15
D8	3.47	3.14	3.01	3.29	0.17	-0.18	-0.27	-0.32
D9	3.22	3.13	2.93	3.28	-0.02	-0.14	-0.37	-0.18
D10 (Top)	3.02	2.89	3.18	2.67	-0.14	-0.32	-0.27	-0.56
D10-D1	-1.08	-1.02	-0.14	-0.61	-0.85	-0.75	-0.41	-0.52
t	(-2.08)	(-1.88)	(-0.32)	(-1.56)	(-2.16)	(-2.10)	(-1.30)	(-1.72)
Corr(WAA, GIV)	0.53	0.39	0.48	0.43	0.42	0.32	0.33	0.44
Corr(WAA, BYE)	0.74	0.54	0.65	0.58	0.74	0.58	0.47	0.56
Corr(GIV,BYS)	0.47	0.60	0.40	0.35	0.36	0.53	0.32	0.28

Table V. Comparison with Aggregate Fund Trading and Breadth of Ownership

We construct aggregate mutual fund trading (TRADE) following Chen, Jegadeesh, and Wermers (2000) and the change in breadth of mutual fund ownership (ΔBREADTH) following Chen, Hong and Stein (2002). Panel A reports average quarterly returns to the top and bottom decile portfolios formed on TRADE and ΔBREADTH during the four quarters after portfolio formation, as well as the return spreads and their time-series t-statistics. Panel B reports the Spearman rank correlations between these two variables and the weighted-average stock alphas. The correlations are first computed across stocks in each quarter and then averaged over time. Panel C reports the average coefficients of Fama-MacBeth regressions where quarterly characteristic-adjusted stock returns during Q1 to Q4 are regressed onto the weighted-average stock alphas, Trades, and ΔBreadth. The average adjusted R-squares are also reported. Stock alphas are estimated using fund holdings (α^H_{WAA}), buys (α^B_{WAA}), and sells (α^S_{WAA}) respectively. Inside the parentheses are time-series t-statistics.

Panel A: Portfolio Returns

	Net Return				Characteristic-adjusted Return			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
A1: TRADE								
D1	2.88	2.79	2.77	3.21	-0.25	-0.41	-0.49	-0.15
D10	3.96	3.63	3.02	2.97	0.55	0.31	-0.21	-0.34
D10-D1	1.07	0.84	0.25	-0.23	0.80	0.73	0.28	-0.20
t	(3.14)	(2.47)	(0.72)	(-0.85)	(2.75)	(2.34)	(1.02)	(-0.87)
A2: ΔBREADTH								
D1	2.08	2.42	2.38	3.15	-0.98	-0.76	-0.77	-0.23
D10	4.60	3.41	3.49	2.36	1.33	0.19	0.36	-0.81
D10-D1	2.53	1.00	1.11	-0.79	2.31	0.95	1.14	-0.57
t	(3.40)	(1.77)	(1.69)	(-1.21)	(3.57)	(1.97)	(2.65)	(-1.26)

Panel B: Spearman Rank Correlations

	TRADE	ΔBREADTH
α^H_{WAA}	0.04	0.04
t	(8.64)	(6.47)
α^B_{WAA}	0.04	0.03
t	(4.96)	(3.13)
α^S_{WAA}	-0.01	-0.03
t	(-0.74)	(-2.33)

Panel C: Fama-MacBeth Regressions

stock alpha	α^H_{WAA}				α^B_{WAA}				α^S_{WAA}			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
α	1.39	1.03	0.67	0.49	1.71	1.29	0.34	0.39	-0.02	0.01	-0.02	0.02
t	(5.48)	(3.92)	(3.14)	(2.17)	(3.97)	(3.19)	(1.02)	(1.00)	(-1.48)	(0.59)	(-1.51)	(0.91)
TRADE	0.26	0.69	0.16	-0.14	0.27	0.64	0.16	-0.07	0.24	0.51	0.35	-0.23
t	(1.24)	(3.05)	(0.75)	(-0.66)	(1.17)	(2.68)	(0.58)	(-0.27)	(0.85)	(1.50)	(1.16)	(-0.76)
ΔBREADTH	0.54	0.23	0.33	-0.11	0.53	0.23	0.34	-0.09	0.53	0.26	0.35	-0.09
t	(3.69)	(1.80)	(2.84)	(-0.92)	(3.58)	(1.80)	(2.93)	(-0.69)	(3.53)	(2.12)	(2.87)	(-0.72)

Table VI. Weekly Performance of Weighted-average Stock Alphas

We define 12 trading weeks from the beginning of Q1, with week 1 being the first 5 trading days of Q1, and week 2 being the second 5 trading days of Q1, and so on. Similarly, we define 4 trading weeks prior to Q1, with week 0 being the last five trading days of the portfolio formation quarter Q0, and week -1 being the five trading days before week 0, and so on. We report equal-weighted returns to stocks in D10 and D1 portfolios, as well as their return spreads, for each of the trading weeks defined. Inside the parentheses are time-series t-statistics.

Week	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Stock Alphas Estimated using Fund Holdings																
D1	0.07	-0.37	0.06	0.67	0.08	0.42	0.42	-0.03	1.05	0.37	0.08	0.20	0.78	-0.15	-0.47	0.17
D10	0.59	0.24	0.39	1.00	0.58	0.80	0.82	0.39	1.33	0.99	0.84	0.46	1.32	0.55	-0.05	0.57
D10-D1	0.52	0.61	0.33	0.33	0.49	0.38	0.40	0.42	0.27	0.63	0.76	0.26	0.54	0.70	0.42	0.40
t	(3.29)	(5.59)	(3.13)	(2.71)	(3.43)	(2.43)	(2.24)	(3.25)	(1.79)	(4.17)	(5.18)	(1.90)	(3.62)	(4.36)	(2.67)	(2.92)
Panel B: Stock Alphas Estimated using Fund Buys																
D1	0.32	-0.07	0.28	0.86	0.41	0.78	0.69	0.37	1.31	0.66	0.35	0.53	1.16	-0.02	-0.38	0.35
D10	0.63	0.24	0.41	1.05	0.57	1.06	1.10	0.58	1.76	1.20	0.97	0.65	1.62	0.76	-0.11	0.79
D10-D1	0.31	0.31	0.12	0.20	0.16	0.28	0.40	0.20	0.45	0.54	0.62	0.12	0.46	0.78	0.27	0.44
t	(2.12)	(2.26)	(1.11)	(1.63)	(1.00)	(1.47)	(2.50)	(1.05)	(2.53)	(3.04)	(4.01)	(0.78)	(3.07)	(3.86)	(1.80)	(3.17)
Panel C: Stock Alphas Estimated using Fund Sells																
D1	0.38	-0.15	0.04	0.78	0.14	0.30	0.30	-0.17	1.15	0.65	0.38	0.34	1.10	0.19	-0.62	0.31
D10	-0.17	-0.58	-0.30	0.42	-0.33	0.21	0.01	-0.27	1.07	0.29	0.12	0.13	0.63	-0.17	-0.64	0.04
D10-D1	-0.55	-0.43	-0.34	-0.36	-0.48	-0.09	-0.30	-0.10	-0.08	-0.35	-0.26	-0.20	-0.47	-0.36	-0.02	-0.26
t	(-3.03)	(-3.26)	(-3.98)	(-3.05)	(-3.09)	(-0.49)	(-1.89)	(-0.51)	(-0.50)	(-2.04)	(-2.16)	(-1.17)	(-2.19)	(-2.69)	(-0.10)	(-1.99)

Table VII. Quantitative Investment Signals and Stock Returns

From 1980 to 2002, in each quarter we construct 12 quantitative investment signals for individual stocks. We report the average coefficients from Fama-MacBeth regressions of stock returns during the next four quarters (Q1 to Q4) onto these quantitative signals. In univariate regressions, we use one of the 12 signals as the regressor. In multivariate regressions, all 12 signals are jointly used as regressors. Inside parentheses are the time-series t-statistics computed following the Newey-West procedure with 2 lags. $\bar{R}^2$ is the average adjusted R-square.

	Univariate Regressions				Multivariate Regressions			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
RETP	0.33	0.31	0.16	-0.07	0.17	0.19	0.11	-0.04
	(6.57)	(5.95)	(3.02)	(-1.52)	(4.11)	(4.97)	(2.99)	(-1.17)
RET2P	0.19	-0.05	-0.14	-0.11	0.10	-0.07	-0.13	-0.05
	(3.45)	(-0.94)	(-2.98)	(-2.58)	(2.70)	(-2.16)	(-2.82)	(-1.70)
FREV	1.05	0.56	0.44	0.05	0.30	0.02	0.11	0.14
	(7.38)	(4.16)	(3.39)	(0.41)	(2.52)	(0.26)	(1.27)	(1.44)
SUE	0.53	0.28	0.14	0.05	0.30	0.22	0.28	0.33
	(3.08)	(1.67)	(0.93)	(0.39)	(2.95)	(2.06)	(2.87)	(3.21)
TURN	-0.02	-0.02	-0.03	-0.03	0.00	-0.00	-0.01	-0.01
	(-1.59)	(-1.83)	(-2.18)	(-2.24)	(0.07)	(-0.11)	(-1.82)	(-1.74)
EP	0.25	0.16	0.19	0.18	-0.14	-0.09	-0.03	0.11
	(3.13)	(1.97)	(2.45)	(2.44)	(-2.75)	(-2.05)	(-0.80)	(2.72)
BP	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01
	(1.28)	(2.05)	(2.84)	(3.49)	(1.25)	(1.20)	(2.60)	(3.82)
LTG	-0.05	-0.05	-0.05	-0.04	0.01	0.02	0.02	0.03
	(-0.91)	(-0.94)	(-0.95)	(-0.86)	(0.43)	(0.61)	(0.68)	(1.11)
SG	-0.01	-0.01	-0.02	-0.02	-0.00	-0.00	-0.01	-0.01
	(-1.65)	(-2.63)	(-3.32)	(-4.49)	(-0.85)	(-1.12)	(-2.02)	(-4.28)
TA	-0.07	-0.08	-0.06	-0.06	-0.08	-0.07	-0.05	-0.06
	(-3.97)	(-5.04)	(-4.44)	(-4.60)	(-7.09)	(-6.40)	(-4.50)	(-5.57)
CAPEX	-0.10	-0.07	-0.07	-0.06	-0.05	-0.05	-0.04	-0.03
	(-3.58)	(-3.38)	(-2.89)	(-2.41)	(-4.17)	(-3.27)	(-2.76)	(-2.46)
SIZE	-0.02	-0.02	-0.02	-0.02	-0.10	-0.08	-0.05	-0.02
	(-0.91)	(-1.07)	(-1.20)	(-1.38)	(-6.85)	(-5.19)	(-3.69)	(-1.07)
$\bar{R}^2$					0.07	0.07	0.07	0.06

Table VIII. Forecasted Stock Alphas and Quantitative Investment Signals

From 1980 to 2002, in each quarter, we regress weighted-average stock alphas onto 12 quantitative investment signals. We report the average coefficients and the time-series t-statistics computed using the Newey-West procedure with 2 lags. Weighted-average alphas are estimated using fund holdings, recent buys, and recent sells, respectively. In univariate regressions, the explanatory variable is each quantitative signal. In multivariate regressions, we include all 12 quantitative signals as joint regressors. $\bar{R}^2$ is the average adjusted R-square.

	Univariate Regressions			Multivariate Regressions		
Stock alpha	Holdings	Buys	Sells	Holdings	Buys	Sells
RETP	1.26	0.38	-9.14	1.17	0.26	-0.56
	(12.02)	(5.64)	(-0.95)	(12.05)	(4.57)	(-0.30)
RET2P	0.79	0.12	-0.61	0.73	0.09	-0.05
	(6.82)	(2.43)	(-0.05)	(7.59)	(2.52)	(-0.02)
FREV	1.60	0.25	22.17	1.01	0.05	3.61
	(6.06)	(1.32)	(1.66)	(2.03)	(0.34)	(0.59)
SUE	0.28	0.27	-1.79	0.84	0.28	-3.79
	(0.56)	(0.46)	(-0.15)	(1.50)	(0.81)	(-1.26)
TURN	0.05	0.05	-1.89	0.00	0.00	0.18
	(1.31)	(1.44)	(-1.53)	(0.79)	(0.96)	(1.02)
EP	-0.02	0.00	0.41	-0.00	0.00	-0.06
	(-1.40)	(0.03)	(1.28)	(-0.52)	(0.36)	(-0.67)
BP	-0.00	-0.17	-0.27	-0.24	-0.16	-0.27
	(-0.00)	(-1.53)	(-0.04)	(-1.39)	(-2.34)	(-0.08)
LTG	0.16	0.10	0.50	0.11	0.00	-0.45
	(1.11)	(1.55)	(0.29)	(1.09)	(0.95)	(-0.42)
SG	0.00	-0.01	-0.28	-0.02	-0.01	-0.12
	(0.11)	(-0.98)	(-0.73)	(-3.12)	(-3.04)	(-0.93)
TA	-0.02	0.01	0.77	-0.02	-0.00	0.94
	(-0.44)	(0.57)	(0.27)	(-0.67)	(-0.10)	(1.28)
CAPEX	0.01	0.00	-1.49	0.04	-0.01	0.87
	(0.16)	(0.12)	(-0.62)	(0.90)	(-0.86)	(0.63)
SIZE	0.00	-0.15	-3.82	-0.25	-0.13	-1.03
	(0.01)	(-5.06)	(-1.00)	(-3.65)	(-5.57)	(-1.29)
$\bar{R}^2$				0.11	0.05	0.01

Table IX. Forecasted Alphas, Quantitative Signals, and Stock Returns

We perform Fama-MacBeth regressions of stock returns during each of the four evaluation quarters Q1 to Q4 onto weighted-average stock alphas and 12 quantitative signals. Weighted-average stock alphas are estimated using fund holdings, buys, and sells respectively. We report the time-series averages of the estimated coefficients as well as the time-series t-statistics computed using the Newey-West procedure with 2 lags. $\bar{R}$ is the average adjusted R-square.

Stock alpha	Holdings				Buys				Sells			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
α	0.87	0.64	0.38	0.42	1.26	0.87	0.19	0.34	0.57	-0.61	-0.05	-0.22
	(4.41)	(3.53)	(2.60)	(2.43)	(3.50)	(3.11)	(0.80)	(1.19)	(0.99)	(-0.99)	(-1.32)	(-0.90)
RETP	0.15	0.18	0.10	-0.04	0.21	0.09	-0.02	0.01	0.11	0.16	0.10	0.01
	(3.88)	(4.83)	(2.88)	(-1.27)	(3.36)	(1.04)	(-0.17)	(0.12)	(2.04)	(3.29)	(2.43)	(0.22)
RET2P	0.09	-0.08	-0.13	-0.05	0.14	-0.12	-0.14	-0.11	0.12	-0.03	-0.15	-0.06
	(2.55)	(-2.31)	(-3.90)	(-1.83)	(2.77)	(-2.00)	(-4.41)	(-1.53)	(2.90)	(-0.64)	(-4.30)	(-1.86)
FREV	0.31	0.02	0.12	0.14	-0.08	0.64	1.06	-0.22	0.36	-0.10	0.01	0.18
	(2.55)	(0.22)	(1.27)	(1.46)	(-0.19)	(1.02)	(1.12)	(-0.68)	(3.33)	(-0.71)	(0.09)	(1.31)
SUE	0.32	0.22	0.27	0.32	0.30	0.41	0.57	0.25	0.35	0.20	0.36	0.17
	(3.29)	(2.16)	(2.92)	(3.22)	(3.14)	(1.83)	(1.72)	(2.50)	(3.28)	(1.91)	(2.67)	(1.22)
TURN	0.00	-0.00	-0.01	-0.01	0.00	-0.00	-0.02	-0.01	-0.00	0.00	-0.01	-0.01
	(0.02)	(-0.14)	(-0.88)	(-1.58)	(0.43)	(-0.52)	(-1.16)	(-0.77)	(-0.53)	(0.28)	(-1.00)	(-1.02)
EP	-0.13	-0.09	-0.03	0.10	0.01	-0.37	-0.40	0.34	-0.17	-0.07	0.03	0.06
	(-2.80)	(-2.05)	(-0.78)	(2.73)	(0.08)	(-1.24)	(-1.06)	(1.48)	(-2.80)	(-1.47)	(0.42)	(0.90)
BP	0.00	0.00	0.01	0.01	-0.00	0.01	0.02	-0.00	0.00	0.00	0.01	0.01
	(1.25)	(1.25)	(2.62)	(3.83)	(-0.34)	(1.26)	(1.41)	(-0.07)	(1.34)	(0.07)	(2.31)	(3.09)
LTG	0.01	0.02	0.02	0.04	0.00	0.02	0.02	0.04	0.02	0.02	0.03	0.04
	(0.34)	(0.62)	(0.71)	(1.20)	(0.12)	(0.55)	(0.62)	(1.16)	(0.61)	(0.69)	(0.85)	(1.23)
SG	-0.00	-0.00	-0.01	-0.01	-0.03	0.02	0.01	-0.01	-0.00	-0.02	-0.01	-0.01
	(-0.76)	(-1.05)	(-2.03)	(-4.21)	(-1.10)	(0.82)	(0.71)	(-3.65)	(-0.13)	(-1.77)	(-2.29)	(-1.85)
TA	-0.08	-0.07	-0.05	-0.06	-0.06	-0.13	-0.10	-0.03	-0.10	-0.09	-0.05	-0.07
	(-7.06)	(-6.41)	(-4.48)	(-5.58)	(-2.31)	(-2.60)	(-2.05)	(-0.67)	(-6.32)	(-5.39)	(-3.03)	(-5.28)
CAPEX	-0.05	-0.05	-0.04	-0.04	-0.06	-0.05	-0.05	-0.03	-0.06	-0.04	-0.06	-0.03
	(-4.20)	(-3.31)	(-2.77)	(-2.46)	(-4.26)	(-3.33)	(-2.66)	(-2.32)	(-4.74)	(-2.83)	(-2.73)	(-2.22)
SIZE	-0.10	-0.08	-0.05	-0.02	-0.11	-0.07	-0.02	-0.03	-0.09	-0.06	-0.05	-0.00
	(-6.76)	(-5.10)	(-3.75)	(-1.07)	(-6.25)	(-4.36)	(-0.54)	(-1.24)	(-5.20)	(-2.92)	(-3.16)	(-0.23)
$\bar{R}^2$	0.08	0.07	0.07	0.06	0.08	0.07	0.07	0.07	0.09	0.08	0.07	0.06

Table X. Stock Alphas Conditional on Fund Characteristics

From 1980 to 2002, in each quarter we regress characteristic-adjusted stock returns during each of the four evaluation periods Q1 to Q4 onto unconditional weighted-average alphas ($\hat{\alpha}$) and stock alphas scaled by cross-sectional ranks of fund total net assets ($\hat{\alpha}^{TNA}$), turnover ($\hat{\alpha}^{TURN}$), expense ratio ($\hat{\alpha}^{EXP}$), age ($\hat{\alpha}^{AGE}$), and portfolio industry concentration ($\hat{\alpha}^{ICON}$). Unconditional weighted-average alphas are estimated using fund holdings. We report the time-series average of the estimated coefficients. In parentheses are time-series t-statistics computed following the Newey-West procedure with two lags.

	Q1	Q2	Q3	Q4
$\hat{\alpha}$	1.46	1.97	1.17	1.24
	(2.87)	(4.23)	(2.86)	(2.74)
$\hat{\alpha}^{TNA}$	-0.30	-0.35	-1.19	-1.88
	(-0.45)	(-0.66)	(-2.01)	(-3.61)
$\hat{\alpha}^{TURN}$	0.90	0.11	0.16	0.66
	(1.99)	(0.21)	(0.31)	(1.28)
$\hat{\alpha}^{EXP}$	-0.21	-0.40	-0.84	-0.91
	(-0.49)	(-0.87)	(-1.96)	(-2.12)
$\hat{\alpha}^{AGE}$	-0.75	0.07	1.23	1.46
	(-1.06)	(0.11)	(2.06)	(2.48)
$\hat{\alpha}^{ICON}$	1.25	-0.61	-0.54	-0.02
	(1.92)	(-1.60)	(-1.33)	(-0.06)

Table XI. Stock Alphas Conditional on Stock Characteristics

From 1980 to 2002, in each quarter we regress characteristic-adjusted stock returns during each of the four evaluation periods Q1 to Q4 onto unconditional weighted-average alphas ($\hat{\alpha}$) and stock alphas scaled by cross-sectional ranks of firm size (SIZE), book-to-market ratio (BTM), trading volume (VOL), breadth of mutual fund ownership (BRD), and return volatility (STDR). Unconditional weighted-average alphas are estimated using fund holdings. We report the time-series average of the estimated coefficients. Inside the parentheses are the time-series t-statistics computed following the Newey-West procedure with two lags.

	Q1	Q2	Q3	Q4
$\hat{\alpha}$	0.49	1.19	1.08	1.29
	(0.86)	(2.30)	(2.04)	(2.46)
SIZE*$\hat{\alpha}$	-0.40	-0.93	-0.97	-1.20
	(-0.62)	(-1.52)	(-1.89)	(-2.31)
BTM*$\hat{\alpha}$	-0.53	-0.27	0.24	0.23
	(-1.24)	(-0.58)	(0.58)	(0.50)
VOL*$\hat{\alpha}$	-0.33	-0.44	-0.29	-0.52
	(-0.78)	(-1.10)	(-0.63)	(-1.28)
BRD*$\hat{\alpha}$	1.96	1.80	1.50	0.83
	(3.23)	(3.01)	(2.87)	(1.51)
STDR*$\hat{\alpha}$	1.46	-0.39	-1.15	-1.12
	(1.63)	(-0.45)	(-1.84)	(-2.01)

Table XII. Out-of-Sample Performance of Conditional Stock Alphas

From 1985Q1 to 2002Q4, in each quarter we construct stock alphas conditional on fund characteristics, stock characteristics, and both. Parameters for constructing conditional alphas are estimated from Fama-MacBeth regressions using data from 1980Q1 up to the portfolio formation quarter. Fund characteristics include cross-sectional ranks of total net assets, turnover, expense ratio, age, and portfolio industry concentration. Stock characteristics include cross-sectional ranks of firm size, book-to-market ratio, trading volume, breadth of mutual fund ownership, and return volatility. Stocks are then sorted based on conditional alphas to form equal-weighted decile portfolios. We report the net return spreads and characteristic-adjusted return spreads between the top and bottom decile portfolios during the following four quarters Q1 to Q4. We also report the return spreads for portfolios formed on unconditional holding-based weighted-average alphas. Inside the parentheses are the time-series t-statistics.

	Net Return				Characteristic-adjusted Return			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A: Unconditional Stock Alphas								
D10-D1	3.04	2.61	1.68	0.97	2.62	2.16	1.61	1.04
t	(3.30)	(2.92)	(1.99)	(1.11)	(3.64)	(3.21)	(2.73)	(1.69)
Panel B: Stock Alphas Conditional on Fund Characteristics								
D10-D1	3.23	2.37	1.41	0.66	2.84	1.94	1.40	0.94
t	(3.52)	(2.53)	(1.75)	(0.94)	(4.04)	(2.70)	(2.46)	(1.90)
Panel C: Stock Alphas Conditional on Stock Characteristics								
D10-D1	3.36	2.75	2.01	1.31	2.90	2.31	1.75	1.14
t	(3.20)	(2.95)	(2.68)	(1.87)	(3.68)	(3.30)	(3.31)	(2.32)
Panel D: Stock Alphas Conditional on Fund and Stock Characteristics								
D10-D1	3.34	2.53	2.07	1.37	2.93	2.19	1.62	1.12
t	(3.11)	(2.71)	(3.41)	(1.93)	(3.63)	(2.90)	(3.48)	(2.23)