Information Content when Mutual Funds Deviate from Benchmarks*

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Abstract

The consensus wisdom of active mutual fund managers, as reflected in their average over- and underweighting decisions, contains valuable information about future stock returns. Analyzing a comprehensive sample of active U.S. equity funds 1984–2008, we find that stocks heavily overweighted by active funds outperform their underweighted counterparts by more than 7% per year, after adjustments for their loadings on the market, size, value, and momentum factors. This large premium dissipates quickly as the consensus view becomes publicly available. These results are consistent with the notion that informed investing by active mutual funds enhances the informativeness of stock prices.

JEL classification: G10; G11; G14; G23

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I Introduction

This paper shows the high investment value of the consensus wisdom displayed by active mutual funds. Analyzing a comprehensive sample of active U.S. equity funds 1984–2008, we find that stocks heavily overweighted by active funds, relative to their benchmark indexes, perform substantially better than their underweighted counterparts. The average return spread is 7.56% per year on an equal-weight basis, after adjustments for loadings on market, size, value, and momentum factors. The spread is 4.56% on a value-weighted basis and 7.20% when the weights reflect the amount of fund investments. The superior performance of stocks that are overweighted by the active funds also is robust to a variety of measures of portfolio tilts, adjustments for risk, and across different subperiods.

These results demonstrate the superior ability of active mutual funds to select stocks and stand in stark contrast with the disheartening message from performance literature that actively managed mutual funds, on average, fail to outperform passive benchmarks (e.g., Jensen, 1968; Daniel et al., 1997; Fama and French, 2010). Rather than examine the total returns to a fund's portfolio, we aggregate decisions by active mutual funds to deviate from benchmarks into a stock-level measure and then assess its information content. If active mutual funds deviate from benchmarks to exploit their information advantages, this measure can aggregate various pieces of information scattered among managers and thus should possess high statistical power to detect information advantages.

Our findings suggest that actively managed mutual funds are informed investors, whose costly acquisition and implementation of information help impound information into asset prices (Grossman and Stiglitz, 1980).[1] Consistent with this view, the return spread between stocks that the active funds overweight and underweight, relative to their benchmark indexes, is higher for stocks with more firm-specific information, as captured by high idiosyncratic volatilities, but it is lower for stocks for which more informed investors compete for private information, as reflected by a higher breadth of active mutual fund ownership. Since large firms are more transparent and adopt better disclosure policies, whereas the gains from trading on private information about small firms tend to be low compared with the cost of information acquisition, the return forecasting power of active funds' deviation from benchmarks concentrates among mid-cap stocks. Consistent with the evidence that growth-oriented mutual funds tend to engage in informed trading, we also find that portfolio tilting decisions made by growth funds contain information that is more valuable than the information derived from decisions made by income funds.

An alternative interpretation of the higher return on the stocks that active funds overweight

[1]In 2009, active equity funds manage approximately 87% of total U.S. equity mutual fund net assets, pushing the average expense ratio for stock funds to be 0.99% (2010 Investment Company Fact Book, p. 33 and p. 64). French (2008) argues that the annual cost of active investing is 0.67% of the aggregate market value.

is that it may reflect the effects of demand pressure on prices (Gompers and Metrick, 2001). In particular, if active funds continue to buy stocks that they overweight, e.g., exhibiting herd behavior (Grinblatt, Titman, and Wermers, 1995), their demand pressure could push stock prices above equilibrium levels and lead to higher in-sample returns. We find evidence that contradicts this view. First, a herd behavior explanation implies a positive serial correlation in the changes of active funds' deviation from benchmarks, whereas we find a strong negative correlation between consecutive changes in deviations from benchmarks. This position reversal suggests that risk-averse informed active managers tend to unwind their profitable positions to mitigate the long-run risk that arises from future price movements due to unpredictable events. Second, we find no evidence of return reversals for stocks that active funds overweight, which suggests that the deviation from benchmarks might reflect information about the firms' fundamental value. Third, the deviation from benchmarks positively predicts firms' future earnings surprises, which reinforces an information-based interpretation of the higher return on the stocks that the active mutual funds overweight.

The issue of how information flows from informed agents to asset prices plays a central role in theories of asset pricing and efficient markets. Recent attempts to identify informed trading have examined stock–investor pairs with specific information links, such as firms and funds in geographic proximity (Coval and Moskowitz, 2001) or that are managed by the same university alumni (Cohen, Frazzini, and Malloy, 2008). Rather than focus on some active fund managers, our comprehensive study of active investing decisions by mutual fund managers spotlights a systematic link between the consensus wisdom of active fund managers and future stock returns, which helps to understand how the price system aggregates different information from different investors.

The investment value of the consensus wisdom of active mutual funds dissipates quickly when it becomes publicly available. A self-financing strategy that buys the stocks that active funds overweight and shorts the stocks that they underweight, implemented with a one-month lag, generates an equal-weight four-factor alpha of 3.36% per year, with a t-statistic of 2.42. The same strategy, implemented with a lag of two months, generates a four-factor alpha of 2.28%, with a t-statistic of 1.60. The Securities and Exchange Commission (SEC) requires all mutual funds to disclose their portfolio holdings with a maximum delay of 45 days, so our results are consistent with strong-form inefficiency but semi-strong efficiency.

We also split the sample into two subperiods 1984–1996 and 1997–2008, and find that the self-financing strategy, implemented with a delay of two months, generates a four-factor alpha of 4.32% per year, with a t-statistic of 2.52, in the first subperiod but only 1.56% per year, with a t-statistic of 0.73, in the second subperiod. The same strategy, implemented without delay, generates high abnormal returns of 5.88% and 10.08% per year in these two subperiods (both are highly statistically significant). These results suggest an intriguing time trend of enhanced stock market efficiency in incorporating the information contained in the consensus wisdom of active mutual funds.

How can we reconcile evidence that points to strong informational advantages of active mutual funds with their overall lackluster performance reported in performance literature? We find that in aggregate, active mutual funds invest less than 10% of their assets in high alpha stocks (Decile 10, on the basis of deviation from benchmarks) but approximately one-third of their fund assets in low alpha stocks (Decile 1). Therefore, a large four-factor stock alpha of 6.60% per year on stocks that they overweight translates into a small mutual fund alpha of less than 1% per year. After accounting for trading costs, fees, and expenses, little, if any, alpha remains for mutual fund investors to capture.

Our results support the notion that an average active mutual fund can generate significant alpha, a crucial assumption maintained by Berk and Green (2004). The appearance of passiveness by mutual funds in aggregate, such that little abnormal returns can be earned on the total fund portfolio, is also consistent with the equilibrium described by Berk and Green. But it naturally raises the question: Could individual fund managers have performed better by being more active? This question is particularly important in light of the declining degree of activeness in the actively managed mutual fund industry (Cremers and Petajisto, 2009) and the diminishing mutual fund alpha over time (Barras et al., 2010; Fama and French, 2010).

To explore this question, for each individual fund we decompose returns on fund holdings into two components: a long–short active portfolio that consists of deviations from benchmarks and a passive portfolio that consists of investments in the benchmarks. The average Sharpe ratio for each individual fund's active portfolio is significantly lower than that of the fund's benchmark portfolio. By combining active and passive portfolios, actively managed mutual funds on average achieve significantly higher Sharpe ratios for their overall portfolios than those for their benchmarks or active portfolios. In a formal test, we find that only 11–15% of all funds in our sample could have achieved significantly higher in-sample Sharpe ratios had they taken more aggressive positions in their active portfolios. These two results suggest that for a typical fund manager who invests in a limited number of stocks, the higher idiosyncratic risk on the alpha-generating stocks in the active portfolio could discourage more aggressive positions in the active portfolio. In other words, the majority of active fund managers appear to combine active and passive portfolios in such a way that being more active cannot lead to marginal improvements in performance.

We organize the rest of this article as follows: In Section II, we introduce our measure of the consensus wisdom of active mutual funds, i.e., their deviations from their benchmarks DFB, and in Section III, we describe our sample selection and summary statistics. With Section IV, we explore the information content of the consensus wisdom of active mutual funds and evaluate its implications for stock market efficiency and mutual fund performance. We provide several robustness checks in Section V. Section VI concludes our paper.

II Measuring the Consensus Wisdom of Active Mutual Funds: Deviations from Benchmarks, DFB

The building block for our measure of the consensus view of active mutual funds is their deviations from benchmarks. If active mutual funds aim to outperform a passive benchmark index, they would overweight a stock, relative to the benchmark, when they expect it to outperform, and underweight it otherwise. In this scenario, each manager's decision of portfolio tilting reflects the expectation of future returns to that stock conditional on the manager's information set. Therefore, a stock level measure that averages the decisions to deviate from benchmarks across active funds whose investment universe includes this stock can aggregate different pieces of information about the future value of individual stocks scattered among fund managers.[2] If this consensus view has information that is not fully reflected in current market prices (i.e., mutual funds as an investor group possess private information), it should predict future stock returns.

Specifically, we measure a mutual fund j's deviation from its benchmark for stock i in quarter t as the difference between this stock's weight in the fund portfolio, $w^j_{i,t}$, and its weight in the stock index against which the fund's performance is benchmarked, $w^b_{i,t}$. Then we create a stock-level measure of mutual funds' deviations from benchmarks, DFB, by averaging the difference in portfolio weights across all mutual funds whose investment universe comprises this stock. A stock enters a mutual fund's investment universe if it (1) is held by the mutual fund or (2) is a member of the fund's benchmark index. We thus can define a measure of mutual funds' deviations from benchmarks for stock i as:

$$DFB_{i,t} = \sum_{j=1}^{N_i} (w^j_{i,t} - w^b_{i,t})/N_i, \tag{1}$$

where N_i is the number of funds whose investment universe includes stock i.

This measure can be viewed as polling fund managers to vote for the stocks they perceive as future winners. A stock receives a score of 1 if the manager overweights the stock and -1 if the manager underweights the stock. We weight each vote based on how aggressive the manager tilts the position of the stock away from the benchmark index and use the weighted average to capture the consensus view of active fund managers.[3] We argue, and provide evidence, that this measure is more powerful to detect active funds' information advantages than previously used proxies based on the level or breadth of active fund ownership.

Naturally, active fund managers might deviate from their benchmarks for other reasons,

[2] In Appendix A, we provide a simple mathematical illustration of this idea.

[3] We explore other ways to aggregate the votes, e.g., weighting each fund's vote based on net fund assets or how active the fund is in deviating from the benchmark. Our results remain robust when we use such weighting schemes, but we present our main results using the simple intuitive scheme in Equation (1).

e.g., liquidity-related motives or agency problems emphasized in studies of incentives of fund managers.[4] We control for the influence of liquidity on our asset pricing tests using the Pastor and Stambaugh (2003) liquidity risk factor. The portfolio distortion effects arising from agency-related problems could lead us to find evidence against the information advantages of active mutual funds.

III Sample and Summary Statistics

In this section, we describe our data set and sample selection criteria, as well as our methods for selecting funds' performance benchmarks, followed by summary statistics for the mutual fund sample and the characteristics of stocks with large mutual funds' deviations from benchmarks, DFB.

A *Data and Sample Selection*

To construct our mutual fund database, we combine the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database (MFDB) with the CDA/Spectrum Mutual Fund Holdings Database from Thomson Financial via the MFLINKS. Because we wish to examine the informational advantages of mutual funds in stock markets, we only include active mutual funds that invest primarily in U.S. common stocks; we eliminate balanced, bond, money market, international, index funds, and sector funds, as well as funds not invested primarily in equity securities (for details on our selection, see Appendix B). Our sample covers the period from 1984 to 2008.

Data on the monthly returns, prices, and market values of equity for common stocks traded on the NYSE, AMEX, and NASDAQ come from the CRSP. Consistent with previous literature, we exclude closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes, and scores (we keep only shares with codes of 10 or 11). To mitigate the concern that our stock return tests might be influenced by return outliers, we eliminate stocks with prices below $5 as of the portfolio formation date (typically the end of the previous quarter).

B *Benchmark Index Holdings*

We next must compute the weights of each fund's holdings against its performance benchmark; the crucial step is selecting the stock index that the fund seeks to outperform. We use two methods to identify each fund's performance benchmark index. First, because there might be

[4]See, e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Goetzmann, Ingersoll, Spiegel, and Welch (2007), and Huang, Sialm, and Zhang (2010).

a discrepancy between a mutual fund's self-declared performance benchmark and the actual benchmark the fund follows (Sensoy, 2009), we adopt Cremers and Petajisto's (2009) method and select 19 benchmark indexes commonly 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 19 indexes the one that minimizes the average distance between the fund portfolio weights and the benchmark index weights.[5] Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from Compustat. For the remaining indexes and time periods, we use the holdings of index funds to approximate the index holdings.[6] In Appendix C, we describe in detail our selection of benchmark indexes.

Second, for each individual fund, we tailor a performance benchmark by constructing a value-weighted portfolio of all stocks the fund actually holds. Since these two approaches generate qualitatively similar results, we report our main results based on the first approach.

C *Summary Statistics for the Mutual Fund Sample*

Table 1 reports the summary statistics for our mutual fund sample, which includes 2,691 distinct active U.S. equity funds. During 1984–2008, the industry of active equity mutual funds experienced dramatic expansion: The number of actively managed funds increased from 237 in 1984 to 1,510 in 2008, with total assets under their management increasing from $45.47 billion to $1.02 trillion. On average, these funds invested 90.71% of their assets in common stocks, which suggests that our sample effectively represents the universe of U.S. active funds with an investment focus on domestic equity. Throughout our sample period, the expansion of mutual funds outpaced the growth of stock markets, which led them to become increasingly important shareholders of common equity. In particular, mutual funds' ownership of U.S. stocks in the CRSP database increased from 2.71% to 10.26%.

D *Characteristics of Stocks with Extreme* DFB

What are the characteristics of stocks with large mutual fund over- and underweighting? Table 2 presents the results based on the decile portfolios. Specifically, at the end of each quarter, we sort stocks into deciles according to their DFB, calculate the cross-sectional averages of the characteristics, and report their time-series averages.

[5] Our scheme of dynamically selecting benchmark indexes follows Cremers and Petajisto (2009). We also experiment with selecting benchmarks on the basis of moving averages of the distance between fund portfolio weights and benchmark index weights in the past five years and obtain qualitatively similar results.

[6] We obtain qualitatively similar results if we use index fund holdings throughout our sample period.

The results indicate that stocks in Decile 10 about which active funds display the most conviction tend to be the least popular among mutual funds; they reside in the investment universe of only 38 funds. On the contrary, stocks in Decile 1 appear in the investment universe of 220 funds. On average, only 17 mutual funds hold stocks in Decile 10, compared with 40 funds holding stocks in Decile 1. These results indicate that stocks with high active fund bets do not pertain just to a few "hot" or popular names among money managers.

We find also that stocks heavily overweighted by active funds tend to be relatively small with an average decile rank value of 3.05, based on NYSE market-cap decile breakpoints in ascending order. They have a slight tendency to be winners in the previous year.[7] There exists no apparent relation between DFB and the book-to-market ratio. Interestingly, stocks overweighted by funds tend to have higher idiosyncratic volatilities. If stocks with high idiosyncratic volatilities on average earn lower returns, as argued by Ang, Hodrick, Xing, and Zhang (2006), we might expect them to contribute negatively to active fund performance, unless active funds posses significant stock-picking skills.

IV Information Content of the Consensus Wisdom of Active Mutual Funds

In this section, we evaluate the investment value of the consensus view of active mutual funds, as revealed through their deviations from benchmarks. We start by looking at the relation between DFB and future stock returns using both univariate portfolio sorts and the Fama and MacBeth (1973) cross-sectional regressions. Then we examine and find evidence contradicting an alternative interpretation of the return forecasting power of DFB, namely, the demand pressure from mutual funds. We further evaluate the information content of DFB and examine its implications for stock market efficiency and mutual fund performance.

A *Return Forecasting Power of* DFB

To evaluate the investment value of the consensus view of active mutual funds, we first sort stocks into deciles based on DFB and examine the subsequent performance of these decile portfolios. As we update DFB each quarter, the portfolios accordingly get rebalanced. Fama and French (2008) point out that equal-weight portfolio returns may be driven by tiny stocks that are numerous in number but small in economic significance, whereas value-weight portfolio returns may be driven by a few very large caps. We present both equal-weight and value-weight returns on the decile portfolios in Table 3.

The first columns in Panels A (equal-weight returns) and B (value-weight returns) of Table

[7] We note that the high excess weights of Decile 10 stocks in mutual fund portfolios should not result mechanically from their high past returns: Large increases in the relative prices of those stocks increase their weights not only in the mutual fund portfolio but also in the benchmark index.

3 show that DFB strongly predicts future returns. A portfolio that buys stocks in Decile 10 and sells short stocks in Decile 1 generates average returns of 0.77% and 0.64% per month on an equal- and value-weight basis. These returns are statistically significant, with t-statistics of 4.30 and 2.62, respectively. To examine whether the high returns on stocks heavily overweighted by mutual funds simply reflect fund managers' propensity to take high risks, we employ standard risk-adjustment models to examine the abnormal returns. The specific risk-adjustment models include the Capital Asset Pricing Model (CAPM), the Fama and French three-factor model, a four-factor model including momentum, and a five-factor model that also includes Pastor and Stambaugh's (2003) liquidity factor.[8] In addition to linear factor models, we employ a characteristic-adjustment procedure, as proposed by Daniel, Grinblatt, Titman, and Wermers (hereafter, DGTW, 1997).

Columns 2–6 in Panels A and B provide the results. The high returns on stocks heavily overweighted by mutual funds, in excess of the returns on their underweighted counterparts, remains large and statistically significant after those adjustment procedures. For example, the spread portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 earns equal-weighted abnormal returns of 0.69%, 0.75%, 0.63%, 0.65%, and 0.61% per month after the adjustments according to the CAPM, three-factor model, four-factor model, five-factor model, and DGTW adjustment procedure, respectively. All five versions of the alphas are highly statistically significant, with t-statistics ranging between 3.92 and 6.07. We note that a portfolio characterized by long stocks in Decile 9 and short stocks in Decile 2 also delivers superior performance on an equal-weighted basis. Consistent with stocks highly overweighted by mutual funds tending to be relatively small, as shown in Section III.D, the value-weighted return on a long-short portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 is smaller but still economically meaningful and statistically significant.

To examine the return predictive power of DFB in the presence of other return predictors, we employ the Fama and MacBeth cross-sectional regressions. To examine large overweights and underweights separately, we discretize DFB into two dummy variables: $D1$ that represents the membership in the decile of stocks with the lowest DFB and $D10$ that represents the membership in the decile with the highest DFB. The slope coefficient for the dummy variables in the Fama and MacBeth regressions can be interpreted as the difference in quarterly returns between stocks in each respective decile and all stocks in other deciles, while controlling for stock characteristics.

Specifically, at the end of each quarter from 1984Q1 to 2008Q3, we perform cross-sectional regressions specified as follows:

$$R_{i,t+1} = \alpha + \beta D1_{i,t} + \gamma D10_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

[8] We obtain qualitatively similar results if we use a six-factor model that also includes a volatility factor (Ang, Hodrick, Xing, and Zhang, 2006).

where $R_{i,t+1}$is the return on stock i in quarter t in excess of the market return in quarter t, and $X_{i,t}$ includes a bunch of stock characteristics such as firm size, the book-to-market ratio, past one-year (skipping the most recent month) returns, idiosyncratic volatilities, turnover, and past one-month (month t) return. Following Fama and MacBeth (1973), we conduct statistical inference based on the time-series variation of the coefficient estimates.

The results in columns 1 and 2 of Panel A in Table 4 show that stocks in Decile 1 significantly underperform other stocks and stocks in Decile 10 significantly outperform other stocks, even after we control for the influence of other firm characteristics such as firm size, the book-to-market ratio, past one-year returns, idiosyncratic volatilities, turnover, and past one-month return.

Chen, Jegadeesh, and Wermers (2000) argue that a trade-based measure of changes in the fraction of shares owned by mutual funds ($\triangle MFO$) is a significant predictor of future stock returns. Chen, Hong, and Stein (2002) argue that changes in the number of mutual funds that hold the stock, $\triangle Breadth$, correlate with future stock returns. Motivated by these two prior studies, we include these variables in our cross-sectional regressions to stress-test the return forecasting power of our measure of deviations from benchmarks. The results in columns 3 and 4 of Panel A indicate that these two variables leave the return forecasting power of DFB intact.[9]

In summary, we find strong evidence that a stock-level measure that proxies for the consensus wisdom of active fund managers, DFB, strongly and positively forecasts the cross-sectional variation in future returns. The superior (inferior) performance of stocks heavily overweighted (underweighted) by mutual funds is consistent with the notion that actively managed mutual funds behave as informed investors in stock markets. In the next subsection, we investigate an alternative interpretation of the return forecasting power of DFB, that is, mutual funds' demand pressure.[10]

[9] We verify that these two fund trade-based measures significantly predict returns in the authors' original sample periods, but exhibit insignificant return forecasting power in our extended sample period. Nagel (2005) finds consistent evidence that the change in mutual fund breadth has on average no relationship to future returns, when he expands the original authors' sample by five years. In Appendix D, we provide a detailed analysis of the fund trade measure.

[10] We also evaluate the influence of the best ideas that Cohen, Polk and Silli (2010) consider on our results. We find that our results remain virtually unchanged after we exclude each manger's best one to three ideas from the computation of DFB. A related but different literature looks at how outside investors can benefit from the disclosed portfolio compositions of mutual fund managers. The focus of that literature, however, is on how investors can most efficiently free-ride on the information disclosed by fund managers (see, e.g., Frank, Poterba, Shackelford, and Shoven, 2004, and Wermers, Yao, and Zhao, 2010). We are able to show that the return forecasting power of our measure of deviations from benchmarks remains strong and significant, even after we control for the efficient algorithm proposed in that literature, e.g., the past fund alpha-weighted portfolio weights as in Wermers, Yao, and Zhao (2010). The results are available upon request.

B *Informed Fund Managers or Mutual Fund Herding?*

Although consistent with the notion that active funds possess value-relevant information that is not fully reflected in stock prices, the higher returns on stocks with higher DFB may have alternative interpretations as well. For example, Gompers and Metrick (2001) argue that the expansion of institutional investors in U.S. stock markets impacted stock prices, driving up the prices of the stocks they preferred to hold beyond equilibrium levels and thus increasing the in-sample returns on those stocks. Does a demand pressure story explain the higher future returns on stocks with large active mutual fund bets? In the context of mutual funds, there is evidence that mutual funds tend to herd (Grinblatt, Titman, and Wermers, 1995, Wermers, 1999, and Sias, 2004). If funds continue to buy stocks they previously overweighted, their demand pressure may push up stock prices, leading to positive returns.

To differentiate this alternative interpretation based on price pressure from our story of informed fund managers, we conduct a number of tests, which uniformly support the information-based interpretation for our finding. First, we explore their distinct implications for the dynamics of changes in mutual funds' deviations from benchmarks. Specifically, suppose that, in the world with informed fund managers, a risk-averse manager receives a positive signal about a stock in period t and decides to increase her portfolio weight in this stock relative to her benchmark, which results in an increase in DFB from $t-1$ to t. In the next period $t+1$, as her positive private information flows into the stock price, the risk-averse manager has incentives to at least partially unwind the position that she has built up to capture the gains to her information. This "position reversal" takes place because the manager desires to reduce the long-term risk of future price movements arising from future unpredictable events. In this scenario, a large increase in DFB in one period should predict a subsequent decline in DFB. In the world dominated by mutual fund herds, however, a large increase in the excess weight of a stock in an average fund's portfolio attracts further demand from the herd, which leads to increases in the stock price. According to this interpretation, a large increase in DFB in one period should forecast a further increase in DFB.

Before testing for these different predictions, Panel A of Table 5 presents the performance of portfolios sorted according to changes in DFB. The results indicate that changes in DFB have even stronger return forecasting power than the level of DFB, consistent with the notion that revisions in the consensus wisdom could more cleanly capture the new information obtained by active fund managers. We then move to the tests for the different predictions of informed manager and mutual fund herding hypotheses. Specifically, for each quarter from 1984Q3 to 2008Q3, we perform cross-sectional regressions of changes in DFB on the lagged changes in DFB and the lagged level of DFB. We use the Fama-MacBeth (1973) procedure with the Newey-West (1987) adjustment for serial correlation to conduct statistical significance. Panel B of Table 5 shows that an increase in DFB in one quarter reliably predicts a decline in DFB in the subsequent quarter, which concurs with the story of informed fund managers but contradicts the price pressure-based interpretation. The negative correlation between consecutive changes in DFB holds for both the full sample 1984–2008, and two subsamples with different SEC disclosure regulations: 1984–2004 and 2005–2008.[11]

To provide direct evidence on position reversal, we use lagged changes in DFB and the lagged level of DFB to predict changes in average portfolio weights of active mutual funds Δw^f ($\Delta DFB = \Delta(w^f - w^b) = \Delta w^f - \Delta w^b$), which directly reflect the trading decisions of active mutual funds. Panel C of Table 5 shows that an increase in DFB in one quarter reliably predicts a decline in average portfolio weights in the subsequent quarter. Considering the fact that stocks with an increase in DFB on average have higher future returns, which translate into a mechanical increase in portfolio weights, this result suggests strong selling of this stock by active funds during the period when the higher returns are earned. In summary, our analysis of the dynamics of changes in DFB supports the unwinding of profitable position by informed fund managers but contradicts the herding story.[12]

Second, a simple approach to examine the influence of demand pressure on our findings is to test the return forecasting power of our measure of deviations from benchmarks in the presence of realized future demand shocks. If active funds' deviations from benchmarks can forecast future returns due mainly to their correlation with future demand shocks, the return predictive power should cease to exist once the association between future returns and future demand shocks is controlled for. We conduct this test in column 5 of Panel A of Table 4. The results indicate that the return forecasting power of active funds' deviations from benchmarks remains intact after we control for future changes in mutual fund demand.

Last, we examine the persistence of the performance of stocks overweighted by mutual funds: If the high returns on stocks with high DFB arise mainly from demand pressure, these returns subsequently should reverse. If, however, the high returns come mostly from value-relevant information possessed by fund managers and the market reacts properly to that information, we expect to observe no subsequent return reversal.[13] In Panels B, C, and D of Table 4, we perform regressions similar to Equation 2 with the cumulative market-adjusted returns in the subsequent quarters as dependent variables. The results show that the positive association between DFB and future excess returns concentrates for the most proximate quarter, and this positive association shows no tendency to reverse for the subsequent two to four quarters. Thus,

[11] The regulatory environment for mutual funds to disclose their portfolio compositions has varied over our sample period. For example, in 1985 the U.S. Securities and Exchange Commission (SEC) reduced the mandatory portfolio disclosure frequency from every quarter to every six months; effective May 2004, the SEC increased the required portfolio disclosure frequency from every six months to every quarter.

[12] Alternatively, one could argue that the DFB measure may be laden with measurement error, which leads to mean-reversion in ΔDFB. We view this alternative interpretation as implausible, because ΔDFB appears to have stronger return forecasting power than the level of DFB, which contradicts the view of measure error as the key driver of the dynamics of DFB.

[13] One caveat about this prediction on long-term performance is that as managers unwind the positions they have overweighted relative to their benchmark, other market participants might continue to buy those shares, which could influence future price movements.

DFB appears to forecast returns due primarily to the value-relevant information that DFB aggregates from diverse mutual fund managers, as revealed through their portfolio decisions.

C *Stock Characteristics*

To increase our confidence in this information-based story, we conduct a series of tests based on stock attributes. First, we examine the return forecasting power of DFB across size groups. The idea is that very large firms tend to be more transparent, with better disclosure policies. They also tend to be more closely followed and researched by market participants. It is therefore more difficult for individual funds to gain information advantages on those firms. On the other hand, returns to analyzing tiny firms appear to be small relative to the costs of information acquisition. These considerations prompt us to conjecture that mid-cap stocks could be the fields where information miners or stock pickers have the greatest information advantage. Second, along a similar vein of thinking, if mutual funds have informational advantages about individual stocks, we expect their advantages to be greater among stocks with more firm-specific information. Third, we expect active funds' informational advantages to be more valuable when the funds have fewer competitors. In their seminal article, Grossman and Stiglitz (1980) conjecture that "the more individuals who are informed, the more informative is the price system." A corollary of that conjecture is that the consensus view of active funds would have a lower investment value for stocks with a large number of informed mutual fund holders.[14]

To examine these hypotheses, we perform two-way sorts of stocks independently on DFB and firm size as well as proxies for the amount of firm-specific information and the number of mutual funds competing for private information. We use the idiosyncratic volatility, computed as the standard deviation of residuals from regressions of daily excess stock returns on the Fama and French factors in the past quarter, to proxy for the amount of firm-specific information, and the number of active funds that hold the stock at each quarter end to proxy for the number of investors competing for private information. Specifically, along one dimension we sort stocks into quartiles based on DFB, and in the other dimension we sort stocks into quartiles based on their stock attributes such as size, idiosyncratic volatilities or the number of mutual fund holders. Sixteen portfolios thus emerge from the intersection of the two-way sorts. We hypothesize that a strategy that buys high DFB stocks and sells low DFB stocks generates higher abnormal returns among mid-caps and stocks with higher idiosyncratic volatilities and a lower number of mutual fund investors.

Table 6 presents the results. To conserve space, we only present equal- and value-weight four-factor alphas, but the results are qualitatively similar if we use other specifications of asset pricing models. Panel A of Table 6 shows that a strategy that buys high DFB and shorts

[14] A caveat is that the precision of aggregated signals increases with the number of votes included in the computation, which could countervail the effects of competition among informed investors.

low DFB stocks generates insignificant four-factor alpha among very large firms (Quartile 4) and tiny firms (Quartile 1) but produces large and significant four-factor alphas for mid-cap stocks in Quartiles 2 and 3, ranging between 0.54 and 0.64% per month on both equal- and value-weight basis. These results support our conjecture based on the economics of information acquisition.

Panel B of Table 6 shows that a strategy that is long high DFB and short low DFB stocks for stocks with high idiosyncratic volatilities yields average monthly four-factor alphas of 0.95% (t=5.43) on the equal-weight basis and 0.91% (t=3.46) on the value-weight basis. A similar strategy invested among stocks with low idiosyncratic volatilities generates average monthly four-factor alphas of only 0.21% (t=3.06) on the equal-weight basis and only 0.17% (t=1.43) on the value-weight basis. The difference in abnormal returns between these two strategies is large and statistically significant for both equal- and value-weighting. These results support our conjecture that informed mutual funds could have better information advantages in stocks with more firm-specific information.

The results in Panel C of Table 6 also support the information-based story. A strategy that buys high DFB stocks and sells low DFB stocks generates a value-weight monthly four-factor alpha of 0.84% (t=4.29) when implemented among stocks with a low number of mutual fund investors; the same strategy when implemented among stocks with a high number of mutual fund investors produces a value-weight monthly four-factor alpha of only 0.18% (t=1.43). This difference in abnormal returns also is large and statistically significant.

D *Fund Characteristics*

In this subsection, we consider how different fund characteristics might influence the return forecasting power of DFB. Prior literature shows heterogeneous levels of skills or alphas across mutual funds (e.g., Fama and French, 2010). If fund managers with a higher level of alphas have better informational advantages (e.g., Cohen, Coval, and Pastor, 2005), a DFB measure constructed from the universe of those funds could be a better return predictor than that from the universe of all active funds. To examine this conjecture, we partition funds into three groups based on their past performance, construct the measure of DFB using the portfolio compositions for each group of funds, and test for the forecasting power of DFB. If past performance relates to the level of skills of managers and thus to their informational advantages, a strategy that buys high DFB stocks and sells low DFB stocks should generate higher abnormal returns based on the portfolio decisions of funds with higher past performance. We measure fund performance using the Carhart (1997) four-factor alpha from rolling-window regressions of monthly fund returns during the past 24 or 36 months. We use both alphas and the precision-adjusted alphas, the t-statistics. As the results are qualitatively similar, we report those based on alphas estimated in the past 24 months.

Panels A of Table 7 shows the results. We find that a strategy that buys high DFB stocks and sells low DFB stocks based on the portfolio decisions of mutual funds with high past two-year alphas generates an equal-weight monthly four-factor alpha of 0.54% (t = 5.42), which is more than twice as large as the four-factor alpha of 0.25% (t = 2.64) on a similar strategy based on the portfolio decisions of low-performing funds. This difference in returns is large and statistically significant. These results support the notion that higher alpha fund managers have better informational advantages.

One concern with these results is that mutual fund flows tend to chase past fund performance (e.g., Sirri and Tufano, 1998; Chevalier and Ellison, 1997). If high inflows into top-performing funds induce fund managers to purchase the stocks they have overweighted, their buying pressure may lead to higher returns on these stocks. A similar story can be told for bottom-performing managers driven by fund outflows to sell the stocks they have underweighted. Contradicting these stories, we find that the higher returns on the DFB strategy implemented for higher-alpha managers come from both the higher returns on stocks that they overweight and the lower returns on stock they underweight. These results cast doubt on the flow-based explanation but lend further credit to the story of skilled managers.

We also consider whether funds with different investment styles could have different information advantages. For example, growth-oriented mutual funds tend to have better performance than income funds (e.g., Grinblatt and Titman, 1993). Da, Gao, and Jagannathan (2010) argue that income funds tend to provide liquidity, whereas growth funds, likely driven by their superior information, tend to engage in informed trading. Based on these considerations, we conjecture that a DFB strategy based on the portfolio selection of growth funds could generate higher performance than does a similar strategy based on the investment decisions of income funds. Panel B of Table 7 provides evidence that concurs with our conjecture.

E DFB *and Earnings News*

If mutual funds have informational advantages about the stocks they overweight relative to their benchmarks, we expect those stocks to perform particularly well around the days their positive information gets released to the market. In stock markets, one of the most important corporate news events is the release of corporate earnings.

To explore the nature of the information content captured by DFB, we start by examining the relation between DFB and firms' future earnings surprises. We use two proxies for earnings surprises: the difference between actual earnings and the consensus analyst earnings forecasts from the Institutional Brokers' Estimate System (I/B/E/S) divided by the absolute value of actual earnings and that divided by the stock price at the end of the previous quarter. For each quintile portfolio based on DFB, we calculate the earnings surprises for the median firm in the following four quarters and report their time-series averages. Panels A and B of Table

8 show that stocks with high DFB tend to experience large and positive earnings surprises for up to the next four quarters, and the effect, strongest for the most proximate quarter, decays substantially through time. There is evidence of earnings momentum (e.g., Chan, Jegadeesh, and Lakonishok, 1996). If active mutual funds trade on earnings momentum, we could observe a positive association between DFB and subsequent earnings surprises. To examine this conjecture, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on DFB. We average the difference in earnings surprises between high and low DFB stocks across the three terciles and report this averaged difference as momentum-adjusted earnings surprises. Our results show that this adjustment eliminates the higher earnings surprises in the next two to four quarters for stocks active funds overweight, but for the most proximate quarter, stocks with higher DFB remain to experience significantly higher earnings surprises.

We also examine the three-day abnormal returns surrounding earnings announcements for each portfolio of stocks sorted on the basis of DFB. Panel C of Table 8 shows that an average stock in the top quintile of stocks heavily overweighted by mutual funds earns, in the time around earnings announcements in the following quarter, a three-day cumulative abnormal return of 29.8 basis points, which is statistically significant. In contrast, an average stock in the bottom quintile heavily underweighted by mutual funds generates a three-day cumulative abnormal return of only 3.4 basis points, or approximately 90% lower. Even after adjustments for earnings momentum, the difference in three-day abnormal returns around earnings announcements is 24 basis points and statistically significant. These results suggest that a significant portion of the return premiums on the stocks mutual funds heavily overweight occurs around corporate earnings releases, which in turn implies that part of active funds' superior information relates to firms' fundamental prospects.[15]

F DFB *and Stock Market Efficiency*

The results so far establish that active mutual funds as a group possess significant value-relevant information that is not fully incorporated into stock prices, which is consistent with strong-form market inefficiency (Fama, 1970 and 1991). In this subsection, we exploit the consensus view of active mutual funds to further study the implications for market efficiency. We are interested in how fast the stock market incorporates the information contained by the consensus wisdom of active mutual funds, so that no abnormal returns can be earned.

[15] Our evidence is consistent with Baker, Litov, Wachter, and Wurgler (2010), who argue that fund managers actively trade stocks prior to earnings announcements to exploit their informational advantages. We recognize that the magnitude of the abnormal performance of stocks heavily overweighted by mutual funds around earnings announcement dates may be insufficient to explain the superior performance of those stocks; the sign of the abnormal performance of stocks heavily underweighted by mutual funds around earnings announcement dates differs from the overall performance of those stocks. This evidence therefore suggests some aspects of informational advantages for mutual funds, other than their ability to forecast near-term earnings news. We leave the further identification of specific informational advantages of mutual funds to future research.

In particular, we form self-financing strategies that buy stocks that active funds overweight in Decile 10 and short stocks that they underweight in Decile 1, implemented with lags from 0 to 3 months. We compute the equal-weight four-factor alpha on these strategies.[16] We use the four-factor alpha on the strategy executed without lag, as a benchmark alpha, to measure the investment value of the information contained by the consensus view of active mutual funds. Then we deflate the alpha on the strategies implemented with various lags by that benchmark alpha to evaluate how fast the information contained by the consensus wisdom of active funds flows into stock prices.

Figure 1 presents the results. We perform the analysis for the full sample (blue columns) and two subsamples 1984–1996 (red columns) and 1997–2008 (green columns). Panel A shows the relative alpha for the strategies implemented with lags from one to three months. Panel B shows the t-statistics for the alpha. The average four-factor alpha for the strategy implemented without lag is 7.56%, 5.88%, and 10.08% per year (with t-statistics of 5.21, 3.38, and 4.32) for the full sample and two subsample periods.

The results indicate that for our full sample period, the self-financing strategy implemented with a lag of one month achieves 44% of the abnormal return generated by the same strategy implemented without lag, or 3.36% per year with a t-statistic of 2.42. Executed with a delay of two months, this self-financing strategy earns 30% of the abnormal return generated by the same strategy implemented without lag, or 2.28% per year with a t-statistic of 1.60. Considering the fact that the SEC requires all mutual funds to disclose their portfolio holdings with a maximum delay of 45 days, the decline of abnormal returns to zero with a delay of two months is consistent with semi-strong efficiency.

When we look at the time-series evidence, we find that in the period 1984–1996 the self-financing strategy executed with a delay of two months generates 73% of the abnormal return yielded by the same strategy implemented without lag, or an abnormal return of 4.32% per year with a t-statistic of 2.52. In the period 1997–2008, the self-financing strategy executed with a delay of two months generates only 15% of the abnormal return yielded by the same strategy implemented without lag, or an abnormal return of only 1.56% per year with a t-statistic of 0.73. These results suggest an intriguing time trend of enhanced stock market efficiency in incorporating the information contained by the consensus wisdom of active mutual funds.[17]

[16] The value-weight four-factor alpha is statistically insignificant when the strategy is implemented with a lag of more than one month.

[17] The sharp increase in the speed for the stock market to incorporate the information contained by the consensus wisdom of active mutual funds is impressive, particularly in light of the higher investment value of the consensus wisdom that we observe in the second subperiod. We conjecture that this increase in the investment value could be due to the expansion of active mutual funds, which allows us to obtain a more precisely measured consensus view and thus a more powerful test of their investment value.

G DFB and Mutual Fund Performance

How can we reconcile our evidence that points to strong informational advantages of mutual funds in stock markets with the overall lackluster performance of mutual funds identified by prior literature? To understand the contribution of stocks with large active fund bets to the overall performance of active funds, for each decile of stocks sorted on the basis of DFB we calculate the fund investments-weighted portfolio returns and report the fraction of total mutual fund assets invested in each decile portfolio. The results in Table 9 indicate that stocks in Decile 10 heavily overweighted by active funds generate high abnormal returns with a four-factor alpha of 6.60% per year. But active funds in aggregate invest less than 10% of their assets in those stocks. On the other hand, although stocks in Decile 1 heavily underweighted by active funds generate a four-factor alpha close to zero, they receive approximately 34% of total active fund assets. Therefore, a large four-factor alpha of 6.60% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year before fees and expenses.

These results support the notion that an average active mutual fund can generate significant alpha, a crucial assumption maintained by Berk and Green (2004). The appearance of passiveness by mutual funds in aggregate, such that little abnormal returns can be earned on the total fund portfolio, is also consistent with the equilibrium described by Berk and Green. But they naturally raise the question: Could individual fund managers have performed better by being more active? To explore this question, for each individual fund we decompose returns on fund holdings into two components: a long-short active portfolio that consists of deviations from benchmarks and a long-only passive portfolio that consists of their investments in the benchmarks. Our first test is a comparison of the distribution of Sharpe ratios of active, passive, and overall fund portfolios for the cross-section of mutual funds. As our sample period from 1984 to 2008 covers the recent financial crisis, we gauge the influence of the financial crisis on the results by using different schemes to remove the crisis period from our sample.

As shown in Table 10, the average Sharpe ratio for each individual fund's active portfolio is significantly lower than that of the fund's benchmark portfolio. By combing the active and passive portfolios, actively managed mutual funds on average achieve significantly higher Sharpe ratios for their overall portfolios than those on their benchmarks or active portfolios. These results hold for the sample periods excluding the recent financial crisis in different ways (Columns 1-4). Even when we include the last six months in 2008 when the benchmark indexes plummeted (Column 5), on average, overall fund portfolios have Sharpe ratios that are 1% higher than those of the active portfolios.

To formally test if individual funds can achieve better performance by tilting their portfolios more toward the active portfolios, for each individual fund we run time-series regressions of monthly returns to the fund's active portfolio R^{active} on the fund's total excess return:

$$R^{active} = \alpha + \beta(R^{fund} - R_f) + \varepsilon. \tag{3}$$

A significantly positive intercept in this regression would indicate that the fund manager could have tilted the fund even more toward the active portfolio to achieve a higher in-sample Sharpe ratio.[18] We compute the percentage of funds for which we are able to reject the null hypothesis that the intercept is equal to zero (t-statistic above 1.96). The results indicate that only 11–15% of all funds in our sample could have achieved significantly higher in-sample Sharpe ratios by tilting more aggressively toward their active portfolios.[19]

These two sets of tests suggest that for a typical fund manager who invests in a limited number of stocks, the higher idiosyncratic risk on the alpha-generating stocks in her active portfolio could discourage her from taking more aggressive positions in her active portfolio. In other words, the majority of active fund managers appear to combine active and passive portfolios in such a way that being more active cannot lead to marginal improvements in performance. The intuition for the difference between fund-level and stock-level analyses lies in the fact that individual fund managers cannot form well-diversified portfolios that aggregate the over-weighting and under-weighting decisions of all active fund managers. Future research might benefit from further investigating whether the fraction of funds who could have achieved higher performance by being more aggressive choose to be not so active for agency reasons or other frictions such as exogenous constraints.

V Robustness Checks

We perform several robustness checks. First, we compute DFB based on an alternative benchmark index: the value-weighted portfolio of stocks that a fund actually holds. Second, we consider conditional performance evaluation. Finally, we consider the influence of mutual funds' potential preferential access to IPO allocations.

A *Alternative Measures of* DFB

We have included 19 stock indexes widely used by practitioners as our primary universe of performance benchmarks. In this subsection, we consider an alternative way to construct a benchmark index for a specific fund, namely, by forming market cap-weighted portfolios that

[18] Imagine that a fund manager invests fund assets fully in a benchmark index and then constructs a self-financing long-short portfolio, with each leg equal to 20% of fund assets. If the active portfolio delivers superior performance, our test asks whether the fund can perform better by increasing the investment size in the active portfolio, e.g., to 30% of fund assets.

[19] We require that a fund have at least 2 years of data to be included in this test. Imposing this requirement leaves us with 2,269 distinct funds.

consist of stocks actually held by each fund.[20]

Panel A of Table 11 reports the performance of DFB when we use these specifically tailored benchmark indexes. Consistent with the results in Table 3, mutual funds' deviations from benchmarks captured by this new measure of DFB strongly and positively forecast future stock returns. For example, Panel A of Table 11 shows that stocks heavily overweighted by mutual funds in Decile 10 generate a monthly equal-weight four-factor alpha of 0.59%, whereas stocks heavily overweighted by mutual funds in Decile 1 earn a negative four-factor alpha of -0.40% per month. Therefore, a portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 earns a four-factor alpha of 0.99% per month, which is statistically significant. This positive association between DFB and future returns is robust to different risk adjustments and reliable for both equal-weighting and value-weighting.

We also consider a variation of the DFB measure by discretizing the distance between a stock's weight in a fund's portfolio and the benchmark portfolio into two categories: over- and underweighting. In particular, we construct an indicator variable that equals one if the stock is overweighted by the fund and zero otherwise. Then we average this indicator variable for all funds whose investment comprises that stock, as in Equation 2. This new measure, DFB^{alt}, captures the fraction of funds that overweight the stock. It also can be viewed as polling each fund manager to vote for stocks that they perceive as future winners based on their portfolio weighting decisions. A stock receives a strong buy recommendation if the majority of the funds polled are bullish about the stock; it receives a strong sell if the majority of the funds are bearish about it.

$$DFB^{alt}_{i,t} = \sum_{j=1}^{N_i} Indicator(w^j_{i,t} - w^b_{i,t} > 0)/N_i, \tag{4}$$

Panel B of Table 11 presents the average returns and factor alphas on decile portfolios formed according to DFB^{alt}. The results indicate that stocks with high DFB^{alt} strongly outperform stocks with low DFB^{alt} and that this outperformance is robust to equal- and value-weighting and remains strong after various risk adjustments. These results reinforce the existence of informational advantages of mutual funds in stock markets.

[20] Because a mutual fund might respond to negative information about a firm by avoiding holding its shares, we also consider a value-weighted benchmark consisting of all stocks that the fund has held during the past five years. The results are qualitatively similar. In an independent study, Shumway, Szefler, and Yuan (2009) propose to elicit fund managers' beliefs about expected stock returns from their portfolio holdings using this set of benchmark. They apply their method to rank active fund managers. Our primary interest, however, is in the investment value of the consensus wisdom of active fund managers.

B *Conditional Performance Evaluation*

Jiang, Yao, and Yu (2007) argue that mutual funds have superior market-timing ability, which translates into superior fund performance.[21] Could the higher returns on stocks heavily overweighed by mutual funds reflect their managers' correct assessment of future market returns, instead of their firm-specific information? In other words, could fund managers make portfolio decisions in such a way that high DFB stocks tend to exhibit higher loadings on the market or other risk factors in periods with higher expected returns and lower loadings on the risk factors in periods with lower expected returns?

To address this question, we need to take into account the time variation in those stocks' loadings on the market or other risk factors. Thus, we employ Ferson and Schadt's (1996) conditional performance evaluation approach to allow for time-varying betas. Specifically, we augment the traditional CAPM and Cahart four-factor model with five conditioning variables: the lagged level of the one-month Treasury bill yield, the lagged dividend yield of the CRSP value-weighted stock index, the lagged measure of the slope of the term structure (a constant-maturity 10-year Treasury bond yield less the 3-month Treasury bill yield), the lagged quality spread in the corporate bond market (corporate bond default yield spread as Moody's BAA-rated corporate bond yield less the AAA-rated corporate bond yield), and a dummy variable for the month of January. Untabulated results show that the return premium on high DFB stocks remains large and significant after the adjustments for time-varying betas.

C *Preferential allocations of IPOs*

Gaspar, Massa, and Matos (2005) and Reuter (2006) argue that preferential access to IPOs could lead to boosted mutual fund performance. To assess the extent to which such preferential allocations of IPOs might influence our results, we exclude all stocks whose return history in CRSP falls below six months from our sample, and repeat our portfolio analysis based on mutual funds' deviations from benchmarks. We find that the exclusion of those stocks results in negligible influence on our results.

VI Conclusions

Despite the consensus view that active mutual funds on average fail to outperform passive benchmarks, we find a high investment value of the consensus wisdom of active mutual funds. In particular, stocks that are heavily overweighted by active funds relative to their benchmark indexes perform substantially better than their underweighted counterparts. This outperfor-

[21] Taliaferro (2009) and Beron-Drish and Sagi (2009) provide recent but less optimistic evidence on the timing ability of mutual funds.

mance is greater in stocks with more firm-specific information, as well as in those with fewer active mutual funds that compete for private information. The large premium dissipates quickly as the consensus view becomes publicly available. The results thus are consistent with the notion that informed investing by active mutual funds enhances the informativeness of stock prices.

Our results provide new insights into the mutual fund industry and stock market efficiency. Economists have long been puzzled by the rapid expansion of the actively managed mutual fund industry and the seemingly futile attempts of active mutual funds to outperform passive benchmarks. Applying a lens that separates active and passive portions of individual fund portfolios, we find that the consensus wisdom of active mutual funds has a high investment value, and most active funds combine their active and passive portfolios, such that on average it is difficult to identify abnormal performance by the total fund portfolios. These results suggest that inferences about managerial skill or market efficiency based on evidence from the mutual fund alphas may be misleading.

Appendix A: An Illustrative Interpretation of DFB

In this appendix, we provide an illustrative interpretation of active funds' deviations from benchmark, DFB, following the intuition in Roll (1992). Suppose there are J fund managers investing in N risky assets. Each manager is attempting to beat the performance benchmark B. Denote the returns on risky assets in excess of the risk-free rate as $\tilde{R} = [\tilde{R}_1, \tilde{R}_2, ..., \tilde{R}_N]'$. Each manager forms conditional expectations about future returns on risky assets in the investment universe based on her information set I. In addition, Σ is the variance-covariance matrix of the risky assets, which is assumed to be known and agreed upon by all managers; $w_j^B = [w_1^b, w_2^b, ..., w_N^b]'$ refers to the portfolio weights for fund manager j's benchmark B_j. Note that certain elements in w_j^B could be equal to 0, depending on the composition of the particular index. Fund manager j makes portfolio choice $w_j = [w_1^j, w_2^j, ..., w_N^j]'$ to maximize the benchmark-adjusted, active return on her portfolio while minimizing the active risk or the tracking error variance of her portfolio.[22]

We can write manager j's objective function as:

$$\underset{w_j}{Max}\{\underbrace{(w_j - w_j^B)'E[\tilde{R}|I_j]}_{Active\ Return} - \frac{\lambda_j}{2}\underbrace{(w_j - w_j^B)'\Sigma(w_j - w_j^B)}_{Active\ Risk}\},$$

where $E[\tilde{R}|I_j]$ is the expected excess returns on risky assets conditional on the information set of manager j, and λ_j is the manager's risk-aversion coefficient. We can easily show that the optimal portfolio solution for manager j is

$$w_j - w_j^B = \frac{1}{\lambda_j}\Sigma^{-1}E[\tilde{R}|I_j].$$

If we further assume that the risk-aversion coefficient is a constant λ across fund managers and Σ is a diagonal matrix, it is apparent that the distance of an asset i's weight in the manager's portfolio from its weight in the benchmark index $w_{i,j} - w_{i,j}^B$ is proportional to the expected excess return of the asset, conditional on manager j's information set. If we further make a simplifying assumption that Σ is an identity matrix, then $w_j - w_j^B = \frac{1}{\lambda}E[\tilde{R}|I_j]$. In other words, for any risky asset i in manager j's investment universe, $w_{i,j} - w_{i,j}^B = \frac{1}{\lambda}E[\tilde{R}_i|I_j]$. Our measure $DFB_i = \sum_{j=1}^{N_i}(w_{i,j} - w_{i,j}^B)/N_i = \frac{1}{\lambda}\sum_{j=1}^{N_i}E[\tilde{R}_i|I_j]/N_i$, where N_i is the number of funds whose investment universe comprises asset i. Therefore, DFB_i aggregates information about the future excess return of asset i scattered among fund managers.[23]

[22] Consistent with our empirical approach, we only consider funds' investments in risky assets and ignore their cash holdings.

[23] These assumptions are certainly restrictive. We do not argue that our approach is the optimal way to extract information from the decisions by active funds to deviate from benchmarks. Empirically though, we find evidence that DFB strongly forecasts future stock returns.

Appendix B: Sample Selection

We start with all U.S. equity mutual funds from the intersection between the CRSP mutual fund database and the CDA/Spectrum mutual fund holdings database. We use the MFLINKS data set available from the WRDS to link the two databases. As our benchmark holdings data start from September 1980, our final sample of stock holdings spans the period from September 1980 through September 2008.

Because we wish to capture active mutual funds that invest primarily in U.S. equities, we follow Pastor and Stambaugh (2002) and Kacperczyk, Sialm and Zheng (2008), by eliminating balanced, bond, money market, sector, and international funds as well as funds that do not primarily invest in U.S. common equity. In particular, we use the following steps in sample selection. We select funds with the following Lipper class codes, provided by the CRSP: EIEI, G, I, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have any of these Lipper class codes, we select funds with the following strategic Insight objectives: SCG, GRO, AGG, ING, GRI, or GMC. If both codes are missing for a fund, we pick funds with the following Wiesenberger objectives: SCG, AGG, G, G-S, S-G, GRO, LTG, I, I-S, IEQ, ING, GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI, or MCG. If none of the objective codes are available, we require that a fund have a CS policy code.

We eliminate funds with any of the following investment objectives as provided by CDA/Spectrum: International, Municipal Bonds, Bond and Preferred, and Balanced. Furthermore, we use the portfolio composition data provided by CRSP to exclude funds that invest less than 80% or more than 105%, on average, in common equity. To address the incubation bias documented by Elton, Gruber and Blake (2001) and Evans (2010), we exclude observations prior to the reported fund inception date, those for which the names of the funds are missing in the CRSP database, and funds whose net assets fall below $5 million. To prevent outliers from driving our measure of mutual funds' deviations from benchmarks, we also require that a fund have at least 10 stock holdings to be eligible for consideration in our analysis.

To ensure that we capture active mutual funds, we eliminate index funds whose names contained the following keywords: INDEX, INDE, INDX, INX, IDX, DOW JONES, ISHARE, S&P, S &P, S& P, S & P, 500, WILSHIRE, RUSSELL, RUSS, or MSCI. To lessen errors due to abbreviation and misspelling, we manually inspected fund names and filtered out remaining international funds, sector funds, tax-managed funds, fixed-income funds, balanced funds, real estate funds and annuities.

Appendix C: Benchmark Holdings

Our main method of selecting benchmark indexes for individual mutual funds follows Cremers and Petajisto (2009). In particular, the universe of benchmark indexes includes the 19 stock indexes widely used by practitioners: 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. Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from Compustat. For the remaining indexes and time periods, we use the holdings data of index funds that track the performance of those indexes as a first approximation. Specifically, for each index, we select one index fund or ETF that has the lowest tracking error over the sample period. We use holdings information reported by that fund to approximate the actual index weights. If, in a particular quarter, the index fund has missing holdings information, we use the holdings data reported by the fund with the second lowest tracking error, and so on.

In Table A1, we present information about the benchmark indexes. The third column of Table A1 shows the source of holdings data we used in our sample, and the fourth and fifth columns show the start and end dates for the holding information.

After we obtain the information on benchmark weights, we select, for each mutual fund in each quarter, one benchmark index that minimizes the distance in portfolio weights between the fund and the index. Our measure of the distance between mutual funds and their benchmarks is the measure of Active Share as proposed by Cremers and Petajisto:

$$ActivewShare = \frac{1}{2}\sum_{i=1}^{N}|w_{fund,i} - w_{index,i}|,$$

where $w_{fund,i}$ and $w_{index,i}$ are the portfolio weights of asset i in the fund and in the index, respectively. For each fund in each quarter, we select the index that generates the lowest Active Share for the fund. The advantage of this dynamic selection of performance benchmarks lies in its flexibility in allowing for drifts in a fund's style over time. We also experiment with selecting benchmarks on the basis of moving averages of the distance between fund portfolio weights and benchmark index weights in the past five years and obtain qualitatively similar results.

We alculate the number of active funds that benchmark against each of the indexes and the total assets under their management. Columns 6 and 7 report these numbers for September 2008. Columns 8 and 9 further show the market share for each of the indexes.

Appendix D: Comparison with Chen, Jegadeesh, and Wermers (2000)

Chen, Jegadeesh, and Wermers (CJW, 2000) assess the value of active portfolio management by examining the association between mutual fund trades and future stock returns. They provide compelling evidence in their sample period that active funds add value through their trading activities. Following Grinblatt and Titman (1993), one could view fund holdings in the prior period as an implicit benchmark to evaluate fund performance. In other words, the CJW trade-based measure may be viewed as another way of measuring deviations from benchmarks. We argue that our measure of active funds' deviations from benchmarks is superior in aggregating fund managers' private information, because (1) our measure can be derived from the behavior of active funds to maximize their benchmark-adjusted returns while minimizing the tracking error variance, which concurs with the industry practice; and (2) the trading decisions of mutual funds could reflect not only informational motives but also other motivations such as flow-driven liquidity needs (e.g., Alexander, Cici, and Gibson, 2007). Our measure of deviations from benchmarks is less subject to the influence of fund flows, because fund managers could scale up or down fund assets in response to flows, without having to substantially alter the composition of their active portfolios. To meet the investment or redemption requests from their clients, however, fund managers must trade.

In Table A2, we provide more evidence that supports our claim. Specifically, at the end of each quarter from 1984Q1 to 2008Q3, we perform two-way independent sorts. Along one dimension, we sorts stocks into quintiles based on the magnitude of their deviations from benchmarks, and along the other dimension, we sort stocks into quintiles based on their quarterly trades measured as the change in the fraction of shares held by mutual fund in our sample. Twenty five portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. We calculate the monthly equal-weight and value-weight returns on each of 25 portfolios for the subsequent quarter, and report their Carhart 4-factor alpha. The results in Table A.2 show that stocks heavily overweighted by active funds significantly outperform those they choose to underweight, while controlling for their stock trades. In contrast, the trade-based measure has no positive return forecasting power once we control for funds' deviations from benchmarks.

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TABLE A1

Summary Statistics for Benchmark Holdings

						Cross-Section of 9/30/2008			
	Index Name	Index Inception Year	Source of Holdings Data	Holdings Data Available Date	Holdings Data Ending Date	No. of Funds	Total Fund Assets (Millions)	Proportion (No. of Funds)	Proportion (Total Fund Assets)
1	S&P500	03/1957	Vanguard Index 500 Fund	9/30/1980	9/30/1994				
			S&P	12/31/1994	9/30/2008	222	534576.86	15.38%	25.34%
2	S&P500 Value	05/1992	iShares S&P 500 Value Index	12/31/2000	9/30/2008	119	214327.40	8.25%	10.16%
3	S&P500 Growth	05/1992	iShares S&P 500 Growth Index	12/31/2000	9/30/2008	205	429213.14	14.21%	20.35%
4	S&P400	07/1991	S&P	12/31/1994	9/30/2008	111	81681.70	7.69%	3.87%
5	S&P600	01/1994	S&P	12/31/1994	9/30/2008	121	80384.98	8.39%	3.81%
6	Russell1000	01/1984	Russell Investments	3/31/1984	9/30/2008	3	1898.60	0.21%	0.09%
7	Russell1000 Value	06/1993	Russell Investments	6/30/1993	9/30/2008	94	81942.30	6.51%	3.88%
8	Russell1000 Growth	06/1993	Russell Investments	6/30/1993	9/30/2008	164	266439.87	11.37%	12.63%
9	Russell2000	01/1984	Russell Investments	3/31/1984	9/30/2008	12	27159.60	0.83%	1.29%
10	Russell2000 Value	06/1993	Russell Investments	6/30/1993	9/30/2008	43	24351.40	2.98%	1.15%
11	Russell2000 Growth	06/1993	Russell Investments	6/30/1993	9/30/2008	133	49738.20	9.22%	2.36%
12	Russell3000	01/1984	Russell Investments	3/31/1984	9/30/2008	5	103312.60	0.35%	4.90%
13	Russell3000 Value	07/1995	Russell Investments	9/30/1995	9/30/2008	0	0.00	0.00%	0.00%
14	Russell3000 Growth	07/1995	Russell Investments	9/30/1995	9/30/2008	0	0.00	0.00%	0.00%
15	Russell MidCap	11/1991	Russell Investments	12/31/1991	9/30/2008	7	26263.50	0.49%	1.24%
16	Russell MidCap Value	02/1995	Russell Investments	3/31/1995	9/30/2008	55	49118.60	3.81%	2.33%
17	Russell MidCap Growth	02/1995	Russell Investments	3/31/1995	9/30/2008	136	120957.60	9.42%	5.73%
18	Wilshire 4500	01/1983	Vanguard Extended Market Index Fund	12/31/1987	9/30/2008	8	12477.50	0.55%	0.59%
19	Wilshire 5000	01/1975	Wilshire 5000 Index Portfolio Fund	6/30/1999	9/30/2008	5	5716.00	0.35%	0.27%

TABLE A2

Deviation from Benchmarks and Chen, Jegadeesh, and Wermers (CJW) Trade Measure

This table compares the return forecasting power of mutual funds' deviations from benchmarks, *DFB*, and the measure of their trades based on Chen, Jegadeesh, and Wermers (CJW 2000). Specifically, at the end of each quarter from 1984Q1 to 2008Q3, we perform two-way independent sorts. Along one dimension, we sorts stocks into quintiles based on the magnitude of their deviations from benchmarks, and along the other dimension, we sort stocks into quintiles based on their quarterly trades measured as the change in the fraction of shares held by mutual fund in our sample. Twenty five portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. We calculate the monthly equal-weight and value-weight returns on each of 25 portfolios for the subsequent quarter, and report their Carhart 4-factor alpha. Stocks with prices lower than 5 dollars at the quarter end are excluded. *** represents statistical significance at the 1% level, ** represents statistical significance at the 5% level, and * represents statistical significance at the 10% level.

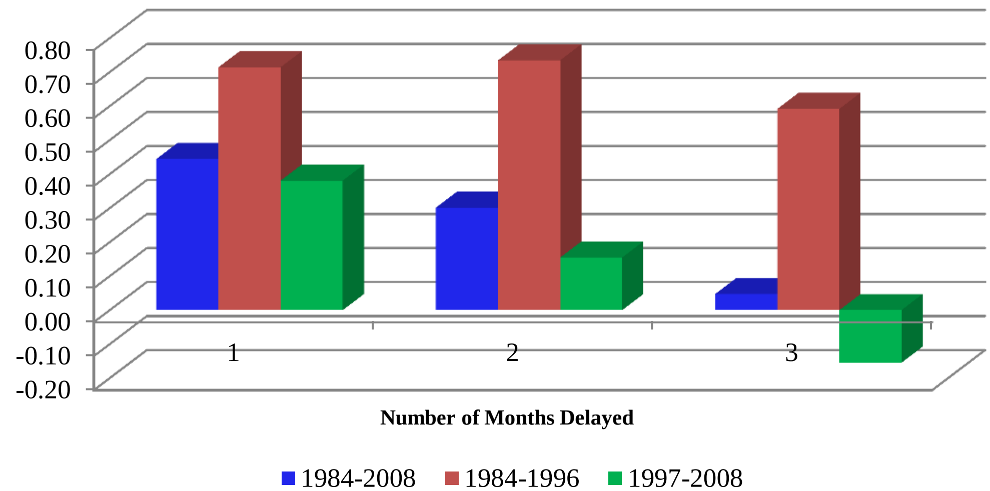
	Equal-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)						Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					
	Deviation from Benchmarks (*DFB*)						Deviation from Benchmarks (*DFB*)					
CJW Trade	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.26	-0.07	-0.01	0.18	0.19	0.45***	-0.07	0.10	-0.03	0.16	-0.05	0.02
	(-2.86)	(-0.6)	(-0.09)	(1.71)	(1.74)	(3.25)	(-0.63)	(1.02)	(-0.26)	(1.59)	(-0.3)	(0.1)
2	-0.19	-0.02	0.12	0.09	0.26	0.45***	0.05	0.05	-0.02	0.02	0.20	0.16
	(-2.46)	(-0.19)	(1.18)	(0.82)	(2.21)	(3.71)	(0.58)	(0.46)	(-0.17)	(0.13)	(0.92)	(0.69)
3	-0.24	-0.12	0.12	0.12	0.24	0.49***	0.12	0.22	0.02	-0.08	0.27	0.15
	(-2.91)	(-1.09)	(1.02)	(1.19)	(2.21)	(3.63)	(0.86)	(1.23)	(0.16)	(-0.56)	(1.41)	(0.56)
4	-0.39	-0.11	-0.17	0.11	0.29	0.67***	-0.25	0.01	-0.16	0.08	0.56	0.81***
	(-5.01)	(-1.17)	(-1.8)	(1.16)	(3)	(5.29)	(-2.36)	(0.07)	(-1.22)	(0.71)	(2.88)	(3.15)
5	-0.42	-0.35	-0.04	-0.10	0.25	0.67***	-0.42	-0.56	0.05	-0.06	0.16	0.58**
	(-3.16)	(-3.44)	(-0.42)	(-1.07)	(2.32)	(4.97)	(-2.39)	(-4.4)	(0.39)	(-0.5)	(0.84)	(2.59)
Q5-Q1	-0.16	-0.29**	-0.03	-0.28***	0.06		-0.35*	-0.66***	0.08	-0.22	0.21	
	(-0.96)	(-2.17)	(-0.29)	(-2.63)	(0.51)		(-1.69)	(-4.38)	(0.55)	(-1.63)	(0.99)	

FIGURE 1

Value of the Consensus Wisdom of Active Mutual Funds and Stock Market Efficiency

This figure shows how fast the stock market incorporates the information contained by the consensus wisdom of active mutual funds so that no abnormal returns can be earned. In particular, we form self-financing strategies that buy stocks active funds overweight in Decile 10 and short stocks they underweight in Decile 1, implemented with lags from 0 to 3 months. We compute the 4-factor equal-weight alpha on these strategies. In Panel A, we use the alpha for the strategy executed without lag as the benchmark to deflate the alpha for the strategies implemented with various lags. In Panel B, we show the t-statistics for the alpha. We perform this analysis for the whole sample (blue columns) and two subsamples 1984–1996 (red columns) and 1997–2008 (green columns). The average four-factor alpha for the strategy implemented without lag is 7.56%, 5.88%, and 10.08% (with *t*-statistics of 5.21, 3.38, and 4.32) per year for the full sample and two subsample periods.

Panel A: Profitability of Trading on the Consensus View with Lags



Panel B: *T*-Statistics of Four-Factor Alpha

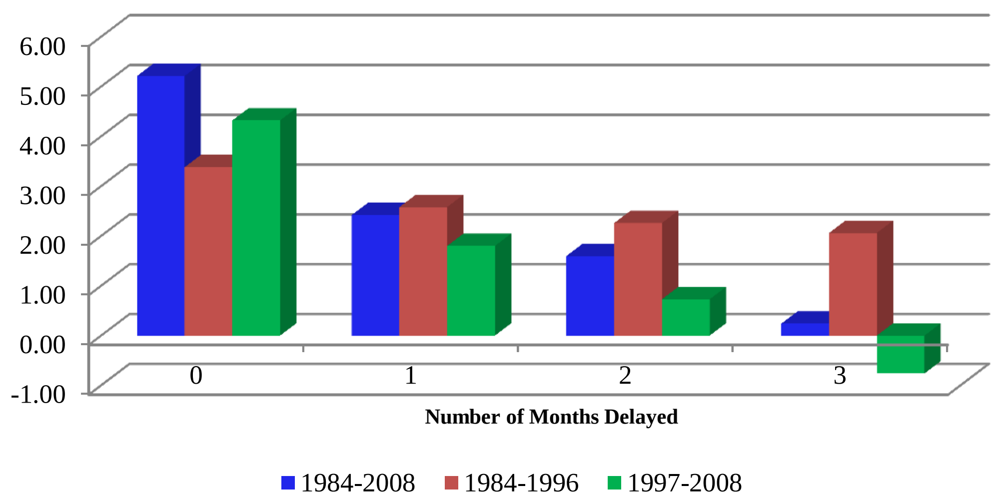


TABLE 1
Stock Holdings of Active Mutual Funds

Each year-end from 1984 to 2008, we calculate the number of distinct actively managed equity mutual funds in our sample (see Appendix B for details on sample selection) and compute the average proportion of fund assets invested in common stocks. We also report the total number and dollar amount of common stocks held by those mutual funds and their proportion in the CRSP stock database. The calculations exclude stocks with prices lower than $5 at the year-end.

Year	No. of Distinct Funds	% of Fund Assets Invested in Common Equity	No. of Distinct Stocks Held by Funds	% of CRSP Stocks (Number)	Total Mutual Funds Assets ($ Billions)	% of CRSP Stocks ($)
1984	237	85.59	3059	52.01	45.47	2.71
1985	261	86.35	3353	56.98	66.59	3.19
1986	300	85.61	3547	57.06	74.99	3.19
1987	339	85.19	3454	53.49	88.50	3.83
1988	358	84.86	3572	57.52	85.60	3.41
1989	392	86.02	3558	59.51	104.80	3.43
1990	421	84.72	3289	56.42	101.14	3.68
1991	450	86.95	3461	58.78	142.29	3.83
1992	552	86.28	3737	62.08	211.73	5.14
1993	681	87.70	4879	74.47	232.21	4.97
1994	793	90.83	5123	74.54	267.72	5.78
1995	907	90.95	5545	78.09	403.14	6.38
1996	1013	92.20	5953	78.72	575.74	7.47
1997	1126	93.25	5997	78.95	823.27	8.22
1998	1218	93.59	5671	78.99	1073.73	8.69
1999	1358	93.06	5633	82.27	1270.82	8.05
2000	1490	92.24	5458	83.25	1283.24	8.96
2001	1541	93.46	4933	84.53	998.35	7.89
2002	1607	94.03	4266	78.84	938.53	9.52
2003	1630	95.29	4481	88.28	1307.75	10.18
2004	1641	94.26	4479	89.99	1684.50	11.80
2005	1617	96.40	4156	84.99	1691.34	11.43
2006	1580	96.83	4188	87.05	2053.51	12.48
2007	1587	96.28	4286	91.46	2004.32	12.15
2008	1510	95.92	3997	90.84	1024.99	10.26
Average	984	90.71	4403	73.56	742.17	7.07

TABLE 2

Summary of the Data: Decile Portfolios

At the end of each quarter, we compute for each stock a measure of mutual funds' deviations from benchmarks, *DFB*, which is the simple average of the stock's weight in a mutual fund portfolio in excess of its weight in the fund's benchmark index, across all mutual funds in the stock-fund cohort. We then sort stocks into deciles in ascending order based on *DFB*, and calculate the stock characteristics for each decile portfolio. A mutual fund belongs to a stock-fund cohort if the stock appears in the mutual fund portfolio or is a member of the index against which the fund is benchmarked. For each mutual fund in each quarter, we select from 19 stock indexes one benchmark index that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Our set of characteristic variables includes the average deviations from benchmarks *DFB*, the average benchmark weight, the average number of funds in the stock-fund cohort, the average number of funds that hold the stocks, the average proportion of stocks outside the benchmarks, the average proportion of funds in the stock-fund cohort for which the stock is not held by funds but in their benchmarks, the market cap, the book-to-market ratio, past one year return (skipping the most recent month), and the residual return volatility in the past quarter. The market cap of a stock is computed by multiplying the stock price with the number of outstanding shares at each quarter end (in millions). The book-to-market ratio is determined for each stock at the end of last calendar year using the book value of the stock at the end of last fiscal year and the market value of the stock at the end of last calendar year. We regress the daily stock returns against daily Fama French factors in a given quarter and use the standard deviation of the residuals as the residual volatility of the stock for that quarter (at least 40 daily observations of stock returns must be available). To facilitate comparison across deciles, we score for each quarter the size, book-to-market, and past returns from 1 to 10, with 10 representing the deciles with the largest market cap (based on NYSE break-points), highest book-to-market, and highest past one-year return. Stocks with prices lower than $5 at the quarter end are excluded.

Decile	*DFB* (%)	Benchmark Weights (%)	No. of Funds in the Stock-Fund Cohort	No. of Funds Holding the Stock	Proportion of Stocks Outside of Benchmarks (%)	Market Cap Score (1-10)	BM Score (1-10)	Pr1Yr Score (1-10)	Residual Volatility (%)
1	-0.14	0.28	220	40	0.00	6.39	4.53	6.04	2.00
2	-0.04	0.09	169	21	0.00	4.24	4.70	5.49	2.46
3	-0.02	0.06	155	18	0.01	3.46	4.95	5.29	2.68
4	0.00	0.04	112	13	0.13	2.81	5.32	5.24	2.81
5	0.01	0.04	120	15	0.22	3.13	5.38	5.36	2.76
6	0.03	0.05	138	20	0.17	3.61	5.24	5.54	2.62
7	0.06	0.06	133	23	0.17	3.83	5.22	5.78	2.57
8	0.11	0.06	113	24	0.21	3.89	5.10	6.08	2.58
9	0.23	0.05	84	24	0.33	3.74	4.96	6.24	2.67
10	0.72	0.03	38	17	0.63	3.05	4.86	6.69	2.86
D10 - D1	0.86	-0.25	-182	-23	0.63	-3.34	0.33	0.65	0.86

TABLE 3

Consensus Wisdom of Active Mutual Funds (*DFB*) and Future Stock Returns: Decile Portfolios

This table presents the performance of decile portfolios formed on the basis of mutual funds' deviations from benchmarks, *DFB*. At the end of each quarter from 1984Q1 to 2008Q3, we sort stocks into deciles in ascending order based on *DFB* and compute the average monthly equal-weight (Panel A) and value-weight (Panel B) portfolio returns in the subsequent quarter. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Finally, we present the portfolio performance using the DGTW (1997) characteristic adjustment. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

	Panel A: Equal-Weight Post-Ranking Portfolio Return (%/month)						Panel B: Value-Weight Post-Ranking Portfolio Return (%/month)					
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return
1	0.60	-0.26	-0.31	-0.31	-0.31	-0.20	0.74	-0.08	-0.03	-0.04	-0.04	-0.11
	(2.09)	(-3.29)	(-5.19)	(-4.76)	(-4.82)	(-4.02)	(2.9)	(-1.13)	(-0.57)	(-0.9)	(-0.76)	(-3.12)
2	0.58	-0.32	-0.42	-0.26	-0.26	-0.18	0.87	0.01	-0.09	0.00	0.00	0.02
	(1.78)	(-2.53)	(-6.03)	(-3.77)	(-3.69)	(-3.66)	(3.06)	(0.17)	(-1.25)	(0.07)	(0.02)	(0.36)
3	0.63	-0.28	-0.39	-0.17	-0.16	-0.15	0.87	-0.02	-0.12	-0.00	0.00	0.03
	(1.86)	(-1.83)	(-4.79)	(-2.21)	(-2.11)	(-2.45)	(2.95)	(-0.21)	(-1.44)	(-0.04)	(0.03)	(0.49)
4	0.74	-0.12	-0.22	-0.06	-0.05	-0.11	0.85	-0.02	-0.10	0.01	0.02	-0.04
	(2.29)	(-0.72)	(-2.08)	(-0.53)	(-0.48)	(-1.06)	(2.85)	(-0.25)	(-1.28)	(0.16)	(0.22)	(-0.54)
5	0.83	-0.05	-0.17	-0.02	-0.02	-0.07	0.93	0.01	-0.08	0.08	0.07	0.05
	(2.51)	(-0.29)	(-2.12)	(-0.21)	(-0.22)	(-0.96)	(2.99)	(0.12)	(-0.77)	(0.74)	(0.61)	(0.55)
6	0.93	0.03	-0.10	0.04	0.05	0.08	0.91	-0.01	-0.10	-0.02	-0.01	0.05
	(2.77)	(0.16)	(-1.2)	(0.47)	(0.6)	(1.29)	(2.97)	(-0.09)	(-1.28)	(-0.27)	(-0.16)	(0.69)
7	1.04	0.13	0.02	0.13	0.15	0.12	1.01	0.11	0.06	0.12	0.13	0.11
	(3.10)	(0.83)	(0.19)	(1.6)	(1.94)	(1.9)	(3.4)	(1.5)	(0.78)	(1.63)	(1.91)	(1.86)
8	1.03	0.11	0.04	0.03	0.06	0.08	0.98	0.05	0.04	-0.02	-0.02	0.05
	(3.01)	(0.66)	(0.47)	(0.39)	(0.73)	(1.19)	(3.1)	(0.56)	(0.43)	(-0.25)	(-0.23)	(0.62)
9	1.17	0.24	0.23	0.15	0.16	0.18	1.31	0.36	0.46	0.24	0.25	0.32
	(3.25)	(1.32)	(2.9)	(2)	(2.15)	(2.42)	(3.71)	(2.23)	(3.35)	(1.9)	(1.94)	(2.88)
10	1.37	0.44	0.44	0.32	0.34	0.41	1.38	0.43	0.62	0.33	0.36	0.35
	(3.63)	(2.15)	(4.28)	(3.35)	(3.49)	(5.36)	(3.67)	(2.27)	(3.61)	(2.4)	(2.61)	(2.22)
D10-D1	0.77***	0.69***	0.75***	0.63***	0.65***	0.61***	0.64***	0.51**	0.65***	0.38**	0.39**	0.46***
	(4.30)	(3.92)	(6.07)	(5.20)	(5.35)	(6.04)	(2.62)	(2.34)	(3.47)	(2.41)	(2.59)	(2.74)
D9-D2	0.59***	0.56***	0.65***	0.41***	0.42***	0.36***	0.44**	0.34*	0.55***	0.24	0.25	0.30**
	(4.67)	(4.44)	(6.05)	(4.01)	(3.97)	(4.06)	(2.21)	(1.82)	(3.29)	(1.59)	(1.64)	(2.12)

TABLE 4

DFB and Future Stock Returns: Fama and MacBeth (1973) Cross-Sectional Regressions

This table uses the Fama and MacBeth (1973) cross-sectional regressions to examine the relation between mutual funds' deviations from benchmarks, *DFB*, at each quarter end and the cumulative market-adjusted returns in the subsequent (up to 4) quarters. R_{t+1} denotes market adjusted return in quarter t+1, $R_{t+1,t+2}$ denotes market-adjusted return over quarters t+1 and t+2, and so forth. To make the results comparable with the portfolio analysis, we discretize *DFB* into two dummy variables, D10 (overweight) that equals one if the stock is in Decile 10 with the highest *DFB* and 0 otherwise, and D1 (underweight) that equals one if the stock is in Decile 1 with the lowest *DFB* and 0 otherwise. Market cap, book-to-market ratio, residual volatility, and turnover ratio are defined as previously. *Pr1Yr* is the past one year return skipping the most recent month and *Pr1Mt* is the past one month return. ΔMFO is the change in the fraction of shares held by mutual funds (Chen, Jegadeesh, and Wermers, 2000), and $\Delta Breadth$ is the change in the number of mutual funds that hold the stock scaled by the total number of mutual funds that exist at the beginning of a given quarter, as in Chen, Hong, and Stein (2002). Stocks with prices lower than $5 at the quarter end are excluded. As the cumulative returns overlap, we compute the *t*-statistics based on the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at the 10% level.

	R_{t+1}					$R_{t+1,t+2}$		$R_{t+1,t+3}$		$R_{t+1,t+4}$	
	1	2	3	4	5	6	7	8	9	10	11
$D1_t$	-0.0097* (-1.93)	-0.0097*** (-3.60)	-0.0099** (-2.05)	-0.0095*** (-3.40)	-0.0101*** (-3.67)	-0.0119*** (-2.95)	-0.0138*** (-3.70)	-0.0154** (-2.63)	-0.0184*** (-3.30)	-0.0174** (-2.36)	-0.0221*** (-3.27)
$D10_t$	0.0225*** (5.81)	0.0190*** (6.61)	0.0223*** (5.79)	0.0187*** (6.61)	0.0192*** (7.22)	0.0310*** (5.79)	0.0320*** (6.42)	0.0386*** (4.84)	0.0416*** (5.56)	0.0398*** (3.70)	0.0449*** (4.50)
Market Cap$_t$		-0.0015 (-1.36)		-0.0017 (-1.65)	-0.0016 (-1.53)	-0.0026 (-1.25)	-0.0021 (-1.02)	-0.0028 (-0.83)	-0.0022 (-0.68)	-0.0024 (-0.53)	-0.0018 (-0.42)
BM_t		0.0019 (0.86)		0.0019 (0.86)	0.0021 (0.96)	0.0049 (1.17)	0.0053 (1.32)	0.0078 (1.32)	0.0081 (1.44)	0.0107 (1.37)	0.0113 (1.56)
$Pr1Yr_t$		0.0258*** (5.58)		0.0258*** (5.71)	0.0231*** (5.02)	0.0420*** (5.39)	0.0354*** (4.49)	0.0455*** (4.50)	0.0362*** (3.55)	0.0455*** (3.80)	0.0350*** (2.89)
Residual Vol		-0.5174** (-2.06)		-0.5211** (-2.06)	-0.4829* (-1.92)	-0.7163 (-1.52)	-0.6419 (-1.38)	-0.8759 (-1.30)	-0.7331 (-1.11)	-0.9401 (-1.17)	-0.7665 (-1.00)
$Turnover_t$		-0.0107* (-1.90)		-0.0101* (-1.80)	-0.0098* (-1.76)	-0.0225* (-1.82)	-0.0203 (-1.63)	-0.0338* (-1.80)	-0.0294 (-1.56)	-0.0404 (-1.64)	-0.0334 (-1.36)
Pr1Mt		-0.0234 (-1.59)		-0.0237* (-1.66)	-0.0353** (-2.50)	0.0064 (0.30)	-0.0236 (-1.19)	0.0422 (1.45)	-0.0076 (-0.28)	0.0716** (2.03)	0.0082 (0.25)
ΔMFO_t			-0.0080 (-0.17)	-0.0546 (-1.28)	-0.0197 (-0.45)	-0.0123 (-0.18)	0.1350* (1.71)	-0.0050 (-0.05)	0.2548** (2.21)	0.0220 (0.19)	0.4575*** (3.01)
$\Delta Breadth_t$			0.2277 (1.46)	0.1112 (1.12)	0.0637 (0.63)	0.3075* (1.74)	0.1968 (1.06)	0.5417** (2.41)	0.4218* (1.85)	0.5591* (1.88)	0.4168 (1.45)
ΔMFO_{t+1}					1.0296*** (10.05)						
$\Delta MFO_{t+1,t+2}$							1.5577*** (10.48)				
$\Delta MFO_{t+1,t+3}$									2.1188*** (9.95)		
$\Delta MFO_{t+1,t+4}$											2.6304*** (9.23)
Intercept	0.0012 (0.21)	0.0198 (1.50)	0.0011 (0.19)	0.0212 (1.63)	0.0179 (1.43)	0.0301 (1.17)	0.0207 (0.83)	0.0353 (0.90)	0.0197 (0.53)	0.0353 (0.68)	0.0134 (0.27)
Avg Adj-R^2	0.53%	6.18%	0.78%	6.26%	7.42%	5.94%	8.24%	5.57%	9.15%	5.21%	9.74%

TABLE 5

Informed Managers or Mutual Fund Herding? Dynamics of Changes in *DFB*, Δ*DFB*

This table tests for different implications of the informed fund manager and mutual fund herding hypotheses. Panel A presents the performance of decile portfolios formed on the basis of the changes in *DFB* between adjacent quarters. Panels B and C present the dynamic relation between consecutive changes in *DFB*. Specifically, at the end of each quarter from 1984Q3 to 2008Q3, we regress changes in a stock's *DFB*, ΔDFB_{t+1}, on the lagged changes in *DFB*, ΔDFB_t, the lagged level of *DFB*, DFB_t, and a bunch of stock characteristics in Panel B. In Panel C, we use the changes in the average portfolio weights of a stock in active funds as the dependent variable. The *t*-statistics are computed using the Fama and MacBeth (1973) procedure with the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A Changes in *DFB* and Future Stock Returns

	Panel A: Equal-Weight Post-Ranking Portfolio Return (%/month)					Panel B: Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.40	-0.57	-0.58	-0.56	-0.55	0.32	-0.59	-0.47	-0.64	-0.63
	(1.02)	(-3.37)	(-4.76)	(-4.6)	(-4.3)	(0.95)	(-4.86)	(-3.69)	(-4.98)	(-4.87)
2	0.50	-0.43	-0.50	-0.42	-0.41	0.43	-0.46	-0.46	-0.48	-0.49
	(1.42)	(-2.96)	(-5.89)	(-5.02)	(-4.81)	(1.38)	(-4.77)	(-4.97)	(-5.07)	(-4.99)
3	0.57	-0.34	-0.46	-0.35	-0.34	0.74	-0.14	-0.20	-0.18	-0.18
	(1.7)	(-2.57)	(-6.16)	(-4.5)	(-4.31)	(2.54)	(-1.56)	(-2.35)	(-1.88)	(-1.83)
4	0.60	-0.29	-0.42	-0.30	-0.29	0.90	0.04	-0.01	0.00	-0.01
	(1.82)	(-1.98)	(-5.9)	(-4.47)	(-4.48)	(3.19)	(0.51)	(-0.11)	(0.01)	(-0.1)
5	0.69	-0.15	-0.29	-0.18	-0.19	0.88	0.03	-0.08	0.04	0.04
	(2.17)	(-0.94)	(-3.3)	(-2.19)	(-2.29)	(3.12)	(0.32)	(-0.85)	(0.42)	(0.41)
6	0.89	0.06	-0.06	0.09	0.10	0.99	0.13	0.03	0.09	0.08
	(2.96)	(0.38)	(-0.62)	(0.96)	(1.05)	(3.62)	(1.39)	(0.37)	(0.98)	(0.84)
7	0.97	0.09	-0.03	0.15	0.16	1.02	0.16	0.08	0.17	0.15
	(3.13)	(0.59)	(-0.41)	(1.71)	(1.81)	(3.61)	(1.89)	(0.99)	(2.29)	(2)
8	1.20	0.30	0.19	0.32	0.33	1.19	0.34	0.27	0.31	0.33
	(3.71)	(2.02)	(2.48)	(4.11)	(4.43)	(4.48)	(3.54)	(3.11)	(3.57)	(3.77)
9	1.44	0.52	0.49	0.51	0.54	1.40	0.55	0.53	0.59	0.60
	(4.34)	(3.16)	(5.53)	(5.88)	(6.24)	(5.36)	(5.7)	(5.82)	(6.23)	(6.28)
10	1.64	0.70	0.75	0.59	0.60	1.57	0.68	0.86	0.80	0.83
	(4.38)	(3.2)	(7.12)	(5.99)	(6.12)	(5.13)	(3.72)	(5.24)	(4.84)	(4.84)
D10-D1	1.24***	1.27***	1.33***	1.15***	1.15***	1.26***	1.26***	1.33***	1.45***	1.46***
	(7.76)	(7.63)	(8.14)	(7.14)	(7.01)	(5.85)	(5.74)	(5.79)	(6.12)	(6.12)
D9-D2	0.94***	0.95***	0.99***	0.94***	0.94***	0.97***	1.01***	0.99***	1.08***	1.09***
	(7.97)	(7.87)	(8.28)	(7.63)	(7.52)	(5.98)	(6.24)	(6.54)	(6.88)	(6.82)

Panels B and C Dynamics of Changes in *DFB*

Panel B:ΔDFB_{t+1}	1984–2008			1984–2004			2005–2008		
	1	2	3	1	2	3	1	2	3
Intercept	-0.0000 (-0.33)	0.0001*** (8.91)	0.0006*** (8.68)	-0.0000 (-0.16)	0.0001*** (9.07)	0.0006*** (8.61)	-0.0000 (-1.34)	0.0000* (2.04)	0.0002** (2.78)
ΔDFB_t	-0.3831*** (-16.58)	-0.2928*** (-16.09)	-0.2889*** (-16.24)	-0.3887*** (-15.14)	-0.2920*** (-15.03)	-0.2876*** (-15.20)	-0.3519*** (-6.76)	-0.2972*** (-5.66)	-0.2963*** (-5.67)
DFB_t		-0.1543*** (-9.67)	-0.1681*** (-10.66)		-0.1665*** (-9.31)	-0.1823*** (-10.38)		-0.0856*** (-3.18)	-0.0886*** (-3.34)
$MktCap_t$			-0.0001*** (-9.15)			-0.0001*** (-9.16)			-0.0000*** (-3.08)
BM_t			0.0000*** (3.53)			0.0000*** (3.15)			0.0000* (1.97)
$Pr1Yr_t$			0.0000 (0.53)			0.0000 (1.20)			-0.0001** (-2.15)
$ResVol_t$			0.0002 (0.32)			-0.0000 (-0.07)			0.0013 (1.10)
$Turnover_t$			-0.0000 (-0.29)			0.0000 (0.05)			-0.0000** (-2.50)
Adj-R^2	18.57%	25.93%	27.24%	19.42%	27.26%	28.56%	13.82%	18.53%	19.86%
Panel C:ΔW^f_{t+1}									
Intercept	0.0000 (0.17)	0.0001*** (8.80)	0.0006*** (8.88)	0.0000 (0.25)	0.0001*** (8.79)	0.0006*** (8.66)	-0.0000 (-0.59)	0.0000** (2.73)	0.0002*** (3.13)
ΔDFB_t	-0.3704*** (-15.96)	-0.2850*** (-15.56)	-0.2814*** (-15.68)	-0.3802*** (-14.88)	-0.2884*** (-14.85)	-0.2844*** (-15.03)	-0.3156*** (-5.79)	-0.2656*** (-4.89)	-0.2643*** (-4.86)
DFB_t		-0.1453*** (-9.31)	-0.1588*** (-10.31)		-0.1571*** (-8.96)	-0.1724*** (-10.02)		-0.0792*** (-3.04)	-0.0826*** (-3.21)
$MktCap_t$			-0.0001*** (-9.22)			-0.0001*** (-9.13)			-0.0000*** (-3.07)
BM_t			0.0000*** (3.55)			0.0000*** (3.22)			0.0000 (1.69)
$Pr1Yr_t$			0.0000 (0.23)			0.0000 (0.96)			-0.0001** (-2.28)
$ResVol_t$			0.0001 (0.29)			0.0000 (0.02)			0.0009 (0.71)
$Turnover_t$			-0.0000 (-0.73)			-0.0000 (-0.38)			-0.0000*** (-3.03)
Adj-R^2	18.04%	24.95%	26.38%	19.05%	26.41%	27.78%	12.43%	16.74%	18.53%

TABLE 6

Return-Predictive Power of *DFB* and Stock Characteristics

This table presents the relation between the return-predictive power of *DFB* and stock characteristics. Specifically, at the end of each quarter from 1984Q1 to 2008Q3, we sort stocks independently based on their characteristics and *DFB* into quartiles. Sixteen portfolios thus form from these double sorts, with portfolio (1,1) containing stocks with the lowest value of the sorting variables and vice versa. The characteristics include market cap (Panel A), residual volatilities (Panel B), and the number of funds that hold the stock (Panel C). Then we calculate the average monthly equal-weight and value-weight returns for each of 16 portfolios for the subsequent quarter. We also report the Carhart 4-factor alpha differences between the extreme portfolios. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

	Equal-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)				
Ranking Variable	*DFB*					*DFB*				
Panel A: Stock Size	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	-0.18	-0.13	0.09	0.17	0.35	-0.25	-0.12	0.11	0.23	0.49*
	(-0.8)	(-0.83)	(0.62)	(1.25)	(1.28)	(-1.12)	(-0.89)	(0.8)	(1.73)	(1.8)
2	-0.27	-0.12	0.09	0.27	0.54***	-0.23	-0.10	0.09	0.32	0.55***
	(-2.63)	(-1.04)	(0.88)	(2.52)	(3.94)	(-2.33)	(-0.86)	(1.04)	(3.14)	(4.18)
3	-0.36	-0.03	0.09	0.27	0.63***	-0.35	-0.00	0.09	0.29	0.64***
	(-4.24)	(-0.36)	(0.94)	(2.01)	(3.51)	(-4.41)	(-0.03)	(1.05)	(2.12)	(3.51)
4	-0.17	-0.02	0.08	0.13	0.30*	-0.03	0.01	0.03	0.23	0.25*
	(-3.41)	(-0.3)	(1.17)	(0.82)	(1.87)	(-0.66)	(0.07)	(0.48)	(1.98)	(1.92)
Q4-Q1	0.00	0.10	-0.01	-0.04	-0.04	0.23	0.13	-0.08	-0.01	-0.23
	(0.02)	(0.6)	(-0.04)	(-0.17)	(-0.13)	(1.05)	(0.84)	(-0.53)	(-0.03)	(-0.77)
Panel B: Residual Vol	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	0.05	0.23	0.28	0.26	0.21***	-0.04	0.21	0.06	0.14	0.17
	(0.5)	(1.96)	(2.74)	(2.38)	(3.06)	(-0.49)	(2.03)	(0.62)	(1.28)	(1.43)
2	-0.13	0.10	0.19	0.26	0.39***	-0.25	-0.29	0.01	0.41	0.67***
	(-1.4)	(0.87)	(1.76)	(2.34)	(4.05)	(-2.29)	(-2.02)	(0.07)	(2.61)	(3.4)
3	-0.24	-0.00	0.08	0.32	0.56***	-0.20	-0.11	-0.10	0.39	0.59**
	(-2.95)	(0)	(0.92)	(2.8)	(4.03)	(-1.1)	(-0.79)	(-0.77)	(1.96)	(2.28)
4	-1.10	-0.48	-0.28	-0.15	0.95***	-1.08	-0.65	-0.33	-0.17	0.91***
	(-7.35)	(-3.28)	(-2.12)	(-1.09)	(5.43)	(-5.7)	(-3.05)	(-1.38)	(-0.53)	(3.46)
Q4-Q1	-1.15***	-0.71***	-0.56***	-0.41**	0.74***	-1.04***	-0.86***	-0.39	-0.30	0.74***
	(-5.33)	(-3.39)	(-2.84)	(-2.02)	(4.11)	(-4.59)	(-3.15)	(-1.4)	(-0.91)	(2.68)
Panel C: # of Funds	1	2	3	4	Q4-Q1	1	2	3	4	Q4-Q1
1	-0.49	-0.15	0.05	0.13	0.63***	-0.70	-0.14	0.01	0.13	0.84***
	(-3.81)	(-0.99)	(0.37)	(1)	(3.96)	(-5.08)	(-0.92)	(0.05)	(0.87)	(4.29)
2	-0.30	-0.11	0.13	0.15	0.45***	-0.34	-0.06	0.16	0.13	0.47***
	(-3.25)	(-0.97)	(1.34)	(1.43)	(3.01)	(-3.12)	(-0.56)	(1.41)	(1.01)	(2.99)
3	-0.23	-0.03	0.13	0.31	0.54***	-0.22	0.01	0.17	0.53	0.75***
	(-2.25)	(-0.24)	(1.46)	(2.6)	(3.28)	(-2.31)	(0.09)	(1.94)	(2.83)	(3.54)
4	-0.12	-0.05	0.02	0.15	0.27**	-0.01	-0.00	0.01	0.17	0.18
	(-1.81)	(-0.51)	(0.25)	(1.21)	(2.09)	(-0.22)	(-0.04)	(0.18)	(1.65)	(1.43)
Q4-Q1	0.37**	0.11	-0.04	0.03	-0.33*	0.69***	0.13	0.00	0.06	-0.64***
	(2.28)	(0.56)	(-0.24)	(0.14)	(-1.72)	(5.08)	(0.75)	(0.01)	(0.32)	(-3.18)

TABLE 7

Return Predictive Power of *DFB* and Fund Characteristics

This table presents the return forecasting power of *DFB* constructed using the portfolio holdings of mutual funds grouped on the basis of fund characteristics. Panel A uses past fund alphas, estimated as intercepts from rolling-window regressions of excess net fund returns on the market, size, value, and momentum factors in the past two years. Specifically, at the end of each quarter from 1984Q1 to 2008Q3, we divide all mutual funds by their characteristics into terciles based on fund alphas. Within each tercile, we compute mutual funds' deviations from benchmarks, *DFB*, as the simple average of the stock's weight in a mutual fund portfolio in excess of its weight in the fund's benchmark index across all mutual funds. We sort stocks into quintiles in ascending order based on *DFB* for each tercile of funds and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. We also present the risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Panel B groups funds based on their investment objectives. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Grouping Funds into Terciles Based on Past Two-Year Alpha

Sorting Variable		Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Past alpha	*DFB*	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
Low	1	0.80	-0.09	-0.21	-0.16	-0.16	0.78	-0.06	0.02	0.01	0.01
		(2.81)	(-1.08)	(-3.89)	(-2.67)	(-2.61)	(3.17)	(-1.05)	(0.4)	(0.16)	(0.16)
	5	1.15	0.21	0.14	0.09	0.12	1.09	0.17	0.25	0.11	0.12
		(3.34)	(1.34)	(1.82)	(1.19)	(1.55)	(3.63)	(1.94)	(3.33)	(1.4)	(1.5)
	Q5-Q1	0.36***	0.30**	0.36***	0.25***	0.27***	0.31**	0.23*	0.23**	0.10	0.11
		(2.74)	(2.34)	(3.7)	(2.64)	(2.79)	(2.36)	(1.87)	(2.54)	(1.05)	(1.15)
Medium	1	0.73	-0.16	-0.28	-0.24	-0.23	0.77	-0.07	-0.00	-0.00	-0.00
		(2.51)	(-1.82)	(-5.2)	(-3.91)	(-3.82)	(3.13)	(-1.25)	(-0.11)	(-0.11)	(-0.05)
	5	1.26	0.34	0.24	0.20	0.22	1.19	0.29	0.35	0.22	0.23
		(3.79)	(2.25)	(3.23)	(2.81)	(3.21)	(4)	(3.09)	(4.05)	(2.77)	(2.95)
	Q5-Q1	0.53***	0.50***	0.52***	0.44***	0.46***	0.42***	0.36***	0.35***	0.22**	0.23**
		(4.96)	(4.64)	(6.05)	(5.14)	(5.36)	(3.13)	(2.8)	(3.39)	(2.16)	(2.31)
High	1	0.68	-0.19	-0.34	-0.28	-0.28	0.77	-0.06	-0.02	-0.02	-0.02
		(2.48)	(-2.25)	(-6.12)	(-4.54)	(-4.48)	(3.26)	(-1.11)	(-0.58)	(-0.5)	(-0.43)
	5	1.34	0.39	0.38	0.26	0.28	1.26	0.30	0.49	0.26	0.26
		(3.74)	(2.29)	(4.74)	(3.53)	(3.8)	(3.63)	(2.26)	(4.05)	(2.35)	(2.39)
	Q5-Q1	0.66***	0.58***	0.72***	0.54***	0.56***	0.49**	0.35**	0.51***	0.28**	0.28**
		(4.2)	(3.88)	(7.12)	(5.42)	(5.48)	(2.57)	(2.19)	(3.58)	(2.04)	(2.06)
High-Low	1	-0.11***	-0.10**	-0.13***	-0.12***	-0.12**	-0.01	0.00	-0.04	-0.03	-0.02
		(-2.7)	(-2.26)	(-2.84)	(-2.6)	(-2.58)	(-0.27)	(0.08)	(-1.44)	(-0.92)	(-0.81)
	5	0.19**	0.18**	0.23***	0.17***	0.17***	0.16	0.13	0.24**	0.15	0.14
		(2.55)	(2.3)	(3.3)	(2.71)	(2.67)	(1.55)	(1.25)	(2.19)	(1.47)	(1.43)
	Q5-Q1	0.30***	0.27**	0.36***	0.29***	0.29***	0.17	0.13	0.28**	0.17	0.17
		(2.96)	(2.57)	(3.6)	(3.1)	(3.05)	(1.35)	(1.03)	(2.16)	(1.44)	(1.38)

Panel B: Grouping Funds based on Investment Objectives

Sorting Variable		Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Investment Objectives	*DFB*	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
Aggressive Growth	1	0.86	-0.01	-0.19	-0.11	-0.12	0.83	-0.01	-0.00	0.01	0.01
		(3.28)	(-0.16)	(-3.84)	(-2.16)	(-2.27)	(3.58)	(-0.29)	(-0.12)	(0.3)	(0.36)
	5	1.23	0.23	0.23	0.15	0.20	1.04	0.06	0.17	0.07	0.10
		(3.41)	(1.49)	(2.7)	(1.79)	(2.48)	(3.2)	(0.61)	(2.12)	(0.81)	(1.22)
	Q5-Q1	0.36**	0.24*	0.42***	0.26***	0.32***	0.21	0.07	0.18*	0.06	0.09
		(2.25)	(1.68)	(4.28)	(2.7)	(3.38)	(1.36)	(0.57)	(1.74)	(0.54)	(0.83)
Growth	1	0.69	-0.21	-0.36	-0.28	-0.27	0.79	-0.06	-0.02	-0.02	-0.01
		(2.43)	(-2.19)	(-6.58)	(-4.63)	(-4.48)	(3.35)	(-1.09)	(-0.46)	(-0.47)	(-0.31)
	5	1.28	0.34	0.29	0.19	0.21	1.21	0.24	0.41	0.19	0.20
		(3.77)	(2.08)	(3.96)	(2.83)	(3.02)	(3.67)	(2.04)	(3.87)	(2.13)	(2.25)
	Q5-Q1	0.59***	0.54***	0.64***	0.47***	0.47***	0.42**	0.30**	0.42***	0.21*	0.22**
		(4.7)	(4.39)	(7.2)	(5.41)	(5.28)	(2.43)	(2.02)	(3.41)	(1.89)	(1.97)
Growth & Income	1	1.01	0.08	-0.02	-0.06	-0.04	0.81	-0.07	0.03	0.02	0.01
		(3.39)	(0.76)	(-0.25)	(-0.79)	(-0.62)	(3.18)	(-1.18)	(0.67)	(0.38)	(0.3)
	5	1.09	0.19	-0.01	0.02	0.04	0.99	0.11	0.08	-0.01	0.02
		(3.74)	(1.56)	(-0.1)	(0.34)	(0.58)	(3.91)	(1.58)	(1.15)	(-0.08)	(0.22)
	Q5-Q1	0.08	0.10	0.01	0.08	0.08	0.18	0.19*	0.05	-0.02	0.00
		(0.92)	(1.26)	(0.11)	(1.02)	(1.08)	(1.65)	(1.67)	(0.57)	(-0.22)	(0.03)
Growth & Income-Aggressive Growth	1	0.14*	0.09	0.17***	0.06	0.08	-0.02	-0.06	0.03	0.00	-0.00
		(1.74)	(1.19)	(2.76)	(0.88)	(1.22)	(-0.45)	(-1.25)	(0.77)	(0.12)	(-0.01)
	5	-0.14	-0.04	-0.23***	-0.13*	-0.16**	-0.05	0.06	-0.09	-0.07	-0.09
		(-1.1)	(-0.39)	(-3.07)	(-1.7)	(-2.19)	(-0.42)	(0.55)	(-1.05)	(-0.82)	(-0.93)
	Q5-Q1	-0.28	-0.14	-0.41***	-0.18	-0.24**	-0.03	0.11	-0.12	-0.08	-0.08
		(-1.45)	(-0.79)	(-3.4)	(-1.55)	(-2.05)	(-0.18)	(0.81)	(-1.03)	(-0.65)	(-0.69)

TABLE 8

DFB and Future Earnings News

This table presents the forecasting power of *DFB* for subsequent earnings surprises. At the end of each quarter from 1984Q1 to 2008Q3, we sort stocks into quintiles, based on *DFB*, in ascending order and compute the average quarterly earnings surprise and the cumulative abnormal returns around the earnings announcement in the four quarters following the portfolio formation date. The earnings surprise is the difference between actual earnings and consensus analyst forecast, divided by the absolute value of actual earnings or stock price. The earnings announcement cumulative abnormal return is calculated for the three days around the earnings announcement date. Earnings data and earnings announcement dates come from I/B/E/S. To adjust for earnings momentum, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on *DFB*. We average the difference in earnings surprises for subsequent quarters between high and low *DFB* stocks across the three terciles and report the averaged difference as momentum-adjusted earnings surprises. Stocks with prices lower than $5 at the quarter end are excluded. The *t*-statistics are computed using the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

		Quarters			
		t+1	t+2	t+3	t+4
A: Earnings Surprise Scaled by Actual Earnings (%)					
	Q1	0.159	0.393	0.462	0.453
		(0.32)	(1.05)	(1.26)	(1.19)
	Q5	2.470	1.840	1.262	0.858
		(5.62)	(4.35)	(2.81)	(1.85)
	Q5-Q1	2.353***	1.447***	0.800***	0.405**
		(6.03)	(9.05)	(5.69)	(2.22)
	Q5-Q1 (Momentum-Adj)	1.384***	0.474	0.468	0.467
		(5.31)	(0.93)	(1.38)	(1.12)
B: Earnings Surprise Scaled by Price (%)					
	Q1	-0.004	0.002	0.003	0.003
		(-0.39)	(0.3)	(0.44)	(0.42)
	Q5	0.033	0.025	0.015	0.010
		(5.6)	(4.27)	(2.44)	(1.46)
	Q5-Q1	0.038***	0.023***	0.012***	0.007**
		(4.06)	(6.93)	(6.36)	(2.1)
	Q5-Q1 (Momentum-Adj)	0.024***	-0.010	0.004*	0.062
		(4.23)	(-0.74)	(1.7)	(1.02)
C: CARs around Earnings Announcement (%)					
	Q1	0.034	0.086	0.075	0.063
		(1.2)	(3.13)	(3.01)	(2.47)
	Q5	0.298	0.163	0.157	0.140
		(5.06)	(3.25)	(3.18)	(2.88)
	Q5-Q1	0.260***	0.077	0.082*	0.076*
		(4.32)	(1.46)	(1.97)	(1.93)
	Q5-Q1 (Momentum-Adj)	0.243***	-0.005	0.017	0.053
		(3.13)	(-0.15)	(0.35)	(1.18)

TABLE 9

DFB and Mutual Fund Performance

This table presents the contribution of portfolios sorted on the basis of *DFB* to the aggregate mutual fund performance. At the end of each quarter from 1984Q1 to 2008Q3, we sort stocks into deciles, based on *DFB*, in ascending order and compute the aggregate fund dollar holdings for each decile. We calculate the average monthly holdings-weighted portfolio returns in the subsequent quarter, and also present the risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with the Pastor and Stambaugh (2003) liquidity factor. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

		Holdings-Weighted Post-Ranking Portfolio Return (%/month)				
Decile	% of Aggregate Fund Investments	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	33.76%	0.77	-0.08	-0.02	-0.05	-0.05
		(2.86)	(-1.18)	(-0.41)	(-1.03)	(-0.95)
2	7.33%	1.04	0.15	0.06	0.15	0.14
		(3.44)	(1.49)	(0.61)	(1.53)	(1.44)
3	5.39%	0.95	0.04	-0.07	0.04	0.04
		(3.11)	(0.29)	(-0.65)	(0.39)	(0.38)
4	3.46%	0.91	0.01	-0.08	0.04	0.04
		(2.76)	(0.1)	(-0.77)	(0.28)	(0.32)
5	4.59%	1.01	0.07	-0.03	0.15	0.14
		(3.14)	(0.54)	(-0.22)	(1.22)	(1.09)
6	6.63%	1.01	0.07	-0.05	0.07	0.07
		(3.15)	(0.52)	(-0.46)	(0.62)	(0.67)
7	8.70%	1.13	0.21	0.16	0.22	0.24
		(3.61)	(2.21)	(1.73)	(2.42)	(2.72)
8	9.77%	1.07	0.13	0.11	0.07	0.08
		(3.29)	(1.13)	(1.03)	(0.59)	(0.71)
9	11.06%	1.40	0.44	0.51	0.34	0.36
		(4.11)	(3.01)	(4.09)	(2.97)	(3.26)
10	9.30%	1.62	0.63	0.84	0.55	0.59
		(3.89)	(2.67)	(3.65)	(3.04)	(3.34)
D10-D1		0.85***	0.71***	0.87***	0.60***	0.64***
		(2.96)	(2.72)	(3.6)	(3.04)	(3.32)
D9-D2		0.37**	0.29*	0.46***	0.19	0.22
		(2.07)	(1.68)	(3.04)	(1.35)	(1.56)

TABLE 10

Could Individual Fund Managers Have Performed Better by Being More Active?

This table shows average Sharpe ratios for the active portfolio, benchmark index, and the total fund portfolio of individual mutual funds. It also shows the proportion of mutual funds that could have improved their in-sample Sharpe ratios by tilting their portfolios more toward their active portfolios. Specifically, for each individual fund, we run a time-series regression of the return to the fund's active portfolio on the return to the fund's total portfolio. We report the fraction of funds for which the *t*-statistics of the intercept have values no less than 1.96. The tests involve 2,273 distinct funds with at least 2 years of return history. We use five sample periods: Period (1):1984/04–2006/12; Period (2):1984/04–2007/06; Period (3):1984/04–2007/12; Period (4):1984/04–2008/06; Period (5):1984/04–2008/12. *** Statistical significance at 1%.

	Average Sharpe Ratio (SR)					Proportion of Funds with Potential Increase in SR (%)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Active Portfolio	0.30	0.31	0.30	0.28	0.24	11.06	11.12	11.85	13.15	14.60
Benchmark	0.49	0.51	0.45	0.35	0.18					
Fund Portfolio	0.55	0.58	0.52	0.42	0.25					
Benchmark-Active Portfolio	0.19***	0.20***	0.15***	0.07***	-0.06***					
Fund Portfolio-Active Portfolio	0.25***	0.27***	0.22***	0.14***	0.01					
Fund Portfolio-Benchmark	0.06***	0.07***	0.07***	0.07***	0.06***					

TABLE 11

Alternative Measure of *DFB* and Future Stock Returns

This table presents the performance of decile portfolios formed on the basis of alternative measures of *DFB*. Panel A uses an alternative set of benchmark index. At the end of each quarter from 1984Q1 to 2008Q3, we select for each mutual fund a benchmark portfolio containing stocks that are held by the fund. We construct the benchmark as the market-capitalization-weighted portfolio of these stocks. Panel B uses an alternative measure DFB^{alt} based on the fraction of funds that overweight the stock, as defined in Equation 3. We sort stocks into deciles, based on these alternative measures of mutual funds' deviations from benchmarks in ascending order and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with Pastor and Stambaugh's (2003) liquidity. Stocks with prices lower than $5 at the quarter end are excluded. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10%.

Panel A: Alternative Benchmark Index

	Equal-Weight Post-Ranking Portfolio Return (%/month)					Value-Weight Post-Ranking Portfolio Return (%/month)				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.39	-0.52	-0.53	-0.40	-0.42	0.77	-0.09	-0.03	-0.01	-0.00
	(1.18)	(-5.16)	(-6.04)	(-4.98)	(-5.22)	(2.84)	(-1.32)	(-0.8)	(-0.23)	(-0.06)
2	0.57	-0.28	-0.38	-0.27	-0.26	0.61	-0.30	-0.35	-0.13	-0.12
	(1.66)	(-1.55)	(-3.82)	(-2.51)	(-2.4)	(1.9)	(-2.77)	(-3.09)	(-1.08)	(-1.04)
3	0.64	-0.18	-0.31	-0.13	-0.11	0.58	-0.31	-0.35	-0.18	-0.19
	(1.96)	(-0.97)	(-2.89)	(-1.41)	(-1.21)	(1.89)	(-2.86)	(-3.64)	(-2.03)	(-2.11)
4	0.77	-0.13	-0.26	-0.07	-0.06	0.82	-0.08	-0.17	-0.05	-0.05
	(2.27)	(-0.75)	(-3.12)	(-0.82)	(-0.75)	(2.72)	(-0.81)	(-2.2)	(-0.57)	(-0.57)
5	0.76	-0.14	-0.27	-0.07	-0.06	0.80	-0.08	-0.17	-0.12	-0.12
	(2.31)	(-0.9)	(-3.55)	(-0.91)	(-0.88)	(2.83)	(-0.87)	(-2.05)	(-1.49)	(-1.49)
6	0.86	-0.04	-0.17	-0.03	-0.03	0.97	0.09	-0.00	0.03	0.03
	(2.59)	(-0.26)	(-2.27)	(-0.48)	(-0.38)	(3.36)	(0.93)	(-0.04)	(0.46)	(0.41)
7	0.94	0.04	-0.07	0.01	0.01	0.99	0.13	0.03	0.06	0.05
	(2.87)	(0.25)	(-0.95)	(0.08)	(0.18)	(3.62)	(1.42)	(0.42)	(0.71)	(0.62)
8	1.03	0.12	0.04	0.05	0.07	1.15	0.27	0.19	0.13	0.14
	(3.18)	(0.84)	(0.52)	(0.7)	(1.03)	(4.13)	(3.1)	(2.7)	(1.76)	(1.91)
9	1.21	0.29	0.25	0.17	0.20	1.29	0.41	0.38	0.18	0.20
	(3.68)	(2)	(3.18)	(2.09)	(2.53)	(4.43)	(3.89)	(4.3)	(2.39)	(2.75)
10	1.73	0.79	0.80	0.59	0.62	1.85	0.93	1.02	0.64	0.66
	(4.65)	(4.15)	(7.94)	(6.2)	(6.78)	(5)	(5.14)	(5.95)	(4.63)	(4.83)
D10-D1	1.34***	1.31***	1.33***	0.99***	1.04***	1.09***	1.01***	1.05***	0.65***	0.66***
	(7.75)	(7.11)	(8.63)	(7.24)	(7.92)	(4.7)	(4.63)	(5.51)	(4.06)	(4.15)
D9-D2	0.64***	0.58***	0.63***	0.44***	0.46***	0.68***	0.71***	0.74***	0.30**	0.32**
	(5.5)	(4.45)	(4.8)	(3.03)	(3.15)	(4.79)	(5.01)	(4.38)	(2.03)	(2.22)

Panel B: *DFB*^{alt} based on the Fraction of Active Funds that Overweight the Stock

	Equal-Weight Post-Ranking Portfolio Return (%/month)						Value-Weight Post-Ranking Portfolio Return (%/month)					
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	DGTW-Adj Return
1	0.31 (0.91)	-0.58 (-4.08)	-0.66 (-6.2)	-0.48 (-4.62)	-0.49 (-4.84)	-0.43 (-4.63)	0.45 (1.55)	-0.38 (-3.4)	-0.52 (-5.81)	-0.38 (-4.26)	-0.39 (-4.34)	-0.33 (-4.99)
2	0.70 (2.11)	-0.21 (-1.46)	-0.34 (-3.99)	-0.12 (-1.44)	-0.12 (-1.5)	-0.12 (-1.94)	0.81 (3.05)	-0.01 (-0.1)	-0.16 (-1.97)	-0.04 (-0.46)	-0.05 (-0.68)	-0.07 (-0.92)
3	0.87 (2.61)	-0.03 (-0.24)	-0.17 (-2.32)	0.01 (0.09)	0.01 (0.14)	0.02 (0.4)	0.90 (3.26)	0.06 (0.61)	-0.06 (-0.89)	0.01 (0.14)	-0.01 (-0.07)	0.01 (0.13)
4	0.95 (2.89)	0.04 (0.31)	-0.09 (-1.07)	0.04 (0.59)	0.05 (0.61)	0.03 (0.45)	0.95 (3.45)	0.10 (1.38)	0.01 (0.17)	0.02 (0.26)	0.02 (0.22)	-0.01 (-0.16)
5	0.95 (2.92)	0.04 (0.27)	-0.08 (-1.13)	0.03 (0.39)	0.04 (0.49)	0.07 (1.21)	0.87 (3.21)	0.02 (0.28)	-0.04 (-0.66)	-0.03 (-0.54)	-0.05 (-0.95)	0.01 (0.12)
6	1.00 (3.04)	0.08 (0.58)	0.00 (0.04)	0.06 (0.9)	0.08 (1.14)	0.12 (2.09)	0.91 (3.31)	0.05 (0.64)	0.07 (0.87)	0.02 (0.24)	0.02 (0.3)	0.02 (0.45)
7	1.05 (3.16)	0.15 (1)	0.09 (1.39)	0.11 (1.56)	0.13 (1.9)	0.15 (2.8)	1.07 (3.49)	0.20 (2.32)	0.20 (2.38)	0.20 (2.42)	0.21 (2.48)	0.14 (1.5)
8	1.00 (2.42)	0.23 (1.08)	0.14 (0.85)	0.02 (0.14)	0.04 (0.2)	0.20 (0.99)	0.51 (1.46)	-0.23 (-1.53)	-0.13 (-0.79)	-0.31 (-1.69)	-0.30 (-1.54)	-0.05 (-0.5)
9	1.07 (2.96)	0.18 (0.85)	0.17 (1.37)	0.14 (1.1)	0.15 (1.21)	0.02 (0.17)	0.97 (2.55)	0.07 (0.27)	0.30 (1.4)	0.00 (0.02)	0.03 (0.15)	0.05 (0.43)
10	1.19 (2.96)	0.46 (1.85)	0.29 (1.84)	0.22 (1.35)	0.24 (1.43)	0.23 (1.78)	1.25 (3.38)	0.52 (2.18)	0.42 (1.95)	0.34 (1.51)	0.39 (1.74)	0.27 (1.69)
D10-D1	0.75*** (3.77)	0.84*** (4.29)	0.81*** (4.44)	0.64*** (3.55)	0.67*** (3.67)	0.63*** (4.31)	0.71*** (3.23)	0.76*** (3.38)	0.79*** (3.45)	0.63*** (2.67)	0.69*** (2.96)	0.55*** (3.56)
D9-D2	0.40** (2.48)	0.39** (2.43)	0.51*** (3.6)	0.26* (1.83)	0.28* (1.89)	0.15 (1.35)	0.17 (0.56)	0.08 (0.27)	0.46* (1.79)	0.04 (0.19)	0.08 (0.38)	0.12 (0.84)