Identifying Skilled Mutual Fund Managers by their Ability to Forecast Earnings

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ABSTRACT

This article proposes a new measure, the Ability to Forecast Earnings (AFE), to identify skilled mutual fund managers. This measure combines the quantity and quality of active management by examining how well a fund's active stock holdings (deviations from its benchmark) forecast firms' abnormal returns, realized during subsequent earnings announcements. By focusing on a short event time window, in which the price movements in underlying assets are predominantly due to firm-specific fundamental information, AFE is less affected by noise and other shocks in the stock market. We estimate AFE for 2,455 unique U.S. equity funds over the period 1984–2008 and find strong persistence in AFE for skilled funds in the subsequent three years. Moreover, skilled funds in the top decile with the highest AFE outperform those with the lowest AFE by 3.12 percent per year in terms of raw returns and 2.64 percent in terms of Carhart's four-factor alpha.

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1. Introduction

An active portfolio manager creates value by offering successful forecasts of future returns. Therefore, a natural approach to identifying active managers with superior skills is to compare their forecasts against future stock performance and assess their forecasting abilities. In practice, the forecasts of portfolio managers are often unobservable, and realized stock returns are noisy. As a result, most performance evaluators refrain from using this approach and instead rely on alpha values, or the difference in average realized returns between a managed portfolio and passive benchmark portfolios, to identify skilled managers.

Despite its wide popularity, the use of alpha invokes costs too. In particular, alpha measurements are sensitive to whether the selected benchmark portfolio is ex ante mean-variance efficient. For example, Roll (1978) shows that a randomly selected passive portfolio can have a positive alpha if the benchmark portfolios lie within the mean-variance frontier. Moreover, because observed mutual fund alphas typically are small but volatile, an evaluator would need an unfeasibly long return series to identify a skilled manager reliably.[1] In a simulation-based study, Kothari and Warner (2001) argue that typical alpha-based performance measures have low power to detect economically large, abnormal fund performance.

In this article, we develop a new approach to identify skilled managers that overcomes these hurdles. Our method reflects two observations. First, managers of actively managed funds in general devote substantial efforts to fundamental analyses, and

[1] For example, Fama and French (2010) argue that if the cross-section of mutual fund alphas has a normal distribution with mean zero, then a cross-sectional standard deviation of 1.25% per year, or 0.10% per month, captures the tails of the cross-section of alpha estimates in their full sample of actively managed funds. For our sample of active funds, 1984–2008, the time-series standard deviation of alpha is 1.96% (1.87%) per month for the Fama and French three-factor (Carhart four-factor) model. Therefore, to observe a statistically significant alpha with a *t*-statistic of at least 1.96 for a truly skilled fund manager endowed with an alpha that is one standard deviation above average, the performance evaluator would need more than 100 years of return history (i.e., $t=\frac{\mu}{\sigma}\sqrt{T}\geq 1.96 \Rightarrow T \geq (\frac{1.96\times\sigma}{\mu})^2=(\frac{1.96\times 1.96}{0.10})^2=1{,}475$ months). In a Bayesian learning framework, Pastor and Stambaugh (2012) emphasize the difficulty for investors to learn managerial skill based on observed fund returns, even after observing a long history.

forecasting firm earnings is a crucial element in many valuation models. Baker, Litov, Wachter, and Wurgler (2010) document empirical evidence that aggregate mutual fund trades forecast earnings surprises, which suggests that some fund managers are skilled in forecasting earnings-related fundamentals.[2] Second, to translate forecasts to superior performance, an active manager must deviate from her performance benchmark (e.g. Cremers and Petajisto, 2009; Cremers, Ferreira, Matos, and Starks, 2013). Combining the above two observations, the covariance between an active manager's active holdings—that is, a stock's weight in the fund's portfolio in excess of that in the fund's benchmark index—and the stock's performance during subsequent earnings announcements thus may offer a good metric to identify skilled managers.

We call this proposed measure the ability to forecast earnings (AFE). It uses a portfolio's deviations from its benchmark as a proxy for the manager's forecasts, and compares these forecasts with the returns realized during the earnings announcements, when returns are less noisy and more likely to reflect the firm's fundamental information. Because covariance is the product of the correlation coefficient and standard deviations, AFE combines information about the quantity of active management (standard deviation of active weights for a given fund) with the quality of active management (correlation between active weights and earnings shocks, as reflected in earnings announcement returns).

Our approach has several advantages. First, the measure has greater statistical power than alpha or other measures based on fund returns, because we can exploit a large cross-section of earnings events for any given fund in each time period. Second, we focus on a

[2] Baker et al. (2010) mainly analyze the behavior of mutual funds as a group and investigate whether mutual fund managers in aggregate have skills. Our investigation builds on their aggregate evidence but proposes a performance measure for evaluating individual funds. That is, we seek to answer the question: Which fund managers have skills?

short-time window, in which the price movements in underlying assets are predominantly due to the specified information source (earnings announcements) and less affected by noises or other shocks in the stock market. Our approach is in the spirit of Kothari and Warner (2001), who argue that an event study–based analysis can substantially improve the power of tests for abnormal fund performance. Third, the AFE measure does not require an ex ante mean-variance efficient portfolio as a performance benchmark, nor an estimation of a linear factor model. Fourth, AFE focuses on firm-specific information, such that it is not affected by the issue of market timing. In contrast, standard alpha estimates in linear regression models offer biased indicators of managerial skills, if the manager has strong market timing abilities (e.g., Dybvig and Ross, 1985). Finally, AFE is less subject to manipulation by fund managers than traditional measures, such as alpha or the Sharpe ratio, for which the magnitudes are easily influenced by the amount of risk taking or risk shifting over time (e.g., Goetzmann, Ingersoll, Spiegel, and Welch, 2007).

The benchmark-free performance measure in Grinblatt and Titman (1993) and the characteristic-based performance measure in Daniel, Grinblatt, Titman and Wermers (1997) are based on fund holdings and subsequent stock returns. AFE instead is based on active fund holdings and subsequent stock returns during earnings announcement. It sharpens the signals from holdings by comparing holdings weights with benchmark weights. It also sharpens the signals from subsequent stock performance by focusing on a short event window, in which realized returns are less noisy.

The trade-off is that this measure captures only one type of investment skills, namely, the ability to forecast earnings. In reality, managers may have other investment skills, for example, market timing and asset allocation. However, firm earnings is a crucial variable for leading valuation models, such as the dividend discount or free cashflow models (e.g., Brealey, Myers, and Allen, 2011), and projecting the level of firms' future earnings and its growth rate is the central task for fundamental analyses.[3] Moreover, if a manager who

[3] Market participants pay close attention to firm earnings. For example, financial analysts devote most of their time to forecasting earnings; stock market reacts strongly to earnings announcements. Ball and Brown (1968) provide the first evidence of the reaction of stock prices to earnings announcements, and Kandel and Pearson (1995) document large increases in stock trading associated with earnings releases.

has superior skills in forecasting earnings tends to be skilled in other aspects, AFE could help indicate managerial skills beyond the ability to forecast firm earnings and might be useful for predicting overall fund performance.

We analyze quarterly holdings data for 2,455 unique, actively managed U.S. equity funds over the period of 1984–2008. For each fund in each quarter, we compute the ability to forecast earnings, on the basis of the covariance between a fund's deviations from benchmarks and the stock's performance during subsequent earnings announcements. The AFE measure is positive on average, with a cross-fund mean of 9.74 basis points (per three-day window) and a standard deviation of 34.30 basis points. These results suggest substantial cross-sectional heterogeneity in mutual funds' ability to forecast earnings; at least some managers are skilled. In addition, the measure shows a moderate correlation with other commonly used performance measures. For example, the AFE achieves average cross-sectional correlations of 23%, 21%, 19%, and 16% with raw fund returns, the four-factor alpha, Daniel et al.'s (1997) characteristic selectivity measure, and the Grinblatt-Titman (1989) measure, respectively. Thus, compared with other performance measures, AFE appears to capture unique fund characteristics and substantial incremental information.

The AFE measure also exhibits strong time-series persistence. Mutual funds in the top decile with the highest AFE continue to exhibit significantly higher AFE than those in the bottom decile in the subsequent six quarters. This persistence is largely due to the superior AFE of skilled funds in the top decile. Such funds tend to exhibit significant ability to forecast future earnings, even in the three years subsequent to portfolio formation. In comparison, we find that mutual funds sorted on past one-year returns exhibit performance persistence only in the subsequent three quarters. Moreover, consistent with Carhart (1997), the performance persistence based on prior alpha is driven almost entirely by the persistent underperformance of funds with low prior alphas. Thus, AFE appears to offer a more accurate measure for identifying skilled managers than past fund performance.

Finally, we find that AFE strongly predicts subsequent fund performance. In univariate sorts, mutual funds in the top decile with the highest AFE outperform those in the bottom decile with the lowest AFE by 3.12 percent per annum. The outperformance of funds with high AFE cannot be accounted for by their different exposures to risk or style factors. For example, after adjusting for their differential loadings on the market, size, value, and momentum factors, mutual funds in the top decile with the highest AFE continue to outperform those in the bottom decile by 2.64 percent per year. In other tests, we control for the effects of liquidity, post-earnings announcement drifts, and time-varying factor exposures in multifactor models. We also account for the influence of fund characteristics, such as age, size, expense ratios, turnover, past flow, and past performance, in multivariate regressions. After all the controls and adjustments, the results remain largely intact.

Our fund portfolio strategy is based on stale information about fund holdings, lagged for at least two months. Because the Securities and Exchange Commission (SEC) requires mutual funds to disclose their portfolio composition with a delay of at most two months, this strategy is implementable for mutual fund investors or funds of mutual funds that intend to improve their fund selection performance.

We further investigate the potential sources of information that managers use to forecast earnings. We find that funds exhibit stronger skills in forecasting earnings for stocks with greater information asymmetry, for instance, firms with less analyst coverage, or those in technology oriented industries. We also find that AFE has a stronger association with future fund alphas during economic expansions, when firm-specific information is a more important determinant of stock returns.

An alternative to our focus on firm performance during earnings announcements would be to examine the covariance between active fund weights and subsequent stock returns. This approach lacks power though, because the realized stock returns on non-event days are noisy, which could weaken our ability to identify managers with superior forecasting ability. We find that when we replace earnings announcement returns with stock returns in the subsequent quarter, the predictability of future fund performance disappears.

It is interesting to note that though we focus on individual funds' ability to forecast earnings, the outperformance of funds with superior ability to forecast earnings cannot be explained solely by their superior performance during subsequent earnings announcements. Therefore, the ability to forecast earnings appears to correlate positively with other investment skills, which makes the AFE measure more useful for mutual fund investors. Overall, our findings suggest that the ability to forecast earnings is a useful measure of managerial skill and predicts fund performance.

Our paper thus contributes to broad literature on mutual fund performance and market efficiency by providing new evidence about the value of active management. One strand in this literature estimates alpha values using fund returns and documents that mutual funds, on average, underperform passive benchmarks (e.g., Jensen, 1968; Malkiel, 1995; Gruber, 1996; Carhart, 1997; Fama and French, 2010). Another strand examines the portfolio holdings of mutual funds to study managers' investment abilities (e.g., Grinblatt and Titman, 1989, 1993; Daniel et al., 1997; Wermers, 2000). More recent literature also suggests that some active managers can consistently deliver positive returns, despite the average underperformance (e.g., Chevalier and Ellison, 1999; Cohen, Coval, and Pastor, 2005; Kacperczyk and Seru, 2007; Kacperczyk, Sialm, and Zheng, 2008; Barras, Scaillet and Wermers, 2010).[4]

Some recent papers indicate that one can detect skilled managers by quantifying the extent of active portfolio management. For example, Kacperczyk, Sialm, and Zheng (2005) measure the extent of active bets placed by fund managers, based on the level of industry concentration. Cremers and Petajisto (2009) quantify the extent of a fund manager's deviation from her benchmark index. Kacperczyk and Seru (2007) identify

[4] Chevalier and Ellison (1999) look at the personal attributes of fund managers; Cohen et al. (2005) emphasize the extent to which a manager's stock holdings resemble those of mutual fund stars; Kacperczyk and Seru (2007) focus on the reliance of fund managers on public information; and Kacperczyk et al. (2008) study the unobserved actions of mutual funds.

informed mutual fund managers by quantifying their reliance on public information (the R-squared measure from a regression of mutual fund trades on changes in analyst recommendations). Amihud and Goyenko (2011) propose the R-squared measure in a regression of mutual fund returns on a multifactor benchmark model to assess active portfolio management. These studies suggest that funds that deviate more from their benchmarks tend to deliver better performance. We extend this stream of study by integrating information about the extent of active management and the quality of active management into a single measure. As we show, it is particularly important to focus on the short window of earnings announcements, to reduce noise. Our study sheds further light on how active management creates value. Finally, our study provides new evidence about performance persistence. Previous studies indicate some persistence in fund returns but also note that the persistence can be explained away largely by the momentum factor, except for the worst performers (e.g., Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996; Carhart, 1997). We show that our proposed AFE performance measure is persistent for the best performers for the subsequent three years. Thus, we offer novel evidence of a lasting, positive investment skill for mutual fund managers.

The rest of this article is organized as follows: Section 2 presents the sample construction. Section 3 shows the predictive power of the active fund weights for subsequent earnings surprises and details our AFE measure. In Section 4 we examine the relation between the AFE measure and future fund performance. Section 5 contains the robustness checks, and Section 6 concludes.

2. Sample Construction

We obtain the portfolio holdings for actively managed equity mutual funds from Thomson Financial's CDA/Spectrum Mutual Fund Holdings Database. We obtain returns for the individual mutual funds and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database. To merge the two databases, we then use the MFLINKS data set. We exclude balanced funds, bond funds, money market funds, international funds, index funds, and sector funds, as well as funds not invested primarily in equity securities. After applying this filter, the sample consists of 2,455 unique funds, ranging in time from the first quarter of 1984 to the fourth quarter of 2008.

Our selection of the benchmark index for fund managers follows that of Cremers and Petajisto (2009). The universe of benchmark indexes includes 19 benchmark versions widely used by practitioners: the S&P 500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, the value and growth variants of the four Russell indexes, Wilshire 5000, and Wilshire 4500. For each fund in each quarter, we select from the one index that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on the S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are provided by COMPUSTAT. For the remaining indexes and periods, we use the index funds holdings to approximate the index holdings.[5]

The information on the daily stock prices and returns for common stocks traded on the NYSE, AMEX, and NASDAQ is obtained from the CRSP daily stock files. We obtain firms' announcement dates for quarterly earnings from COMPUSTAT and analysts' consensus earnings forecasts from I/B/E/S.

Panel A of Table 1 shows the summary statistics for mutual funds in our sample. An average fund in our sample manages $1.18 billion of assets, with an age of 14 years. Mutual fund investors in those funds achieve an average return of 1.81% per quarter. The net percentage fund flow is skewed to the right: the quarterly fund flow has a mean of 2.47% but a median of only -0.68%. On average, mutual funds in our sample incur an annual expense ratio of 1.25% and turn over their portfolios by 88.86% per year. These numbers are in line with those in previous literature.

[5] See Jiang, Verbeek, and Wang (2012) for more details on benchmark selection.

Panel B of Table 1 shows the average Spearman cross-sectional correlation coefficients among fund characteristics. The results confirm our intuition: The average 46% correlation coefficient between fund size and age indicated that large funds tend to have a longer track record; the correlation between fund size and expense ratio is -34%, such that large funds tend to incur lower expense ratios. We also found a negative correlation of -22% between fund age and fund flow, consistent with the idea that established mutual funds with longer life spans tend to be stable, with smaller percentage inflows. In the next section, we move to an analysis of the ability of mutual funds to forecast firms' future earnings.

3. Mutual Funds' Ability to Forecast Earnings

In this section, we create a measure of individual funds' ability to forecast earnings, and show that the ability to forecast earnings is a persistent attribute of a mutual fund. We show in the appendix that actively managed funds in aggregate are able to forecast future firm earnings.[6] Motivated by this evidence, we create a measure of a fund's ability to forecast earnings to gauge the skill of a fund manager. Specifically, we define *AFE* as:

$$AFE_{j,t} = \sum_{i=1}^{N_j} (w_{i,t}^{j} - w_{i,t}^{b_j}) CAR_{i,t+1}, \qquad (1)$$

where $AFE_{j,t}$ is mutual fund *j*'s ability to forecast earnings based on its portfolio selection in quarter *t*, $\boldsymbol{w_{i,t}^{j}}$ is the weight of stock *i* in fund *j*'s portfolio at the end of quarter *t*, $\boldsymbol{w_{i,t}^{b_j}}$ is the weight of stock *i* in fund *j*'s benchmark portfolio at the end of quarter *t*, and $CAR_{i,t+1}$ is stock *i*'s three-day abnormal return surrounding the announcement of its quarterly earnings, immediately following quarter *t*. As the following equations show,

[6] This finding is consistent with Baker et al. (2010). However, Baker et al. (2010) focus on the trading behavior of mutual funds, as inferred from the quarterly changes in fund stock holdings, while we emphasize the deviations of mutual funds from their performance benchmarks. In general, the holdings data are also more readily available and reliable than the inferred trades.

this measure is equivalent to the sample analogue of the covariance between active fund weights and abnormal returns during the subsequent earnings announcements. It therefore measures the ability of fund *j* to forecast future firm earnings:

$$\begin{aligned} E[(w-w^b)\times CAR] &= Cov(w-w^b, CAR) + E(w-w^b)\times E(CAR) \\ &= Cov(w-w^b, CAR) + 0\times E(CAR) \\ &= Cov(w-w^b, CAR). \end{aligned}$$

For each fund in each quarter, we compute its *AFE*. Most earnings announcements occur in the first two months after the quarter ends, so we use the following timeline: The stock holdings for fund *j* are measured at the end of quarter *t* (e.g., March), and the earnings announcements are observed in the two months subsequent to quarter *t* (e.g., April or May). We use Equation 1 to compute the ability to forecast earnings for fund *j*, or $AFE_{j,t}$. In the analysis of fund performance in the next section, we track the performance of fund *j* for three months, from the third month after quarter *t* (e.g., June to August), to ensure that both the holdings information and the earnings announcement returns are available (the SEC requires that mutual funds disclose their portfolio holdings within 45 days).

To provide further justification for our timeline, in Figure 1 we plot the average AFE values for a median fund cumulated over 13 weeks following a typical quarter end. It indicates that for an average fund, the value of AFE stabilizes during the eighth or ninth week after the quarter end, when we compute the fund's excess weights. It appears that incorporating earnings events that occur after the first two months offers little contribution to the value of a fund's AFE.

For an average fund in a typical quarter, AFE is equal to 9.08 basis points, with a standard deviation of 90.02 basis points. A substantial proportion of the high variability of AFE comes from cross-fund dispersion. For each fund, we compute the average AFE over its entire life. The cross-fund standard deviation is 34.30 basis points, which is 3.5 times the mean of 9.74 basis points. This high cross-fund dispersion in AFE is the main interest of this research.

Panel A of Table 2 summarizes the findings about the persistence of individual managers' ability to forecast earnings. For each quarter during 1984 and 2008, we sort mutual funds into decile portfolios on the basis of their AFE and compute the average AFE for the subsequent six quarters. The results indicate that the divergence in AFE between mutual funds in the top decile, with high ability to forecast firm earnings, and those in the bottom decile, with low ability to forecast earnings, remains economically meaningful and statistically significant for the six quarters after portfolio formation. After six quarters, the compounded uncertainties drive the dispersion in AFE toward statistical insignificance. Notably, this persistence of AFE is particularly pronounced for funds with superior forecasting ability in Decile 10. Figure 2 shows that these funds tend to exhibit significant ability to forecast future earnings, even in the three years after portfolio formation. As a comparison, we show in Panel B of Table IV the persistence of mutual fund performance, measured in terms of alpha. For each quarter during 1984 and 2008, we sort mutual funds into decile portfolios on the basis of their past one-year return and computed the average quarterly four-factor alpha estimates (factor loadings are estimated with the prior three years of data) for the subsequent six quarters.[7] The results indicate that mutual fund performance persists for three quarters after portfolio formation. Moreover, this persistence comes largely from the extended underperformance of funds with low alpha, a point highlighted by Carhart (1997). Taken together, these results indicate that the ability of mutual fund managers to forecast future earnings is a relatively persistent attribute of funds, which suggests that it is likely to capture a dimension of managerial skills.

4. Predicting Mutual Fund Performance by Ability to Forecast Earnings

In this section, we examine whether the ability of mutual funds to forecast firm earnings has predictive power for their future performance. That is, we assess the value of our proposed AFE measure for mutual fund investors. We start with a portfolio analysis

[7] As Carhart (1997) points out, if we sort funds on the basis of their past alpha, the same model of performance evaluation is used in both the ranking and the performance evaluation, which is likely to create an upward bias in performance persistence. Therefore, we sort funds on the basis of their prior one-year returns. Untabulated results for sorts based on past quarterly alphas indicate a similar pattern.

and then use multivariate regressions to examine the predictive power of mutual funds' ability to forecast earnings for their future performance. We evaluate how AFE's performance predictive power relates to fund characteristics, through double sorts on AFE and past fund performance, fund turnover, and active share. We conclude with additional analyses designed to shed light on active fund managers' ability to forecast earnings.

4.1. Portfolio Sorts

Using portfolio-based analysis, we examine the profitability of a strategy that invests in mutual funds according to their ability to forecast earnings. Specifically, at the end of each May, August, November, and February, we sort mutual funds into ten portfolios according to their AFE. We hold these portfolios for one quarter, then rebalance them. We compute equally weighted returns for each decile portfolio over the following quarter, net of and before fees and expenses. In addition, we estimate the risk-adjusted returns on the portfolios as intercepts from time-series regressions, according to the Capital Asset Pricing Model (CAPM) with the market factor; the three-factor model by Fama and French (1993) with the market, size, and value factors; the four-factor model of Carhart (1997) that augments the Fama and French factors with the Jegadeesh and Titman (1993) momentum factor; and the five-factor model that also includes Pastor and Stambaugh's (2003) liquidity risk factor. For instance, the Carhart four-factor alpha is the intercept from the following time-series regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_m (R_{m,t} - R_{f,t}) + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{umd} UMD_t + \varepsilon_{p,t}, \quad (2)$$

where $R_{p,t}$ is the return in month t for fund portfolio p, $R_{f,t}$ is the one-month Treasury-bill rate in month t, $R_{m,t}$ is the value-weighted stock market return in month t, SMB_t is the difference in returns between small and large capitalization stocks in month t, HML_t is the return difference between high and low book-to-market stocks in month t, and UMD_t is the return difference between stocks with high and low past returns in month t. Furthermore, to allow for time variation in the funds' factor loadings, we follow Ferson and Schadt (1996) and assumed a linear relation between factor loadings and five conditioning variables, namely, a January dummy and four lagged macroeconomic variables: the 1-month Treasury bill yield, the aggregate dividend yield, the term spread, and the default spread.

Table 3 presents the portfolio results. Panel A shows the net returns for portfolios of funds sorted on the basis of their ability to forecast earnings, AFE. In the quarter following portfolio formation, mutual funds with high AFE in Decile 10 outperform the funds with the lowest AFE in Decile 1 by 26 basis points per month, which is 3.12 percent per year. The superior performance of funds with high AFE in Decile 10 cannot be attributed to their high propensity to take risk or to their different investment styles: The differences in alphas from the CAPM, Fama and French three-factor, Carhart four-factor, and Pastor and Stambaugh five-factor models are 24, 31, 22, and 24 basis points per month, and all of these differences are statistically significant. The Ferson and Schadt (1996) alpha shows that, after taking into account time-varying factor exposures, the superior performance of high AFE funds is 23 basis points per month.

Panel B shows the results based on gross fund returns by adding back fees and expenses, which could provide a clearer picture of the value in terms of the alpha created by fund managers. These results indicated that fund managers with a high ability to forecast earnings produce a monthly Carhart four-factor alpha of 17 basis points, with a *t*-statistic of 2.96, whereas managers with a low ability to forecast earnings produce a monthly four-factor alpha of –5 basis points that is statistically indistinguishable from zero, even before fees and expenses. These differences in fees and expenses cannot explain the differential performance between funds with high and low AFE, in further support for the notion that fund managers with high ability to forecast future earnings tend to be skilled and generate significant value for their investors.

4.1.1. Accounting for the Post-Earnings Announcement Drift

Starting with Ball and Brown (1968) and Bernard and Thomas (1989), researchers have documented the tendency of stock prices to drift in the direction of earnings surprises during several weeks following earnings announcements, a trend referred to as the post-earnings announcement drift (PEAD). Although the PEAD cannot account for the high persistence of AFE for up to three years, one could argue that part of the performance predictability captured by AFE arises from it. To address this concern, we form hedge portfolios in which we replicate the payoffs of strategies exploiting post-earnings announcement drifts. Specifically, we follow Livnat and Mendenhall (2006) and compute the standardized earnings surprise (SUE) for each stock in each quarter:

$$SUE_{i,t} = \frac{X_{i,t} - E(X_{i,t})}{P_{i,t}},$$

where $X_{i,t}$ is earnings per share for stock i in quarter t, $E(X_{i,t})$ is expected earnings per share for stock i in quarter t, and $P_{i,t}$ is the price for stock i at the end of quarter t. We use the seasonal random walk model and consensus analyst earnings forecasts to proxy for expected earnings per share. The primary earnings per share before extraordinary items provides our primary measure of quarterly earnings, and we also consider the earnings surprises after excluding special items. We label the standardized earnings surprise based on the seasonal random walk model as SUE1, the standardized earnings surprise after the exclusion of special items as SUE2, and the standardized earnings surprise based on consensus analyst forecasts as SUE3. At the end of each month, we form decile portfolios, based on the SUE in the previous month, and compute the equal-weight returns from a strategy that buys stocks in the top 3 deciles with high SUE and shorts stocks in the bottom 3 deciles with low SUE. To refer to the returns on the three strategies based on three SUEs, we use the terms PEAD1, PEAD2, and PEAD3. The results in Table 4 show that, even after we control for the exposures of those fund portfolios to the strategies that seek to profit from the post-earnings announcement drifts, the superior performance of high AFE funds remains large and significant.

4.2. Predictive Panel Regressions

The preceding results indicate that AFE strongly predicts mutual fund performance. We also use multivariate regressions to examine the robustness of the performance predictive power of AFE. Our measure of mutual fund performance is the four-factor alpha of Carhart (1997), measured as the difference between the realized fund return in excess of the risk-free rate and the expected excess fund return from a four-factor model, including the market, size, value, and momentum factors. To estimate the factor loadings, we use rolling-window time-series regressions of fund returns in the previous three years. The fund characteristics we consider include fund size, measured as the natural log of fund assets under management; the natural log of fund age in years; the expense ratio; fund turnover; percentage flows in the past quarter; and fund alpha estimated in the past three years.

Table 5 presents the results from the predictive panel regressions. The first column measures fund performance using net fund returns, whereas the second column measures fund performance using gross fund returns, which add back fees and expenses. To control for aggregate movements in fund returns over time, we include fixed time effects in the regressions. Furthermore, because the residuals might correlate within funds, we cluster standard errors by fund.

The results show that AFE reliably predicts future fund performance in the presence of other characteristics. In terms of the four-factor net alpha, the slope coefficient for AFE is 2.39, with a *t*-statistic of 3.07. When we measure fund performance using the four-factor gross alpha, we obtain qualitatively and quantitatively similar results. The fund characteristics included in the regression relate to future fund performance in ways consistent with the previous findings. For example, fund size is negatively related to future performance, consistent with large funds underperforming small funds, as documented by Chen et al. (2004). Fund turnover also is negatively related to future performance. Past flows have a positive relation with future performance, consistent with the smart-money effect documented by Gruber (1996) and Zheng (1999). A fund's past alpha is insignificantly related to its future performance when we exclude the stock price momentum effect (Carhart, 1997). Although a fund's expense ratio is unrelated to its future gross alpha, it negatively predicts future net alpha, which deducts fees and expenses from gross alpha.

4.3. Double Sorts

In this subsection, we evaluate whether the performance predictive power of AFE might concentrate on certain types of mutual funds. The fund characteristics we look at include funds' returns in the past year, the holdings-based performance measure characteristic selectivity, fund turnover, and active share. Past return is a central variable in prior literature related to the "hot hands" effect (e.g., Brown and Goetzmann, 1995; Carhart, 1997). The characteristic selectivity (CS) measure is the product of a stock's weight in the fund's portfolio and the stock's return, in excess of its characteristic-based benchmark portfolio, which then can be summed across all stocks held by the fund. The characteristic-based benchmark portfolio is formed on the basis of size, industry-adjusted book-to-market, and momentum, following Daniel et al. (1997). Fund turnover measures how actively a fund manager trades, and the active share variable, as proposed by Cremers and Petajisto (2009), gauges how aggressively a fund manager deviates from the benchmark. These two metrics of activeness relate intuitively to our measure of AFE.

To evaluate the influence of fund characteristics on AFE's performance predictive power, for each quarter from 1984 to 2008, we sort the funds independently into four groups based on their AFE and into four groups based on their fund characteristics.[8] We thus form 16 portfolios, then compute the Carhart (1997) four-factor α as a monthly percentage, based on net returns for each of the 16 portfolios. We present the results in Table 6.

Panel A provides the results, using independent sorts on AFE and past one-year returns. They indicate that AFE predicts future fund performance for funds with mediocre

[8] Our results are robust to sequential sorts.

and high past returns. Only for funds with extremely low past returns does *AFE* offer no statistically significant performance predictive power. Consistent with prior literature, past performance cannot reliably predict future fund performance (after controlling for the price momentum effect) for any of the four quartiles sorted on AFE. These results suggest that past fund performance, when interacted with our indicator of fund skill, adds value for mutual fund investors.

Panel B presents the results for the double sorts on the basis of AFE and CS. The results show that mutual funds with high AFE significantly outperform their peers with low AFE across all four groups of funds with different levels of CS. In contrast, CS does not show a significant relation to future fund performance. Panels C and D provide the results for fund turnover and active share. They indicate that the performance predictive power of AFE is especially strong among active managers, though the extent of activeness per se is a weaker predictor of future fund returns.[9] For example, among mutual funds with high fund turnover or active share in quartile 4, high AFE funds outperform their low AFE peers by 3.48% or 3.36% per year, in terms of the four-factor alpha. These results supported the view that the extent of activeness, interacted with AFE, adds value for mutual fund investors. Moreover, AFE helps identify skilled versus unskilled active managers.

Panel E shows the results for fund size. Berk and Green (2004) argue that skilled mutual fund managers have incentives to grow the assets under their management to capture their economic rents. Due to diseconomies of scale (Chen et al., 2004), the link between managerial skill and observed fund alpha tends to diminish as the manager expands the fund size. According to this hypothesis, the association between AFE and future fund alpha should be weak for large funds. The results indicate that indeed for large funds in Quartile 4, the difference in subsequent fund alpha between funds with high and low AFE, though positive, is statistically indistinguishable from zero. In contrast, among smaller funds in Quartile 1 through Quartile 3, the difference in future

[9] Our results on fund turnover are broadly consistent with previous literature; those related to active shares are also consistent with Cremers and Petajsto (2009, e.g., their table 8).

performance between funds with high and low AFE is statistically significant and economically large. This result is particularly interesting, in light of the finding that AFE, per se, tends to be scale-free and has a correlation of only 2% with fund size.

4.4. Understanding the Drivers of the Ability to Forecast Earnings

What sources of information do managers use to forecast earnings? To shed light on this question, we explore how fund managers' ability to forecast earnings relates to stock characteristics, such as analyst coverage and industry membership.

We start by asking whether the investment decision of mutual fund managers contains information about firms' future earnings, beyond the earnings forecasts that financial analysts issue before earnings announcements. The first column in Table 7 indicated that active weights significantly predict analyst earnings forecast errors. Therefore, buy-side mutual fund managers possess valuable information about firms' future earnings aspects, incremental to the information obtained by sell-side analysts.

An important role of sell-side analysts in equity markets is to provide market participants with timely and accurate earnings forecasts, which may reduce the information advantages of a particular group of investors. We hypothesize that the superior ability of active fund managers to forecast future earnings relative to the market is more pronounced for stocks with low analyst coverage, and thus presumably more information asymmetry. In Column 2 of Table 7, we find that the association between active fund weights and future earnings surprises is stronger for stocks with less analyst coverage, in support of the notion that fund managers' AFE is independent of sell-side analysts' forecasts. Moreover, fund managers have more incentive and exhibit more skill in evaluating stocks with more information asymmetry.

Finally, we examine whether the ability to forecast earnings varied across industries, for which the degrees of information asymmetry differ. To provide some guidance in our thinking, we first look at the average absolute earnings surprises for each industry in our sample. Stocks in technology-oriented industries, such as high-tech, tend to have high earnings surprises, whereas stocks in utility industry tend to have low earnings surprises. In Column 3 of Table 7, for stocks in technology-oriented industries, active fund managers reveal stronger earnings forecasting ability, whereas for the utility industry, the earnings' predictive ability is statistically insignificant and economically small. Overall, the findings suggest that fund managers show stronger skills in forecasting earnings when there is greater information asymmetry.

4.5. Time-Varying Fund Performance

In this subsection, we exploit the variation of the performance predictive power of AFE through time. Specifically, we look at how the association between AFE and future fund performance varies over the business cycle and after the introduction of the Regulation Fair Disclosure (Reg FD).

The cyclical variation of AFE's performance forecasting power is of interest, because AFE, by construction, is driven primarily by firm-specific information and can thus capture fund managers' skill in stock picking. A large literature on asset pricing shows that the tendency of assets to co-move is counter-cyclical, which suggests that firm-specific information is a less important determinant of stock returns in economic downturns. Consistent with this intuition, Kacperczyk, van Nieuwerburgh, and Veldkamp (2012) find that skilled fund managers rationally allocate less attention to stock picking in down markets. Motivated by their evidence, we hypothesize that the performance forecasting power of AFE is lower in economic downturns.

To test this hypothesis, we use two real-time recession indicators: –CFNAI and RecessionProb. CFNAI is the Chicago Fed National Activity Index multiplied by -1, to proxy for recession, and then standardized to have means of zero and standard deviations of one. RecessionProb is the Chauvet and Piger (2003) real-time recession probability measure. We perform the following time-series regression, which includes an interaction term of the AFE variable with the recession indicators. The results in Columns 1 to 8 of Table 8 indicate that AFE has a lower association with both gross and net future fund alphas during economic downturns, which is consistent with the notion that the value of stock picking is greater when firm-specific information is a more important determinant of stock returns.

The SEC instated the Reg FD in October 2000, with the goal of creating a level playing field for all investors by eliminating firms' selective disclosures to a subset of market participants. How does this regulation regime change influence the performance of mutual funds with superior ability to forecast earnings? To assess the influence of Reg FD, we construct a dummy variable, equal to 1 for observations that fall in the period after January 2001 and 0 otherwise. We expand the predictive panel regressions by adding an interaction term between AFE and RegFD. The results in Columns 9 and 10 of Table 8 indicate that though the adoption of RegFD weakens associations between ability to forecast earnings and future fund performance, this effect is statistically insignificant. In other words, the skill of mutual funds in analyzing firms' fundamentals is still important for their performance and the AFE remains a useful indicator of future fund performance in the post–Reg FD regime.

In summary, the findings presented in Section 4 show that a mutual fund's ability to forecast earnings is a robust predictor of its future performance and that the predictive power of AFE is incremental to the effect of other fund characteristics. Moreover, the ability of fund managers to forecast future earnings appears to stem from their superior private information or ability to process public information.

5. Robustness Tests

In this section, we report on several robustness tests. We assess the importance of focusing on earnings announcement performance, by replacing it with stock returns. Next, we consider the influence of orthogonalizing abnormal returns surrounding earnings announcements with respect to firm characteristics. Finally, we investigate how the earnings announcement premium influences our results.

5.1. Replacing Earnings Announcement Returns with Stock Returns

The advantage of focusing on a short event window is its ability to limit the movements in prices to fundamental firm news, such that the prices are less affected by noise and shocks. We assess the importance of focusing on earnings announcement performance by replacing it in Equation 1 with stock returns in the following quarter. In particular, similar to the way we compute the AFE, we calculate a measure of ability to forecast returns, or the covariance between the fund's deviations from benchmarks and stocks returns in the subsequent two months.[10] At the beginning of the third month, we form portfolios of mutual funds on the basis of our ability to forecast returns measure and track their portfolio performance in the subsequent quarter.

Table 9 presents the performance of these fund portfolios. The results indicate that the difference in returns between mutual funds in the top and bottom deciles is statistically insignificant, both before and after fees and expenses. Therefore, noise in stock returns appears to render the measure of ability to forecast returns less powerful in terms of identifying skilled managers, which reinforces the advantages of focusing on earnings announcement performance.

5.2. Residual Earnings Announcement Returns

Several studies show that certain stock characteristics are associated with abnormal returns around firm earnings announcements. For example, stocks with high past returns tend to have positive earnings surprises (Jegadeesh and Titman 1993); value firms tend to have positive earnings surprises (La Porta et al, 1997); and earnings surprises tend to be persistent (Bernard and Thomas, 1989, 1990). If certain mutual fund managers have preferences for stocks with these characteristics and tilt their portfolios accordingly, we might mechanically pick up the influence of the stock characteristics.

[10] The results remain unchanged if we use stock returns in the subsequent quarter.

To address this concern, for each quarter, we run cross-sectional regressions of the three-day abnormal returns during earnings announcements on stock characteristics and use the regression residuals as inputs to compute mutual funds' *AFE*. We sort mutual funds into ten portfolios, on the basis of this modified measure of *AFE*, holding them for one quarter and then rebalancing the portfolios. The average and risk-adjusted returns on these fund portfolios, net of and before fees and expenses, are presented in Table 10. The results indicate that that even after we orthogonalize abnormal returns surrounding earnings announcements to past returns, the book-to-market ratio, and past earnings surprises, the ability of fund managers to forecast future earnings remains a strong predictor of future performance. For example, mutual funds with a high ability to forecast earnings outperform their peers with low ability by 0.18% per month, which cannot be explained by their differential exposures to risk or risk factors.

5.3. Earnings Announcement Premium

Frazzini and Lamont (2007) and Barber, DeGeorge, Lehavy, and Trueman (2013) provide evidence that firms tend to generate high returns in the months when they announce their earnings. How does this earnings announcement premium influence our AFE? We note that as the active holdings sum up to zero by construction, AFE can be viewed as a self-financing portfolio that is long and short earnings announcing firms with a net weight of zero. Therefore, the earnings announcement premium should not materially influence AFE. To verify this empirically, for each firm that announces its earnings in a given month, we cross-sectionally demean its three-day abnormal return (subtract the mean abnormal returns for all earnings announcers from the abnormal return for a given earnings announcer in the same month). We find similar results using AFE computed using the de-meaned abnormal return.

6. Conclusion

In this article, we propose a new measure, the ability to forecast earnings, to identify skilled mutual fund managers. The AFE measure reflects the covariance between a fund's active stock holdings (deviations from its benchmark) and firms' abnormal returns, realized during subsequent earnings announcements. By combining both the quantity and quality of active management, AFE offers several advantages over traditional performance measures and is more powerful for identifying skilled managers. As opposed to examining the performance of the overall portfolio, AFE focuses on a specific and important type of investment skills, which yields a sharper performance measure.

Analyzing 2,455 actively managed U.S. equity funds over the period 1984–2008, we find a positive skill (AFE) for an average mutual fund manager. Moreover, this identified skill tends to be strongly persistent over time. Investigating the variation in AFE across funds also yields useful observations. Perhaps most important, we find that AFE can predict future fund performance: Funds in the top decile with the highest ability to forecast earnings outperform those with the lowest ability by 3.12 percent in terms of raw returns and 2.64 percent in terms of Carhart's four-factor alpha. The performance difference cannot be explained by risk adjustments, controls for liquidity, post-earnings announcement drifts, time-varying factor exposures in multi-factor models, or other fund characteristics.

This article identifies persistent, positive investment skills of mutual fund managers. Our findings offer new evidence about the value of active management and provide new insights into market efficiency issues. We show that the Ability to Forecast Earnings is a useful measure for identifying skilled mutual fund managers and predicting fund performance.

Appendix. Do Active Fund Weights Predict Future Earnings Surprises?

To examine the ability of mutual funds to forecast firms' future earnings, we start with a regression that associates active fund weights with future earnings surprises. We measure earnings surprises as the three-day cumulative abnormal return (CAR) surrounding the announcement of firms' quarterly earnings. The daily abnormal returns refer to the difference in daily returns between a stock and a size and book-to-market matched portfolio. We sum the daily abnormal returns from one day before to one day after earnings announcements to obtain the three-day abnormal return. Because the analysis involves a particular fund's holdings of a particular stock at a specific time point, we use the Fama-MacBeth (1973) regressions. In the first stage, for each quarter, we regress each firm's future earnings surprises on the active weights of the stock in each fund's portfolio. In the second stage, we use the time-series variation in the slope coefficient (Newey-West 1987 autocorrelation-consistent standard errors) to obtain the statistical inference. In the first stage, the unit of observations is a fund–stock pair, such that for each fund, we obtain a unique benchmark and thus could cleanly detect how adjusting for benchmark weights from fund weights contributes to the predictive power for earnings surprises.[11]

Table A1 presents the results. The first column indicates that active fund weights positively and significantly predict future earnings surprises (CAR in percent). The slope coefficient for active weights of 4.11 indicates that a 1% overweighting of the stock is associated with abnormal returns that were 4.11 basis points higher during the three days surrounding earnings announcements. This effect is economically large: If half of the deviations from benchmarks is due to an active fund manager's bet on future earnings (e.g., a manager finances the higher weights invested in certain informed bets by underweighting other stocks), a manager with a 77% active share (the mean active share in our sample) would realize 3.16% (0.000411×77) abnormal returns during earnings announcements in a typical quarter. It is also statistically significant, with a *t*-statistic of

[11] For an application of this style of Fama-MacBeth (1973) regressions, see Grinblatt, Keloharju, and Linnainmaa (2011).

4.54. The second column shows that fund weights alone exhibit only moderate power to predict future earnings surprises. The slope coefficient declines by approximately two-thirds, from 4.11 to 1.40, and the *t*-statistic drops from 4.54 to 1.70. The difference between the predictive power of active weights and raw fund weights illustrates the importance of adjusting for benchmark weights. In turn, the third column shows that in the presence of fund weights, a stock's weight in the fund's benchmark index negatively predicts the stock's future earnings surprises. Taken together, the results in Table II indicate that active weights chosen by fund managers are powerful predictors of firms' future earnings surprises.

We also consider a simple stock-level analysis. For each stock in each quarter, we compute the average active holdings, or the mean active weights across all active mutual funds whose investment universe includes the stock. A stock enters a fund's investment universe if it is held by the fund or is in the benchmark index of the fund. Then we sort stocks into quintile portfolios and calculate the mean and median earnings surprises (CAR in percent) in the subsequent quarter for each portfolio. Table A2 presents the time-series averages of the earnings surprises for each portfolio, with *t*-statistics based on the time-series variation with Newey-West (1987) adjustments. The results indicate that stocks with large underweighting by active funds tend to experience negative earning shocks, with an average three-day abnormal return of –8 basis points, whereas stocks with large overweighting by active funds tend to experience positive earnings surprises, with an average three-day abnormal return of 26 to 28 basis points.

Table A1

Active Fund Holdings and Future Earnings Surprises: Regressions Analysis

This table presents the regression results using active fund weights to predict future earnings surprises, defined as the three-day abnormal returns in percentage terms surrounding earnings announcements. Active Weights is the weight of a stock in a fund's portfolio (Fund Weights) in excess of the stock's weight in the fund's benchmark index (Benchmark Weights). Firm Size is the natural log of the market cap in millions of dollars, BM is the book-to-market ratio, and MOM12 is the cumulative returns on a stock in the past year. These regressions are run using stock-fund pooled data for each quarter, from Q1 of 1984 to Q4 of 2008. The statistical inference is based on the Fama-MacBeth (1973) procedure with Newey-West (1987) adjustments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Active Weights	4.112***		
	(4.54)		
Fund Weights		1.395*	2.759***
		(1.70)	(3.92)
Benchmark Weights			-11.063**
			(-2.13)
Size	0.057***	0.055***	0.066***
	(4.13)	(3.94)	(4.29)
BM	0.007	0.008	0.005
	(0.21)	(0.23)	(0.16)
MOM12	0.180**	0.181**	0.181**
	(2.32)	(2.34)	(2.34)
Intercept	-0.317***	-0.304***	-0.376***
	(-2.99)	(-2.86)	(-3.42)
Average Adj-R^2	0.005	0.005	0.005

Table A2

Active Fund Holdings and Future Earnings Surprises: Portfolio Analysis

This table presents the portfolio results using active fund weights to predict future earnings surprises, defined as the three-day abnormal returns in percentage terms surrounding earnings announcements. In particular, for each quarter from Q1 of 1984 to Q4 of 2008, we sort stocks on the basis of their average active weights, defined as the weight of a stock in a fund's portfolio (Fund Weights) in excess of the stock's weight in the fund's benchmark index (Benchmark Weights), averaged across all funds whose investment universe includes the stock. A stock enters a fund's investment universe if it is held by the fund or is in the benchmark index of the fund. We compute both mean and median earnings surprises for each portfolio and the time-series average. The statistical inference is based on the time-series variation with Newey-West (1987) adjustments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Underweight	2	3	4	Overweight	Over-Underweight
Mean	-0.08	-0.06	0.06	0.17	0.28	0.37
	(-2.11)**	(-1.47)	(1.37)	(3.92)***	(6.16) ***	(5.78) ***
Median	-0.08	-0.12	0.02	0.16	0.26	0.34
	(-2.04)**	(-3.71) ***	(0.49)	(4.23) ***	(6.54) ***	(7.82) ***

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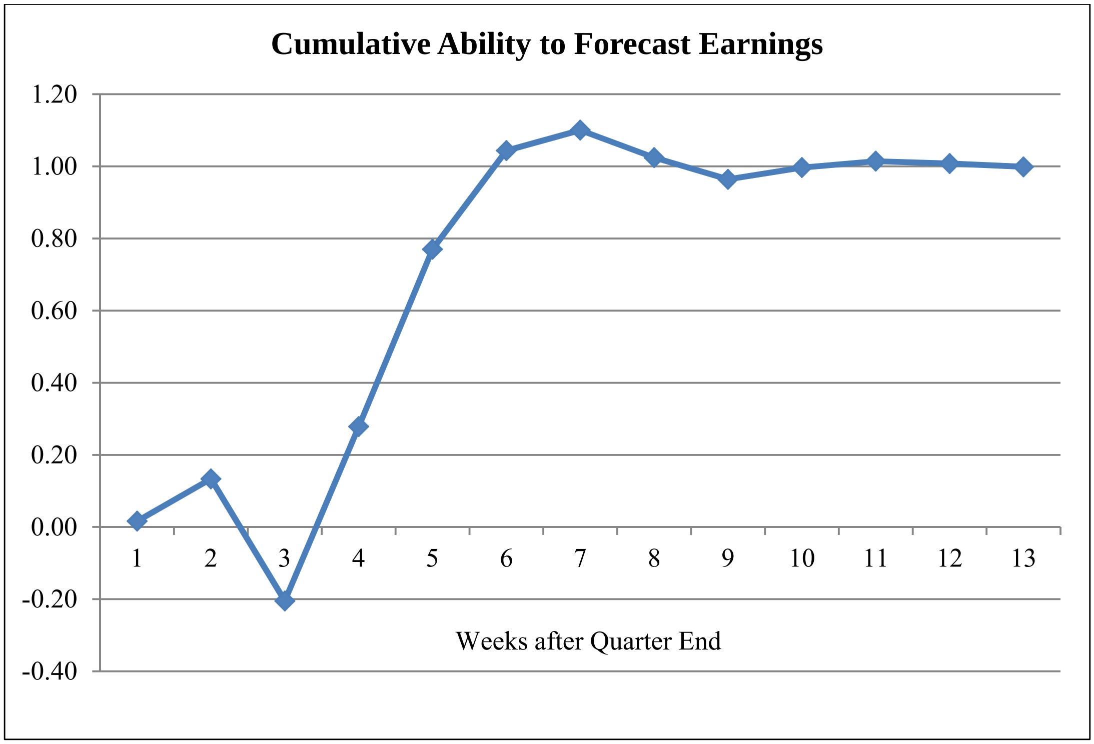

Figure 1 Ability to Forecast Earnings, Cumulative over the Weeks Following Quarter Ends. This figure plots the ability to forecast earnings for a median mutual fund in our sample, cumulative over the weeks following quarter ends, when the active fund weights are measured. The *AFE* is the covariance of active fund weights and subsequent earnings surprises, measured as the three-day abnormal returns surrounding earnings announcements. The value of cumulative AFE at the end of week 13 is scaled to equal 1.

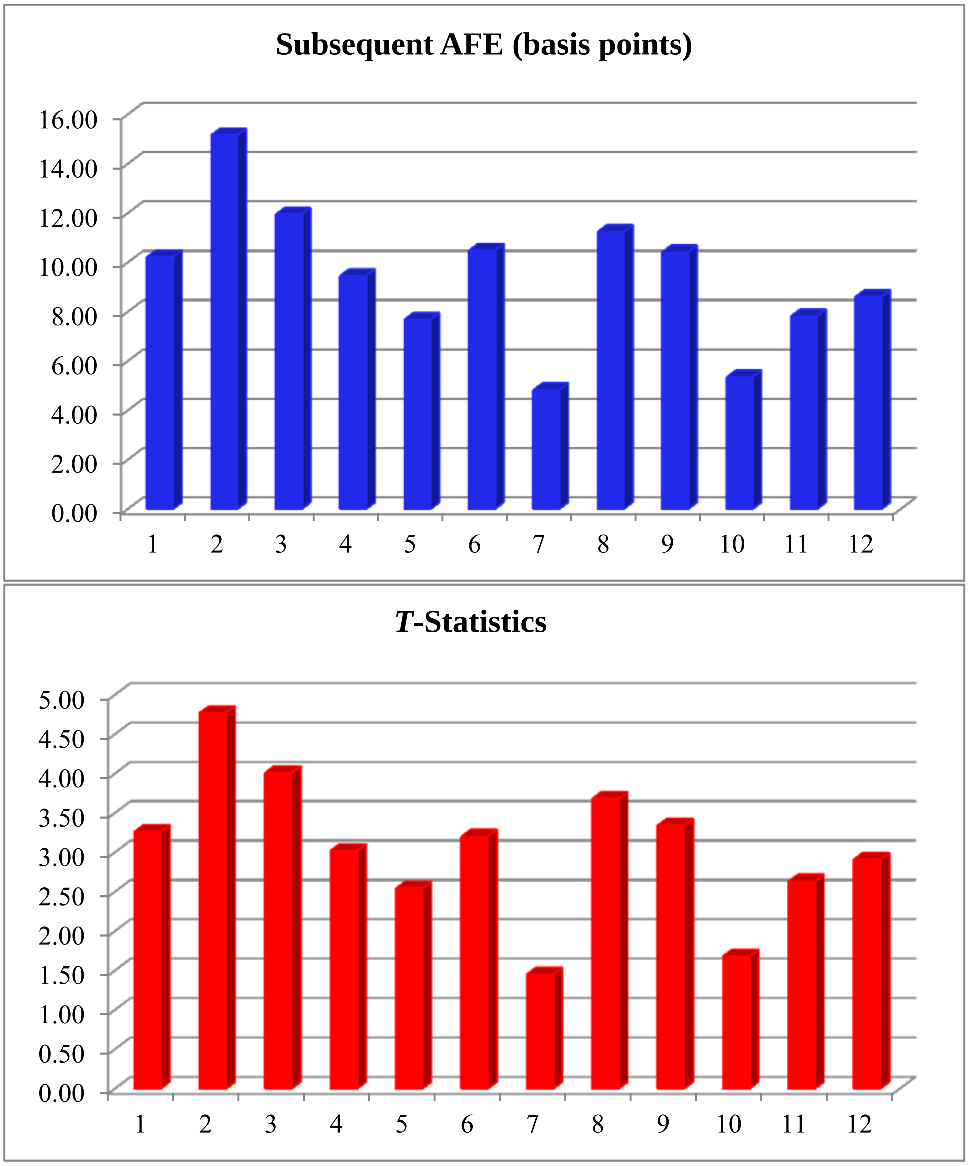

Figure 2 Persistent Ability to Forecast Earnings for Skilled Funds with Superior Ability. This figure plots the average ability to forecast earnings in basis points for mutual funds ranked as the top 10 percent in Quarter *t* during the subsequent three years. The *AFE* is the covariance of active fund weights and subsequent earnings surprises, measured as the three-day abnormal returns surrounding earnings announcements.

Table 1

Descriptive Statistics

This table presents descriptive statistics for our sample of mutual funds. The sample consists of 2,455 distinct mutual funds from the first quarter of 1984 to the fourth quarter of 2008. Panel A presents the summary statistics for fund characteristics. TNA is the quarter-end total net fund assets in millions of dollars, Age is the fund age in years, Quarterly Return is the quarterly net fund return as a percentage, Flow is the quarterly growth rate of assets under management as a percentage after adjusting for the appreciation of the fund's assets, Expense is the fund expense ratio as a percentage, and Turnover is the turnover ratio of the fund as a percentage. Panel B shows the time-series average of the cross-sectional Spearman correlation coefficients for the variables of interest.

Panel A: Summary Statistics of Fund Characteristics

	Mean	Std Dev	25th Pctl	Median	75th Pctl
Total Number of Funds	2,455				
TNA ($ Million)	1183.75	4722.96	62.10	209.20	735.93
Age (Years)	14.03	14.32	5.00	9.00	17.00
Quarterly Return (%)	1.81	10.30	-3.05	2.39	7.42
Flow (%)	2.47	16.14	-4.00	-0.68	4.36
Expense (%)	1.25	0.49	0.96	1.21	1.50
Turnover (%)	88.86	107.53	35.00	66.00	113.00

Panel B: Average Spearman Cross-Sectional Correlation Coefficients

	TNA	Age	Quarterly Return	Flow	Expense
Age	0.46				
Quarterly Return	0.03	0.00			
Flow	0.02	-0.22	0.15		
Expense	-0.34	-0.21	-0.02	-0.01	
Turnover	-0.08	-0.10	0.01	-0.02	0.22

Table 2
Persistence of Ability to Forecast Earnings

This table shows the persistence of the ability to forecast earnings (Panel A) and four-factor alphas (Panel B) for mutual fund managers. The *AFE*, in basis points, is the covariance of active fund weights and subsequent earnings surprises measured as the three-day abnormal returns surrounding earnings announcements. For each quarter during 1984 and 2008, we sort funds into decile portfolios on the basis of their AFE and compute the average *AFE* for the subsequent six quarters. In Panel B, we sort funds into decile portfolios on the basis of their past one-year return. The quarterly four-factor alpha is the Carhart (1997) four-factor alpha with fund betas estimated using rolling-window regressions in the past three years.

Panel A: Ability to Forecast Earnings

	AFE_{t+1}	*t*-statistic	AFE_{t+2}	*t*-statistic	AFE_{t+3}	*t*-statistic	AFE_{t+4}	*t*-statistic	AFE_{t+5}	*t*-statistic	AFE_{t+6}	*t*-statistic
Low	0.21	0.07	1.72	0.56	1.47	0.49	6.88	2.41	2.72	1.00	2.31	0.78
2	2.00	0.80	1.65	0.67	1.78	0.71	5.22	2.24	2.69	1.07	6.59	2.98
3	3.51	1.52	3.73	1.57	1.72	0.78	4.95	2.39	4.66	2.03	5.54	2.59
4	2.37	1.15	4.32	2.01	2.08	0.87	5.09	2.23	4.80	2.02	3.97	1.88
5	4.11	1.82	5.88	2.57	2.94	1.27	4.13	2.00	2.55	1.02	3.53	1.36
6	5.13	2.44	3.31	1.70	6.24	3.02	4.56	2.04	4.71	2.12	7.91	3.56
7	3.81	1.70	6.11	2.98	4.40	1.94	4.52	2.11	3.79	1.69	6.04	2.95
8	6.43	2.74	6.74	3.53	7.73	3.21	4.53	1.79	3.54	1.34	5.18	2.02
9	7.52	2.81	10.75	4.27	6.23	2.68	7.79	3.23	7.44	2.89	6.24	2.40
High	10.21	3.26	15.16	4.77	11.94	4.01	9.46	3.02	7.68	2.54	10.48	3.20
H-L	10.01	3.37	13.44	4.51	10.47	3.37	2.57	0.91	4.96	1.86	8.16	2.58

Panel B: Four-Factor Alpha

	α_{t+1}	*t*-statistic	α_{t+2}	*t*-statistic	α_{t+3}	*t*-statistic	α_{t+4}	*t*-statistic	α_{t+5}	*t*-statistic	α_{t+6}	*t*-statistic
Low	-1.12	-4.62	-1.06	-4.30	-0.81	-3.44	-0.56	-2.06	-0.60	-2.33	-0.56	-2.05
2	-0.59	-5.11	-0.51	-4.00	-0.47	-4.03	-0.39	-3.51	-0.40	-3.14	-0.36	-2.90
3	-0.44	-4.55	-0.36	-3.81	-0.32	-3.35	-0.32	-3.49	-0.28	-2.91	-0.30	-2.95
4	-0.24	-2.76	-0.21	-2.40	-0.27	-3.25	-0.24	-2.95	-0.24	-2.60	-0.23	-2.54
5	-0.22	-2.74	-0.25	-3.58	-0.21	-2.78	-0.21	-2.95	-0.21	-2.57	-0.23	-2.66
6	-0.28	-3.58	-0.17	-2.22	-0.17	-2.03	-0.22	-3.01	-0.16	-1.93	-0.22	-2.51
7	-0.20	-2.26	-0.18	-2.37	-0.15	-2.13	-0.09	-1.04	-0.19	-2.18	-0.22	-2.49
8	-0.11	-1.23	-0.10	-1.02	-0.20	-2.24	-0.16	-1.69	-0.20	-2.13	-0.24	-2.75
9	0.04	0.29	-0.17	-1.41	-0.15	-1.26	-0.21	-1.71	-0.23	-1.79	-0.23	-1.83
High	0.21	0.79	0.05	0.20	-0.20	-0.76	-0.63	-2.39	-0.51	-2.16	-0.46	-2.24
H-L	1.34	3.54	1.11	2.95	0.61	1.71	-0.07	-0.18	0.09	0.25	0.10	0.29

Table 3
Ability to Forecast Earnings and Mutual Fund Performance: Decile Portfolios

This table presents the performance of decile fund portfolios formed on the basis of their ability to forecast earnings. The AFE is defined as the covariance between active fund weights and subsequent earnings surprises, measured as three-day abnormal returns during earnings announcements. The decile portfolios are formed and rebalanced at the end of two months each quarter from 1984Q1 to 2008Q4, and the return series range from June 1984 to May 2009. Decile 10 is the portfolio of funds with the highest AFE value. We compute monthly equally weighted percentage net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Pastor and Stambaugh (PS, 2003) five-factor model, and the Ferson and Schadt (1996) conditional model. We report the alphas in monthly percentages. The *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Net Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.75	0.80	0.83	0.81	0.82	0.81	0.85	0.92	0.90	1.01	0.26***
	(2.60)	(2.93)	(3.11)	(3.10)	(3.09)	(3.08)	(3.15)	(3.38)	(3.20)	(3.36)	(2.90)
CAPM α	-0.19	-0.11	-0.07	-0.08	-0.08	-0.08	-0.06	0.01	-0.02	0.06	0.24***
	(-2.6)	(-2.14)	(-1.54)	(-1.78)	(-2.02)	(-1.93)	(-1.32)	(0.21)	(-0.37)	(0.68)	(2.81)
FF α	-0.20	-0.13	-0.09	-0.10	-0.09	-0.10	-0.06	0.02	0.00	0.11	0.31***
	(-3.28)	(-2.79)	(-2.15)	(-2.51)	(-2.62)	(-2.66)	(-1.78)	(0.46)	(-0.08)	(1.82)	(3.53)
Carhart α	-0.16	-0.11	-0.08	-0.09	-0.09	-0.11	-0.08	-0.01	-0.03	0.07	0.22***
	(-2.71)	(-2.34)	(-2.02)	(-2.12)	(-2.24)	(-2.73)	(-2.2)	(-0.17)	(-0.7)	(1.12)	(3.07)
PS α	-0.15	-0.11	-0.08	-0.09	-0.08	-0.10	-0.08	0.00	-0.02	0.09	0.24***
	(-2.65)	(-2.24)	(-1.84)	(-2.08)	(-2.1)	(-2.65)	(-2.02)	(0.03)	(-0.47)	(1.44)	(3.29)
FS α	-0.17	-0.11	-0.09	-0.08	-0.09	-0.11	-0.08	-0.02	-0.03	0.05	0.23***
	(-3.51)	(-3.07)	(-2.58)	(-2.62)	(-2.88)	(-3.24)	(-2.49)	(-0.48)	(-0.66)	(0.88)	(3.16)

Panel B Gross Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.85	0.90	0.93	0.91	0.91	0.91	0.95	1.02	1.00	1.11	0.26***
	(2.98)	(3.31)	(3.47)	(3.47)	(3.46)	(3.45)	(3.51)	(3.74)	(3.56)	(3.72)	(2.90)
CAPM α	-0.08	-0.01	0.03	0.02	0.02	0.01	0.04	0.11	0.08	0.17	0.25***
	(-1.09)	(-0.2)	(0.54)	(0.38)	(0.39)	(0.29)	(0.88)	(2.16)	(1.23)	(1.90)	(2.81)
FF α	-0.09	-0.03	0.01	0.00	0.00	0.00	0.03	0.12	0.10	0.22	0.31***
	(-1.5)	(-0.6)	(0.32)	(-0.05)	(0.10)	(-0.01)	(0.88)	(3.01)	(2.08)	(3.55)	(3.53)
Carhart α	-0.05	-0.01	0.02	0.01	0.01	-0.01	0.01	0.09	0.07	0.17	0.22***
	(-0.88)	(-0.22)	(0.39)	(0.25)	(0.24)	(-0.27)	(0.36)	(2.33)	(1.58)	(2.96)	(3.07)
PS α	-0.05	0.00	0.02	0.01	0.01	-0.01	0.02	0.10	0.08	0.19	0.24***
	(-0.81)	(-0.1)	(0.48)	(0.27)	(0.36)	(-0.22)	(0.48)	(2.47)	(1.78)	(3.24)	(3.29)
FS α	-0.07	-0.01	0.01	0.02	0.01	-0.01	0.02	0.08	0.07	0.16	0.23***
	(-1.35)	(-0.34)	(0.17)	(0.48)	(0.27)	(-0.33)	(0.59)	(2.22)	(1.76)	(2.75)	(3.16)

Table 4
Ability to Forecast Earnings and Mutual Fund Performance: Controlling for the Influence of the Post-Earnings Announcement Drift

This table presents the performance of decile fund portfolios formed on the basis of their ability to forecast earnings, controlling for the influence of the post-earnings announcement drift. Specifically, we construct hedge portfolios that seek to replicate the payoffs of strategies exploiting the post-earnings announcement drift. We follow Livnat and Mendenhall (2006) and compute the standardized earnings surprise (SUE) for each stock in each quarter: We use the seasonal random walk model and consensus analyst earnings forecast to proxy for expected earnings per share. We use the primary earnings per share before extraordinary items as our primary measure of quarterly earnings, and we consider the earnings surprise after the exclusion of special items. We label the standardized earnings surprise based on the seasonal random walk model as SUE1, the standardized earnings surprise after the exclusion of special items as SUE2, and the standardized earnings surprise based on consensus analyst forecasts as SUE3. At the end of each month, we form decile portfolios based on the SUE in the previous month and compute the equal-weight returns on a strategy that buys stocks in the top 3 deciles with high SUE and shorts stocks in the bottom 3 deciles with low SUE. The returns on the three strategies based on three SUEs are called returns to PEAD1, PEAD2, and PEAD3. We report the alphas in monthly percentages using three versions of six-factor models that augment the five-factor model in Table V with the return to a strategy that exploits the post-earnings announcement drift. The *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Net Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
6-Factor: PEAD1	-0.32	-0.27	-0.22	-0.23	-0.21	-0.23	-0.20	-0.09	-0.12	0.01	0.33***
	(-3.97)	(-4.35)	(-4.84)	(-4.33)	(-4.02)	(-4.84)	(-3.65)	(-1.91)	(-1.77)	(0.06)	(3.18)
6-Factor: PEAD2	-0.34	-0.29	-0.23	-0.24	-0.23	-0.25	-0.20	-0.10	-0.13	0.00	0.34***
	(-4.29)	(-4.79)	(-5.32)	(-4.8)	(-4.53)	(-5.34)	(-4.01)	(-2.13)	(-1.86)	(-0.03)	(3.18)
6-Factor: PEAD3	-0.24	-0.16	-0.13	-0.15	-0.13	-0.16	-0.13	-0.03	-0.08	0.03	0.27***
	(-4.19)	(-3.23)	(-3.2)	(-3.53)	(-3.04)	(-4.04)	(-3.31)	(-0.74)	(-1.61)	(0.48)	(3.58)

Panel B Gross Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
6-Factor: PEAD1	-0.21	-0.17	-0.12	-0.13	-0.11	-0.13	-0.10	0.00	-0.02	0.11	0.33***
	(-2.63)	(-2.72)	(-2.66)	(-2.45)	(-2.15)	(-2.8)	(-1.83)	(0.09)	(-0.32)	(1.27)	(3.18)
6-Factor: PEAD2	-0.24	-0.19	-0.14	-0.14	-0.13	-0.15	-0.11	0.00	-0.03	0.11	0.34***
	(-2.94)	(-3.14)	(-3.1)	(-2.85)	(-2.58)	(-3.25)	(-2.1)	(-0.08)	(-0.37)	(1.18)	(3.18)
6-Factor: PEAD3	-0.13	-0.06	-0.03	-0.05	-0.03	-0.06	-0.03	0.07	0.03	0.14	0.27***
	(-2.32)	(-1.14)	(-0.77)	(-1.16)	(-0.71)	(-1.61)	(-0.82)	(1.64)	(0.57)	(2.21)	(3.58)

Table 5

Ability to Forecast Earnings and Mutual Fund Performance: Predictive Panel Regressions

This table presents coefficient estimates from predictive panel regressions estimating the association between the ability to forecast earnings and future fund performance. The *AFE* is the covariance of active fund weights and subsequent earnings surprises, measured as three-day abnormal returns during earnings announcements. Future mutual fund performance is measured using Carhart's (1997) four-factor alpha (percentage), where fund betas are estimated using rolling-window regressions in the past three years. The panel regressions control for fund size, fund age, expense ratio, fund turnover, fund percentage flow in the past quarter, and fund alpha in the past three years. The regressions include fixed time effects, and the standard errors are clustered by fund. The *t*-statistics are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Four-Factor Net Fund α	Four-Factor Gross Fund α
AFE	2.392***	2.373***
	(3.07)	(3.05)
Log(TNA)	-0.0105***	-0.0123***
	(-3.03)	(-3.54)
Log(Age)	-0.00350	-0.00249
	(-0.51)	(-0.36)
Expense	-7.983***	-1.279
	(-5.49)	(-0.88)
Turnover	-0.0212***	-0.0205***
	(-2.70)	(-2.65)
PastFlow	0.0271*	0.0254
	(1.69)	(1.59)
PastAlpha	2.528	2.213
	(1.51)	(1.32)
Adj. R-squared	0.0689	0.0684
N	173,656	173,656

Table 6
Performance Predictive Power of Ability to Forecast Earnings: Double Sorts

This table presents the performance of 16 portfolios formed on the basis of the ability to forecast earnings and fund characteristics that reflect the past performance and activity of the fund. We sort funds independently into four groups based on *AFE* and into four groups based on the following fund characteristics: past one-year return (Panel A), the DGTW characteristic selectivity (CS, Panel B), fund turnover (Panel C), the active share (Panel D), and fund size (Panel E). We compute the Carhart (1997) four-factor α as a monthly percentage, based on net returns for each of the 16 portfolios. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Past One-Year Return				
AFE	Low	2	3	High	High-Low
Loser	-0.11	-0.13	-0.12	-0.07	0.04
	(-1.23)	(-1.48)	(-1.44)	(-0.74)	(0.64)
2	-0.07	-0.07	-0.09	0.05	0.12**
	(-1.42)	(-1.66)	(-1.81)	(0.87)	(2.59)
3	-0.10	-0.09	-0.05	0.03	0.12**
	(-1.98)	(-2.4)	(-1.52)	(0.56)	(2.36)
Winner	-0.16	-0.10	-0.02	0.03	0.19***
	(-2.21)	(-1.43)	(-0.24)	(0.35)	(3.18)
Winner-Loser	-0.05	0.03	0.10	0.10	0.15*
	(-0.38)	(0.19)	(0.74)	(0.70)	(1.82)

Panel B: Characteristic Selectivity (CS)					
AFE	Low	2	3	High	High-Low
Low CS	-0.10	-0.09	-0.11	0.01	0.11*
	(-1.58)	(-1.44)	(-1.84)	(0.11)	(1.67)
2	-0.10	-0.08	-0.07	0.01	0.11**
	(-1.87)	(-1.91)	(-1.63)	(0.15)	(1.98)
3	-0.12	-0.07	-0.06	0.03	0.14***
	(-2.62)	(-1.63)	(-1.4)	(0.61)	(2.73)
High CS	-0.16	-0.13	-0.10	0.04	0.19***
	(-2.52)	(-2.29)	(-1.74)	(0.57)	(2.99)
High-Low	-0.06	-0.04	0.01	0.03	0.09
	(-0.88)	(-0.6)	(0.10)	(0.36)	(1.25)

Panel C: Fund Turnover					
AFE	Low	2	3	High	High-Low
Low Turnover	-0.06	0.03	-0.09	-0.08	-0.02
	(-0.96)	(0.40)	(-1.21)	(-1.24)	(-0.3)
2	-0.13	-0.12	-0.11	-0.03	0.10
	(-1.91)	(-2.28)	(-1.75)	(-0.4)	(1.29)
3	-0.09	-0.16	-0.12	-0.05	0.04
	(-1.19)	(-2.78)	(-1.97)	(-0.66)	(0.54)
High Turnover	-0.29	-0.20	-0.12	0.00	0.29**
	(-2.71)	(-3.42)	(-1.78)	(-0.01)	(2.55)
High-Low	-0.22**	-0.23***	-0.03	0.08	0.31***
	(-2.37)	(-3.11)	(-0.4)	(0.96)	(2.76)

Panel D: Active Share					
AFE	Low	2	3	High	High-Low
Inactive	-0.04	-0.05	-0.11	-0.04	-0.01
	(-0.7)	(-1.35)	(-3.22)	(-0.84)	(-0.07)
2	-0.16	-0.11	-0.17	-0.11	0.05
	(-2.25)	(-2.22)	(-2.89)	(-1.66)	(0.55)
3	-0.22	-0.19	-0.12	0.01	0.23***
	(-2.62)	(-2.26)	(-1.53)	(0.18)	(2.71)
Active	-0.25	-0.16	-0.12	0.03	0.28***
	(-2.58)	(-1.9)	(-1.06)	(0.36)	(3.21)
Active-Inactive	-0.21**	-0.11	-0.01	0.07	0.28***
	(-2.03)	(-1.35)	(-0.06)	(0.91)	(2.86)

Panel E: Fund Size					
AFE	Low	2	3	High	High-Low
Small	-0.08	-0.08	-0.13	0.03	0.11*
	(-1.38)	(-1.59)	(-2.53)	(0.48)	(1.75)
2	-0.12	-0.07	-0.09	0.04	0.16**
	(-1.97)	(-1.4)	(-1.73)	(0.71)	(2.38)
3	-0.17	-0.08	-0.03	0.00	0.17**
	(-2.83)	(-1.57)	(-0.56)	(0.05)	(2.50)
Large	-0.07	-0.13	-0.08	0.02	0.09
	(-1.43)	(-3.02)	(-2.29)	(0.38)	(1.42)
Large-Small	0.01	-0.04	0.05	-0.01	-0.02
	(0.17)	(-0.79)	(1.11)	(-0.22)	(-0.34)

Table 7

Understanding Fund Managers' Ability to Forecast Earnings

This table presents the regression results using active fund weights to predict analyst earnings forecast errors and future earnings surprises, defined as the three-day abnormal returns in percentage terms surrounding earnings announcements. Active Weights is the weight of a stock in a fund's portfolio in excess of the stock's weight in the fund's benchmark index. Analyst Coverage is the natural log of 1 + the number of analysts covering the firm. The industry classification is the Fama and French 10-industry classification. The control variables include firm Size, BM, and MOM12, as defined in Table II. These regressions are run using stock–fund pooled data for each quarter from Q1 of 1984 to Q4 of 2008. The statistical inference is based on the Fama-MacBeth (1973) procedure with Newey-West (1987) adjustments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Analyst Forecast Errors	(2) CAR	(3) CAR
Active Weights	1.90**	6.220***	
	(2.28)	(4.69)	
Active Weights×Analyst Coverage		-1.485*	
		(-1.84)	
Active Weights×Non Durable			1.905
			(0.86)
Active Weights×Durable			12.523***
			(2.98)
Active Weights×Manufacturing			3.641**
			(2.59)
Active Weights×Energy			1.965
			(0.63)
Active Weights×High Tech			5.546***
			(3.73)
Active Weights×Telecom			11.981**
			(2.13)
Active Weights×Shops			2.336
			(1.66)
Active Weights×Health Care			3.157
			(1.63)
Active Weights×Utility			1.300
			(0.79)
Active Weights×Others			2.517**
			(2.15)
With Controls	Yes	Yes	Yes
Average Adj-R^2	0.016	0.006	0.016

Table 8

Time-Varying Performance Predictive Power of Ability to Forecast Earnings

This table shows the variation in the association between the Ability to Forecast Earnings and future fund performance over the business cycle and the influence of the Regulation Fair Disclosure (Reg FD) on the performance of earnings forecasters using predictive panel regressions. The *AFE* is the covariance of active fund weights and subsequent earnings surprises measured as three-day abnormal returns during earnings announcements. –CFNAI is the Chicago Fed National Activity Index multiplied by -1 and then standardized to have means of zero and standard deviations of one. RecessionProb is the Chauvet and Piger (2003) real-time recession probability measure. RegFD is a dummy variable that equals 1 if the fund performance is measured after 2000 and 0 otherwise. Future mutual fund performance is measured using Carhart's (1997) four-factor alpha (percentage), where fund betas are estimated using rolling-window regressions in the past three years. The panel regressions control for fund size, fund age, expense ratio, fund turnover, fund percentage flow in the past quarter, and fund alpha in the past three years. The regressions include fixed time effects, and the standard errors are clustered by fund. The *t*-statistics are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net	Net	Gross	Gross	Net	Net	Gross	Gross	Net	Gross
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AFE	3.819***	2.970***	3.816***	2.947***	4.091***	3.186***	4.085***	3.161***	4.453***	4.450***
	(4.96)	(3.72)	(4.97)	(3.70)	(4.97)	(3.74)	(4.96)	(3.71)	(2.68)	(2.68)
AFE×(-CFNAI)	-1.622***	-1.157*	-1.610***	-1.149*						
	(-2.64)	(-1.86)	(-2.62)	(-1.84)						
AFE×RecessionProb					-4.810**	-3.675	-4.769**	-3.642		
					(-2.13)	(-1.63)	(-2.12)	(-1.62)		
AFE×RegFD									-2.949	-2.971
									(-1.60)	(-1.61)
Log(TNA)		-0.0105***		-0.0123***		-0.0105***		-0.0123***	-0.0106***	-0.0124***
		(-3.03)		(-3.55)		(-3.03)		(-3.55)	(-3.05)	(-3.57)
Log(Age)		-0.00330		-0.00229		-0.00333		-0.00232	-0.00328	-0.00227
		(-0.48)		(-0.34)		(-0.48)		(-0.34)	(-0.48)	(-0.33)
Expense		-7.961***		-1.257		-7.966***		-1.263	-8.002***	-1.299
		(-5.47)		(-0.87)		(-5.48)		(-0.87)	(-5.50)	(-0.89)
Turnover		-0.0212***		-0.0205***		-0.0212***		-0.0205***	-0.0214***	-0.0206***
		(-2.70)		(-2.64)		(-2.70)		(-2.64)	(-2.71)	(-2.65)
PastFlow		0.0271*		0.0253		0.0270*		0.0253	0.0270*	0.0252
		(1.69)		(1.58)		(1.69)		(1.58)	(1.69)	(1.58)
PastAlpha		2.538		2.224		2.536		2.222	2.51	2.195
		(1.51)		(1.33)		(1.51)		(1.33)	(1.50)	(1.31)
Adj. R-squared	0.0731	0.0689	0.0729	0.0685	0.0730	0.0689	0.0729	0.0685	0.0689	0.0685
N	198,371	173,656	198,371	173,656	198,371	173,656	198,371	173,656	173,656	173,656

Table 9

How Important Is Earnings Announcement Performance? Replacing Earnings Announcement Returns with Stock Returns

This table presents the performance of decile fund portfolios formed on the basis of the covariance of active fund weights and subsequent stock returns. The decile portfolios are formed and rebalanced at the end of two months each quarter from 1984Q1 to 2008Q4, and the return series range from June 1984 to May 2009. Decile 10 is the portfolio of funds with the highest value of the covariance. We compute monthly equally weighted percentage net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Pastor and Stambaugh (PS, 2003) five-factor model, and the Ferson and Schadt (1996) conditional model. We report the alphas in monthly percentages. The *t*-statistics are shown in parentheses.

Panel A Net Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.82	0.89	0.85	0.79	0.84	0.84	0.83	0.86	0.85	0.92	0.10
	(2.68)	(3.19)	(3.17)	(2.96)	(3.22)	(3.19)	(3.16)	(3.17)	(3.03)	(2.91)	(0.59)
CAPM α	-0.13	-0.02	-0.05	-0.11	-0.05	-0.06	-0.06	-0.05	-0.06	-0.03	0.10
	(-1.17)	(-0.35)	(-0.94)	(-2.63)	(-1.16)	(-1.29)	(-1.4)	(-0.8)	(-0.76)	(-0.25)	(0.55)
FF α	-0.11	-0.04	-0.07	-0.13	-0.07	-0.07	-0.08	-0.05	-0.05	0.03	0.14
	(-1.07)	(-0.57)	(-1.35)	(-3.14)	(-1.84)	(-1.88)	(-1.95)	(-1.01)	(-0.67)	(0.33)	(0.80)
Carhart α	-0.01	0.00	-0.04	-0.11	-0.08	-0.08	-0.10	-0.10	-0.11	-0.07	-0.05
	(-0.14)	(-0.01)	(-0.79)	(-2.59)	(-1.8)	(-1.91)	(-2.5)	(-2.45)	(-2.13)	(-0.85)	(-0.37)
PS α	0.00	0.01	-0.04	-0.10	-0.07	-0.07	-0.10	-0.10	-0.11	-0.06	-0.06
	(0.03)	(0.19)	(-0.74)	(-2.46)	(-1.7)	(-1.71)	(-2.47)	(-2.35)	(-1.99)	(-0.7)	(-0.41)
FS α	0.02	-0.01	-0.05	-0.12	-0.09	-0.08	-0.11	-0.10	-0.12	-0.08	-0.10
	(0.25)	(-0.28)	(-1.17)	(-3.66)	(-2.97)	(-2.42)	(-3.19)	(-2.53)	(-2.15)	(-0.98)	(-0.75)

Panel B Gross Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.93	0.99	0.95	0.88	0.94	0.94	0.92	0.95	0.95	1.03	0.10
	(3.04)	(3.55)	(3.54)	(3.33)	(3.59)	(3.56)	(3.53)	(3.53)	(3.40)	(3.26)	(0.60)
CAPM α	-0.02	0.08	0.05	-0.02	0.05	0.04	0.03	0.05	0.04	0.08	0.10
	(-0.17)	(1.09)	(0.89)	(-0.38)	(1.03)	(0.95)	(0.68)	(0.87)	(0.50)	(0.62)	(0.56)
FF α	0.00	0.06	0.03	-0.04	0.02	0.02	0.02	0.05	0.06	0.14	0.14
	(0.01)	(0.88)	(0.48)	(-0.84)	(0.60)	(0.58)	(0.43)	(0.97)	(0.78)	(1.44)	(0.81)
Carhart α	0.10	0.10	0.06	-0.01	0.02	0.02	0.00	0.00	-0.01	0.05	-0.05
	(0.97)	(1.53)	(1.03)	(-0.3)	(0.48)	(0.49)	(-0.07)	(-0.01)	(-0.15)	(0.59)	(-0.36)
PS α	0.11	0.11	0.06	-0.01	0.03	0.03	0.00	0.00	-0.01	0.05	-0.06
	(1.14)	(1.70)	(1.06)	(-0.17)	(0.60)	(0.69)	(-0.03)	(0.03)	(-0.11)	(0.68)	(-0.4)
FS α	0.13	0.09	0.05	-0.02	0.01	0.02	-0.02	0.00	-0.01	0.03	-0.10
	(1.61)	(1.64)	(1.19)	(-0.68)	(0.32)	(0.60)	(-0.47)	(-0.06)	(-0.27)	(0.43)	(-0.73)

Table 10
Ability to Forecast Earnings and Mutual Fund Performance: Robust AFE Using Residual Earnings Announcement Returns

This table presents the performance of decile fund portfolios formed on the basis of their ability to forecast earnings. The *AFE* is defined as the covariance between active fund weights and subsequent residual earnings surprises that are residuals from cross-sectional regressions of three-day abnormal returns during earnings announcements on firm size, book-to-market, past 12-month return, and the three-day abnormal returns on earnings announcement days in the previous quarter. The decile portfolios are formed and rebalanced at the end of two months each quarter from 1984Q1 to 2008Q4, and the return series range from June 1984 to May 2009. Decile 10 is the portfolio of funds with the highest AFE value. We compute monthly equally weighted percentage net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Pastor and Stambaugh (PS, 2003) five-factor model, the Ferson and Schadt (1996) conditional model, and three versions of the six-factor models that include the return to a strategy that exploits the post-earnings announcement drift. We report the alphas in monthly percentages. The *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Net Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.81	0.80	0.82	0.83	0.81	0.81	0.85	0.85	0.92	0.99	0.18**
	(2.82)	(2.93)	(3.09)	(3.12)	(3.07)	(3.08)	(3.18)	(3.13)	(3.28)	(3.29)	(2.09)
CAPM α	-0.12	-0.11	-0.08	-0.07	-0.09	-0.08	-0.05	-0.06	0.00	0.04	0.17**
	(-1.76)	(-2.02)	(-1.56)	(-1.63)	(-2.03)	(-1.93)	(-1.17)	(-1.18)	(-0.08)	(0.47)	(1.98)
FF α	-0.13	-0.13	-0.09	-0.09	-0.10	-0.11	-0.05	-0.06	0.01	0.10	0.23***
	(-2.32)	(-2.73)	(-1.88)	(-2.4)	(-2.76)	(-2.79)	(-1.4)	(-1.45)	(0.23)	(1.58)	(2.69)
Carhart α	-0.10	-0.11	-0.08	-0.09	-0.10	-0.11	-0.06	-0.08	-0.02	0.05	0.15**
	(-1.78)	(-2.32)	(-1.6)	(-2.18)	(-2.59)	(-2.7)	(-1.46)	(-2)	(-0.37)	(0.83)	(2.12)
PS α	-0.10	-0.10	-0.07	-0.09	-0.10	-0.10	-0.05	-0.07	-0.01	0.07	0.17**
	(-1.75)	(-2.18)	(-1.52)	(-2.12)	(-2.55)	(-2.46)	(-1.26)	(-1.73)	(-0.19)	(1.18)	(2.40)
FS α	-0.13	-0.12	-0.07	-0.08	-0.10	-0.10	-0.08	-0.09	-0.02	0.05	0.18***
	(-2.58)	(-3.07)	(-2.01)	(-2.44)	(-3.31)	(-3.3)	(-2.31)	(-2.43)	(-0.44)	(0.88)	(2.61)
6-Factor: PEAD1	-0.26	-0.23	-0.24	-0.23	-0.24	-0.24	-0.17	-0.15	-0.12	-0.01	0.25**
	(-3.23)	(-3.71)	(-4.36)	(-4.93)	(-4.94)	(-4.6)	(-3.65)	(-2.66)	(-1.77)	(-0.06)	(2.54)
6-Factor: PEAD 2	-0.28	-0.25	-0.26	-0.24	-0.26	-0.26	-0.18	-0.15	-0.12	-0.01	0.27**
	(-3.56)	(-4.1)	(-4.85)	(-5.34)	(-5.47)	(-5.12)	(-4.08)	(-2.84)	(-1.94)	(-0.15)	(2.55)
6-Factor: PEAD3	-0.20	-0.15	-0.12	-0.14	-0.14	-0.15	-0.10	-0.10	-0.07	0.01	0.20***
	(-3.49)	(-3.21)	(-2.48)	(-3.53)	(-3.43)	(-3.63)	(-2.5)	(-2.7)	(-1.45)	(0.12)	(2.82)

Panel B Gross Fund Returns

	Low	2	3	4	5	6	7	8	9	High	High-Low
Average Return	0.91	0.90	0.92	0.92	0.91	0.91	0.95	0.95	1.02	1.10	0.18**
	(3.20)	(3.30)	(3.46)	(3.49)	(3.43)	(3.45)	(3.55)	(3.49)	(3.64)	(3.65)	(2.09)
CAPM α	-0.02	-0.01	0.02	0.03	0.01	0.01	0.05	0.04	0.10	0.15	0.17**
	(-0.23)	(-0.2)	(0.45)	(0.61)	(0.26)	(0.30)	(1.07)	(0.80)	(1.57)	(1.65)	(1.98)
FF α	-0.02	-0.02	0.01	0.01	-0.01	-0.01	0.05	0.04	0.11	0.21	0.23***
	(-0.42)	(-0.53)	(0.27)	(0.17)	(-0.14)	(-0.26)	(1.28)	(1.12)	(2.34)	(3.30)	(2.69)
Carhart α	0.01	-0.01	0.02	0.01	-0.01	-0.01	0.04	0.02	0.08	0.16	0.15**
	(0.12)	(-0.18)	(0.48)	(0.26)	(-0.19)	(-0.29)	(1.06)	(0.54)	(1.82)	(2.67)	(2.13)
PS α	0.01	0.00	0.03	0.01	-0.01	0.00	0.05	0.03	0.09	0.18	0.17**
	(0.15)	(-0.04)	(0.57)	(0.28)	(-0.17)	(-0.11)	(1.18)	(0.75)	(1.94)	(2.98)	(2.41)
FS α	-0.02	-0.01	0.03	0.02	-0.01	0.00	0.02	0.01	0.08	0.16	0.18***
	(-0.41)	(-0.38)	(0.85)	(0.45)	(-0.18)	(-0.16)	(0.64)	(0.36)	(1.86)	(2.79)	(2.61)
6-Factor: PEAD1	-0.15	-0.13	-0.14	-0.13	-0.14	-0.15	-0.07	-0.05	-0.01	0.10	0.25**
	(-1.88)	(-2.1)	(-2.56)	(-2.77)	(-2.94)	(-2.78)	(-1.57)	(-0.89)	(-0.21)	(1.14)	(2.54)
6-Factor: PEAD2	-0.17	-0.15	-0.16	-0.14	-0.16	-0.16	-0.08	-0.05	-0.02	0.09	0.27**
	(-2.19)	(-2.46)	(-3)	(-3.14)	(-3.41)	(-3.21)	(-1.9)	(-1)	(-0.36)	(1.03)	(2.55)
6-Factor: PEAD3	-0.09	-0.05	-0.02	-0.05	-0.05	-0.05	0.00	0.00	0.03	0.12	0.20***
	(-1.59)	(-1.04)	(-0.42)	(-1.11)	(-1.12)	(-1.25)	(-0.06)	(-0.12)	(0.70)	(1.91)	(2.82)