The Investment Value of Mutual Fund Portfolio Disclosure

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Abstract

This paper shows that publicly disclosed mutual fund portfolio holdings have investment value. Our approach is based on the intuition that an overweighting by successful managers, or an underweighting by unsuccessful managers signals that a stock is currently underpriced. Investment strategies based on portfolio holdings, weighted by past fund performance, generate returns exceeding seven percent during the following year, adjusted for the size, book-to-market, and momentum characteristics of stocks. The return-predictive power of the models is not explained by the effect of fund herding or fund flows; rather, it is derived largely from the ability to predict firms' future operating profitability. Further, investment signals generated by the models are distinct from a large number of stock return signals documented by existing literature. Our results indicate that some fund managers have persistent skills in uncovering private information on fundamental stock values.

I. Introduction

A rich history of research has analyzed whether mutual fund managers possess private information about stock values. 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, even for this subset, superior performance may be fleeting, as outperforming funds can quickly grow to an uneconomic scale.

Another approach to determining whether fund managers have private information about stock values is made possible through an examination of the periodic disclosure of fund portfolio holdings. This approach has become increasingly relevant since the recent SEC regulation requiring all U.S.-domiciled 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 fund 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 "copycat" portfolios that mimic the disclosed positions of mutual funds generate hypothetical returns similar to the after-expense returns of the actual funds.

While a positive correlation exists between the performance of fund stockholdings and the actual net fund return (Wermers 2000), investing in funds based on the past performance of their stock picks does not necessarily lead to substantial net-return performance, perhaps because outperforming funds either incur higher trading costs as they attract substantial inflows, or capture a greater share of the economic rents their talents produce through higher fees (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 positions in underperformers, thus limiting profit opportunities.

In this study, we implement a new approach to aggregating the private information possessed by mutual fund managers. Our approach starts from the simple intuition that stocks picked by skilled fund managers should outperform those picked by unskilled managers if stockpicking skills persist over time. We aggregate the private information of fund managers through a statistical model that

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

predicts the future performance of stocks based on how heavily they are held or purchased by fund managers with varying past track records. 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. Simply put, the size of the portfolio "bet" conveys the magnitude of the manager's information, while the manager's past alpha 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 inversion approach developed in the statistical literature to solve ill-posed regression problems, while the third estimator is based on a Bayesian approach.

We use 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, using the simple weighted-average fund alpha estimator (WAA) described above, we find that the return difference between equal-weighted decile portfolios of stocks with the highest and lowest WAAs is about 3 percent during the quarter immediately following portfolio formation. Further, the second-quarter spread between these two portfolios is about 2.5 percent, while the full-year compounded spread exceeds 8 percent. The significant return-predictive power of our stock-selection models during the second to fourth quarters is valuable to investors in light of the time lag of portfolio disclosure: under current SEC rules, mutual funds have sixty days after their fiscal quarter-ends to file portfolio holdings through the EDGAR system. Notably, after adjusting for the size, book-to-market, and momentum characteristics of stocks using the Daniel, Grinblatt, Titman, and Wermers (1997) benchmarks, the resulting return spread has a similar magnitude (exceeding seven percent per year), while exhibiting lower volatility and, therefore, higher levels of statistical precision than the unadjusted return spread reported above.

We also explore the use of fund trades rather than static portfolio weights in forming the weighted-average alpha signals. We find that stock alphas estimated using fund buys exhibit return-predictive power, but their performance is somewhat weaker than the baseline holding-based stock alpha estimators. On the other hand, alphas estimated using fund sells are much less informative about future stock returns. The weaker performance of both the buy- and sell-based alpha models may be due to the fact that the sample size for fund trades is substantially smaller than that of fund holdings; the particularly weak performance of the sell-based stock alpha estimators is likely due to the fact that short-sale constraints self-imposed by most mutual funds limit their ability to express negative opinions about stocks.

Apparently, the stock market only partially reacts to the information contained in fund portfolio disclosure. Stocks ranked highly by our models 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 stockholdings for a maximum of 8 weeks. However, highly-ranked stocks continue to outperform low-ranked stocks for the remainder of the year following the snapshot, indicating that the market is somewhat slow to incorporate the disclosed information into stock prices.

While investors may view our stock alpha estimators as valuable stock-selection signals, an alternative interpretation of our results is that they provide stock-level evidence for the persistence of fund manager skills. That is, by examining the returns of individual stocks chosen by skilled fund managers, we provide new evidence on the value of active management beyond that documented in prior studies at the fund level. We find that information possessed by fund managers about future stock returns is relatively short-lived, lasting roughly one year–consistent with the level of turnover observed for the average actively managed equity fund (which exceeds 100% per year).

We show that the performance of our stock alpha models is distinct from the aggregate fund trading effect of Chen, Jegadeesh, and Wermers (2000) and the effect of changes in the breadth of mutual fund ownership documented by Chen, Hong, and Stein (2002). Both studies weight funds equally in forming stock return signals, assuming implicitly that funds have uniform skills. By contrast, our aggregation approach weights funds differently, depending on their measured skills.

Further, we find that the predictive performance of our models is not due to mechanical price pressure induced by either fund herding or performance-chasing fund flows. Rather, our stock alpha estimators strongly predict firms' operating performance in addition to predicting stock returns. Therefore, the success of our approach reflects the ability of fund managers in uncovering value-relevant information about firm fundamentals.

We further investigate whether our models truly uncover private information possessed by fund managers by controlling for a large number of return-predictive investment signals. These investment signals, such as price momentum, analyst forecast revisions, and accounting accruals, are based on market anomalies documented in prior studies; most importantly, they represent the main sources of cross-sectional stock return predictability using publicly available information. We find that model-forecasted stock alphas are positively correlated with momentum signals but have low correlations with other types of quantitative signals. Moreover, we continue to find significant return-predictive power of our models after jointly controlling for the 12 quantitative signals, including momentum. Therefore, the performance of our stock alpha models apparently reflects active fund managers' private information produced through fundamental analysis.

Finally, we analyze the performance of a set of enhanced stock alpha estimators, where we condition on fund characteristics and stock characteristics. Our analysis of these conditional models reveals heterogeneity in skill persistence across fund types and across stock types. 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 abilities in selecting smaller stocks, and significantly better abilities in picking stocks with higher breadth of mutual fund ownership and lower return volatility. However, skilled managers pick value and growth stocks equally well. In an out-of-sample setting, the conditional models that incorporate information about stock characteristics generate alpha forecasts that outperform those of the unconditional models.

Our study is related to a long stream of literature that, starting from Grinblatt and Titman (1989), shows that equity portfolios held by successful funds (as measured by prior performance) outperform portfolios held by unsuccessful funds. The approach of this study is built on the same intuition, but we convert fund-level information into information about individual stock returns. This step, as demonstrated in the paper, is not trivial, and depends critically on the method of aggregating portfolio information across funds. Using the stock-level approach, we are able to bring new insights onto the issue of persistent mutual fund skills.

Our approach is also distinct from several studies that focus on price pressure effects induced by fund herding or fund flows. Specifically, Wermers (1999) finds that mutual funds herd when trading stocks, and that stocks that herds buy subsequently outperform stocks they sell, while

Brown, Wei, and Wermers (2007) find that, more recently, fund herding activity induces stock price reversals. In addition, Coval and Stafford (2006) and Frazzini and Lamont (2006) show that investor money flows in and out of funds exert price pressure on individual stocks held by funds, resulting in temporary price distortion and subsequent price reversals. By contrast, the main source of the return-predictive power of our models is the ability of fund managers to uncover fundamental information, rather than simply exploiting price pressure effects.

Finally, it is interesting to relate our approach of selecting stocks to the approach of Cohen, Coval, and Pastor (2005) for selecting funds. Our first model (WAA) is related to theirs, in that we weigh portfolio holdings by past fund alphas to aggregate information across funds. While Cohen, Coval, and Pastor (2005) show that this procedure improves the precision of fund-selection signals, our results show that even greater gains can be achieved by applying the model to selecting individual stocks.

The remainder of our paper proceeds as follows. Section II introduces model assumptions and develops three stock alpha estimators. Section III presents the main empirical results on the performance of the stock alpha models, while Section IV provides further analysis and develops extended stock-selection models that condition on fund and stock characteristics. 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-cost* (i.e., fund expenses) fund alpha and α^s_{it+1} is the stock alpha for the period from t to t+1. The above equation becomes an identity for a fund employing a buy-and-hold strategy during the period. If, instead, the fund trades, (1) holds in approximation due to the effect of interim trading and trading costs.

The second assumption is that pre-cost fund alphas persist. We model such persistence through a simple AR(1) process:

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

where α_0 is a constant, which, without loss of generality, is set to zero, and ρ is a constant between 0 and 1; for simplicity of exposition below, we assume it is the same across all funds. In a later section of this paper, we relax this assumption to allow ρ to be a function of fund characteristics.

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 estimated fund alpha, and ϵ_{jt} is the estimation error.

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

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

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." Below, 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 Simple 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 amounts to ignoring the correlations in portfolio weights between different stocks held by a given fund. This 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 simple weighted-average alpha (WAA) 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

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

Note that we have deflated stock alphas by the sum of portfolio weights, across funds, rather than the sum of squared portfolio weights, which would be suggested by inverting the diagonalized $W'W$. Our approach has the intuitive portfolio interpretation that a stock's alpha (ignoring ρ) is equal to the weighted average of fund alphas, where the weights are proportional to fund portfolio weights and sum to one. Intuitively, the portfolio weight, ω_{ijt}, measures the size of the "bet" by a fund manager (i.e., the level of information possessed by the manager about stock i at time t), while the past fund alpha, $\hat{\alpha}^f_{jt+1}$, measures the precision of the manager's private information. Computation of the simple weighted-average alpha does not involve numerical inversion of large matrices, and therefore is fast and potentially robust.[2]

2. The Generalized-Inverse Weighted-Average 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 (Moore (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

[2]Note that $\hat{\boldsymbol{\alpha}}_{WAA}$ is similar to the measure of "stock quality" used by Cohen, Coval, and Pastor (2005) as an intermediate step in computing enhanced mutual fund alphas.

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 $d_{ii}^+ = d_{ii}^{-1}$ 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 is

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

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 Weighted-Average 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

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

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

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

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

In the above, for expositional purposes, we have treated the estimated fund alpha vector, $\hat{\boldsymbol{\alpha}}^f$, as observed with normally distributed 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. For brevity, we leave the details of this procedure 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.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:

$$W_t = W_{t-1} + \Delta W_t^+ + \Delta W_t^- \tag{15}$$

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

Based on the above, the simple weighted-average alpha estimator (10) at the end of quarter t can be decomposed into:

$$\hat{\boldsymbol{\alpha}}^L_{WAA,t} = \rho[W'_{t-1}\hat{\boldsymbol{\alpha}}^f_t]./[W'_t\iota] \tag{16}$$

$$\hat{\boldsymbol{\alpha}}^B_{WAA,t} = \rho[(\Delta W_t^+)'\hat{\boldsymbol{\alpha}}^f_t]./[W'_t\iota] \tag{17}$$

$$\hat{\boldsymbol{\alpha}}^S_{WAA,t} = \rho[(\Delta W_t^-)'\hat{\boldsymbol{\alpha}}^f_t]./[W'_t\iota] \tag{18}$$

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

Similarly, we can decompose the generalized-inverse (12) and the Bayesian weighted-average alpha estimators (14) into:

$$\hat{\boldsymbol{\alpha}}^L_{GIWAA,t} = \rho V_t D_t^+ V_t' W'_{t-1}\hat{\boldsymbol{\alpha}}^f_t \tag{19}$$

$$\hat{\boldsymbol{\alpha}}^B_{GIWAA,t} = \rho V_t D_t^+ V_t' (\Delta W_t^+)'\hat{\boldsymbol{\alpha}}^f_t \tag{20}$$

$$\hat{\boldsymbol{\alpha}}^S_{GIWAA,t} = \rho V_t D_t^+ V_t' (\Delta W_t^-)'\hat{\boldsymbol{\alpha}}^f_t \tag{21}$$

and

$$\hat{\boldsymbol{\alpha}}^L_{BWAA,t} = \rho(W_t'\Omega^{-1}W_t + \sigma^{-2}I)^{-1}W'_{t-1}\Omega^{-1}\hat{\boldsymbol{\alpha}}^f_t \tag{22}$$

$$\hat{\boldsymbol{\alpha}}^B_{BWAA,t} = \rho(W_t'\Omega^{-1}W_t + \sigma^{-2}I)^{-1}(\Delta W_t^+)'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f_t \tag{23}$$

$$\hat{\boldsymbol{\alpha}}^S_{BWAA,t} = \rho(W_t'\Omega^{-1}W_t + \sigma^{-2}I)^{-1}(\Delta W_t^-)'\Omega^{-1}\hat{\boldsymbol{\alpha}}^f_t \tag{24}$$

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, not reversal, in skills).

III. Empirical Evidence: Performance of Forecasted Stock Alphas

III.A. Data

Mutual fund data are from two sources. First, we use data from Thomson Financial on mutual fund portfolio holdings and self-declared investment objectives. Such portfolio holdings are available at a quarterly frequency for the majority of funds, and at a semi-annual frequency for almost all of the remainder of funds. 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, turnover, and expense ratio. Funds in these two databases are matched using the MFLINKS dataset (available from Wharton Research Data Services, WRDS). The sample period for our study starts with the first quarter of 1980 and ends with the last quarter of 2002. Since our focus is on actively managed US equity funds, we include only funds with investment objectives of aggressive growth, growth, or growth and income in the Thomson dataset. We take additional steps 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 combine different share classes of the same fund so that monthly fund returns are computed as the weighted-average returns across share classes, with weights proportional to the beginning-of-month total net assets of each share 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 mutual funds in our sample. We report the number of funds and the number of stocks they hold, at the end of each year from 1980 to 2002. For funds that do not report portfolio holdings at year-end, we use their last reported portfolio snapshot during the year, and assume they hold this portfolio until year-end (on a split-adjusted basis). The table shows that there are 284 actively-managed, domestic equity funds in our sample on December 1980. They collectively hold 2,102 unique common stocks, and the market value of their aggregate equity holdings is $33.48 billion. By comparison, there are 4,726 unique common stocks in the entire CRSP universe, with a total market capitalization of $1.3 trillion. 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 few years. By 2002, there are 1,284 actively-managed, domestic equity funds which collectively hold 4,574 unique common stocks with an aggregate market value of $1.2 trillion. At the same time, there are 5,253 unique common stocks in the CRSP universe, with a total market value of $9.9 trillion. Note that in each year, the number of funds is always far lower than the number of stocks in the sample.

III.B. Empirical Procedures

III.B.1. Calculating Portfolio Weights and Weight Changes

Since our interest is in the persistent stock selection ability of mutual fund managers, we focus on the equity portion of a fund portfolio. Investments in non-equity securities are small for our sample of domestic-equity funds, and do not contribute significantly to fund alphas. Therefore, we compute fund portfolio weights as:

$$\omega_{ijt} = \frac{s_{ijt} p_{it}}{\sum_{i=1}^{N} s_{ijt} p_{it}} \tag{25}$$

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 changes as:

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

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 six months apart. To make $\Delta\omega_{ijt}$ invariant to 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 on a split-adjusted basis.

III.B.2. Measuring Fund Alphas

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

$$r_t - r_{ft} = \alpha + \beta \cdot (r_{mt} - r_{ft}) + s \cdot \text{SMB}_t + h \cdot \text{HML}_t + u \cdot \text{UMD}_t + e_t \tag{27}$$

where r_t is the *pre-expense* monthly fund return, computed as the net fund return plus $\frac{1}{12}$ times the annual expense ratio. The riskfree rate, r_{ft}, is the yield on treasury bills with one-month maturity at the beginning of month t, obtained from CRSP. The market return, r_{mt}, is the month-t CRSP value-weighted NYSE/AMEX/Nasdaq index return, while SMB_t, HML_t, and UMD_t are month-t 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.B.3. Evaluating Stock Portfolio Performance

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 the various estimators developed in Section II. Then, we sort stocks into equal-weighted decile portfolios according to the forecasted stock alphas, and examine portfolio returns during the following four quarters (denoted as Q1 to Q4, the performance evaluation quarters). We impose two restrictions to ensure that the portfolio strategies can realistically be implemented. First, we 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.

To evaluate the buy-and-hold performance of the stock decile portfolios, we compute the characteristic-adjusted return of each stock during each quarter with the characteristic benchmarks developed by Daniel, Grinblatt, Titman, and Wermers (1997; 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 further rank stocks into quintiles based 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

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

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] For each of the 126 stock groups, we form quarterly-rebalanced, equal-weighted portfolio returns during the following year. The characteristic group membership for each stock is held fixed during this period. Since we exclude mutual fund holdings of stocks with a beginning-of-quarter price below $5 in this paper, we similarly exclude these stocks from the benchmark portfolios. Finally, characteristic-adjusted stock returns are quarterly buy-and-hold individual stock returns, in excess of their respective quarterly buy-and-hold benchmark portfolio returns.

After adjusting individual stock returns as above, we calculate equal-weighted quarterly returns and characteristic-adjusted returns of the decile portfolios formed using our stock selection signals during Q1, Q2, Q3, and Q4, then compute their time-series averages over all portfolio formation quarters. 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 accrues from April 1, 1980 to June 30, 1980 to equal-weighted portfolios of stocks selected on March 31, 1980 (which is based on mutual fund holdings at that date, as well as mutual fund alphas computed over the period April 1, 1979 to March 31, 1980). The second accrues from 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.

III.C. 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 simple weighted-average alpha (WAA) approach. Stocks in the bottom decile (D1) of forecasted alphas produce a time-series average return during Q1 of 2.21%, while stocks in the top decile (D10) produce an average return of 5.25%; the return spread between top and bottom deciles is a statistically significant 3.05%. Moreover, as the portfolio rank increases

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

from D1 to D10, the average portfolio return increases monotonically. During the three subsequent quarters (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, although the Q4 spread is statistically insignificant. Compounded from Q1 to Q4, the return spread totals 8.06% per year – economically, a very large spread.[5]

The results for characteristic-adjusted returns are similar. During 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 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 statistically significant at the 10% level. Compounded over the four quarters, the characteristic-adjusted return spread between top and bottom deciles is 7.12% per year. Again, this is a very large return, adjusted for size, book-to-market, and momentum.[6]

In Panel B, stock alphas are estimated using the generalized inverse weighted-average alpha approach (GIWAA). 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 WAA approach in Panel A, but the t-statistics are higher (except for Q4), suggesting that GIWAA produces more accurate return-predictive signals since it extracts more information from portfolio weights than WAA (as described in Section II.B.2). Therefore, to maximize the Sharpe ratio (or information ratio) instead of merely the abnormal return of the investment strategy, the GIWAA approach may be preferable.

In Panel C, we estimate stock alphas using the Bayesian weighted-average alpha approach

[5]Returns averaged across all decile portfolios are 3.69%, 3.59%, 3.45%, and 3.53% from Q1 to Q4, respectively, consistent with the average quarterly return of the equal-weighted CRSP index portfolio during the same period, 3.64%. Thus, the universe of funds do not hold stocks that outperform the broad market.

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

(BWAA), which is described in Appendix A. Here, Q1 to Q4 characteristic-adjusted return spreads are 2.60%, 1.97%, 1.04%, and 0.60%, respectively, and only the average Q4 return is insignificant. Again, spreads are slightly lower in magnitude than those under the WAA approach, but t-statistics are higher under BWAA for Q1, Q2, and Q3.

It is worth noting that in untabulated tests, we have calculated time-series alphas for these decile portfolios using the Carhart (1997) four-factor model of Equation (27), and have obtained similar results.

The last three rows of the table report time-series correlations between D10-D1 return spreads obtained using the three different approaches. All correlations between net return spreads exceed 0.80, while correlations between characteristic-adjusted return spreads are only slightly lower. Simply put, returns generated by the three alpha-estimation approaches are highly correlated, which indicates that they capture similar stock return information from fund portfolio holdings.

In sum, stock alphas estimated using fund holdings hold significant power in predicting stock returns. Such predictive power is not explained by stock characteristics, including size, book-to-market, and momentum – after stock-characteristic adjustment, return spreads between top and bottom decile portfolios remain economically large, and exhibit even stronger statistical significance than unadjusted return spreads.[7] Also, the high correlations among return spreads obtained under the three different approaches indicate that the stock return information we capture is robust to the different approaches employed.

It is also notable that our forecasted stock alphas reliably predict returns beyond the first quarter after portfolio formation, making it feasible to exploit such stock return predictability after fund portfolio disclosure. Current SEC regulations require funds to report their holdings within 60 days after their fiscal quarter-ends. Thus, 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 WAA, the average characteristic-adjusted return spread during Q2 is 2.20%, which compounds to over 9% per year.[8] In a later section of this paper, we will

[7]Further, in untabulated tests, we examine the concentration of top- and bottom-decile portfolios within certain industry sectors, and find no systematic differences between these two portfolios, on average over time.

[8]Although we do not provide direct estimates of transaction costs, we note that the persistence in the ranking of the estimated stock alphas makes it feasible to lower such costs by holding positions for longer than one quarter. For example, we find that about 35% of the top-decile (D10) stocks of a given quarter remain in the top decile during the following quarter. Further, 52% of D10 stocks remain in the top two deciles, while 63% remain in the top three

explore higher frequency stock returns (e.g., weekly) to further explore the patterns in returns following disclosure.

III.D. Stock Alphas Based on Fund Trades

Next, we examine the performance of stock alphas based on recent fund trades, as computed using Equations (16) through (24). In Table III, stock alphas are based on fund buys. Under the WAA 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%, respectively. However, during Q3 and Q4, the spreads are statistically insignificant.

As shown in Panels B and C respectively, the patterns are similar for GIWAA and BWAA. Again, relative to WAA, both GIWAA and BWAA produce smaller spreads in Q1 and Q2, but higher t-statistics.

The high correlations between realized return spreads among the three approaches, as reported in the last three rows of the table, again indicate robustness of the results. In addition (not tabulated), we find high correlations between return spreads derived from buy-based alphas and spreads from holding-based alphas.[9]

Why do stock alpha models based on recent fund buys perform worse than those based on fund holdings? There are two factors that affect the relative performance of holding- vs. trade-based stock alpha models. First, recent fund trades contain fresh information about stock values, whereas fund holdings may contain some stale information. Ceteris paribus, stock alpha models based on recent fund trades (buys) should outperform those based on holdings. Second, the predictive power of the stock alpha models stems from aggregating over a large cross-section of observations – specifically, the number of observations of portfolio holdings or trades in each quarter. In our sample, on average a fund holds 81 stocks, versus 66 fund trades, among which 36 are purchases and 30 are sells. The substantially smaller sample of fund buys is a crucial factor that significantly limits the power of the buy-based models.

Stock alphas based on recent fund sales, as reported in Table IV, fare much worse in predicting

deciles. Among bottom-decile (D1) stocks, 37%, 55%, and 65% remain in the bottom decile, bottom two deciles, or bottom three deciles, respectively, during the following quarter.

[9] In untabulated tests, we combine the forecasts generated by the holding-based and buy-based alphas of the WAA model. We find little improvement over forecasts generated solely by the holding-based model.

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 are often negative. For example, using WAA, the characteristic-adjusted return spread is a significant -1.17% for Q1. Under GIWAA and BWAA, characteristic-adjusted spreads during Q1 and Q2 are negative and statistically significant.

The time-series correlations between return spreads generated by 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, a further indication that stock return information contained in fund sells, if any, is different.

There are two potential reasons why the sell-based signals perform poorly. First, most mutual funds have a self-imposed constraint on short-selling, which 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.

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 alpha signals, while sell-based alphas actually reduce the power of the signal. 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 and two quarters, respectively. The power of lagged holdings in predicting stock returns reinforces the notion that the market does not fully and immediately adjust to the information revealed by portfolio holdings.

III.E. Variations and Robustness

In this section, we present results from several alternative approaches to computing and implementing the WAA model. For brevity, all results discussed in this section are untabulated.

III.E.1. Alternative Measures of Fund Performance

We consider several alternative measures of fund performance as inputs to the computation of WAA in Equation (11). First, we replace the four-factor fund alpha by the unadjusted fund return, cross-sectional rank of return, CAPM alpha, and Fama-French three-factor alpha, all based on rolling 12-month fund net returns. Since these alternative measures do not control for the price momentum effect, the resulting WAA signals tend to generate short-term momentum-like patterns. Specifically, the WAA using these alternative fund performance measures generates D10-D1 stock return spreads that are higher, with greater statistical significance during Q1 and Q2, relative to the WAA using the four-factor fund alpha, but lower and with less significance during Q3 and Q4.

Second, to control for estimation error in fund alphas, we substitute the t-statistic of the Carhart four-factor fund alpha in place of the fund alpha itself when computing the WAA, and refer to the resulting signal the "weighted average t-statistic," or WAT.[10] Under this approach, the portfolio bets of a fund with a noisy alpha are downweighted, relative to a fund with the same alpha but less noise. We find that the resulting D10-D1 return spreads are smaller, but the t-statistics are higher (except for Q4), relative to the results based on the four-factor alpha. Indeed, the patterns in portfolio returns from Q1 to Q4 under the WAT approach are similar to those under the Bayesian approach, which also takes into account the estimation error in evaluating fund performance.

Third, we lengthen the time window used to compute WAA. Specifically, we estimate the four-factor fund alpha using 36 months of lagged fund returns. The resulting stock alphas predict stock returns during Q1 at the 10% significance level, but the predictive power quickly dissipates thereafter. Comparing these results with our prior results using 12-month fund alphas, we can infer that the stockpicking ability of mutual fund managers is fleeting, consistent with the theoretical prediction of Berk and Green (2004) and confirming the findings of several empirical studies (Carhart 1997; DGTW; Hendricks, Patel, and Zechhauser 1993; and Kosowski, Timmermann, Wermers, and White 2006).

Finally, we compute the WAA signal using DGTW-adjusted fund returns, which are based on the reported stockholdings of the funds. That is, the same benchmarking technique is used to measure fund alphas and the resulting stock portfolio alphas. Here, we find that the equally-weighted DGTW-adjusted return of the spread portfolio (D10 minus D1) is only significant (marginally) during Q1. It is likely that estimating fund performance using holdings is not effective because of

[10]The t-statistic of the fund alpha is related to the information ratio of a fund.

the infrequency of such holdings data. In fact, Kacperczyk, Sialm, and Zheng (2006) show that holding-based fund performance measures fail to capture hidden fund actions that are important for explaining the *persistence* of fund performance, which is important for the success of our stock selection strategies.

III.E.2. Value-weighted and Alpha-weighted Stock Portfolios

In addition to the equal-weighted portfolios, we form value-weighted stock decile portfolios sorted on estimated stock alphas. For the baseline case of holding-based WAA formed on four-factor fund alphas, we find results that are similar to those of the equal-weighted portfolios reported in Table II, except that value-weighted D10-D1 spreads during Q3 are insignificant. For instance, value-weighted characteristic-adjusted return spreads between D10 and D1 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 alpha-weighting the portfolios, where within a given decile portfolio each stock is weighted by its forecasted alpha. Here, results are slightly stronger compared to the equal-weighted spreads. Specifically, characteristic-adjusted spreads during the four quarters are 3.1%, 2.5%, 1.2%, and 1.2%, respectively, and all are statistically significant.

III.E.3. Subsample Analysis

At this point, we may wonder whether information about portfolios of outperforming funds or information about portfolios of underperforming funds contributes more to the success of our model. To explore this issue, we generate holding-based WAAs separately for managers with positive and negative past alphas. 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. We find that 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 the model.

In addition, we apply the WAA model using only holdings of the subgroups of funds having large inflows or outflows – defined as absolute value of net flows during the formation quarter above 5% of beginning-of-period total net assets. We find that the holding-based WAA signal derived from heavy inflow funds outperforms that derived from heavy outflow funds during Q1 through Q3. For example, the characteristic-adjusted D10-D1 return spreads during Q1 is 2.8% based on funds with large inflows vs. 1.2% based on funds with large outflows. This is 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 also divide funds into self-declared investment objective groups, then compute return spreads based on the WAA signal derived from the holdings of each group alone. This approach might improve the forecasting power of our model 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 suggest that some differences in skill persistence exist across funds with different investment objectives. Growth-and-income funds produce less precise alpha forecasts 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 well as the overall fund universe, which indicates that the increased estimation error from the reduced fund samples overwhelms any benefits that may arise from focusing on subgroups with higher average skill persistence.[11]

We next implement the model using only portfolio holdings from funds that report calendar quarter-end snapshots – ignoring the information contained in funds that report portfolios at dates earlier in the quarter. This 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 WAAs generated from March, June, September, and December portfolio snapshots. For example, we average across all years the returns for the top minus bottom decile portfolio formed based on March holdings, then held for one year. Similar average returns are computed for the other three quarter-end portfolios. The results show little variation in model performance across holdings from the four

[11] It is also likely that extreme (underperforming and outperforming) funds are dispersed across different investment objective categories, making it important to include all categories to fully capture the signals of these extreme funds.

calendar quarter-ends.

Initiating buys or terminating sales by mutual funds may carry a stronger signal of stock value than other trades (Alexander et al. 2007). Following this idea, we recompute buy-based WAA, using only initiating buys, and compare the resulting portfolio returns with our baseline strategy based on all fund buys. The characteristic-adjusted D10 minus D1 portfolio return for the initiating buy WAA is only about 1.5% during the following year, while our baseline buy model generates an adjusted return of 4.1% (from Table III). We attribute the failure of the initiating-buy model to two potential reasons. First, using the vastly reduced subsample of initiating buys likely adds substantial noise to the model. And second, initiating buys are likely at least partly motivated by inflows, and not superior 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 the 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: higher turnover funds generate a better signal, but so do funds having a higher disclosure frequency. However, WAA signals based on these subgroups do not generate substantially different returns from signals based on the full sample of mutual funds.

III.F. 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 price pattern, 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 WAA model. These portfolios are formed at the end of each formation 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 V.

An examination of the D10-D1 portfolio return spread for the holding-based WAA model during weeks 1 through 12 reveals an interesting pattern (Panel A). These returns are generally largest during weeks 6 through 10; this result is notable, in light of the 60-day maximum delay in the public release of fund holdings following the end of the fiscal quarter. For most funds (those reporting a portfolio snapshot taken at the end of a calendar quarter), public disclosure likely occurs during weeks 6-9, as funds probably delay disclosure to maintain secrecy, especially when implementing their strategies through prolonged trade packages. Consistent with our prior results shown in Table II, the WAA signal continues to generate superior D10-D1 returns during weeks 10-12. Thus, only a portion of the superior Q1 returns from the WAA signal appears to be concentrated around the date of disclosure of fund holdings. The market appears to react only partially to the information content of such disclosure.

Similar results obtain for the buy-based WAA 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 WAAs (Panels A and B, respectively). Overall, the market appears to partially react to public disclosure of fund holdings and to the information about fund purchases that is implied by such holdings disclosure.

IV. Further Analysis

IV.A. Comparison with Other Holdings-Based Stock Signals

Several 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 (reduced 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 measuring the aggregate fractional mutual fund trades (TRADE) as the one-quarter change in total mutual fund holdings (in dollars) of a stock divided by the market capitalization of that stock. Following Chen, Hong, and Stein (2002), we measure the change in breadth of ownership of a stock (ΔBREADTH) as the one-quarter change in the number of mutual funds who hold a long position in the stock divided by the total number of mutual funds that exist during both the formation quarter and the prior quarter.

During 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 VI, confirm the prior-documented effects of the two variables. 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 WAA approach, using fund holdings and buys, respectively. The results, reported in Panel B, show 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 the WAA 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 WAA based on fund holdings and buys respectively, in two sets of four cross-sectional regressions. The time-series average coefficients, except for intercepts, and their time-series t-statistics based on the Newey-West procedure with 2 lags, are reported in Panel C of Table VI .

Note that, even in the presence of TRADE and ΔBREADTH, the average coefficient for the holding-based WAA is significantly positive during each of the four evaluation periods (Q1 through Q4). In fact, coefficients for the holding- and buy-based WAA signals exhibit higher significance levels than either TRADE or ΔBREADTH. Overall, our stock alpha estimators reflect an aspect of stock return predictability different from that captured by aggregate fund trading or changes in the breadth of ownership.

IV.B. Price Pressure or Fundamental Information?

Next, we examine whether the return-predictive performance of estimated stock alphas is driven by information about fundamentals, or merely reflects price pressure from mechanical, non-informational trading by the funds. We consider two sources of price pressure. The first is the tendency of managers to herd on (mimic) the prior trades of top-performing funds. Wermers (1999) documents that fund herding moves stock prices; in our context, herding might push up the prices of stocks held by winning funds even when there is no private information conveyed by winning fund trades. The second type of price pressure is induced by fund flows. It is well-documented that fund flows chase past performance (e.g., Sirri and Tufano 1998). If winning funds respond to new money inflows by adding to already-held stock positions, they may push up the prices of these stocks. Wermers (2003) finds some evidence of price-pressure in stock trades that are motivated by fund flows.

We use two variables to quantify the effects of price pressure. First, we measure herding-motivated trades for a given quarter t using the aggregate fund trading measure of Chen, Jegadeesh, and Wermers (2000). Since we wish to measure aggregate trading contemporaneous with our WAA test period to proxy for follower herding (i.e., during portfolio holding quarters Q1 to Q4), we denote this measure CTRADE to differentiate from the lagged aggregate trading measure TRADE in Section IV.A. Second, to quantify the price-pressure effect of fund flows, we create a weighted-average flow measure (WFLOW_{it}) for stock i during quarter t that is similar to the weighted average alpha:

$$\text{WFLOW}_t = \frac{\sum_{j=1}^{M} \omega_{ijt} \text{FLOW}_{jt}}{\sum_{j=1}^{M} \omega_{ijt}} / \text{MKTCAP}_{it} \tag{28}$$

where FLOW_{jt} is the dollar flow to fund j during quarter t and MKTCAP_{it} is the market capitalization of stock i at the beginning of quarter t. Intuitively, WFLOW_{it} is a measure of the aggregate dollar amount of trading by funds of a stock as a proportion of its market capitalization, assuming that funds proportionally allocate net flows to stocks according to their existing portfolio weights. Again, we measure WFLOW_{it} during Q1 to Q4 to determine the impact of flows that may have reacted to Q0-measured fund performance on test-period stock returns.

We perform quarterly Fama-MacBeth regressions, where the successive dependent variables are the characteristic-adjusted returns of individual stocks during quarters Q1 to Q4, and the explanatory variables include the Q0 WAA (based on fund holdings and fund buys respectively), as well as CTRADE (or WFLOW) that is measured during Q1 to Q4, respectively. It should be noted that CTRADE and WFLOW measured contemporaneous to stock returns may contain information other than mechanical price pressure. Specifically, CTRADE could partially be driven by fundamental information. For example, fund trading in response to news about firms' earnings released during the quarter. Similarly, fund flows may reflect the smart-money effect (Zheng 1999; Wermers 2003). Therefore, any residual predictive power of WAA after controlling for CTRADE and WFLOW may be considered strong evidence of a unique private information content of WAA.

As the results in Table VII show, both CTRADE and WFLOW are strongly correlated with contemporaneous stock returns. However, even after controlling for their effects, WAA continues to exhibit significant return-predictive power. The coefficient for holding-based WAA remains significant for the first three evaluation quarters (Q1 to Q3), while the buy-based WAA coefficient remains significant during Q1 and Q2. Therefore, fund herding or investment flows cannot fully explain the predictive performance of the WAA models.

In untabulated analysis, we further use the fund herding measure of Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999) as well as change in breadth of ownership (both measured during the test periods of Q1 to Q4) as control variables. After controlling for these measures, WAA continues to significantly predict stock returns. Thus, the return-predictive power of WAA is not simply due to its ability to predict these two variables.

Further, we provide evidence that WAA contains fundamental information about firms' future operating performance. Operating performance is measured by the accounting return on equity for the fiscal quarter reported during Q1 (ROEQ1) and the change of ROEQ1 from four quarters ago (ΔROEQ1), where return on equity (ROE) is obtained from the quarterly Compustat file (data item 69 divided by item 59). We also compute the average ROE over Q1 to Q4 (ROE4), and the one-year change in this measure (ΔROE4). To determine the fiscal quarter data that becomes public during a given calendar quarter, we assume a two-month reporting lag after the fiscal quarter-end. Further, we make characteristic-based adjustments to ROEQ1 and ROE4 by subtracting the corresponding operating performance measure of the median stock (to mitigate the influence of outliers) belonging to the same DGTW characteristic benchmark portfolio (see Section III.B.3.). In each quarter, we compute the median characteristic-adjusted measure within each decile portfolio sorted on WAA. In Table VIII, we report the time-series averages of these decile measures of ROEQ1 and ROE4, as well as their changes from a year ago.[12]

[12]The cross-sectional distributions of these operating performance measures are positively skewed. As a result, the

Table VIII shows that the WAA signal strongly predicts the future operating performance of firms. When stocks are sorted on the holding-based WAA, the median-adjusted ROEQ1 for the top decile (D10) averages 0.41%, while the bottom decile (D1) averages 0.19%; the difference is statistically significant. Similarly, the D10-D1 difference in ΔROEQ1 is 0.12%. Further, the D10-D1 differences in ROE4 and ΔROE4, at 0.20% and 0.09%, respectively, are significant. Finally, when stocks are sorted on the buy-based WAA, the resulting D10-D1 differences in ROEQ1, ROE4, ΔROEQ1, and ΔROE4 are also significantly positive. Therefore, the WAA signals contain predictive information about firms' fundamental performance.

IV.C. Public or Private Information? Relation with Quantitative Signals

One might further question whether we have identified stocks for which managers truly possess private information on valuations. For instance, if top performing managers simply trade on prior-documented market anomalies based on publicly available financial information – such as an accruals-based strategy documented by Sloan (1996) – then we might not conclude that our approach truly uncovers fund managers' private information on stocks. Therefore, we next examine the relation of the WAA signals with prior-documented stock return anomalies.

IV.C.1. Quantitative Investment Signals

Academic studies have found that cross-sectional stock returns are predictable based on firm-specific financial and accounting variables, which are sometimes referred to as "quantitative characteristics" or "quantitative investment signals". There is evidence that mutual funds trade on at least some of these variables, such as price momentum (e.g., Carhart 1997; 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 definitions of these variables, and provide a detailed description of the construction of each variable in Appendix B.

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average median-adjusted measures tend to be positive. This, however, does not affect the robustness of our results. We have also calculated operating performance measures without adjusting for stock characteristics, then calculated portfolio means of cross-sectionally winsorized operating performance measures. The results are similar.

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, relative to the end 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 ending date of Q0, while SUE measures earnings momentum as the standardized unexpected actual earnings during Q0 minus its four-quarter lagged value, scaled by the standard deviation of such earnings changes during the previous eight quarters.

The next seven variables are contrarian signals. TURN is the exchange-specific percentile ranking of stock trading turnover during the past six months. 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. 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. Further, TA is the ratio of total accounting accruals during the four quarters prior to the end of Q0, divided by the average of total book assets measured during Q0, and its value four-quarters prior to Q0. CAPEX is capital expenditure during the past four quarters divided by the average total assets over the same period. Finally, we include the log of stock market capitalization (SIZE) at the end of Q0 as a predictive signal.

We use Fama-MacBeth regressions to confirm the ability of these quantitative signals to predict stock returns. The successive dependent variables are stock returns during the next four quarters (Q1 to Q4). The explanatory variables include the 12 quantitative signals, separately and jointly. The regressions are performed in each quarter, from 1980Q1 to 2002Q4. 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 generally consistent with those documented in previous studies. For brevity, the results are not tabulated in the paper.

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

We next employ Fama-MacBeth regressions to examine the relation between the WAA stock-selection signals and the 12 quantitative signals. The dependent variable is the WAA, based on fund holdings and buys, respectively. In univariate regressions, the explanatory variable is one of the 12 signals. In multivariate regressions, all 12 signals are used as joint regressors.[13] Cross-sectional regressions are performed during each quarter. Table IX reports time-series averages of 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.

The WAA based on fund holdings has a momentum tilt: in both univariate and multivariate regressions, holding-based WAAs have significantly positive loadings on three of the four momentum variables – RETP, RET2P, and FREV. On the other hand, with the exception of SG and SIZE (only in multivariate regressions), the coefficients on the remaining signals are insignificant. For stock alphas based on fund buys, similar but slightly weaker patterns of correlation emerge. While FREV is no longer significant, BP is significant (in multivariate regressions).

Overall, WAA has a very weak correlation with prior-documented strategies, with the exception of momentum. This finding appears to be consistent with previous literature in that momentum is an important factor in explaining performance persistence.[14]

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

To further confirm that our WAA signal contains unique information not previously documented, we run a "horserace" between forecasted stock alphas and quantitative signals to predict returns. Specifically, we perform quarterly Fama-MacBeth regressions, where the successive dependent variables are cross-sectional stock returns during each of the four evaluation quarters (Q1 through Q4, respectively), and the explanatory variables include all 12 quantitative signals as well as the WAA signal based on either fund holdings or fund buys. In Table X, we report time-series average estimated coefficients (except for the intercepts), the corresponding time-series t-statistics

[13] During any given quarter, especially in early sample periods, a significant number of 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 approach for Table X as well.

[14] The positive correlation between the WAA signals and momentum could also be due to a mechanical effect: the portfolio weights for computing WAA are measured at the end of Q0, and stocks with higher returns prior to the end of Q0 naturally have higher portfolio weights if funds do not quickly rebalance.

(computed with Newey-West standard errors with 2 lags), and time-series averages of adjusted R-squares for the regressions. Notably, after controlling for the 12 quantitative signals, loadings on the holdings-based WAA are significantly positive for all four evaluation quarters, and loadings on the buy-based stock alpha are significantly positive for Q1 and Q2.

While the results suggest that the performance of the WAA signals remains significant after controlling for the linear relations between quantitative signals and stock returns, a remaining concern is whether the WAA signals merely pick up a nonlinear form of return predictability based on these previously-documented signals. To address this issue, we construct dummy variables representing the top and bottom quintiles of each signal, and include the interactions of these dummies with the quantitative signals as additional control variables. In addition, the return predictive power of quantitative signals could potentially be different among subsamples of stocks in the dimensions of market capitalization and value/growth. To control for such effects, we create large-cap/small-cap dummies (top and bottom quintiles of size), as well as value/growth dummies (top and bottom quintiles of book-to-market ratio), and include the interaction of these dummies with the quantitative signals as additional explanatory variables. In all of these variations of our regression specification, the coefficients on the holding-based WAA always remain significant for at least the first three evaluation quarters (Q1 to Q3), and the coefficients for buy-based WAA are always significant for Q1 and Q2. Thus, the WAA does not merely pick up specification errors in the linear model used in generating Table X. For brevity, these results are not tabulated.

The evidence suggests that fund trading on momentum and other market anomalies does not completely explain the persistent skills of mutual fund managers in selecting stocks. What, then, is the source of the return-predictive power of our stock alpha models, and, ultimately, what is the source of fund managers' persistent stock-selection skills? We note that most fund managers make stock-selection decisions based on fundamental analysis, a process that may enable them to obtain private information about stock values. Our findings provide an interesting perspective for understanding the value of fundamental analysis vs. quantitative research. The results suggest that fundamental analysis could be quite different from quantitative stock selection (which is based on publicly available financial information), as they capture different aspects of stock return predictability.

IV.D. 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. Below, we relax these assumptions to examine the effect of fund and stock characteristics in conditional WAA models. Such an analysis may expose factors that affect fund performance persistence, and may lead to an improved predictive performance of the WAA stock signal.

IV.D.1. Conditional Models

We first relax the assumption that the persistence parameter, ρ, in (2) is the same across all funds. 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 WAA, 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.

Next, to examine whether mutual fund managers have more persistent skills in selecting stocks with certain characteristics, we construct stock alphas scaled by stock characteristics:

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

where $\hat{\alpha}^C_{it+1}$ 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 consider a set of five ($P = 5$) fund characteristics. They include fund total net assets (TNA) at the end of Q0, fund turnover (TURN) during the prior year, expense ratio (EXP) during the prior year, fund age (AGE) as of Q0, and portfolio industry concentration (ICON) during Q0 (following the definition of Kacperczyk, Sialm, and Zheng (2005)). In order to control for nonstationarity or time trend in these characteristics, we convert the variables into cross-sectional percentile ranks (quintile ranks for AGE).

The stock characteristics we examine include firm size (SIZE), book-to-market ratio (BTM), trading turnover (VOL), breadth of mutual fund ownership (BRD), and daily return volatility (STDR). All these variables are measured as of Q0, and are converted into cross-sectional percentile ranks (quintile ranks for BRD). In addition, since the trading volume is defined differently at NASDAQ than at NYSE/AMEX, for VOL, we rank stocks traded on NASDAQ separately from those traded on NYSE/AMEX.

We perform Fama-MacBeth regressions to estimate the parameters of the two conditional models. For the model conditional on fund characteristics, 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 $\hat{\alpha}^H_{ipt+1}, p = 1, ..., P$. We then take the time-series averages of estimated coefficients, and compute the time-series t-statistics. Panel A of Table XI reports results. 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.

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.

Panel B of Table XI reports results for the model conditional on stock characteristics. 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.[15] 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 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.

[15]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.

IV.D.2. Predictive Performance of Conditional Stock Alphas

Our last set of tests examine whether, in an out-of-sample setting, the conditional stock alpha models truly improve return-predictive performance. The predictive conditional alphas are obtained from the following models (dropping the time subscript for simplicity):

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

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

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

where $\tilde{r}_{iq}$ is the characteristic-adjusted stock return during an evaluation quarter q (q=1, ..., 4). Note that the parameters are specific to each evaluation period, q. To obtain these parameters for a given quarter t, we perform quarterly Fama-MacBeth regressions for the above models, using all data available from 1980Q1 up to that quarter t, and then compute the time-series averages of estimated coefficients from quarterly regressions. The average coefficients are then used in the above models, together with unconditional stock alphas and fund/stock characteristics measured at quarter t, to generate forecasted alphas for the following four quarters, t+1 through t+4.

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 Table XI.

In Table XII, we report net return spreads and characteristic-adjusted return spreads between equal-weighted top (D10) and bottom (D1) decile portfolios for the conditional holding-based WAAs. For comparison, we also report results for unconditional holding-based WAAs (our baseline stock-selection signal) during the same period. The characteristics-adjusted D10-D1 return spreads are 2.62%, 2.16%, 1.61%, and 1.04% for the four evaluation quarters respectively. Therefore, despite shorter sample period here (starting from 1985), the performance of the unconditional WAA is similar to that during the longer period (starting from 1980) reported in Table II.

We next include all five fund characteristics, but no stock characteristics, in forming 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% for Q1 through Q4, respectively. Note that these spreads are comparable to those for unconditional alphas, with similar t-statistics. Therefore, incorporating fund characteristics into conditional models does not improve the out-of-sample model performance in an economically meaningful 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, respectively. Both the spreads and the t-statistics are higher than those of the unconditional models.

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, respectively. The performance is improved relative to unconditional models, but there is no clear improvement relative to alphas conditional on stock characteristics only.

To conclude, conditional WAAs produce a modest improvement over the unconditional WAA in predicting stock 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 significantly 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. The predictive power of our models does not stem from mechanical price pressure, and 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 provides useful insights in understanding 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. The fact that our models predict both stock returns and operating performance, and the fact that the models' return-predictive power is not subsumed by public stock selection signals suggest that fund managers' stock selection information, as captured by our models, is related to firms' business fundamentals and is largely private. 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:

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

where $r_{j\tau}$ is fund j's return in excess of the riskfree rate at time τ, $\alpha^f_{j\tau}$ is the fund alpha, $\boldsymbol{f}_\tau$ is a vector of four factors (e.g., Carhart (1997) four factors), and $\boldsymbol{b}_{j\tau}$ is a vector of four factor loadings. $\alpha^f_{j\tau}$ and $\boldsymbol{b}_{j\tau}$ 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 $\tilde{V}_{\theta j} = (F'F)^{-1}\sigma^2_{jt}$ 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:

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

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 non-linear 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,

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

where $\cdot\times$ is a dot multiplication operator, VAR(σ_{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 to 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 is the last month of quarter t [CRSP]
2. RET2P	Cumulative market-adjusted return for the second preceding six months (months -12 through -7) [CRSP]	$[\Pi_{i=m-12}^{m-7}(1+\text{monthly return}_i)]-1$ -$[\Pi_{i=m-12}^{m-7}(1+\text{value-weighted market monthly return}_i]-1$,
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 [IBES] P_{m-1} = price at the end of month m-1 [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 $\text{EPS}_q-\text{EPS}_{q-4}$= 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 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 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 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	$\frac{\begin{array}{l}(\triangle\text{Current Assets}_q\text{ [D40]}\\ -\triangle\text{Cash}_q\text{[D36])(based on balance sheet accounts)}\\ -(\triangle\text{Current Liabilities}_q\text{ [D49]}\\ -\triangle\text{Current LTD}_q\text{ [D45])}\\ -\triangle\text{Deferred Taxes}_q\text{ [D35]}\\ -\text{Depreciation and Amortization}_q\text{[D5]}\end{array}}{(TA_q+TA_{q-4})/2\text{ [D44]}}$ $\triangle X_q=X_q-X_{q-4}$, e.g., $\triangle$Current Assets$_{t-1}$ = Current Assets$_{t-1}$ $-$Current Assets$_{t-5}$
11. CAPEX	Capital expenditures to total assets	$\frac{\text{CAPEX}_q}{(TA_q+TA_{q-4})/2[D44]}$ 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 for each year, from 1980 to 2002. To obtain the sample, we merge the Thomson 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. 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, we 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. The number of stocks and value of stocks held by mutual funds, as well as the number of stocks and their total market capitalization for the CRSP universe, are computed at the end of each year. For funds that do not report at year-end, we use their last reported portfolio snapshots of the year, and assume that they hold the reported shares until year-end (on a split-adjusted basis).

	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 of Stocks (%)	Value of Stocks (%)
1980	284	2102	33.48	4726	1315.72	44.48	2.54
1981	280	2289	29.95	5089	1227.51	44.98	2.44
1982	270	2469	38.77	5059	1408.54	48.80	2.75
1983	297	3082	53.97	5672	1740.04	54.34	3.10
1984	313	3177	56.01	5796	1681.25	54.81	3.33
1985	342	3447	74.08	5773	2095.47	59.71	3.54
1986	403	3659	91.39	6057	2359.57	60.41	3.87
1987	461	3568	102.14	6362	2320.84	56.08	4.40
1988	500	3708	111.21	6101	2520.46	60.78	4.41
1989	545	3638	142.82	5908	3067.46	61.58	4.66
1990	589	3345	136.43	5764	2753.70	58.03	4.95
1991	691	3598	214.74	5809	3721.78	61.94	5.77
1992	800	3783	277.68	5926	4121.41	63.84	6.74
1993	1074	5095	392.08	6470	4681.99	78.75	8.37
1994	1212	5398	415.11	6784	4636.40	79.57	8.95
1995	1347	5782	673.87	7016	6328.62	82.41	10.65
1996	1502	6209	891.84	7478	7717.91	83.03	11.56
1997	1653	6260	1232.55	7465	10054.86	83.86	12.26
1998	1651	5870	1632.49	7038	12424.61	83.40	13.14
1999	1583	5652	2055.01	6683	15892.12	84.57	12.93
2000	1432	5435	1912.99	6379	14438.21	85.20	13.25
2001	1339	4898	1662.02	5677	12806.15	86.28	12.98
2002	1284	4574	1236.42	5253	9937.82	87.07	12.44

Table II. Performance of Stock Alphas Estimated Using Fund Holdings

At the end of each quarter from 1980 to 2002, we use fund portfolio holdings to estimate stock alphas using the simple weighted average alpha (WAA), the generalized inverse weighted average alpha (GIWAA), and the Bayesian weighted average alpha (BWAA), respectively. Stocks are then ranked by these forecasted alphas to form equal-weighted decile portfolios. We report the average quarterly buy-and-hold 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: Simple Weighted-Average Alpha (WAA)								
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 Weighted-Average Alpha (GIWAA)								
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 Weighted-Average Alpha (BWAA)								
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, GIWAA)	0.85	0.87	0.81	0.90	0.82	0.82	0.83	0.81
Corr(WAA, BWAA)	0.86	0.85	0.86	0.91	0.84	0.83	0.56	0.78
Corr(GIWAA, BWAA)	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

At the end of each quarter from 1980 to 2002, we use that quarter's fund buys to estimate stock alphas with the simple weighted average alpha (WAA), the generalized inverse weighted average alpha (GIWAA), and the Bayesian weighted average alpha (BWAA), respectively. Stocks are then ranked by forecasted alphas to form equal-weighted decile portfolios. We report the average quarterly buy-and-hold 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: Simple Weighted-Average Alpha (WAA)								
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 Weighted-Average Alpha (GIWAA)								
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 Weighted-Average Alpha (BWAA)								
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, GIWAA)	0.82	0.83	0.65	0.77	0.81	0.82	0.60	0.73
Corr(WAA, BWAA)	0.91	0.81	0.82	0.90	0.79	0.86	0.77	0.87
Corr(GIWAA, BWAA)	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

At the end of each quarter from 1980 to 2002, we use recent fund sells to estimate stock alphas under the simple weighted average alpha (WAA), the generalized inverse weighted average alpha (GIWAA), and the Bayesian weighted average alpha (BWAA), respectively. Stocks are then ranked by forecasted alphas to form equal-weighted decile portfolios. We report the average quarterly buy-and-hold 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: Simple Weighted-Average Alpha (WAA)							
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 Weighted-Average Alpha (GIWAA)							
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 Weighted-Average Alpha (BWAA)							
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, GIWAA)	0.53	0.39	0.48	0.43	0.42	0.32	0.33	0.44
Corr(WAA, BWAA)	0.74	0.54	0.65	0.58	0.74	0.58	0.47	0.56
Corr(GIWAA,BWAA)	0.47	0.60	0.40	0.35	0.36	0.53	0.32	0.28

Table V. Weekly Performance of Simple Weighted-Average Alpha (WAA)

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. Stock alphas are estimated using the simple weighted-average alpha (WAA), based on fund holdings and fund buys, respectively. Inside the parentheses are time-series t-statistics.

Panel A: WAA based on Holdings								
Week	-3	-2	-1	0	1	2	3	4
D1	0.07	-0.37	0.06	0.67	0.08	0.42	0.42	-0.03
D10	0.59	0.24	0.39	1.00	0.58	0.80	0.82	0.39
D10-D1	0.52	0.61	0.33	0.33	0.49	0.38	0.40	0.42
t	(3.29)	(5.59)	(3.13)	(2.71)	(3.43)	(2.43)	(2.24)	(3.25)
Week	5	6	7	8	9	10	11	12
D1	1.05	0.37	0.08	0.20	0.78	-0.15	-0.47	0.17
D10	1.33	0.99	0.84	0.46	1.32	0.55	-0.05	0.57
D10-D1	0.27	0.63	0.76	0.26	0.54	0.70	0.42	0.40
t	(1.79)	(4.17)	(5.18)	(1.90)	(3.62)	(4.36)	(2.67)	(2.92)
Panel B: WAA based on Buys								
Week	-3	-2	-1	0	1	2	3	4
D1	0.32	-0.07	0.28	0.86	0.41	0.78	0.69	0.37
D10	0.63	0.24	0.41	1.05	0.57	1.06	1.10	0.58
D10-D1	0.31	0.31	0.12	0.20	0.16	0.28	0.40	0.20
t	(2.12)	(2.26)	(1.11)	(1.63)	(1.00)	(1.47)	(2.50)	(1.05)
Week	5	6	7	8	9	10	11	12
D1	1.31	0.66	0.35	0.53	1.16	-0.02	-0.38	0.35
D10	1.76	1.20	0.97	0.65	1.62	0.76	-0.11	0.79
D10-D1	0.45	0.54	0.62	0.12	0.46	0.78	0.27	0.44
t	(2.53)	(3.04)	(4.01)	(0.78)	(3.07)	(3.86)	(1.80)	(3.17)

Table VI. 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 simple weighted-average alphas (WAA). 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 WAA, TRADE, and ΔBreadth. The average adjusted R-squares are also reported. Stock alphas are estimated using fund holdings and recent buys, 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: Decile Portfolios Sorted on 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: Decile Portfolios Sorted on 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
WAA based on holdings	0.04	0.04
t	(8.64)	(6.47)
WAA based on buys	0.04	0.03
t	(4.96)	(3.13)

Panel C: Fama-MacBeth Regressions

stock alpha	WAA based on Holdings				WAA based on Buys			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
WAA	1.39	1.03	0.67	0.49	1.71	1.29	0.34	0.39
t	(5.48)	(3.92)	(3.14)	(2.17)	(3.97)	(3.19)	(1.02)	(1.00)
TRADE	0.26	0.69	0.16	-0.14	0.27	0.64	0.16	-0.07
t	(1.24)	(3.05)	(0.75)	(-0.66)	(1.17)	(2.68)	(0.58)	(-0.27))
ΔBREADTH	0.54	0.23	0.33	-0.11	0.53	0.23	0.34	-0.09
t	(3.69)	(1.80)	(2.84)	(-0.92)	(3.58)	(1.80)	(2.93)	(-0.69)

Table VII. The Effect of Price Pressure

At the end of each quarter from 1980 to 2002, we perform cross-sectional regressions to control for the effect of price pressure when measuring the predictive power of estimated stock alphas. The dependent variable is characteristic-adjusted stock returns in one of the four holding period (Q1 to Q4). The explanatory variables include the simple weighted average alpha (WAA) based on fund holdings and recent buys respectively, as well as one of the two price pressure measures: CTRADE and WFLOW. CTRADE is the contemporaneous aggregate fund trading during Q1 to Q4. WFLOW is the contemporaneous weighted average dollar fund flows as a proportion of a stock's market cap, from Q1 to Q4. We report the time series averages of estimated coefficients for WAA, CTRADE, and WFLOW. Inside the parentheses are time-series t-statistics.

stock alpha	WAA based on Holdings				WAA based on Buys			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A: Controlling for Aggregate Fund Trading								
WAA	1.11	0.81	0.50	0.38	1.52	1.35	0.24	0.04
t	(3.91)	(3.14)	(2.56)	(1.64)	(2.67)	(2.33)	(0.75)	(0.10)
CTRADE	0.65	0.87	0.82	0.86	0.78	0.10	0.11	0.09
t	(9.13)	(9.53)	(8.07)	(8.55)	(9.26)	(10.40)	(9.98)	(9.93)
Panel B: Controlling for Fund Flows								
WAA	1.71	1.29	0.34	0.39	1.59	1.27	0.59	0.15
t	(3.47)	(2.74)	(1.87)	(1.20)	(2.11)	(1.83)	(1.05)	(0.40)
WFLOW	1.38	1.69	1.74	1.95	1.63	2.18	0.72	2.16
t	(6.31)	(7.65)	(7.83)	(9.13)	(6.68)	(5.31)	(5.12)	(8.66)

Table VIII. Fundamental Information Contained in Forecasted Stock Alphas

From 1980 to 2002, in each quarter we sort stocks into deciles based on the simple weighted-average stock alphas (WAA) estimated using fund holdings and recent fund buys, respectively. We calculate, for each decile, the medians of the following characteristic-adjusted operating performance measures: return on equity for Q1 (ROEQ1), the average return on equity for Q1 to Q4 (ROE4), ROE for Q1 in excess of four quarters ago (ΔROEQ1), the average return on equity for Q1 to Q4 in excess of the average return on equity during the previous four quarters (ΔROE4). The characteristic-adjusted operating measure is the corresponding operating performance measure for a firm in excess of the median measure of the benchmark portfolio, which is constructed following the Daniel, Grinblatt, Titman, and Wermers (1997) procedure. We report the time series averages of these operating performance measures for each decile, as well as the differences in these measures between the top (D10) and bottom (D1) deciles. Inside the parentheses are time-series t-statistics. Operating performance measures are expressed in percent.

stock alpha	WAA based on Holdings				WAA based on Buys			
	ROEQ1	ROE4	ΔROEQ1	ΔROE4	ROEQ1	ROE4	ΔROEQ1	ΔROE4
D1	0.19	0.11	0.03	-0.01	0.28	0.16	0.05	-0.03
D2	0.27	0.19	0.04	-0.01	0.23	0.17	0.04	-0.02
D3	0.25	0.19	0.05	0.00	0.25	0.19	0.07	-0.05
D4	0.22	0.22	0.05	0.02	0.23	0.17	0.05	-0.02
D5	0.26	0.24	0.05	0.01	0.27	0.22	0.04	-0.01
D6	0.27	0.23	0.03	0.02	0.22	0.22	0.06	0.04
D7	0.26	0.22	0.05	0.03	0.22	0.20	0.05	0.01
D8	0.32	0.27	0.10	0.03	0.29	0.21	0.04	-0.01
D9	0.37	0.28	0.10	0.05	0.36	0.23	0.10	0.01
D10	0.41	0.31	0.15	0.08	0.47	0.28	0.26	0.09
D10-D1	0.22	0.20	0.12	0.09	0.19	0.12	0.21	0.12
t	(3.35)	(2.96)	(2.62)	(3.37)	(2.86)	(2.03)	(4.59)	(3.73)

Table IX. Forecasted Stock Alphas and Quantitative Investment Signals

At the end of each quarter from 1980 to 2002, we regress the simple weighted-average stock alphas (WAA) on 12 quantitative investment signals. We report the average coefficients and the time-series t-statistics computed using the Newey-West procedure with 2 lags. WAAs 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	WAA based on Holdings	WAA based on Buys	WAA based on Holdings	WAA based on Buys
RETP	1.26	0.38	1.17	0.26
	(12.02)	(5.64)	(12.05)	(4.57)
RET2P	0.79	0.12	0.73	0.09
	(6.82)	(2.43)	(7.59)	(2.52)
FREV	1.60	0.25	1.01	0.05
	(6.06)	(1.32)	(2.03)	(0.34)
SUE	0.28	0.27	0.84	0.28
	(0.56)	(0.46)	(1.50)	(0.81)
TURN	0.05	0.05	0.00	0.00
	(1.31)	(1.44)	(0.79)	(0.96)
EP	-0.02	0.00	-0.00	0.00
	(-1.40)	(0.03)	(-0.52)	(0.36)
BP	-0.00	-0.17	-0.24	-0.16
	(-0.00)	(-1.53)	(-1.39)	(-2.34)
LTG	0.16	0.10	0.11	0.00
	(1.11)	(1.55)	(1.09)	(0.95)
SG	0.00	-0.01	-0.02	-0.01
	(0.11)	(-0.98)	(-3.12)	(-3.04)
TA	-0.02	0.01	-0.02	-0.00
	(-0.44)	(0.57)	(-0.67)	(-0.10)
CAPEX	0.01	0.00	0.04	-0.01
	(0.16)	(0.12)	(0.90)	(-0.86)
SIZE	0.00	-0.15	-0.25	-0.13
	(0.01)	(-5.06)	(-3.65)	(-5.57)
$\bar{R}^2$			0.11	0.05

Table X. 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 simple weighted-average stock alphas (WAA) and 12 quantitative signals. WAAs 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	WAA based on Holdings				WAA based on Buys			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
WAA	0.87	0.64	0.38	0.42	1.26	0.87	0.19	0.34
	(4.41)	(3.53)	(2.60)	(2.43)	(3.50)	(3.11)	(0.80)	(1.19)
RETP	0.15	0.18	0.10	-0.04	0.21	0.09	-0.02	0.01
	(3.88)	(4.83)	(2.88)	(-1.27)	(3.36)	(1.04)	(-0.17)	(0.12)
RET2P	0.09	-0.08	-0.13	-0.05	0.14	-0.12	-0.14	-0.11
	(2.55)	(-2.31)	(-3.90)	(-1.83)	(2.77)	(-2.00)	(-4.41)	(-1.53)
FREV	0.31	0.02	0.12	0.14	-0.08	0.64	1.06	-0.22
	(2.55)	(0.22)	(1.27)	(1.46)	(-0.19)	(1.02)	(1.12)	(-0.68)
SUE	0.32	0.22	0.27	0.32	0.30	0.41	0.57	0.25
	(3.29)	(2.16)	(2.92)	(3.22)	(3.14)	(1.83)	(1.72)	(2.50)
TURN	0.00	-0.00	-0.01	-0.01	0.00	-0.00	-0.02	-0.01
	(0.02)	(-0.14)	(-0.88)	(-1.58)	(0.43)	(-0.52)	(-1.16)	(-0.77)
EP	-0.13	-0.09	-0.03	0.10	0.01	-0.37	-0.40	0.34
	(-2.80)	(-2.05)	(-0.78)	(2.73)	(0.08)	(-1.24)	(-1.06)	(1.48)
BP	0.00	0.00	0.01	0.01	-0.00	0.01	0.02	-0.00
	(1.25)	(1.25)	(2.62)	(3.83)	(-0.34)	(1.26)	(1.41)	(-0.07)
LTG	0.01	0.02	0.02	0.04	0.00	0.02	0.02	0.04
	(0.34)	(0.62)	(0.71)	(1.20)	(0.12)	(0.55)	(0.62)	(1.16)
SG	-0.00	-0.00	-0.01	-0.01	-0.03	0.02	0.01	-0.01
	(-0.76)	(-1.05)	(-2.03)	(-4.21)	(-1.10)	(0.82)	(0.71)	(-3.65)
TA	-0.08	-0.07	-0.05	-0.06	-0.06	-0.13	-0.10	-0.03
	(-7.06)	(-6.41)	(-4.48)	(-5.58)	(-2.31)	(-2.60)	(-2.05)	(-0.67)
CAPEX	-0.05	-0.05	-0.04	-0.04	-0.06	-0.05	-0.05	-0.03
	(-4.20)	(-3.31)	(-2.77)	(-2.46)	(-4.26)	(-3.33)	(-2.66)	(-2.32)
SIZE	-0.10	-0.08	-0.05	-0.02	-0.11	-0.07	-0.02	-0.03
	(-6.76)	(-5.10)	(-3.75)	(-1.07)	(-6.25)	(-4.36)	(-0.54)	(-1.24)
$\bar{R}^2$	0.08	0.07	0.07	0.06	0.08	0.07	0.07	0.07

Table XI. Stock Alphas Conditional on Fund and Stock Characteristics

At the end of each quarter from 1980 to 2002, we regress characteristic-adjusted stock returns during each of the four evaluation periods Q1 to Q4 on the unconditional WAA ($\hat{\alpha}$) and as well as the 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 ($\hat{\alpha}^{ICON}$). Time-series average estimated coefficients (except for the intercept) are reported in Panel A. Similarly, in each quarter we regress characteristic-adjusted returns during Q1 to Q4 onto unconditional WAA ($\hat{\alpha}$) 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). The time-series averages of estimated coefficients (except for the intercept) are reported in Panel B. WAAs are estimated using fund holdings. In the parentheses are time-series t-statistics computed following the Newey-West procedure with two lags.

	Q1	Q2	Q3	Q4
Panel A: Conditional on Fund Characteristics				
$\hat{\alpha}$	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)
Panel B: Conditional on Stock Characteristics				
$\hat{\alpha}$	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

At the end of each quarter from 1985Q1 to 2002Q4, we construct stock alphas (WAA) 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 the unconditional holding-based WAAs. 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 (WAA)								
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)