Information Content when Mutual Funds Deviate from Benchmarks

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Abstract

This paper creates a stock-level measure that seeks to aggregate various pieces of information scattered among actively managed mutual funds, as revealed through their over- and underweighting decisions. We find that this measure of mutual funds' deviations from benchmarks strongly and positively predicts future stock returns: The return premium on stocks heavily overweighted by mutual funds, relative to their underweighted counterparts, reaches 0.61% per month even after adjustments for their loadings on the market, size, value, momentum, and liquidity factors; and a significant portion of this premium occurs around corporate earnings announcements. We also find that a large increase in the overweight of a stock by active funds in one quarter predicts a decline in the overweight in the next quarter, consistent with informed managers unwinding their profitable positions. These results point to an informational link between mutual fund investing and asset prices.

JEL classification: G10; G11; G14; G23

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1 Introduction

The mutual fund industry is becoming increasingly important in financial markets. At the end of 2009, total assets managed by U.S. mutual funds reached more than $11 trillion, growing by more than 80 times from the $135 billion they managed at the end of 1980 (Investment Company Institute, 2010). As a result of this dramatic expansion, 21% of U.S. households' financial assets are managed by mutual funds.

Despite the increasing importance though, the role that mutual funds play in determining security prices remains poorly understood. Considering the dominance of actively managed mutual funds in this industry and the resulting vast amount of resources they spend on security analysis and research,[1] we might expect active funds to be good candidates as informed investors in the world of Grossman and Stiglitz (1980), where the investment activities of informed investors, through their costly acquisition and implementation of information, help impound information into asset prices. Prior literature on the performance of actively managed mutual funds, however, has painted a picture of active funds generally failing to outperform passive benchmarks, without creating value from active investing.[2] This disheartening image appears to contradict the view of active mutual funds as informed investors in financial markets.

In this study, we provide strong evidence of the informational role of actively managed mutual funds in the determination of stock prices though. We deviate from prior research by studying the deviations of mutual funds from their performance benchmarks. Fund managers could be reluctant to deviate from their benchmarks (Roll, 1992), which

[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.

[2] Analyses of mutual fund returns generally report disappointing fund performance (e.g., Jensen 1968, Malkiel, 1995, Carhart, 1997, Fama and French, 2009). Studies based on fund portfolio holdings suggest better but still moderate fund performance before expenses and trading costs (e.g., Grinblatt and Titman, 1989 and 1993, Daniel, Grinblatt, Titman, and Wermers, 1997, Wermers, 2000).

may lead them to invest a substantial portion of fund assets in benchmarks. Therefore, focusing on the performance of the active portion of their investments, that is, their deviations from those benchmarks, should grant us more power to identify mutual funds' informational advantages.

To assess whether actively managed mutual funds attain informational advantages about individual stocks compared with the market, we create a simple measure that seeks to aggregate various pieces of information scattered among mutual fund managers, as revealed through their over- and underweighting decisions. Specifically, for each stock in our sample, we first compute the difference between the stock's weight in each individual mutual fund portfolio and its weight in the stock index against which that fund is benchmarked. We average this difference in portfolio weights across mutual funds whose investment universe includes this stock, thereby creating a stock-level measure of mutual funds' deviations from benchmarks, DFB.

This measure of mutual funds' deviations from benchmarks strongly predicts future stock returns. In univariate portfolio sorts, for example, stocks in the decile portfolio with the highest DFB, which are those most heavily overweighted by mutual funds, perform substantially better than those with the lowest DFB. Over the period 1980–2008, the average equal-weighted return on the top decile of stocks with the highest DFB was higher than that on the bottom decile of stocks, or those with the lowest DFB, by 0.74% per month, and this return difference was highly statistically significant with a t-statistic of 4.38. The superior performance of the stocks that mutual funds overweight relative to those that they underweight does not simply reflect the high risk propensity of mutual funds. As we show, the risk-adjusted returns on the spread portfolio between high and low DFB stocks are 0.66%, 0.72%, 0.58%, and 0.61% per month, as calculated by the Capital Asset Pricing Model (CAPM), the Fama and French's (1993) three-factor model, a four-factor model that includes momentum (Jegadeesh and Titman, 1993), and a five-factor model that also includes Pastor and Stambaugh's (2003) liquidity factor, respectively. The statistical significance of the returns on the spread portfolio remains high even after various risk adjustments. These results also are robust to the various specifications of Fama and MacBeth's (1973) cross-sectional regressions with common stock return predictors, for different weighting schemes, and across various subperiods. They suggest that actively managed mutual funds possess value-relevant information that is not fully reflected in stock prices.

Although interesting, these results also may be subject to alternative interpretations. For example, the higher returns on stocks with higher DFB may be a result of mutual funds' demand pressure, which pushes stock prices above equilibrium levels and thus generates higher in-sample returns. This interpretation is possible because there is evidence that mutual funds tend to herd (Wermers, 1999, Sias, 2004) and that they may continue to buy the stocks they have overweighted. To differentiate this alternative interpretation based on price pressure from our story of informed fund managers, 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 typical manager receives a positive signal about a stock in period t and decides to increase his portfolio weight in this stock relative to his benchmark, which results in an increase in DFB from $t-1$ to t. In the next period $t+1$, as his positive private information transmits into the stock price, return-maximizing considerations would lead him to unwind the position that he has built up to capture the gains to his information. 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. Our tests show 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.

We also 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. Our tests show that the positive association between DFB and future excess returns concentrates for the most proximate quarter. This positive association shows no tendency to reverse for the subsequent two to four quarters. Thus, DFB appears to forecast returns due primarily to the value-relevant information that DFB aggregates from diverse mutual fund managers, as revealed through their investment decisions.

To increase our confidence in this information-based story, we conduct a series of tests based on stock and fund attributes. First, if mutual funds have informational advantages about individual stocks, we expect these advantages to be greater among stocks with more firm-specific information. Also, we expect the funds' informational advantages to be more valuable when the funds have fewer competitors. Consistent with these predictions, we find that the return forecasting power of DFB is stronger among firms that have higher idiosyncratic volatilities and attract fewer mutual fund investors. Second, our measure of DFB reflects the investment decisions of all active mutual funds in our sample. 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, a DFB measure constructed from the universe of those high-performing funds could be a better return predictor than that from the universe of the low-performing funds with a lower level of alphas. We find that, indeed, a strategy that buys high DFB stocks and sells low DFB stocks based on the portfolio decisions of high-performing funds generates a monthly four-factor alpha of 0.71% (t=6.59), which is more than twice as large as the four-factor alpha of 0.31% (t=2.90) on a similar strategy based on the portfolio decisions of low-performing funds. Interestingly, the higher returns on the DFB strategy implemented on higher-alpha managers come from both the higher returns on stocks that they overweight and the lower returns on stock they underweight.

To explore the nature of the information content captured by DFB, we examine the relation between DFB and firms' future earnings surprises. We find that stocks with high DFB tend to experience large and positive earnings surprises during the following four quarters, and the effect, strongest for the most proximate quarter, decays substantially through time. Even after we adjust for the possibility that active funds might trade on earnings momentum, we still find reliably positive earning surprises in the most proximate quarter for stocks they overweight. We also find that a significant portion of the return premiums on the stocks with high DFB occurs around corporate earnings announcements. These results suggest that part of active funds' superior information relates to firms' fundamental prospects.

Finally, how can we reconcile 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? We find that stocks with the highest DFB tend to be relatively small, with an average New York Stock Exchange (NYSE) size decile rank of 3.3. They also frequently float outside the stock indexes against which mutual funds are benchmarked. On the contrary, the stocks with the lowest DFB tend to be large, with an average NYSE size decile rank of 6.8, and the majority of them appear in the indexes against which active funds are benchmarked. With these characteristics in mind, we find that mutual funds invest less than 10% of their assets in high DFB stocks but approximately 34% in low DFB stocks. Therefore, a large four-factor alpha of 6–7% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year.

Our paper joins a small but growing body of literature that connects mutual fund investing to asset prices. Coval and Moskowitz (2001) use geography to identify a link between mutual fund investments and stock prices. They find that the holdings of geographically proximate firms by local fund managers perform better than their holdings of distant firms, which suggests fund managers have better access to local information and that their investments facilitate the transfer of information into the prices of local stocks. Cohen, Frazzini, and Malloy (2008) exploit educational background to establish a social link between corporate managers and fund managers that in turn influences stock prices. Unlike these two studies, which use a priori links between firms and funds, we track the investment decisions of mutual fund managers and extract and aggregate the information that is scattered among these managers from their portfolio decisions. We also provide strong evidence that this measure of aggregated information predicts future stock returns, which is particularly useful for a better understanding of the informational role played by mutual funds in stock markets.

In some recent studies, Cohen, Polk, and Silli (2010) document the superior performance of fund managers' best idea stocks. Their interesting analysis focuses on the top holdings in each manager's portfolio; we are interested instead in whether a measure that aggregates information dispersed among fund managers captures their informational advantages as an investor group. Our detailed analysis of the entire portfolio composition of mutual funds enables us to detect the negative abnormal returns on stocks that active funds choose to underweight. Moreover, our results are insensitive to the exclusion of each manager's best ideas in computing DFB. Shumway, Szefler, and Yuan (2009) propose a novel technique to elicit fund managers' beliefs about expected stock returns from their portfolio holdings. They apply their method to rank these fund managers and find that skilled managers possess superior information relative to their unskilled peers. Our primary interest, however, is in whether an average mutual fund has informational advantages in stock markets.

To pursue these interests, we organize the rest of this article as follows: In Section 2, we introduce our measure of mutual funds' deviations from benchmarks, DFB, and in Section 3, we describe our sample selection and summary statistics. With Section 4, we explore the information content of mutual funds that deviate from benchmarks, then provide several robustness checks in Section 5. Section 6 concludes our paper.

2 Measuring Mutual Funds' Deviations from Benchmarks, DFB

We measure a mutual fund j's deviation from its benchmark for stock i as the difference between this stock's weight in the fund portfolio, $w_{i,t}^{j}$, and its weight in the stock index against which the fund's performance is benchmarked, $w_{i,t}^{b}$. Our primary interest is in whether mutual funds, as an investor group, have informational advantages for individual stocks in their investment universe; therefore, 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 in Equation 1:

$$DFB_{i,t} = \sum_{j=1}^{N_i}(w_{i,t}^{j} - w_{i,t}^{b})/N_i, \tag{1}$$

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

Our simple measure of mutual funds' deviations from benchmarks equally reflects each fund's distance from its performance benchmark and therefore captures a typical fund's deviation from its benchmark. Other ways to aggregate across mutual funds include weighting each fund's distance from a benchmark based on net fund assets, which captures funds' deviations from benchmarks for every invested dollar; or weighting each fund's distance from a benchmark based on how active the funds are. Our results remain robust when we use such weighting schemes, but we present our main results using the simple equal-weighting scheme, which also is economically intuitive.

If fund managers deviate from their benchmarks for informational reasons, DFB can aggregate diverse pieces of information about the future value of individual stocks scattered among fund managers. If not yet has this aggregated information been fully reflected in current market prices (i.e., mutual funds possess private information as an investor group), DFB should predict future stock returns relatively well. A stock with higher value DFB, ceteris paribus, should have higher future returns. If mutual funds do not possess value-relevant private information or deviate from performance benchmarks for other considerations,[3] we expect DFB to be unrelated, or even negatively related, to future stock returns. In Appendix A, we show that with certain assumptions, DFB linearly relates to expected future excess returns, conditional on fund managers' information set.

[3] Growing literature analyzes the incentives of mutual fund managers, which suggests that they may deviate from their performance benchmarks for agency considerations, beyond the objective of return maximization or portfolio diversification (e.g., Brown, Harlow, and Starks, 1996, Chevalier and Ellison, 1997).

3 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.

3.1 *Data and Sample Selection*

To construct our mutual fund database, we combined the Centre 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.[4] Because we wish to examine the informational advantages of mutual funds in stock markets, we only includeactive 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 1980 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).

[4] Our merging procedure uses the MFLINKS data set maintained by Russ Wermers and the Wharton Research Data Services (WRDS).

3.2 *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 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 one that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from the Compustat. For the remaining indexes and time periods, we use the holdings of index funds to approximate the index holdings.[5] 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. A mutual fund might respond to negative information about a firm by avoiding holding its shares, so we include all stocks that the fund held during the previous five years in the value-weighted portfolio.[6] Since these two approaches generate qualitatively similar results, we report our main results based on the first approach.

[5] We obtain qualitatively similar results if we use index fund holdings throughout our sample period.
[6] Our results are insensitive to the choice of past five years.

3.3 *Summary Statistics for the Mutual Fund Sample*

Table I reports the summary statistics for our mutual fund sample, which includes 2,750 distinct U.S. active equity funds. During 1980–2008, the industry of active equity mutual funds experienced dramatic expansion: The number of actively managed funds increased from 201 in 1980 to 1397 in 2008, with total assets under their management increasing from \$26.55 to \$953.91 billion. On average, these funds invested 93% 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 approximately 2% to around 10%.

3.4 *Characteristics of Stocks with Extreme* DFB

What are the characteristics of stocks with heavy mutual fund bets? In this subsection, we examine the characteristics of stocks with large mutual fund over- and underweighting. We present univariate results based on the decile portfolios in Table II. 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.

The results show that stocks heavily overweighted by mutual funds tend to have low portfolio weights in benchmark indexes, whereas stocks heavily underweighted by mutual funds tend to have high portfolio weights in benchmark indexes. A typical stock in Decile 10 with the highest DFB has an average portfolio weight of only 3 basis points in its benchmark index, which is substantially lower than the average portfolio weight of 29 basis points in the benchmark for a typical stock in Decile 1 with the lowest DFB. We also find that most stocks in Decile 10 remain outside of mutual funds' performance benchmarks. On average, approximately two thirds of the stocks in Decile 10 are outside of benchmark indexes, whereas almost no stocks in Decile 1 are outside of benchmark indexes.

Furthermore, the results show that stocks in Decile 10 tend to be the least popular among mutual funds; they reside in the investment universe of only 34 funds. On the contrary, stocks in Decile 1 appear in the investment universe of 213 funds. On average, only 16 mutual funds hold stocks in Decile 10, compared with 36 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.

Finally, we find that stocks heavily overweighted by mutual funds tend to be relatively small with an average decile rank value of 3.3, based on NYSE market-cap decile breakpoints in ascending order. They also have a slight tendency to be winners in the previous year and have higher idiosyncratic volatilities. There exists no apparent relation between DFB and the book-to-market ratio. We should 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.

4 Information Content of DFB

In this section, we explore whether our measure of mutual funds' deviations from benchmarks contains information relevant for future stock returns. 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 provide further evidence regarding the information content of DFB by investigating the association between DFB and stock returns for different subgroups of stocks and funds, as well as the relation between DFB and corporate earnings surprises. We relate DFB to mutual fund performance and conclude this section by discussing whether outside investors can profit in real time from DFB.

4.1 *Return Forecasting Power of* DFB

To test for the return forecasting power of DFB, 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. To assess whether our results may be representative, we present both equal-weight and value-weight returns on the decile portfolios in Table III.

The first columns in Panels A (equal-weight returns) and B (value-weight returns) of Table III 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 0.74% and 0.56% per month on the equal- and value-weight basis. These returns are statistically significant, with t-statistics of 4.38 and 2.48, respectively. To examine whether the high returns on stocks heavily overweighted by mutual funds simply reflect fund managers' gambling behavior and willingness 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.[7] 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 0.66%, 0.72%, 0.58%, 0.61%, and 0.56% 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 4 and 7. 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; the value-weighted return on this portfolio is still economically meaningful but less 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. Panel A of Table IV shows how DFB relates to the excess returns on stocks in the next quarter. Consistent with the portfolio results, DFB positively relates to future excess returns in the following quarter. We also decompose DFB into two parts as follows: $DFB_t = DFB_{t-1} + \Delta DFB_t$. The idea of this decomposition is that the fresher information contained in changes in DFB could have stronger return forecasting power than the more stale information contained in the lagged level of DFB. The results in the second column show that the slope coefficient for ΔDFB_t is more than twice as large as the coefficient for DFB_{t-1} and it also dominates in terms of statistical significance.

[7] We obtain qualitatively similar results if we use a six-factor model that also includes a factor of volatilities (e.g., Ang et al., 2006).

To allow for potentially asymmetric effects of large overweights and underweights, we discretize DFB into two categorical 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. Another advantage of this discretization is that the slope coefficient for the dummy variables in the Fama and MacBeth regressions can be interpreted as quarterly returns on the portfolio of stocks in each respective decile with portfolio weights constructed such that all other control variables are zeroed out. The results in columns 3 and 4 show that stocks in Decile 1 earn significantly negative returns and stocks in Decile 10 earn significantly positive returns, even after we control for the influence of such firm characteristics as firm size, the book-to-market ratio, past one-year (from months $t-12$ to $t-1$) returns, idiosyncratic volatilities, turnover, and past one-month (month t) return.

We might think of stocks overweighted by mutual funds relative to their benchmarks as likely to exhibit high mutual fund ownership. Could the positive association between DFB and future returns simply reflect then the relation between DFB and mutual fund ownership? To address this question, we include the fraction of shares owned by mutual funds (MFO) as a control variable in our Fama and MacBeth regressions. Chen, Hong, and Stein (2002) also find that changes in the number of mutual funds that hold the stock, $\triangle Breadth$, correlate with future stock returns, so we include this variable in the regressions. The results in Column 6 of Panel A indicate that these two variables leave the return forecasting power of DFB intact.

In summary, we find strong evidence that a stock-level measure that aggregates mutual funds' deviations from benchmarks, 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.

4.2 *Informed Fund Managers or Mutual Fund Herding?*

Although consistent with the notion that mutual 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 (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 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 typical manager receives a positive signal about a stock in period t and decides to increase his portfolio weight in this stock relative to his benchmark, which results in an increase in DFB from $t-1$ to t. In the next period $t+1$, as his positive private information transmits into the stock price, return-maximizing considerations would lead him to unwind the position that he has built up to capture the gains to his information. 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.

To test these different predictions, for each quarter from 1981Q1 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. The results in Table V show 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.

We also 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. Columns 6 to 9 of Table IV show that the positive association between DFB and future excess returns concentrates for the most proximate quarter. This positive association shows no tendency to reverse for the subsequent two to four quarters. Thus, DFB appears to forecast returns due primarily to the value-relevant information that DFB aggregates from diverse mutual fund managers, as revealed through their investment decisions.

4.3 *Stock and Fund Characteristics*

To increase our confidence in this information-based story, we conduct a series of tests based on stock and fund attributes. First, if mutual funds have informational advantages about individual stocks, we expect their advantages to be greater among stocks with more firm-specific information. Also, we expect the funds' informational advantages to be more valuable when the funds have fewer competitors. To examine these conjectures, we perform two-way sorts of stocks independently on DFB and 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 mutual 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 quintiles based on DFB, and in the other dimension we sort stocks into terciles based on their attributes such as idiosyncratic volatilities or the number of mutual fund holders. Fifteen portfolio 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 stocks with higher idiosyncratic volatilities and a lower number of mutual fund investors.

Panels A and B of Table VI present the results for idiosyncratic volatilities and the number of mutual fund investors. 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 V 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 0.89% (t=5.87) on the equal-weight basis and 1.03% (t=4.11) on the value-weight basis. A similar strategy invested among stocks with low idiosyncratic volatilities generates average monthly four-factor alphas of only 0.26% (t=3.59) on the equal-weight basis and only 0.20% (t=1.59) 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 B of Table VI 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 0.89% (t=5.13) 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 0.25% (t=1.94). This difference in abnormal returns also is large and statistically significant.

We notice that this differential in equal-weight abnormal returns is less striking and statistically insignificant, which suggests that firm size also plays a role in the return forecasting power of DFB. Therefore, we conduct similar analyses based on DFB and market cap and present the results in Panel C of Table VI. The results show that the return forecasting power of DFB is the strongest among mid-cap stocks; it is pronounced and statistically significant among large-cap stocks but weak and statistically unreliable among small-cap stocks.

Second, our measure of DFB reflects the investment decisions of all active mutual funds in our sample. 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, 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.

Panels A and B Table VII show the results based on alphas from past 24 and 36 months. 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 a equal-weight monthly four-factor alpha of 0.71% (t=6.59), which is more than twice as large as the four-factor alpha of 0.31% (t=2.90) on a similar strategy based on the portfolio decisions of mutual funds with low past two-year alphas. This difference in returns is large, statistically significant, and robust to equal- and value-weighting. The results based on past three-year alphas reveal a similar pattern. 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., Tufano and Sirri, 1998; Chevalier and Ellison, 1997). If high inflows into top-performing funds induce fund managers to purchase the stocks they have over-weighted, 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. We find that stocks underweighted by top-performing funds, i.e., those likely to experience inflows, earn substantially lower returns and stocks overweighted by bottom-performing funds, i.e., those likely to encounter outflows, earn substantially higher return. In fact, the higher returns on the DFB strategy implemented on 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.

4.4 DFB *and Corporate 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 VIII 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 divide stocks into terciles based on the current quarter's earnings surprises and then group 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 VIII 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 approximately 30 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 basis points, or 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.[8]

4.5 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

[8] Our evidence is consistent with Baker, Litov, Wachter, and Wurgler (2007), 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. Our 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.

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 IX indicate that stocks in Decile 10 heavily overweighted by active funds generate high abnormal returns with a four-factor alpha of 6% 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 approxiately 34% of total active fund assets. In other words, a large four-factor alpha of 6% per year on high DFB stocks translates into a small mutual fund alpha of less than 1% per year.

Up to this point, we have found evidence consistent with the notion that mutual funds deviate from their benchmarks to exploit their informational advantages and that their deviations generate superior performance. Yet we have left unexplained whether funds make optimal portfolio decisions. For example, could a fund manager have performed better by constructing a more aggressive portfolio with larger tilts away from its benchmark?

In the model economy outlined in Appendix A, a manager's portfolio choice is governed by the desire to maximize the portfolio's performance relative to its benchmark and an aversion to taking active risks associated with deviating from that benchmark. The manager's optimal decision therefore is jointly determined by three factors: degree of risk aversion, expected returns of securities conditional on the manager's information set, and risks of securities. We lack accurate estimates of these three variables, so we cannot to provide a definitive answer to the question. The results in Table II show that the stocks with high DFB tend to be relatively small and frequently float outside the stock indexes against which mutual funds are benchmarked; on the contrary, the stocks with low DFB tend to be large and the majority of them appear in the indexes against which active funds are benchmarked. These observations lead us to conjecture that aversion to taking large active risks could have an important role in shaping the activeness of fund managers' portfolios.

In the real world, fund managers seek to maximize their compensation for the portfolio management services they provide to fund investors. Conventional industry practice rewards mutual fund managers mainly on the basis of the size of the assets under their management. Accordingly, they have incentives to grow their assets. Berk and Green (2004) thus tell an interesting story: For skilled fund managers to capitalize on their informational advantages, they combine an active portfolio that consists of stocks that generate alphas and a passive portfolio that is invested primarily in a benchmark index. In equilibrium, these skilled fund managers capture economic rents by managing a large portfolio so that investors, who have no comparative advantages in competitive capital markets, earn a return that is close to the benchmark. Although our study is not a direct test of Berk and Green's model, our evidence is consistent with their predictions about the behavior of fund managers.

5 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. With this approach, we can consider the performance of portfolios sorted according to this measure of DFB. Second, we consider results based on changes in DFB. Third, we examine the performance of portfolios sorted by DFB through different subperiods. Four, we consider conditional performance evaluation.

5.1 *Alternative Measures of* DFB

We have included 19 stock indexes widely used by practitioners as our primary universe of performance benchmarks, and for each fund, we selected for each quarter one index that minimizes the distance between stocks' weights in the fund and those in the index. 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 consist of stocks actually held by each fund. Because a mutual fund might respond to negative information about a firm by avoiding holding its shares, we include all stocks that the fund has held during the past five years in the value-weighted portfolio.[9]

Panel A of Table X reports the performance of DFB when we use these specifically tailored benchmark indexes. Consistent with the results in Table III, 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 X shows that stocks heavily overweighted by mutual funds in Decile 10 generate a monthly equal-weight four-factor alpha of 0.56%, whereas stocks heavily overweighted by mutual funds in Decile 1 earn a negative four-factor alpha of -0.37% per month. Therefore, a portfolio that buys stocks in Decile 10 and shorts stocks in Decile 1 earns a four-factor alpha of 0.93% 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 to one if the stock is overweighted by the fund and zero otherwise. Then we average this

[9] Shumway, Szefler and Yuan (2009) use a similar approach to construct benchmark portfolios for individual mutual funds.

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.

$$DFB_{i,t}^{alt} = \sum_{j=1}^{N_i} Indicator(w_{i,t}^{j} - w_{i,t}^{b} > 0)/N_i, \tag{2}$$

Panel B of Table X 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.

We finally consider 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. To summarize, the return forecasting power of DFB is insensitive to different ways of forming benchmark portfolios and robust to the exclusion of fund managers' best ideas.

5.2 *Changes in* DFB

Our results have shown that DFB captures information relevant for future returns and that the value of the information tends to dissipate after one quarter. If fund managers respond to new information by efficiently adjusting their portfolio weights, a measure based on their portfolio adjustments should relate to future returns. In this subsection, we examine this conjecture by relating changes in DFB and stock returns. The changes in

DFB contain two components: changes in a stock's weights in the mutual fund portfolio and in the benchmark index. If passive managers who track the performance of their benchmarks adjust their portfolio weights according to changes in the benchmark weights, changes in DFB should capture the active trades made by active managers.

Table XI presents the performance of portfolios sorted according to changes in DFB. Consistent with our conjecture, changes in DFB contain strong return-forecasting power. Panel A of Table XI, for example, shows that stocks with the largest increases in DFB outperform, in the subsequent quarter, stocks with the largest decreases in DFB by 1.15% per month on the equal-weighted basis. This difference is highly statistically significant, with a t-statistic of 7.79. Standard risk adjustments have virtually no effect on this return differential. Panel B further shows that value-weighted returns yield a similar pattern both qualitatively and quantitatively. These results lend further support to mutual funds' informational advantages for the stocks for which they display the most conviction.

5.3 *Subperiod Analysis*

The information environment of corporations in United States has changed over time.[10] Does this change influence mutual funds' informational advantages as an investor group? To address this question, we divide our sample into four subperiods (1980–1987, 1988–1994, 1995–2001, and 2002–2008) and consider the performance of DFB through time.

Table XII presents the performance of decile portfolios that is formed on the basis of DFB over four subperiods. Except for the first subperiod, from 1980 to 1987,[11] the

[10]For example, the U.S. Securities and Exchange Commission (SEC) instated the Regulation Fair Disclosure (Reg FD) in October 2000 to eliminate selective disclosure by firms to a subset of market participants. In the SEC release about Reg FD, its stated goal was to eliminate situations in which: "a privileged few gain an informational edge – and the ability to use that edge to profit – from their superior access to corporate insiders, rather than from their skill, acumen, or diligence."

[11]The mutual fund industry was relatively small during the early part of our sample. During 1980–

return forecasting power of DFB remains strong across time. Therefore, despite the changing information environment, active mutual funds appear to maintain a consistent edge in acquiring relevant and costly information. This evidence is consistent with the idea that mutual funds gain their informational advantages from their superior skills.

5.4 *Conditional Performance Evaluation*

Jiang, Yao, and Yu (2007) argue that mutual funds have superior market-timing ability, which translates into superior fund performance.[12] 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 a way such 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.

1987, 200 to 360 funds reported their holdings that accounted for less than 4% of the CRSP sample based on the market cap. Moreover, few benchmark indexes were available during this period, which could be another reason for the weak results.

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

Untabulated results show that the return premium on high DFB stocks remains large and significant after the adjustments for time-varying betas.

6 Conclusions

We find strong evidence that supports an informational role of actively managed mutual funds in determining security prices. Using a comprehensive sample of U.S. equity mutual funds during the period from 1980 to 2008, we find that stocks heavily overweighted by active mutual funds relative to their benchmarks strongly outperform stocks heavily underweighted by those funds. The return premium on stocks heavily overweighted by mutual funds, relative to their underweighted counterparts, reaches 0.61% per month even after adjustments for their loadings on the market, size, value, momentum, and liquidity factors; and a significant portion of this premium occurs around corporate earnings announcements. We also find that a large increase in the overweight of a stock by active funds in one quarter predicts a decline in the overweight in the next quarter, consistent with informed managers unwinding their profitable positions. These results point to an informational link between mutual fund investing and asset prices.

Our research suggests interesting avenues for further research. First, the results indicate that mutual funds acquire information that is not fully reflected in prices for those stocks about which they display the most conviction, according to their over- and underweighting decisions. But it is unclear which potential channels might enable them to gain this superior information. Recent studies by Coval and Moskowitz (2001) and Cohen, Frazzini, and Malloy (2008) make some initial progress by suggesting that geographic proximity and shared educational experiences between corporate and fund managers provide important channels for mutual fund managers to access private information. It would be interesting to connect the findings in our study to these two informational channels and explore additional networks of information flow to gain a better understanding of how information finds its way into security prices.

Second, other types of institutions, such as pension funds, banks, and insurance companies, play expanded roles in security markets. Considering the enormous resources they spend to analyze and research securities, these types of institutions might have important influences on the price discovery of financial assets. It would be interesting to explore whether portfolio decisions made by these institutions similarly contain information relevant for the behavior of future asset returns.

Appendix A: An Illustrative Interpretation of DFB

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 his portfolio while minimizing the active risk or the tracking error variance of his portfolio.[13]

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 $w_{i,j} - w_{i,j}^B$

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

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.[14]

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. Our sample of stock holdings spans the period from June 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 theseLipper 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.

[14] These assumptions are certainly restrictive. To the extent that they introduce noise into our measure of mutual funds' DFB, we expect to observe a weaker relation between DFB and future returns. Empirically though, we find strong evidence that DFB forecasts future stock returns.

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 the 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 errors 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 (2009):

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

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 calculate the number of active funds that benchmark against each of the indexes and the total assets under their management. Columns 6 and 7 report the averages of these numbers from December 2000 to September 2008. Columns 8 and 9 further show the market share for each of the indexes.

References

Baker, Malcolm, Lubomir Litov, Jessica A. Wachter, and Jeffrey Wurgler, 2007, Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements, *Journal of Financial and Quantitative Analysis*, forthcoming.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Breon-Drish, Bradyn, and Jacob S. Sagi, 2009, Do fund managers make informed asset allocation decisions?, Working paper, Vanderbilt University.

Brown, Keith C., W. V. Harlow, and Laura T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85–110.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey Kubik, 2004, Does fund size erode performance? Liquidity, organizational diseconomies and active money management, *American Economic Review* 94(5), 1276–1302.

Chen, Joseph, Harrison Hong, and Jeremy Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109(4), 811–841.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.

Cohen, Randolph B. Christopher K. Polk, and Bernhard Silli, 2010, Best ideas, Working paper, Harvard Business School.

Cremers, Martijn, and Antti Petajisto, 2009, How active is your fund managers? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of CRSP Mutual Fund Database and a comparison of the CRSP and Morningstar Mutual Fund Databases, *Journal of Finance* 56, 2415–2430.

Evans, Richard B., 2010, Mutual fund incubation, *Journal of Finance* 65, 1581-1611.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63, 1653–1678.

Fama, Eugene F., and Kenneth R. French, 2009, Luck versus skill in the cross section of mutual fund returns, *Journal of Finance*, forthcoming.

Fama, Eugene F., and James D. Macbeth, 1973, Risk and return: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.

French, Kenneth R., 2008, Presidential address: The cost of active investing, *Journal of Finance* 63, 1537–1573.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–259.

Grinblatt, Mark, and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business* 62, 393–416.

Grinblatt, Mark, and Sheridan Titman, 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* 66, 47–68.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jensen, Michael, 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389–416.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds. *Review of Financial Studies* 21, 2379–2416.

Malkiel, Burton G., 1995, Returns from investing in equity mutual funds 1971 to 1991, *Journal of Finance* 50, 549–572.

Pastor, Lubos, and Robert F. Stambaugh, 2002, Mutual fund performance and seemingly unrelated assets, *Journal of Financial Economics* 63, 313–349.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 113, 642–685.

Roll, Richard, 1992, A mean/variance analysis of tracking error, *Journal of Portfolio Management* 18, 13–22.

Sensoy, Berk A., 2009, Performance evaluation and self-designated benchmark indexes in the mutual fund industry, *Journal of Financial Economics* 92, 25–39.

Shumway, Tyler, Maciej Szefler, and Kathy Yuan, 2009, The information content of revealed beliefs in portfolio holdings, Working paper, London School of Economics.

Sias, Richard W., 2004, Institutional herding, *Review of Financial Studies* 17, 165–206.

Taliaferro, Ryan, 2009, Market timing and crash timing: Predicting aggregate market returns with mutual fund holdings, Working paper, Harvard Business School.

Wermers, Russ, 1999, Mutual fund herding and the impact on stock prices, *Journal of Finance* 54, 581–622.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses, *Journal of Finance* 55, 1655–1695.

Table A1

Summary Statistics for Benchmark Holdings

	Index Name	Index Inception Year	Source of Holdings Data	Holdings Data Starting Date	Holdings Data Ending Date	Cross-Section of 9/30/2008 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 I
Stock Holdings of Mutual Funds

Each year-end from 1980 to 2008, we calculate the number of distinct active 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 ($)
1980	196	88.01	1900	39.52	26.81	2.04
1981	197	83.05	1865	35.87	18.25	1.49
1982	202	86.40	2055	39.85	27.69	1.97
1983	225	87.22	2934	51.01	43.28	2.49
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	877	90.09	4098	69.15	643.80	6.37

Table II

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 18 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* (cross-sectionally demeaned), the average benchmark weight, the average number of funds in the stock-fund cohort, 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 (11-month cumulative return from the period t-11 to t-1), 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 also 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. The residual return volatility is the standard deviation of the residuals from a regression of the stock's daily returns on Fama and French's (1993) three factors. Stocks with prices lower than $5 at the quarter end are excluded.

Decile	*DFB* (%)	Benchmark Weights (%)	No. of Funds in the Stock-Fund Cohort	Proportion of Stocks Outside of Benchmarks (%)	Market Cap Score (1-10)	BM Score (1-10)	Pr1Yr Score (1-10)	Residual Volatility (%)
1	-0.15	0.29	213	0.00	6.75	4.60	5.95	1.94
2	-0.03	0.08	167	0.90	4.49	4.88	5.45	2.40
3	-0.00	0.05	144	8.15	3.57	4.96	5.37	2.61
4	0.04	0.03	99	23.15	2.80	5.28	5.27	2.74
5	0.09	0.04	106	31.65	3.12	5.27	5.38	2.69
6	0.14	0.04	121	27.34	3.60	5.12	5.58	2.57
7	0.20	0.05	117	27.24	3.83	5.06	5.82	2.52
8	0.29	0.05	99	30.78	3.95	4.94	6.11	2.52
9	0.44	0.05	74	40.91	3.87	4.79	6.28	2.59
10	1.01	0.03	34	67.34	3.28	4.70	6.74	2.76
D10 - D1	1.17	-0.27	-180	67.34	-3.47	0.10	0.79	0.82

Table III
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 1980Q3 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	0.67	-0.21	-0.31	-0.29	-0.30	-0.17	0.77	-0.08	0.00	-0.01	-0.01	-0.10
	(2.5)	(-2.88)	(-5.45)	(-4.72)	(-4.87)	(-3.62)	(3.25)	(-1.15)	(0.02)	(-0.24)	(-0.2)	(-3.16)
2	0.71	-0.19	-0.38	-0.22	-0.22	-0.14	0.93	0.05	-0.08	0.01	0.01	0.04
	(2.32)	(-1.57)	(-5.6)	(-3.23)	(-3.14)	(-2.78)	(3.44)	(0.66)	(-1.26)	(0.08)	(0.11)	(0.61)
3	0.77	-0.16	-0.35	-0.15	-0.13	-0.09	0.95	0.04	-0.08	0.01	0.03	0.07
	(2.35)	(-1.11)	(-4.51)	(-2.08)	(-1.87)	(-1.4)	(3.36)	(0.47)	(-0.9)	(0.17)	(0.41)	(1.19)
4	0.82	-0.07	-0.23	-0.09	-0.07	-0.09	0.91	0.02	-0.09	0.02	0.03	-0.04
	(2.6)	(-0.45)	(-2.21)	(-0.92)	(-0.74)	(-1.08)	(3.19)	(0.22)	(-1.16)	(0.24)	(0.37)	(-0.53)
5	0.89	-0.01	-0.18	-0.06	-0.04	-0.05	0.95	0.02	-0.10	0.04	0.04	0.02
	(2.81)	(-0.05)	(-2.29)	(-0.72)	(-0.53)	(-0.79)	(3.21)	(0.19)	(-1.09)	(0.43)	(0.36)	(0.29)
6	0.99	0.07	-0.12	0.00	0.03	0.06	0.95	0.02	-0.10	-0.03	-0.01	0.02
	(3.08)	(0.45)	(-1.49)	(0.04)	(0.35)	(1.12)	(3.28)	(0.18)	(-1.45)	(-0.33)	(-0.13)	(0.36)
7	1.10	0.17	0.00	0.09	0.13	0.13	1.01	0.09	0.03	0.08	0.11	0.06
	(3.4)	(1.16)	(0.06)	(1.21)	(1.79)	(2.12)	(3.58)	(1.27)	(0.4)	(1.16)	(1.67)	(1.16)
8	1.04	0.09	-0.02	-0.03	0.01	0.05	0.93	-0.01	-0.03	-0.08	-0.07	-0.00
	(3.12)	(0.6)	(-0.25)	(-0.41)	(0.12)	(0.8)	(3.1)	(-0.13)	(-0.38)	(-0.86)	(-0.78)	(-0.02)
9	1.23	0.28	0.23	0.14	0.16	0.20	1.28	0.31	0.43	0.22	0.23	0.29
	(3.6)	(1.74)	(3.13)	(2.05)	(2.33)	(3.01)	(3.84)	(2.17)	(3.38)	(1.83)	(1.88)	(2.92)
10	1.40	0.45	0.41	0.29	0.31	0.39	1.33	0.36	0.57	0.28	0.30	0.31
	(3.93)	(2.48)	(4.39)	(3.28)	(3.49)	(5.58)	(3.73)	(2.1)	(3.54)	(2.11)	(2.29)	(2.2)
D10-D1	0.74***	0.66***	0.72***	0.58***	0.61***	0.56***	0.56**	0.44**	0.57***	0.29*	0.31**	0.41***
	(4.38)	(4.07)	(6.44)	(5.28)	(5.53)	(5.99)	(2.48)	(2.2)	(3.26)	(1.94)	(2.11)	(2.73)
D9-D2	0.51***	0.48***	0.61***	0.36***	0.38***	0.34***	0.35*	0.26	0.51***	0.21	0.22	0.25**
	(4.31)	(4.02)	(6.04)	(3.77)	(3.8)	(4.13)	(1.93)	(1.5)	(3.31)	(1.51)	(1.54)	(2.01)

Table IV

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

This table presents the relation between mutual funds' deviations from benchmarks, *DFB*, at each quarter end and the cumulative market-adjusted returns over the subsequent 4 quarters, controlling for other stock characteristics, following Fama and MacBeth's (1973) procedure. 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 equal one if the stock is in Decile 1 with the lowest *DFB* and 0 otherwise. Market cap, the book-to-market ratio, past one year return, residual volatility and stock turnover ratio are defined as previously. *Pr1Yr* is the past one year return and *Pr1Mt* is the past one month return. *MFO* is the fraction of shares held by mutual funds, and the change in the breadth of ownership (Δ*Breadth*) is the quarterly 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. The *t*-statistics are computed using the Newey-West (1987) standard errors. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

	R_{t+1}						$R_{t\sim t+2}$	$R_{t\sim t+3}$	$R_{t\sim t+4}$
	1	2	3	4	5	6	7	8	9
DFB_t	2.5569***								
	(4.68)								
DFB_{t-1}		1.9438***							
		(3.78)							
Δ DFB_t		5.0243***							
		(5.34)							
$D1_t$			-0.0100**	-0.0087***	-0.0104**	-0.0087***	-0.0098**	-0.0110*	-0.0099
			(-2.09)	(-3.26)	(-2.07)	(-3.10)	(-2.47)	(-1.72)	(-1.14)
$D10_t$			0.0178***	0.0142***	0.0184***	0.0142***	0.0231***	0.0299***	0.0320***
			(4.53)	(3.52)	(4.54)	(3.60)	(3.47)	(3.22)	(2.84)
Market Cap$_t$				-0.0028*		-0.0029*	-0.0054	-0.0079	-0.0100
				(-1.70)		(-1.82)	(-1.54)	(-1.36)	(-1.23)
BM_t				0.0038*		0.0036*	0.0081**	0.0121**	0.0160**
				(1.86)		(1.81)	(2.17)	(2.35)	(2.34)
$Pr1Yr_t$				0.0283***		0.0277***	0.0429***	0.0467***	0.0454***
				(6.16)		(6.20)	(5.97)	(5.16)	(4.30)
Residual Vol				-0.7734***		-0.7773***	-1.1583***	-1.4554**	-1.6454**
				(-3.23)		(-3.31)	(-2.68)	(-2.42)	(-2.18)
$Turnover_t$				-0.0143**		-0.0138*	-0.0313**	-0.0461**	-0.0560*
				(-2.03)		(-1.96)	(-2.01)	(-2.01)	(-1.83)
Pr1Mt				-0.0156		-0.0171	0.0235	0.0657**	0.1066***
				(-1.26)		(-1.42)	(1.16)	(2.25)	(2.84)
MFO_t					-0.0287	-0.0042	-0.0023	-0.0127	-0.0202
					(-1.43)	(-0.26)	(-0.07)	(-0.29)	(-0.38)
$\Delta Breadth_t$					0.3080**	0.1362	0.3281*	0.5318**	0.5595*
					(2.01)	(1.39)	(1.92)	(2.24)	(1.86)
Intercept	0.0009	0.0012	0.0024	0.0318**	0.0044	0.0333**	0.0562*	0.0801	0.0988
	(0.20)	(0.27)	(0.40)	(2.08)	(0.68)	(2.27)	(1.76)	(1.55)	(1.38)
Avg Adj-R^2	0.56%	0.62%	0.60%	7.00%	1.09%	7.19%	7.09%	6.86%	6.54%

Table V

Dynamics of Changes in *DFB*, Δ*DFB*

This table presents the dynamic relation between consecutive changes in *DFB*. Specifically, at the end of each quarter from 1981Q1 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_t, and a bunch of stock characteristics. 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.

	ΔDFB_{t+1}		
	1	2	3
Intercept	-0.0001	0.0002**	0.0011**
	(-0.97)	(2.52)	(2.61)
ΔDFB_t	-0.3644***	-0.2739***	-0.2703***
	(-14.28)	(-12.50)	(-12.79)
DFB_t		-0.1583***	-0.1728***
		(-10.69)	(-11.20)
Market Cap$_t$			-0.0001***
			(-3.09)
BM_t			-0.0000
			(-0.30)
Pr1Yr$_t$			0.0000
			(0.98)
Residual Vol			-0.0036
			(-1.13)
Turnover$_t$			0.0002
			(1.24)
Avg Adj-R^2	17.31%	25.18%	26.56%

Table VI

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 1980Q3 to 2008Q3, we sort stocks independently based on their characteristics into terciles and *DFB* into quintiles. Fifteen portfolios thus form from these double sorts, with the portfolio (1,1) contains stocks with the lowest value of the sorting variables and vice versa. The characteristics include residual volatilities (Panel A), the number of funds that hold the stock (Panel B), and market cap (Panel C). Then we calculate the average monthly equal-weight and value-weight returns for each of 15 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: Residual Vol	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.02	0.18	0.16	0.22	0.24	0.26***	-0.02	0.08	0.01	0.04	0.18	0.20
	(-0.24)	(1.75)	(1.6)	(2.28)	(2.35)	(3.59)	(-0.32)	(0.8)	(0.13)	(0.41)	(1.61)	(1.59)
2	-0.25	0.04	0.14	0.11	0.31	0.56***	-0.16	-0.11	-0.12	0.07	0.39	0.55***
	(-3.22)	(0.48)	(1.53)	(1.14)	(2.88)	(4.86)	(-1.16)	(-1)	(-1.01)	(0.61)	(2.62)	(2.85)
3	-0.87	-0.51	-0.30	-0.24	0.02	0.89***	-0.88	-0.43	-0.39	-0.21	0.15	1.03***
	(-6.44)	(-3.8)	(-2.76)	(-2.14)	(0.17)	(5.87)	(-4.59)	(-2.53)	(-2.55)	(-1.08)	(0.56)	(4.11)
T3-T1	-0.85***	-0.69***	-0.46***	-0.46***	-0.22	0.62***	-0.85***	-0.51**	-0.41**	-0.25	-0.03	0.83***
	(-4.56)	(-3.71)	(-2.84)	(-2.86)	(-1.34)	(4.02)	(-3.86)	(-2.15)	(-2.02)	(-1.1)	(-0.09)	(3.09)
Panel B: # of Funds	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.43	-0.18	-0.10	0.05	0.13	0.57***	-0.70	-0.13	-0.06	0.15	0.19	0.89***
	(-3.8)	(-1.48)	(-0.94)	(0.41)	(1.34)	(3.99)	(-5.52)	(-1.09)	(-0.5)	(0.97)	(1.58)	(5.13)
2	-0.22	-0.17	0.02	0.02	0.31	0.53***	-0.19	-0.15	0.08	-0.04	0.57	0.77***
	(-2.8)	(-1.83)	(0.26)	(0.25)	(3.3)	(4.56)	(-2.2)	(-1.79)	(1.04)	(-0.27)	(3.33)	(4.22)
3	-0.16	-0.02	-0.10	0.03	0.30	0.46***	0.01	0.04	-0.10	-0.02	0.25	0.25*
	(-2.38)	(-0.2)	(-1.05)	(0.36)	(2.17)	(3.31)	(0.17)	(0.51)	(-1.17)	(-0.3)	(2.33)	(1.94)
T3-T1	0.27**	0.16	0.00	-0.02	0.16	-0.11	0.70***	0.17	-0.03	-0.17	0.06	-0.64***
	(1.97)	(1)	(0.02)	(-0.13)	(0.87)	(-0.6)	(5.5)	(1.05)	(-0.19)	(-0.97)	(0.38)	(-3.44)
Panel C: Market Cap	1	2	3	4	5	Q5-Q1	1	2	3	4	5	Q5-Q1
1	-0.12	-0.17	-0.05	0.04	0.23	0.35	-0.05	-0.19	-0.03	0.05	0.28	0.33
	(-0.53)	(-1.38)	(-0.41)	(0.32)	(1.98)	(1.54)	(-0.23)	(-1.7)	(-0.34)	(0.41)	(2.51)	(1.52)
2	-0.20	-0.12	-0.08	0.05	0.37	0.58***	-0.20	-0.10	-0.02	0.07	0.38	0.58***
	(-2.18)	(-1.41)	(-0.99)	(0.57)	(3.19)	(3.89)	(-2.15)	(-1.16)	(-0.21)	(0.72)	(2.88)	(3.56)
3	-0.22	-0.06	0.01	-0.03	0.30	0.53***	-0.01	0.02	-0.02	-0.03	0.28	0.29**
	(-4.27)	(-0.83)	(0.19)	(-0.33)	(1.89)	(3.11)	(-0.22)	(0.29)	(-0.27)	(-0.51)	(2.44)	(2.2)
T3-T1	-0.11	0.11	0.06	-0.07	0.07	0.18	0.04	0.21	0.01	-0.08	-0.00	-0.04
	(-0.45)	(0.76)	(0.47)	(-0.43)	(0.31)	(0.62)	(0.2)	(1.58)	(0.11)	(-0.57)	(-0.01)	(-0.17)

Table VII

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 past fund alphas. We estimate fund alphas as intercepts from rolling-window regressions of excess net fund returns on the market, size, value, and momentum factors in the past two (Panel A) and three years (Panel B). Specifically, at the end of each quarter from 1983Q4 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 deciles 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. 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)				
Fund Alpha (past 24 months)	Deciles by *DFB*	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
Bottom	1	0.78	-0.10	-0.16	-0.19	-0.20	0.77	-0.06	0.03	0.01	0.01
		(2.86)	(-1.42)	(-2.87)	(-3.14)	(-3.29)	(3.15)	(-0.9)	(0.75)	(0.28)	(0.27)
	10	1.22	0.29	0.21	0.12	0.15	1.08	0.15	0.27	0.06	0.06
		(3.48)	(1.68)	(2.24)	(1.43)	(1.7)	(3.34)	(1.07)	(1.9)	(0.46)	(0.45)
	D10-D1	0.44***	0.38**	0.37***	0.31***	0.35***	0.31	0.22	0.23	0.05	0.05
		(2.76)	(2.41)	(3.13)	(2.9)	(3.15)	(1.63)	(1.24)	(1.54)	(0.34)	(0.33)
Medium	1	0.71	-0.16	-0.24	-0.27	-0.27	0.75	-0.08	0.01	0.01	0.01
		(2.59)	(-2.27)	(-3.86)	(-4)	(-4.04)	(3.09)	(-1.15)	(0.26)	(0.14)	(0.2)
	10	1.33	0.40	0.32	0.25	0.27	1.28	0.35	0.50	0.28	0.28
		(3.9)	(2.53)	(3.83)	(3.17)	(3.38)	(3.89)	(2.59)	(3.78)	(2.31)	(2.24)
	D10-D1	0.61***	0.56***	0.56***	0.52***	0.53***	0.53***	0.43***	0.49***	0.28**	0.27**
		(4.32)	(4.06)	(5.39)	(5.07)	(5.29)	(2.88)	(2.6)	(3.36)	(2)	(1.97)
Top	1	0.67	-0.19	-0.30	-0.30	-0.31	0.76	-0.07	-0.01	-0.01	-0.01
		(2.55)	(-2.75)	(-4.87)	(-4.35)	(-4.44)	(3.22)	(-1.07)	(-0.11)	(-0.26)	(-0.21)
	10	1.49	0.53	0.56	0.41	0.43	1.36	0.37	0.68	0.43	0.47
		(4.07)	(2.97)	(6.11)	(4.74)	(5)	(3.45)	(1.92)	(3.65)	(2.55)	(2.69)
	D10-D1	0.82***	0.72***	0.86***	0.71***	0.74***	0.60**	0.44**	0.69***	0.45**	0.48**
		(4.45)	(4.17)	(7.97)	(6.59)	(6.88)	(2.39)	(2.04)	(3.31)	(2.27)	(2.38)
Top-Bottom	1	-0.11*	-0.09	-0.14**	-0.12**	-0.11*	-0.02	-0.01	-0.04	-0.03	-0.02
		(-1.87)	(-1.56)	(-2.25)	(-1.98)	(-1.93)	(-0.49)	(-0.23)	(-1.26)	(-0.78)	(-0.69)
	10	0.27***	0.25**	0.35***	0.28***	0.28***	0.28	0.22	0.42**	0.37**	0.41**
		(2.94)	(2.57)	(3.96)	(3.71)	(3.7)	(1.63)	(1.3)	(2.3)	(2.06)	(2.09)
	D10-D1	0.38***	0.34**	0.49***	0.40***	0.39***	0.30	0.23	0.46**	0.40**	0.43**
		(2.87)	(2.48)	(3.72)	(3.42)	(3.4)	(1.53)	(1.19)	(2.26)	(1.97)	(2)

Panel B: Grouping Funds into Terciles Based on Past Three-Year Alpha

Sorting Variable		Panel A: EW Post-Ranking Portfolio Return					Panel B: VW Post-Ranking Portfolio Return				
Fund Alpha (past 24 months)	Deciles by Avg Excess Weight	Average Return (%/month)	CAPM Alpha (%/month)	FF Alpha (%/month)	Carhart Alpha (%/month)	Pastor & Stambaugh Alpha (%/month)	Average Return (%/month)	CAPM Alpha (%/month)	FF Alpha (%/month)	Carhart Alpha (%/month)	Pastor & Stambaugh Alpha (%/month)
Bottom	1	0.79 (2.81)	-0.13 (-1.82)	-0.18 (-3.12)	-0.19 (-3.09)	-0.20 (-3.17)	0.81 (3.19)	-0.06 (-0.85)	0.02 (0.49)	0.02 (0.31)	0.02 (0.37)
	10	1.32 (3.75)	0.34 (2.01)	0.29 (3.4)	0.18 (2.15)	0.20 (2.29)	1.29 (4.04)	0.31 (2.4)	0.44 (3.68)	0.19 (1.43)	0.19 (1.39)
	D10-D1	0.53*** (3.57)	0.47*** (3.14)	0.47*** (4.42)	0.37*** (3.55)	0.40*** (3.66)	0.47*** (2.71)	0.38** (2.28)	0.42*** (3.11)	0.17 (1.18)	0.17 (1.15)
Medium	1	0.77 (2.71)	-0.15 (-1.97)	-0.22 (-3.65)	-0.25 (-3.94)	-0.26 (-4.08)	0.81 (3.23)	-0.06 (-0.84)	0.02 (0.52)	0.01 (0.29)	0.01 (0.28)
	10	1.39 (3.94)	0.40 (2.39)	0.34 (4.05)	0.25 (3.13)	0.27 (3.41)	1.42 (4.3)	0.45 (3.24)	0.60 (4.51)	0.34 (2.98)	0.36 (3.06)
	D10-D1	0.62*** (4.16)	0.55*** (3.74)	0.56*** (5.08)	0.50*** (4.91)	0.53*** (5.28)	0.61*** (3.33)	0.51*** (2.98)	0.57*** (3.93)	0.32** (2.48)	0.34** (2.57)
Top	1	0.71 (2.67)	-0.18 (-2.53)	-0.28 (-4.36)	-0.29 (-4.39)	-0.30 (-4.51)	0.81 (3.33)	-0.05 (-0.82)	0.01 (0.12)	-0.01 (-0.23)	-0.01 (-0.14)
	10	1.50 (4.1)	0.50 (2.75)	0.53 (5.72)	0.39 (4.44)	0.41 (4.64)	1.44 (3.67)	0.42 (2.18)	0.68 (3.55)	0.38 (2.23)	0.41 (2.35)
	D10-D1	0.78*** (4.19)	0.68*** (3.83)	0.80*** (7.29)	0.68*** (6.13)	0.71*** (6.33)	0.63** (2.48)	0.48** (2.14)	0.67*** (3.2)	0.39** (2.01)	0.42** (2.11)
Top-Bottom	1	-0.08 (-1.18)	-0.05 (-0.76)	-0.10 (-1.41)	-0.09 (-1.43)	-0.10 (-1.46)	-0.00 (-0.08)	0.01 (0.3)	-0.02 (-0.63)	-0.03 (-0.92)	-0.03 (-0.88)
	10	0.17** (2.34)	0.16** (2.01)	0.24*** (3.36)	0.21*** (3.15)	0.22*** (3.23)	0.16 (1.09)	0.11 (0.79)	0.23* (1.68)	0.19 (1.39)	0.22 (1.57)
	D10-D1	0.25** (2.18)	0.21* (1.72)	0.33*** (3.04)	0.31*** (2.85)	0.32*** (2.92)	0.16 (0.98)	0.10 (0.64)	0.25 (1.64)	0.21 (1.43)	0.25 (1.58)

Table VIII

DFB and Future Earnings News

This table presents the forecasting power of *DFB* for subsequent earnings surprises. At the end of each quarter from 1980Q3 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. The difference in earnings and stock price are both adjusted for stock splits using the CRSP cumulative share and price adjustment factors, so they are truly comparable. Stocks with prices lower than $5 at the quarter end are excluded. The *t*-statistics are computed using the Newey-West 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 IX

DFB and Mutual Fund Performance

This table relates the aggregate mutual fund performance to the performance of *DFB*. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into deciles, based on *DFB*, in ascending order and compute the aggregate fund dollar holdings and the average monthly holdings-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. 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-Weight Post-Ranking Portfolio Return (%/month)				
Decile	% of Aggregate Fund Investments	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	33.79%	0.80	-0.08	0.00	-0.02	-0.02
		(3.16)	(-1.23)	(0.09)	(-0.4)	(-0.4)
2	7.38%	1.08	0.18	0.05	0.14	0.14
		(3.81)	(1.88)	(0.54)	(1.49)	(1.43)
3	5.46%	1.03	0.10	-0.03	0.05	0.07
		(3.49)	(0.86)	(-0.24)	(0.55)	(0.68)
4	3.45%	0.97	0.05	-0.06	0.04	0.05
		(3.06)	(0.45)	(-0.56)	(0.33)	(0.42)
5	4.57%	1.02	0.07	-0.06	0.10	0.11
		(3.29)	(0.51)	(-0.53)	(0.84)	(0.84)
6	6.60%	1.03	0.07	-0.07	0.05	0.06
		(3.31)	(0.62)	(-0.69)	(0.44)	(0.59)
7	8.66%	1.12	0.17	0.11	0.17	0.20
		(3.67)	(1.77)	(1.25)	(1.83)	(2.31)
8	9.74%	1.04	0.08	0.05	0.02	0.04
		(3.3)	(0.68)	(0.52)	(0.16)	(0.38)
9	11.04%	1.38	0.40	0.49	0.32	0.35
		(4.2)	(2.95)	(4.32)	(2.95)	(3.36)
10	9.30%	1.57	0.56	0.81	0.50	0.55
		(3.95)	(2.61)	(3.81)	(2.98)	(3.34)
D10-D1		0.77***	0.64***	0.80***	0.52***	0.57***
		(2.92)	(2.68)	(3.64)	(2.82)	(3.17)
D9-D2		0.30*	0.22	0.44***	0.18	0.22
		(1.81)	(1.34)	(3.2)	(1.33)	(1.62)

Table X

Alternative Measure of *DFB* and Future Stock Returns

This table presents the performance of decile portfolios formed on *DFB* calculated using alternative measures of *DFB*. Panel A uses an alternative set of benchmark index. At the end of each quarter from 1980Q3 to 2008Q3, we select for each mutual fund a benchmark portfolio containing stocks that are being or have been held by the fund in the past five years. 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 2. 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

	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	0.53	-0.46	-0.50	-0.37	-0.40	0.83	-0.11	-0.02	-0.00	-0.00
	(1.73)	(-5.03)	(-6.43)	(-5.17)	(-5.45)	(3.3)	(-1.75)	(-0.6)	(-0.05)	(-0.05)
2	0.74	-0.20	-0.38	-0.27	-0.26	0.72	-0.27	-0.35	-0.12	-0.12
	(2.27)	(-1.21)	(-4.23)	(-2.88)	(-2.65)	(2.42)	(-2.76)	(-3.38)	(-1.13)	(-1.1)
3	0.80	-0.12	-0.32	-0.17	-0.14	0.75	-0.23	-0.31	-0.13	-0.14
	(2.5)	(-0.7)	(-3.23)	(-1.85)	(-1.54)	(2.58)	(-2.21)	(-3.37)	(-1.58)	(-1.62)
4	0.94	-0.04	-0.25	-0.08	-0.06	0.95	-0.03	-0.16	-0.04	-0.03
	(2.9)	(-0.27)	(-3.19)	(-1.08)	(-0.83)	(3.35)	(-0.37)	(-2.14)	(-0.55)	(-0.44)
5	0.93	-0.06	-0.26	-0.07	-0.06	0.91	-0.05	-0.18	-0.13	-0.13
	(2.93)	(-0.39)	(-3.63)	(-1.02)	(-0.85)	(3.38)	(-0.63)	(-2.33)	(-1.69)	(-1.62)
6	1.03	0.03	-0.17	-0.05	-0.03	1.08	0.11	-0.01	0.02	0.02
	(3.18)	(0.21)	(-2.33)	(-0.72)	(-0.45)	(3.93)	(1.3)	(-0.21)	(0.24)	(0.29)
7	1.13	0.13	-0.03	0.02	0.04	1.12	0.16	0.06	0.06	0.07
	(3.5)	(0.96)	(-0.45)	(0.3)	(0.58)	(4.14)	(1.9)	(0.75)	(0.78)	(0.82)
8	1.17	0.18	0.04	0.04	0.07	1.24	0.28	0.19	0.10	0.12
	(3.75)	(1.36)	(0.57)	(0.53)	(0.98)	(4.61)	(3.31)	(2.71)	(1.44)	(1.67)
9	1.36	0.35	0.25	0.16	0.20	1.39	0.42	0.37	0.17	0.19
	(4.22)	(2.58)	(3.36)	(2.07)	(2.69)	(4.94)	(4.34)	(4.5)	(2.29)	(2.69)
10	1.86	0.82	0.77	0.56	0.60	1.90	0.89	0.95	0.60	0.62
	(5.22)	(4.83)	(8.31)	(6.32)	(7.06)	(5.5)	(5.62)	(6.1)	(4.5)	(4.77)
D10-D1	1.32***	1.28***	1.27***	0.94***	1.00***	1.08***	1.00***	0.97***	0.60***	0.62***
	(8.34)	(7.72)	(9.01)	(7.38)	(8.24)	(5.15)	(5.1)	(5.62)	(3.89)	(4.09)
D9-D2	0.62***	0.55***	0.63***	0.43***	0.46***	0.67***	0.69***	0.73***	0.29**	0.31**
	(5.83)	(4.77)	(5.25)	(3.3)	(3.44)	(5.26)	(5.34)	(4.7)	(2)	(2.23)

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

	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	0.49 (1.53)	-0.41 (-2.9)	-0.58 (-5.73)	-0.39 (-3.91)	-0.40 (-4.2)	-0.35 (-4.08)	0.56 (2.06)	-0.29 (-2.7)	-0.49 (-5.78)	-0.34 (-3.99)	-0.35 (-4.1)	-0.27 (-4.28)
2	0.79 (2.56)	-0.13 (-1)	-0.34 (-4.14)	-0.13 (-1.65)	-0.13 (-1.71)	-0.09 (-1.45)	0.86 (3.44)	0.00 (0.03)	-0.18 (-2.25)	-0.08 (-1.05)	-0.09 (-1.27)	-0.05 (-0.81)
3	0.93 (2.96)	-0.02 (-0.19)	-0.20 (-2.81)	-0.05 (-0.63)	-0.04 (-0.47)	0.03 (0.58)	0.93 (3.53)	0.03 (0.32)	-0.09 (-1.19)	-0.04 (-0.52)	-0.05 (-0.65)	-0.00 (-0.06)
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	0.94 (2.88)	0.05 (0.41)	-0.02 (-0.29)	0.03 (0.46)	0.05 (0.76)	0.11 (2.03)	0.86 (3.15)	0.03 (0.37)	0.05 (0.68)	0.00 (0.03)	0.01 (0.11)	0.02 (0.42)
7	1.16 (3.59)	0.20 (1.47)	0.09 (1.48)	0.10 (1.58)	0.13 (2.07)	0.15 (3.09)	1.11 (3.77)	0.18 (2.27)	0.20 (2.48)	0.19 (2.39)	0.20 (2.52)	0.11 (1.32)
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)

Table XI
Changes in *DFB* and Future Stock Returns

This table presents the performance of decile portfolios formed on the changes in *DFB* between adjacent quarters. At the end of each quarter from 1980Q4 to 2008Q3, we sort stocks into deciles in ascending order based on the changes in *DFB* over the quarter 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. 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: 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	0.48	-0.49	-0.56	-0.53	-0.51	0.44	-0.48	-0.35	-0.51	-0.50
	(1.32)	(-3.15)	(-4.99)	(-4.65)	(-4.24)	(1.42)	(-4.2)	(-2.85)	(-3.93)	(-3.89)
2	0.57	-0.37	-0.50	-0.42	-0.39	0.47	-0.44	-0.42	-0.43	-0.43
	(1.7)	(-2.76)	(-6.16)	(-5.2)	(-4.78)	(1.62)	(-4.75)	(-4.64)	(-4.7)	(-4.58)
3	0.65	-0.27	-0.45	-0.36	-0.34	0.72	-0.18	-0.23	-0.22	-0.21
	(2.03)	(-2.23)	(-6.23)	(-4.74)	(-4.41)	(2.63)	(-2.19)	(-2.87)	(-2.4)	(-2.29)
4	0.68	-0.22	-0.42	-0.32	-0.31	0.89	0.01	-0.05	-0.04	-0.05
	(2.2)	(-1.71)	(-6.18)	(-5.09)	(-4.99)	(3.32)	(0.13)	(-0.61)	(-0.51)	(-0.58)
5	0.82	-0.04	-0.25	-0.16	-0.16	0.94	0.07	-0.07	0.03	0.03
	(2.76)	(-0.26)	(-3.02)	(-2.15)	(-2.27)	(3.57)	(0.77)	(-0.86)	(0.39)	(0.34)
6	0.98	0.11	-0.06	0.07	0.08	0.99	0.11	-0.01	0.05	0.05
	(3.41)	(0.83)	(-0.73)	(0.77)	(0.95)	(3.94)	(1.3)	(-0.11)	(0.59)	(0.51)
7	1.06	0.15	-0.03	0.13	0.15	1.07	0.19	0.09	0.17	0.16
	(3.53)	(1.09)	(-0.44)	(1.52)	(1.76)	(4.05)	(2.43)	(1.15)	(2.42)	(2.13)
8	1.25	0.33	0.17	0.27	0.30	1.18	0.30	0.23	0.28	0.29
	(3.96)	(2.34)	(2.23)	(3.58)	(4.1)	(4.71)	(3.35)	(2.65)	(3.17)	(3.28)
9	1.47	0.53	0.46	0.46	0.50	1.42	0.54	0.54	0.60	0.61
	(4.58)	(3.51)	(5.54)	(5.69)	(6.28)	(5.57)	(5.86)	(6.23)	(6.62)	(6.75)
10	1.63	0.67	0.69	0.53	0.54	1.49	0.57	0.80	0.72	0.75
	(4.55)	(3.42)	(7.04)	(5.81)	(5.99)	(4.97)	(3.4)	(5.19)	(4.67)	(4.7)
D10-D1	1.15***	1.16***	1.25***	1.06***	1.05***	1.05***	1.05***	1.15***	1.23***	1.25***
	(7.79)	(7.58)	(8.14)	(6.96)	(6.76)	(5.19)	(5)	(5.18)	(5.28)	(5.37)
D9-D2	0.90***	0.90***	0.95***	0.88***	0.88***	0.95***	0.98***	0.96***	1.03***	1.04***
	(8.49)	(8.26)	(8.6)	(7.72)	(7.44)	(6.35)	(6.5)	(6.74)	(7.04)	(7.01)

Table XII
Return Predictive Power of *DFB* across Subperiods

This table presents the performance of decile portfolios formed on *DFB* over four 7-year periods: 1980–1987, 1988–1994, 1995–2001, and 2002–2008. At the end of each quarter from 1980Q3 to 2008Q3, we sort stocks into deciles in ascending order based on *DFB* and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter for the four subperiods. 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: 1980–1987

	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	1.12	-0.03	-0.22	-0.18	-0.20	1.22	0.08	0.03	-0.00	-0.01
	(2.02)	(-0.26)	(-1.8)	(-1.32)	(-1.5)	(2.35)	(0.89)	(0.43)	(-0.05)	(-0.23)
2	1.25	0.09	-0.10	-0.00	-0.02	1.33	0.16	-0.00	0.08	0.07
	(1.93)	(0.38)	(-0.94)	(-0.02)	(-0.17)	(2.2)	(1.09)	(-0.01)	(0.6)	(0.55)
9	1.35	0.12	0.31	0.31	0.32	1.18	-0.06	0.18	0.15	0.17
	(1.88)	(0.54)	(2.56)	(2.66)	(2.6)	(1.79)	(-0.5)	(1.46)	(1.15)	(1.15)
10	1.35	0.10	0.31	0.24	0.23	1.16	-0.09	0.26	0.09	0.08
	(1.81)	(0.47)	(2.44)	(1.95)	(1.87)	(1.62)	(-0.53)	(1.63)	(0.56)	(0.46)
D10-D1	0.23	0.14	0.52***	0.42**	0.42**	-0.06	-0.17	0.23	0.10	0.09
	(0.84)	(0.61)	(3.12)	(2.34)	(2.39)	(-0.21)	(-0.81)	(1.32)	(0.48)	(0.44)
D9-D2	0.10	0.03	0.42**	0.31*	0.34*	-0.15	-0.22	0.19	0.08	0.09
	(0.52)	(0.18)	(2.53)	(1.81)	(1.82)	(-0.77)	(-1.15)	(0.98)	(0.4)	(0.44)

Panel B: 1988–1994

	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	0.93	-0.07	-0.13	-0.11	-0.12	1.01	0.03	0.04	0.05	0.04
	(2.26)	(-0.5)	(-1.36)	(-1.04)	(-1.17)	(3.48)	(0.27)	(0.7)	(0.83)	(0.62)
2	0.93	-0.14	-0.20	-0.15	-0.17	1.07	0.01	-0.05	0.02	-0.00
	(1.79)	(-0.59)	(-2.59)	(-1.72)	(-2.06)	(2.48)	(0.09)	(-0.64)	(0.17)	(-0.05)
9	1.29	0.12	0.20	0.16	0.19	1.19	0.03	0.12	0.00	0.05
	(2.26)	(0.49)	(2.19)	(1.63)	(1.82)	(2.53)	(0.15)	(0.97)	(0.01)	(0.47)
10	1.48	0.27	0.36	0.28	0.31	1.62	0.35	0.49	0.36	0.42
	(2.32)	(0.87)	(2.93)	(2.22)	(2.44)	(2.83)	(1.75)	(3.33)	(2.12)	(2.29)
D10-D1	0.55*	0.34	0.49***	0.39**	0.43**	0.61*	0.32	0.45***	0.32	0.39*
	(1.68)	(1.2)	(3.25)	(2.32)	(2.46)	(1.67)	(1.22)	(2.65)	(1.57)	(1.83)
D9-D2	0.36**	0.27	0.40***	0.31**	0.36***	0.13	0.02	0.18	-0.02	0.06
	(2.1)	(1.56)	(3.29)	(2.25)	(2.68)	(0.58)	(0.07)	(1.14)	(-0.11)	(0.37)

Table XI-continued

Panel C: 1995–2001

	EW Post-Ranking Portfolio Return					VW Post-Ranking Portfolio Return				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.75	-0.50	-0.58	-0.53	-0.52	1.09	-0.13	0.01	-0.04	-0.03
	(1.42)	(-2.58)	(-4.09)	(-3.25)	(-3.14)	(2.07)	(-0.71)	(0.13)	(-0.33)	(-0.24)
2	0.77	-0.52	-0.71	-0.36	-0.37	1.13	-0.05	-0.30	-0.11	-0.13
	(1.3)	(-1.62)	(-4.41)	(-2.41)	(-2.42)	(2.23)	(-0.22)	(-1.83)	(-0.66)	(-0.8)
9	1.61	0.30	0.26	0.10	0.13	2.48	1.00	1.20	0.72	0.73
	(2.28)	(0.58)	(1.19)	(0.55)	(0.69)	(3.15)	(2.05)	(3.08)	(1.97)	(1.95)
10	1.96	0.62	0.58	0.47	0.50	2.03	0.51	0.86	0.29	0.29
	(2.66)	(1.14)	(2.42)	(2.1)	(2.17)	(2.24)	(0.95)	(1.87)	(0.88)	(0.91)
D10-D1	1.21***	1.12**	1.16***	1.00***	1.01***	0.94	0.63	0.85*	0.33	0.31
	(2.84)	(2.51)	(3.89)	(3.27)	(3.27)	(1.33)	(1.05)	(1.71)	(0.89)	(0.91)
D9-D2	0.84**	0.81**	0.97***	0.46**	0.50**	1.36**	1.05*	1.50***	0.83**	0.86**
	(2.38)	(2.28)	(3.44)	(2.13)	(2.2)	(2.29)	(1.85)	(3.58)	(2.24)	(2.27)

Panel D: 2002–2008

	EW Post-Ranking Portfolio Return					VW Post-Ranking Portfolio Return				
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	-0.15	-0.23	-0.43	-0.44	-0.46	-0.24	-0.34	-0.20	-0.16	-0.12
	(-0.26)	(-1.86)	(-4.58)	(-4.02)	(-4.37)	(-0.49)	(-2.96)	(-1.89)	(-1.77)	(-1.32)
2	-0.12	-0.18	-0.53	-0.49	-0.43	0.19	0.11	0.01	0.02	0.05
	(-0.18)	(-0.87)	(-4.8)	(-4.24)	(-3.83)	(0.32)	(0.91)	(0.08)	(0.26)	(0.5)
9	0.66	0.60	0.23	0.21	0.18	0.26	0.20	0.16	0.11	0.08
	(0.91)	(2.41)	(2.16)	(1.81)	(1.5)	(0.42)	(1.46)	(1.14)	(0.8)	(0.61)
10	0.82	0.75	0.41	0.31	0.30	0.51	0.43	0.44	0.36	0.36
	(1.13)	(2.7)	(2.68)	(2.16)	(1.97)	(0.87)	(2.04)	(1.73)	(1.62)	(1.67)
D10-D1	0.97***	0.98***	0.84***	0.76***	0.76***	0.75***	0.76***	0.63*	0.52*	0.47*
	(3.88)	(4.09)	(4.21)	(3.68)	(3.71)	(2.77)	(2.87)	(1.92)	(1.88)	(1.79)
D9-D2	0.78***	0.78***	0.77***	0.69***	0.61***	0.08	0.09	0.15	0.08	0.04
	(4.53)	(4.56)	(5.04)	(4.72)	(3.78)	(0.45)	(0.53)	(0.95)	(0.57)	(0.24)