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Information Content When Mutual Funds Deviate from Benchmarks

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

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1. Introduction

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

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

Our findings suggest that actively managed mutual funds are informed investors, whose costly acquisition and implementation of information help impound information into asset prices (Grossman and Stiglitz 1980).[1] Consistent with this view, the return spread between stocks that the active funds overweight and underweight, relative to their benchmark indexes, is higher for stocks with more firm-specific information, as captured by high idiosyncratic volatilities, but it is lower for stocks for which more

[1] In 2010, active equity funds managed approximately 86% of total U.S. equity mutual fund net assets, pushing the average expense ratio for stock funds to be 0.95% (Investment Company Institute 2011, pp. 33, 64). French (2008) argues that the annual cost of active investing is 0.67% of the aggregate market value.

informed investors compete for private information, as reflected by a higher breadth of active mutual fund ownership. We also find that the deviation from benchmarks positively predicts firms' future earnings surprises, which suggests the ability of active fund managers to forecast firms' fundamental performance.

An alternative interpretation of the higher return on the stocks that active funds overweight is that it may reflect the effects of demand pressure on prices (Gompers and Metrick 2001). In particular, if active funds continue to buy stocks that they overweight, e.g., exhibiting herd behavior (Sias 2004), their demand pressure could push stock prices above equilibrium levels and lead to higher in-sample returns. One implication of this view is that the higher returns on stocks that active funds overweight should subsequently reverse. However, we find no evidence of return reversal in the subsequent three years, which contradicts this prediction.[2]

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

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

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

The appearance of passiveness by mutual funds in aggregate, such that little abnormal return can be earned on the total fund portfolio, is consistent with the equilibrium described by Berk and Green (2004), but it naturally raises the question, Could individual fund managers have performed better by being more active? This question is particularly important in light of the declining degree of activeness in the actively managed mutual fund industry (Cremers and Petajisto 2009) and the diminishing mutual fund alpha over time (Fama and French 2010). To explore this question, for each individual fund we decompose returns on fund holdings into two components: a long–short active portfolio that consists of deviations from benchmarks and a passive portfolio that consists of investments in the benchmarks. The average Sharpe ratio for individual funds' active portfolios is significantly lower than that of their benchmark portfolios. By combining active and passive portfolios, actively managed mutual funds, on average, achieve significantly higher Sharpe ratios for their overall portfolios than those for their benchmarks or active portfolios. We also create hypothetical fund portfolios by forcing managers to be more active, scaling up their active portfolios. However, we find little improvement in Sharpe ratios when fund managers are more aggressive in active investing. This evidence suggests that, on average, active fund managers tend to combine active and passive portfolios in such a way that being more active leads to little marginal improvement in performance.

A number of recent studies provide results that are related to ours. Kacperczyk et al. (2005) and Cremers and Petajiso (2009) provide evidence that more active mutual funds tend to achieve better performance. Our paper is particularly related to that of Cremers and Petajisto (2009), who analyze the performance of mutual funds with different levels of active share (i.e., deviations from index benchmarks). Our study, however, differs in several important aspects. First, we focus on the performance of the stocks that are over- and underweighted by mutual funds, rather than the performance of mutual funds. Second, analyzing the performance of stocks can provide more powerful

[2] We also find a strong negative correlation between consecutive changes in deviations from benchmarks. This position reversal suggests that risk-averse informed active managers tend to unwind their profitable positions to mitigate the long-run risk that arises from future price movements due to unpredictable events.

and more reliable tests than analyzing the performance of well-diversified funds that closely resemble their benchmarks. For example, Cremers and Petajiso (2009) show that the superior performance of active funds relative to their benchmarks is driven primarily by the underperformance of the benchmarks, but not by the outperformance of the funds with high active share (see, e.g., Cremers and Petajisto 2009, Table 8; Cremers et al. 2013). Third, our stock-level analysis also points to a specific element of skill exhibited by active funds, namely, the ability to forecast future earnings surprises. Finally, we are able to quantify the potential gains for mutual funds to become more active. Hence, focusing on the performance of stocks over- or underweighted by active funds can help us to better understand the investment ability of fund managers.

Our paper is also related to those by Cohen et al. (2010) and Pomorski (2009), who analyze the performance of best ideas of mutual funds. Whereas their analyses focus on the top holdings or trades in each individual manager's portfolio, we are interested in whether a measure that aggregates the active weights across all relevant fund managers captures their informational advantages as an investor group. Moreover, our 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. The analysis of the performance of stocks that fund managers choose to under- or overweight also sheds new light on aggregate mutual fund performance. Last, we show that our results are robust to controlling for fund managers' best idea stocks.

Lewellen (2011) analyzes the holdings and returns of institutional investors and finds that institutions as a group show little tendency to deviate from the market portfolio. Our analysis of the aggregate passiveness of active mutual funds provides complementary evidence by examining the universe of active mutual funds with cleanly defined performance benchmarks. Importantly, however, we find that a measure that aggregates individual funds' deviations from benchmarks has strong information content for firms' future stock returns and fundamental performance, which suggests the existence of stock-picking skill. Our analysis therefore provides a case for active portfolio management.

2. Consensus Wisdom of Active Mutual Funds

This section introduces the construction of the consensus wisdom of active mutual funds, namely, their deviation from benchmarks, our data and sample construction, and the summary statistics.

2.1. Deviation from Benchmarks

The building block for our measure of the consensus view of active mutual funds is their deviations from benchmarks. If active mutual funds aim to outperform a passive benchmark index, they will overweight a stock, relative to the benchmark when they expect it to outperform, and underweight it otherwise. In this scenario, each manager's decision of portfolio tilting reflects the expectation of future returns to that stock conditional on the manager's information set (Roll 1992). Therefore, a stock level measure that averages the decisions to deviate from benchmarks across active funds whose investment universe includes this stock can aggregate different pieces of information about the future value of individual stocks scattered among fund managers. If this consensus view has information that is not fully reflected in current market prices (i.e., mutual funds as an investor group possess private information), it should predict future stock returns.

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

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

where N_i is the number of funds whose investment universe includes stock i.[3] We argue, and provide evidence, that this measure is more powerful to detect active funds' information advantages than previously used proxies based on the level or breadth of active fund ownership.

Naturally, active fund managers might deviate from their benchmarks for other reasons, e.g., liquidity-related motives or agency problems emphasized in studies of incentives of fund managers.[4] The portfolio distortion effects arising from agency-related

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

[4] See, e.g., Brown et al. (1996), Chevalier and Ellison (1997), and Huang et al. (2011).

problems could lead us to find evidence against the information advantages of active mutual funds.

2.2. Data and Sample Selection

To construct our mutual fund database, we combine the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database with the CDA/Spectrum Mutual Fund Holdings Database from Thomson Financial via the MFLINKS. Following Kacperczyk et al. (2008), we only include active mutual funds that invest primarily in U.S. common stocks; we eliminate balanced, bond, money market, international, index, and sector funds, as well as funds not invested primarily in equity securities. Our sample includes 2,691 distinct active U.S. equity funds, with the number increasing from 237 in 1984 to 1,510 in 2008.

Data on the monthly returns, prices, and market values of equity for common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange, and NASDAQ come from the CRSP. Consistent with previous literature, we exclude closed-end funds, real estate investment trusts, American depository receipts, 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).

2.3. Benchmark Index Holdings

We next 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 the one that minimizes the average distance between the fund portfolio weights and the benchmark index weights.[5] Data on the index holdings of the 12 Russell indexes since their inception come from the Frank Russell Company, and data on S&P 500, S&P 400, and S&P 600 index holdings since December 1994 are from Compustat. For the remaining indexes and time periods, we use the holdings of index funds to approximate the index holdings.[6] Second, for each individual fund, we tailor a performance benchmark by constructing a value-weighted portfolio of all stocks the fund actually holds. Since these two approaches generate qualitatively similar results, we report our main results based on the first approach.

2.4. Characteristics of Stocks with Extreme *DFB*

In panel A of Table 1, we show the distribution of *DFB* and its two components, fund portfolio weights and benchmark index weights. The results indicate that for a median stock in our sample, the *DFB* is close to zero, 0.01%. The mean *DFB* is 0.09%, and the mean fund weight is 0.17%. *DFB* has substantial dispersion, with a standard deviation of 0.31%. As the distribution of *DFB* tends to be skewed to the right, we focus on the decile ranks in our main analyses.

What are the characteristics of stocks with large mutual fund over- and underweighting? Panel B of Table 1 presents the results based on the decile portfolios. 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 indicate that stocks in decile 10 about which active funds display the most conviction tend to be the least popular among mutual funds; they reside in the investment universe of only 38 funds. On the contrary, stocks in decile 1 appear in the investment universe of 220 funds. On average, only 17 mutual funds hold stocks in decile 10, compared with 40 funds holding stocks in decile 1. These results indicate that stocks with high active fund bets do not pertain just to a few "hot" or popular names among money managers.

We find also that stocks heavily overweighted by active funds tend to be relatively small, with an average decile rank value of 3.05, based on NYSE market-cap decile breakpoints in ascending order. They have a slight tendency to be winners in the previous year.[7] There exists no apparent relation between *DFB* and the book-to-market ratio. Interestingly, stocks overweighted by funds tend to have higher idiosyncratic volatilities.

[5] We also experiment with selecting benchmarks on the basis of moving averages of the distance between fund portfolio weights and benchmark index weights in the past five years and obtain qualitatively similar results.

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

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

Table 1 Summary of the Data: Decile Portfolios

Panel A: Distribution of *DFB* and the components

	Mean	SD	10th percentile	25th percentile	Median	75th percentile	90th percentile
Fund weights (%)	0.17	0.31	0.00	0.03	0.08	0.19	0.42
Benchmark weights (%)	0.06	0.16	0.00	0.00	0.03	0.07	0.15
DFB (%)	0.09	0.31	−0.05	−0.01	0.01	0.08	0.29

Panel B: Characteristics of decile portfolios sorted on the basis of *DFB*

Decile	*DFB* (%)	Benchmark weights (%)	No. of funds in the stock-fund cohort	No. of funds holding the stock	Proportion of stocks outside of benchmarks (%)	Market cap score (1–10)	BM score (1–10)	Pr1Yr score (1–10)	Residual volatility (%)
1	−0.14	0.28	220	40	0.00	6.39	4.53	6.04	2.00
2	−0.04	0.09	169	21	0.00	4.24	4.70	5.49	2.46
3	−0.02	0.06	155	18	0.01	3.46	4.95	5.29	2.68
4	0.00	0.04	112	13	0.13	2.81	5.32	5.24	2.81
5	0.01	0.04	120	15	0.22	3.13	5.38	5.36	2.76
6	0.03	0.05	138	20	0.17	3.61	5.24	5.54	2.62
7	0.06	0.06	133	23	0.17	3.83	5.22	5.78	2.57
8	0.11	0.06	113	24	0.21	3.89	5.10	6.08	2.58
9	0.23	0.05	84	24	0.33	3.74	4.96	6.24	2.67
10	0.72	0.03	38	17	0.63	3.05	4.86	6.69	2.86
*D*10–*D*1	0.86***	−0.25***	−182***	−23***	0.63***	−3.34***	0.33**	0.65***	0.86***

Notes. At the end of each quarter, we compute for each stock a measure of mutual funds' deviations from benchmarks, *DFB*, which is the simple average of the stock's weight in a mutual fund portfolio in excess of its weight in the fund's benchmark index, across all mutual funds in the stock-fund cohort. We then sort stocks into deciles in ascending order based on *DFB* and calculate the stock characteristics for each decile portfolio. A mutual fund belongs to a stock-fund cohort if the stock appears in the mutual fund portfolio or is a member of the index against which the fund is benchmarked. For each mutual fund in each quarter, we select from 19 stock indexes one benchmark index that minimizes the average distance between the fund portfolio weights and the benchmark index weights. Panel A shows the distribution of *DFB* and the components. Panel B shows the characteristics of the decile portfolios. Our set of characteristic variables includes the average deviations from benchmarks *DFB*, the average benchmark weight, the average number of funds in the stock-fund cohort, the average number of funds that hold the stocks, the average proportion of stocks outside the benchmarks, the average proportion of funds in the stock-fund cohort for which the stock is not held by funds but in their benchmarks, the market cap, the book-to-market (BM) ratio, past one-year return (Pr1Yr; skipping the most recent month), and the residual return volatility in the past quarter. The market cap of a stock is computed by multiplying the stock price with the number of outstanding shares at each quarter end (in millions). The book-to-market ratio is determined for each stock at the end of last calendar year using the book value of the stock at the end of last fiscal year and the market value of the stock at the end of last calendar year. We regress the daily stock returns against daily Fama and French (1993) 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 ratio, and past returns from 1 to 10, with 10 representing the deciles with the largest market cap (based on NYSE breakpoints), highest book-to-market ratio, and highest past one-year return. Stocks with prices lower than $5 at the previous quarter end are excluded.

**Statistical significance at the 5% level; ***statistical significance at the 1% level.

3. Information Content of the Consensus Wisdom of Active Mutual Funds

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

3.1. Return Forecasting Power of *DFB*

To evaluate the investment value of the consensus view of active mutual funds, we first sort stocks into deciles based on *DFB* and examine the subsequent performance of these decile portfolios. As we update *DFB* each quarter, the portfolios accordingly get rebalanced. Fama and French (2008) point out that equal-weight portfolio returns may be driven by tiny stocks that are numerous in number but small in economic significance, whereas value-weighted portfolio returns may be driven by a few very large caps. Table 2 presents both equal-weighted and value-weighted returns on the decile portfolios.

The first columns in panels A (equal-weighted returns) and B (value-weighted returns) of Table 2 show that *DFB* strongly predicts future returns. A portfolio that buys stocks in decile 10 and sells stocks

Table 2 Consensus Wisdom of Active Mutual Funds (*DFB*) and Future Stock Returns: Decile Portfolios

	Panel A: Equal-weighted postranking portfolio return (%/month)						Panel B: Value-weighted postranking portfolio return (%/month)					
Decile	Average return	CAPM alpha	FF alpha	Carhart alpha	Five-factor alpha	DGTW-adj. return	Average return	CAPM alpha	FF alpha	Carhart alpha	Five-factor alpha	DGTW-adj. return
1	0.60	−0.26	−0.31	−0.31	−0.31	−0.20	0.74	−0.08	−0.03	−0.04	−0.04	−0.11
	(2.09)	(−3.29)	(−5.19)	(−4.76)	(−4.82)	(−4.02)	(2.90)	(−1.13)	(−0.57)	(−0.9)	(−0.76)	(−3.12)
2	0.58	−0.32	−0.42	−0.26	−0.26	−0.18	0.87	0.01	−0.09	0.00	0.00	0.02
	(1.78)	(−2.53)	(−6.03)	(−3.77)	(−3.69)	(−3.66)	(3.06)	(0.17)	(−1.25)	(0.07)	(0.02)	(0.36)
3	0.63	−0.28	−0.39	−0.17	−0.16	−0.15	0.87	−0.02	−0.12	0.00	0.00	0.03
	(1.86)	(−1.83)	(−4.79)	(−2.21)	(−2.11)	(−2.45)	(2.95)	(−0.21)	(−1.44)	(−0.04)	(0.03)	(0.49)
4	0.74	−0.12	−0.22	−0.06	−0.05	−0.11	0.85	−0.02	−0.10	0.01	0.02	−0.04
	(2.29)	(−0.72)	(−2.08)	(−0.53)	(−0.48)	(−1.06)	(2.85)	(−0.25)	(−1.28)	(0.16)	(0.22)	(−0.54)
5	0.83	−0.05	−0.17	−0.02	−0.02	−0.07	0.93	0.01	−0.08	0.08	0.07	0.05
	(2.51)	(−0.29)	(−2.12)	(−0.21)	(−0.22)	(−0.96)	(2.99)	(0.12)	(−0.77)	(0.74)	(0.61)	(0.55)
6	0.93	0.03	−0.10	0.04	0.05	0.08	0.91	−0.01	−0.10	−0.02	−0.01	0.05
	(2.77)	(0.16)	(−1.2)	(0.47)	(0.60)	(1.29)	(2.97)	(−0.09)	(−1.28)	(−0.27)	(−0.16)	(0.69)
7	1.04	0.13	0.02	0.13	0.15	0.12	1.01	0.11	0.06	0.12	0.13	0.11
	(3.10)	(0.83)	(0.19)	(1.60)	(1.94)	(1.90)	(3.40)	(1.50)	(0.78)	(1.63)	(1.91)	(1.86)
8	1.03	0.11	0.04	0.03	0.06	0.08	0.98	0.05	0.04	−0.02	−0.02	0.05
	(3.01)	(0.66)	(0.47)	(0.39)	(0.73)	(1.19)	(3.10)	(0.56)	(0.43)	(−0.25)	(−0.23)	(0.62)
9	1.17	0.24	0.23	0.15	0.16	0.18	1.31	0.36	0.46	0.24	0.25	0.32
	(3.25)	(1.32)	(2.90)	(2.00)	(2.15)	(2.42)	(3.71)	(2.23)	(3.35)	(1.90)	(1.94)	(2.88)
10	1.37	0.44	0.44	0.32	0.34	0.41	1.38	0.43	0.62	0.33	0.36	0.35
	(3.63)	(2.15)	(4.28)	(3.35)	(3.49)	(5.36)	(3.67)	(2.27)	(3.61)	(2.40)	(2.61)	(2.22)
*D*10–*D*1	0.77***	0.69***	0.75***	0.63***	0.65***	0.61***	0.64***	0.51**	0.65***	0.38**	0.39**	0.46***
	(4.30)	(3.92)	(6.07)	(5.20)	(5.35)	(6.04)	(2.62)	(2.34)	(3.47)	(2.41)	(2.59)	(2.74)
*D*9–*D*2	0.59***	0.56***	0.65***	0.41***	0.42***	0.36***	0.44**	0.34*	0.55***	0.24	0.25	0.30**
	(4.67)	(4.44)	(6.05)	(4.01)	(3.97)	(4.06)	(2.21)	(1.82)	(3.29)	(1.59)	(1.64)	(2.12)

Notes. 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 1984 Q1 to 2008 Q3, we sort stocks into deciles in ascending order based on *DFB* and compute the average monthly equal-weighted (panel A) and value-weighted (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 (FF), the Carhart (1997) four-factor model, and a five-factor model that further includes the Pastor and Stambaugh (2003) liquidity risk factor. Finally, we present the portfolio performance using the DGTW characteristic adjustment. Stocks with prices lower than $5 at the previous quarter end are excluded.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

in decile 1 generates average returns of 0.77% and 0.64% per month on equal- and value-weighted bases, respectively. These returns are statistically significant, with t-statistics of 4.30 and 2.62, respectively. To examine whether the high returns on stocks heavily overweighted by mutual funds simply reflect fund managers' propensity to take high risks, we employ standard risk-adjustment models to examine the abnormal returns. The specific risk-adjustment models include the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model, a four-factor model including momentum, and a five-factor model including the Pastor and Stambaugh (2003) liquidity factor. In addition to linear factor models, we employ a characteristic-adjustment procedure, as proposed by Daniel et al. (1997; hereafter, DGTW).

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

To examine the return predictive power of *DFB* in the presence of other return predictors, we employ Fama and MacBeth (1973) cross-sectional regressions.

In column (1) of Table 3 we show that *DFB* significantly predicts future stock returns, whereas in column (2) we show that this effect remains intact after controlling for stock characteristics. To examine large overweights and underweights separately, we discretize *DFB* into two dummy variables: $D1$, which represents the membership in the decile of stocks with the lowest *DFB*, and $D10$, which represents the membership in the decile with the highest *DFB*. The slope coefficient for the dummy variables can be interpreted as the difference in quarterly returns between stocks in each respective decile and all stocks in other deciles, while controlling for stock characteristics. Specifically, at the end of each quarter from Q1 of 1984 to Q3 of 2008, we perform cross-sectional regressions specified as follows:

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

where $R_{i,t+1}$ is the return on stock i in quarter $t+1$ in excess of the market return in $t+1$, and $X_{i,t}$ includes stock characteristics such as the stock's average weight in the benchmark indexes, firm size, the book-to-market ratio, past one-year (skipping the most recent month) returns, idiosyncratic volatilities, turnover, and past one-month return. The results in columns (3) and (4) of Table 3 show that stocks in decile 1 significantly underperform other stocks, and stocks in decile 10 significantly

Table 3 *DFB* **and Future Stock Returns: Fama and MacBeth (1973) Cross-Sectional Regressions**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFB_t	3.5093***	3.5596***						
	(5.79)	(8.23)						
$D1_t$			−0.0135***	−0.0108***	−0.0134***	−0.0105***	−0.0086***	−0.0112***
			(−3.26)	(−3.71)	(−3.30)	(−3.69)	(−3.14)	(−4.02)
$D10_t$			0.0254***	0.0244***	0.0254***	0.0242***	0.0221***	0.0244***
			(5.30)	(6.41)	(5.36)	(6.55)	(6.20)	(7.12)
$Benchmark\ Weights_t$		1.9064***		0.6756		0.6653	0.697	0.8379*
		(4.22)		(1.27)		(1.31)	(1.38)	(1.72)
$\text{Log}(Market\ Cap_t)$		−0.0029***		−0.0023**		−0.0024**	−0.0034***	−0.0023**
		(−2.96)		(−2.13)		(−2.40)	(−3.41)	(−2.27)
$\text{Log}(BM_t)$		0.0039		0.0039		0.0038	0.004	0.0041
		(1.45)		(1.43)		(1.43)	(1.48)	(1.54)
$\text{Log}(Pr1Yr_t)$		0.0056***		0.0057***		0.0057***	0.0055***	0.0051***
		(5.81)		(5.57)		(5.89)	(5.82)	(5.71)
$Residual\ Vol_t$		−0.3389		−0.3487		−0.3461	−0.346	−0.3536
		(−1.29)		(−1.34)		(−1.32)	(−1.31)	(−1.39)
$Turnover_t$		−0.0089*		−0.0088*		−0.0087*	−0.0092*	−0.0095**
		(−1.91)		(−1.87)		(−1.88)	(−1.98)	(−2.07)
$Pr1Mt$		−0.0054		−0.0019		−0.0029	−0.006	−0.0142
		(−0.32)		(−0.11)		(−0.17)	(−0.35)	(−0.84)
$\triangle MFO_t$		−0.0442			−0.0096	−0.0426	−0.0436	0.0083
		(−0.78)			(−0.14)	(−0.76)	(−0.79)	(0.13)
$\triangle Breadth_t$		0.1306			0.1328	0.1304	0.0874	0.0843
		(1.13)			(0.83)	(1.08)	(0.71)	(0.71)
$Best\ Ideas_t$							0.0282***	
							(6.34)	
$\triangle MFO_{t+1}$								0.9625***
								(8.46)
Intercept	0.0052	0.0152	0.0073*	0.0142	0.0073	0.0151	0.0207	0.0141
	(1.31)	(1.08)	(1.69)	(0.98)	(1.57)	(1.09)	(1.49)	(1.03)
R^2 (%)	0.44	6.11	0.69	6.04	1.01	6.15	6.26	7.29

Notes. This table uses the Fama and MacBeth (1973) cross-sectional regressions to examine the relationship between mutual funds' deviations from benchmarks, *DFB*, at each quarter end and the market-adjusted returns in the subsequent quarters, R_{t+1}. To make the results comparable with the portfolio analysis, we discretize *DFB* into two dummy variables, $D10$ (overweight), which equals 1 if the stock is in decile 10 with the highest *DFB* and 0 otherwise, and $D1$ (underweight), which equals 1 if the stock is in decile 1 with the lowest *DFB* and 0 otherwise. Market cap, book-to-market ratio, residual volatility, and turnover ratio are defined as previously. The variable *Benchmark Weights* is the average weight of a stock in the benchmark indexes; $Pr1Yr$ is the past one-year return skipping the most recent month; $Pr1Mt$ is the past one-month return; $\triangle MFO$ is the change in the fraction of shares held by mutual funds (Chen et al. 2000); and $\triangle Breadth$ is the change in the number of mutual funds that hold the stock scaled by the total number of mutual funds that exist at the beginning of a given quarter, as in Chen et al. (2002). *Best Ideas* is a dummy variable that represents the top holdings of individual fund managers as defined in Cohen et al. (2010). Stocks with prices lower than $5 at the previous quarter end are excluded. We compute the t-statistics based on the Newey and West (1987) standard errors.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

outperform other stocks, even after we control for the influence of those firm characteristics.[8]

Chen et al. (2000) argue that a trade-based measure of changes in the fraction of shares owned by mutual funds ($\triangle MFO$) is a significant predictor of future stock returns. Chen et al. (2002) argue that changes in the number of mutual funds that hold the stock, $\triangle Breadth$, correlate with future stock returns. When we include these variables in our cross-sectional regressions to stress test the return forecasting power of our measure of deviations from benchmarks in columns (5) and (6), the results indicate that the return forecasting power of *DFB* remains intact.[9] Cohen et al. (2010) argue that the top holdings of fund managers, i.e., their best idea stocks, achieve superior performance. In column (7), we include a dummy variable that represents the best ideas of fund managers.[10] The results indicate that controlling for the best ideas, the return forecasting power of *DFB* is strong and significant. Finally, to assess the influence of the contemporaneous demand shocks on stock prices, we include the change in the fraction of shares owned by mutual funds in quarter $t+1$ in the regression, and the results in column (8) confirm that *DFB* is a reliable return predictor, even when we control for the influence of the demand shocks in the next quarter.

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

3.2. Informed Investing or Price Pressure?

Although consistent with the notion that active funds possess value-relevant information that is not fully reflected in stock prices, the higher returns on stocks with higher *DFB* may have alternative interpretations as well. For example, Gompers and Metrick (2001) argue that the expansion of institutional investors in U.S. stock markets impacted stock prices, driving up the prices of the stocks they preferred to hold beyond equilibrium levels and thus increasing the in-sample returns on those stocks. Does a demand pressure story explain the higher future returns on stocks with large active mutual fund bets?

In this subsection, we examine the implication of the price pressure story for long-horizon stock returns: 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.

To test for these hypotheses, we perform regressions similar to Equation (2) with the market-adjusted returns in quarters $t+k$ (k ranging from 1 to 12) as dependent variables. Figure 1 presents the average slope coefficients for $D1$ and $D10$ and their 95th percent confidence intervals. The results indicate that the coefficients for $D1$ and $D10$ revert quickly to zero after one quarter and then fluctuate around zero. Importantly, we find no evidence of return reversal, which contradicts the price pressure story.

3.3. Stock Characteristics

To increase our confidence in this information-based story, we conduct a series of tests based on stock attributes. First, we examine the return forecasting power of *DFB* across size groups. The idea is that very large firms tend to be more transparent, with better disclosure policies. They also tend to be more closely followed and researched by market participants. It is therefore more difficult for individual funds to gain information advantages on those firms. Second, along a similar vein of thinking, if mutual funds have informational advantages about individual stocks, we expect their advantages to be greater among stocks with more firm-specific information. Third, we expect active funds' informational advantages to be more valuable when the funds have fewer competitors. Grossman and Stiglitz (1980, p. 394) conjecture that "the more individuals who are informed, the more informative is the price system." A corollary of that conjecture is that the consensus view of active funds would have a lower investment value for stocks with a large number of informed mutual fund holders.[11]

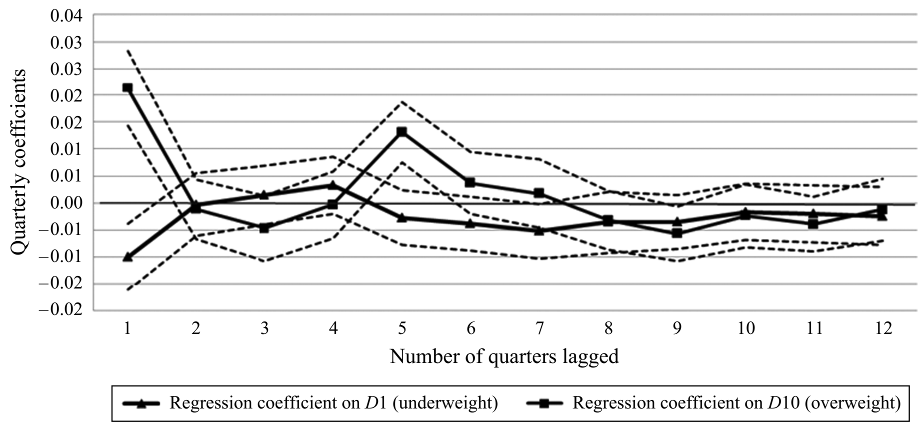
[8] Note that Table 3 uses quarterly stock returns as the dependent variable, instead of monthly returns as in Table 2. Moreover, the sample of stocks included in Table 3 is smaller than that in Table 2, because the requirement of the availability of data on stock characteristics such as the book-to-market ratio.

[9] We verify that these two fund trade-based measures significantly predict returns in the original sample periods of Chen et al. (2000, 2002), but exhibit insignificant return forecasting power in our extended sample period. Nagel (2005) finds consistent evidence that the change in mutual fund breadth has on average no relationship to future returns, when he expands the Chen et al. (2002) sample by five years.

[10] We use the top holding of each fund manager. The results are very similar if we use top five holdings of fund managers.

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

Figure 1 **Persistence of the Return Forecasting Power of *DFB*: Quarterly Fama–MacBeth Regression Coefficients**



Notes. This figure plots the average Fama and MacBeth (1973) cross-sectional regression coefficients for two dummy variables *D*1 and *D*10 (stocks heavily underweighted and overweighted by active mutual funds respectively) and their 95% confidence intervals. *D*1 (*D*10) equals 1 if a stock belongs to the bottom (top) decile of *DFB* heavily underweighted (overweighted) by active mutual funds. The dependent variables in the regressions are market-adjusted returns in quarter $t+k$, with k ranging from 1 to 12, and k corresponds to the ticks in the horizontal axis. Other independent variables include the natural logarithm of market cap in millions of dollars; book-to-market ratio; return in the past year, *Pr*1*Yr*; idiosyncratic volatility; turnover ratio; return in the past month, Pr1Mt; △ *MFO*; and △ *Breadth*. The variable △ *MFO* is the change in the fraction of shares held by mutual funds, as in Chen et al. (2000), and △ *Breadth* is the change in the number of mutual funds that hold the stock scaled by the total number of mutual funds that exist at the beginning of a given quarter, as in Chen et al. (2002). Stocks with prices lower than $5 at the end of quarter t are excluded.

To examine these hypotheses, we perform two-way sorts of stocks independently on *DFB* and firm size as well as proxies for the amount of firm-specific information and the number of mutual funds competing for private information. We use the idiosyncratic volatility, computed as the standard deviation of residuals from regressions of daily excess stock returns on the Fama and French (1993) factors in the past quarter, to proxy for the amount of firm-specific information, and the number of active funds that hold the stock at each quarter end to proxy for the number of investors competing for private information. Specifically, we sort stocks into quartiles based independently on *DFB* and stock characteristics such as size, idiosyncratic volatilities, or the number of mutual fund holders. Sixteen portfolios thus emerge from the intersection of the double sorts. We hypothesize that a strategy that buys high *DFB* stocks and sells low *DFB* stocks generates higher abnormal returns among mid-caps and stocks with higher idiosyncratic volatilities and a lower number of mutual fund investors.

Table 4 presents the results. To conserve space, we only present equal- and value-weighted four-factor alphas, but the results are qualitatively similar if we use other specifications of asset pricing models. Panel A of Table 4 shows that a strategy that buys high *DFB* and shorts low *DFB* stocks generates the lowest four-factor alpha among very large firms in quartile 4, but produces large and significant four-factor alphas for mid-cap stocks in quartiles 2 and 3, ranging between 0.54 and 0.64% per month on both equal- and value-weighted bases. Possibly because of the noise of small stock returns, we do not find significant return spread associated with *DFB* for tiny firms in quartile 1. Panel B of Table 4 shows that a strategy that is long high *DFB* and short low *DFB* stocks for stocks with high idiosyncratic volatilities yields average monthly four-factor alphas of 0.95% ($t=5.43$) on the equal-weighted basis and 0.91% ($t=3.46$) on the value-weighted basis. A similar strategy using stocks with low idiosyncratic volatilities generates average monthly four-factor alphas of only 0.21% ($t=3.06$) on the equal-weighted basis and only 0.17% ($t=1.43$) on the value-weighted basis. The difference in abnormal returns between these two strategies is large and statistically significant for both equal and value weighting. These results support our conjecture that informed mutual funds could have better information advantages in stocks with more firm-specific information.

The results in panel C of Table 4 also support the information-based story. A strategy that buys high *DFB* stocks and sells low *DFB* stocks generates a value-weighted monthly four-factor alpha of 0.84% ($t=4.29$) when implemented among stocks with a low number of mutual fund investors; the same strategy when implemented among stocks with a high number of mutual fund investors produces a value-weighted monthly four-factor alpha of only 0.18% ($t=1.43$). This difference in abnormal returns also is large and statistically significant.

3.4. *DFB* and Earnings News

If mutual funds have informational advantages about the stocks they overweight relative to their benchmarks, we expect those stocks to perform particularly

Table 4 Return-Predictive Power of *DFB* and Stock Characteristics

	Equal-weighted portfolio return (Carhart alpha percent/month)			Value-weighted portfolio return (Carhart alpha percent/month)		
	DFB			*DFB*		
Rank variables	1	4	Q4–Q1	1	4	Q4–Q1
			Panel A: Stock size			
1	−0.18	0.17	0.35	−0.25	0.23	0.49*
	(−0.8)	(1.25)	(1.28)	(−1.12)	(1.73)	(1.80)
2	−0.27	0.27	0.54***	−0.23	0.32	0.55***
	(−2.63)	(2.52)	(3.94)	(−2.33)	(3.14)	(4.18)
3	−0.36	0.27	0.63***	−0.35	0.29	0.64***
	(−4.24)	(2.01)	(3.51)	(−4.41)	(2.12)	(3.51)
4	−0.17	0.13	0.30*	−0.03	0.23	0.25*
	(−3.41)	(0.82)	(1.87)	(−0.66)	(1.98)	(1.92)
Q4–Q1	0.00	−0.04	−0.04	0.23	−0.01	−0.23
	(0.02)	(−0.17)	(−0.13)	(1.05)	(−0.03)	(−0.77)
			Panel B: Residual volatilities			
1	0.05	0.26	0.21***	−0.04	0.14	0.17
	(0.50)	(2.38)	(3.06)	(−0.49)	(1.28)	(1.43)
2	−0.13	0.26	0.39***	−0.25	0.41	0.67***
	(−1.4)	(2.34)	(4.05)	(−2.29)	(2.61)	(3.40)
3	−0.24	0.32	0.56***	−0.2	0.39	0.59**
	(−2.95)	(2.80)	(4.03)	(−1.1)	(1.96)	(2.28)
4	−1.1	−0.15	0.95***	−1.08	−0.17	0.91***
	(−7.35)	(−1.09)	(5.43)	(−5.7)	(−0.53)	(3.46)
Q4–Q1	−1.15***	−0.41**	0.74***	−1.04***	−0.3	0.74***
	(−5.33)	(−2.02)	(4.11)	(−4.59)	(−0.91)	(2.68)
			Panel C: Number of funds			
1	−0.49	0.13	0.63***	−0.7	0.13	0.84***
	(−3.81)	(1.00)	(3.96)	(−5.08)	(0.87)	(4.29)
2	−0.3	0.15	0.45***	−0.34	0.13	0.47***
	(−3.25)	(1.43)	(3.01)	(−3.12)	(1.01)	(2.99)
3	−0.23	0.31	0.54***	−0.22	0.53	0.75***
	(−2.25)	(2.60)	(3.28)	(−2.31)	(2.83)	(3.54)
4	−0.12	0.15	0.27**	−0.01	0.17	0.18
	(−1.81)	(1.21)	(2.09)	(−0.22)	(1.65)	(1.43)
Q4–Q1	0.37**	0.03	−0.33*	0.69***	0.06	−0.64***
	(2.28)	(0.14)	(−1.72)	(5.08)	(0.32)	(−3.18)

Notes. This table presents the relationship between the return-predictive power of *DFB* and stock characteristics. Specifically, at the end of each quarter from 1984 Q1 to 2008 Q3, we sort stocks independently based on their characteristics and *DFB* into quartiles. Sixteen portfolios thus form from these double sorts, with portfolio (1, 1) containing stocks with the lowest value of the sorting variables and vice versa. The characteristics include market cap (panel A), residual volatilities (panel B), and the number of funds that hold the stock (panel C). Then we calculate the average monthly equal-weighted and value-weighted returns for each of 16 portfolios for the subsequent quarter. We also report the Carhart (1997) four-factor alpha differences between the extreme portfolios. Stocks with prices lower than $5 at the quarter end are excluded.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

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 relationship between *DFB* and firms' future earnings surprises. We use two proxies for earnings surprises. The first proxy is 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 the second is the same difference deflated 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 5 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 et al. 1996). If active mutual funds trade on earnings momentum, we could observe a positive association between *DFB* and subsequent earnings surprises. To examine this conjecture, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on *DFB*. We average the difference in earnings surprises between high and low *DFB* stocks across the three terciles and report this averaged difference as momentum-adjusted earnings surprises. This adjustment eliminates the higher earnings surprises in the next two to four quarters for stocks that active funds overweight, but for the most proximate quarter, stocks with higher *DFB* continue 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 5 shows that an average stock in the top quintile of stocks heavily overweighted by mutual funds earns, in the time around earnings announcements in the following quarter, a three-day cumulative abnormal return of 29.8 basis points, which is statistically significant. In contrast, an average stock in the bottom quintile heavily underweighted by mutual funds generates a three-day cumulative abnormal return of only 3.4 basis points. 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. Baker et al. (2010) provide important evidence that aggregate trades of mutual fund managers associate with future earnings surprises, which suggests that

Table 5 *DFB* **and Future Earnings News**

	Quarters			
	$t+1$	$t+2$	$t+3$	$t+4$
Panel 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)
Panel B: Earnings surprise scaled by price (%)				
Q1	−0.004	0.002	0.003	0.003
	(−0.39)	(0.30)	(0.44)	(0.42)
Q5	0.033	0.025	0.015	0.010
	(5.60)	(4.27)	(2.44)	(1.46)
Q5–Q1	0.038***	0.023***	0.012***	0.007**
	(4.06)	(6.93)	(6.36)	(2.10)
Q5–Q1 (momentum-adj.)	0.024***	−0.010	0.004*	0.002
	(4.23)	(−0.74)	(1.70)	(0.65)
Panel C: CARs around earnings announcement (%)				
Q1	0.034	0.086	0.075	0.063
	(1.20)	(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)

Notes. This table presents the forecasting power of *DFB* for subsequent earnings surprises. At the end of each quarter from 1984 Q1 to 2008 Q3, 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 (CAR) is calculated for the three days around the earnings announcement date. Earnings data and earnings announcement dates come from I/B/E/S. To adjust for earnings momentum, we first group stocks into terciles based on the current quarter's earnings surprises and then divide the stocks within each tercile into five quintiles based on *DFB*. We average the difference in earnings surprises for subsequent quarters between high and low *DFB* stocks across the three terciles and report the averaged difference as momentum-adjusted earnings surprises. Stocks with prices lower than $5 at the previous quarter end are excluded. The t-statistics are computed using the Newey and West (1987) standard errors.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

fund managers actively trade stocks prior to earnings announcements to exploit their informational advantages. Jiang and Zheng (2012) propose a measure to rank mutual fund managers based on their ability to forecast earnings. They find strong persistence and performance predictive power of active funds' ability to forecast earnings.

3.5. *DFB* and Stock Market Efficiency

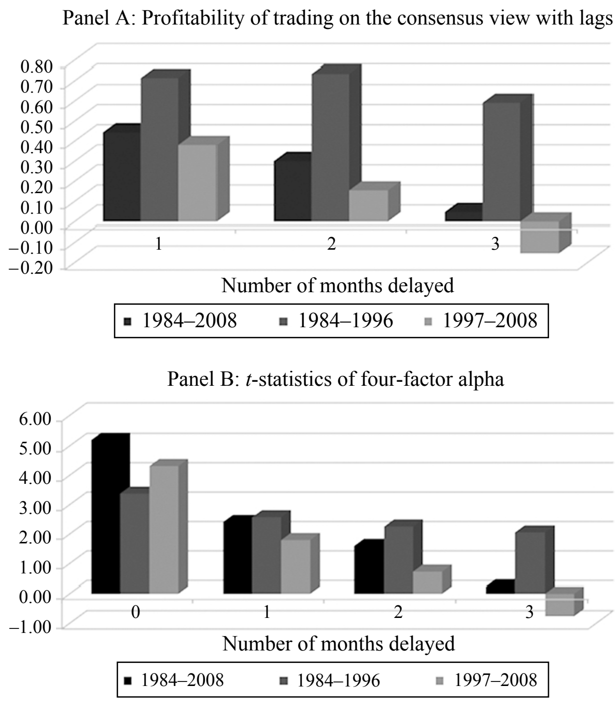
The results so far establish that active mutual funds as a group possess significant value-relevant information that is not fully incorporated into stock prices, which is inconsistent with strong-form market efficiency (Fama 1970). In this subsection, we exploit the consensus view of active mutual funds to further study the implications for market efficiency. We are interested in how fast the stock market incorporates the information contained by the consensus wisdom of active mutual funds, so that no abnormal returns can be earned. In particular, we form self-financing strategies that buy stocks that active funds overweight in decile 10 and short stocks that they underweight in decile 1, implemented with lags from zero to three months. We compute the equal-weighted four-factor alpha on these strategies.[12] We use the four-factor alpha on the strategy executed without lag, as a benchmark alpha, to measure the investment value of the information contained by the consensus view of active mutual funds. Then we deflate the alpha on the strategies implemented with various lags by that benchmark alpha to evaluate how fast the information contained by the consensus wisdom of active funds flows into stock prices.

Figure 2 presents the results. We perform the analysis for the full sample and two subsamples 1984–1996 and 1997–2008. Panel A shows the relative alpha for the strategies implemented with lags from one to three months. Panel B shows the t-statistics for the alpha. The average four-factor alphas for the strategy implemented without lag are 7.56%, 5.88%, and 10.08% per year (with t-statistics of 5.21, 3.38, and 4.32) for the full sample and two subsample periods. For our full sample period, the self-financing strategy implemented with a lag of one month achieves 44% of the abnormal return generated by the same strategy implemented without lag, or 3.36% per year with a t-statistic of 2.42. Executed with a delay of two months, this self-financing strategy earns 30% of the abnormal return generated by the same strategy implemented without lag, or 2.28% per year with a t-statistic of 1.60. Considering the fact that the SEC requires all mutual funds to disclose their portfolio holdings with a maximum delay of 45 days, the decline of abnormal returns to zero with a delay of two months is consistent with semistrong efficiency.

When we look at the time-series evidence, we find that in the period 1984–1996 the self-financing strategy executed with a delay of two months generates 73% of the abnormal return yielded by the same strategy implemented without lag, or an abnormal return

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

Figure 2 Value of the Consensus Wisdom of Active Mutual Funds and Stock Market Efficiency



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

of 4.32% per year with a t-statistic of 2.52. In the period 1997–2008, the self-financing strategy executed with a delay of two months generates only 15% of the abnormal return yielded by the same strategy implemented without lag, or an abnormal return of only 1.56% per year with a t-statistic of 0.73.[13]

3.6. *DFB* and Mutual Fund Performance

How can we reconcile our evidence that points to strong informational advantages of mutual funds in stock markets with the overall lackluster performance of mutual funds identified by prior literature? To understand the contribution of stocks with large active fund bets to the overall performance of active funds, for each decile of stocks sorted on the basis of *DFB* we calculate the fund investment-weighted portfolio returns and report the fraction of total mutual fund assets invested in each decile portfolio. The results in Table 6 indicate that stocks in decile 10 heavily overweighted by active funds generate high abnormal returns with a four-factor alpha of 6.60% per year. But active funds in aggregate invest less than 10% of their assets in those stocks. On the other hand, although stocks in decile 1 heavily underweighted by active funds generate a four-factor alpha close to zero, they receive approximately 34% of total

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

Table 6 *DFB* and Mutual Fund Performance

Decile	Percentage of aggregate fund investments	Holdings-weighted postranking portfolio return (percentage/month): Average return	CAPM alpha	FF alpha	Carhart alpha
1	33.76	0.77	−0.08	−0.02	−0.05
		(2.86)	(−1.18)	(−0.41)	(−1.03)
2	7.33	1.04	0.15	0.06	0.15
		(3.44)	(1.49)	(0.61)	(1.53)
3	5.39	0.95	0.04	−0.07	0.04
		(3.11)	(0.29)	(−0.65)	(0.39)
4	3.46	0.91	0.01	−0.08	0.04
		(2.76)	(0.10)	(−0.77)	(0.28)
5	4.59	1.01	0.07	−0.03	0.15
		(3.14)	(0.54)	(−0.22)	(1.22)
6	6.63	1.01	0.07	−0.05	0.07
		(3.15)	(0.52)	(−0.46)	(0.62)
7	8.70	1.13	0.21	0.16	0.22
		(3.61)	(2.21)	(1.73)	(2.42)
8	9.77	1.07	0.13	0.11	0.07
		(3.29)	(1.13)	(1.03)	(0.59)
9	11.06	1.40	0.44	0.51	0.34
		(4.11)	(3.01)	(4.09)	(2.97)
10	9.30	1.62	0.63	0.84	0.55
		(3.89)	(2.67)	(3.65)	(3.04)
*D*10–*D*1		0.85***	0.71***	0.87***	0.60***
		(2.96)	(2.72)	(3.60)	(3.04)
*D*9–*D*2		0.37**	0.29*	0.46***	0.19
		(2.07)	(1.68)	(3.04)	(1.35)

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

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

active fund assets. Therefore, despite the large four-factor alpha of 6.60% per year on high *DFB* stocks in decile 10, the value-weighted average four-factor alpha for active mutual funds as a group is only 1.49% per year before fees and expenses.

Lewellen (2011) documents the declining performance of institutional investors. Barras et al. (2010) make a similar observation for mutual funds. What leads to the declining alpha for mutual funds? One possibility is that mutual funds as a group are losing their information advantage relative to other market participants (e.g., the growing hedge fund industry), which leads to their deteriorating performance. Our evidence in the previous subsection contradicts this view by showing that the consensus wisdom of active mutual funds has higher investment values in the more recent decade. Therefore, it is likely that the active mutual fund industry has been trending toward being less active. In untabulated results, we follow the technique of grouping mutual funds on the basis of their active share, as proposed by Cremers and Petajisto (2009), and compute the fraction of mutual fund assets invested in each category of active share. This evidence confirms and extends the analysis of Cremers and Petajisto (2009) by showing the shrinking fraction of assets managed by active fund managers.

Our results support the notion that an average active mutual fund can generate significant alpha, a crucial assumption maintained by Berk and Green (2004). The appearance of passiveness by mutual funds in aggregate, such that little abnormal return can be earned on the total fund portfolio, is also consistent with the equilibrium described by Berk and Green (2004). But they naturally raise the question, Could individual fund managers have performed better by being more active? To explore this question, for each individual fund we decompose returns on fund holdings into two components: a long–short active portfolio that consists of deviations from benchmarks and a long-only passive portfolio that consists of their investments in the benchmarks.[14] Our first test is a comparison of the distribution of Sharpe ratios of active, passive, and overall fund portfolios for the cross-section of mutual funds. Because our sample period from 1984 to 2008 covers the recent financial crisis, we gauge the influence of the financial crisis on the results by using different schemes to remove the crisis period from our sample. The tests involve 2,273 distinct funds with at least two years of return history.

Table 7 **Could Individual Fund Managers Have Performed Better by Being More Active?—Average Sharpe Ratios**

	(1)	(2)	(3)	(4)	(5)
Active portfolio	0.30	0.31	0.30	0.28	0.24
Benchmark	0.49	0.51	0.45	0.35	0.18
Fund portfolio	0.56	0.59	0.53	0.42	0.25
Hypothetical fund portfolio	0.56	0.59	0.53	0.43	0.26
Benchmark–active portfolio	0.19	0.2	0.15	0.07	−0.06
Fund portfolio–active portfolio	0.25	0.27	0.22	0.14	0.01
Fund portfolio–benchmark	0.06	0.07	0.07	0.07	0.06
Hypothetical–actual fund	0.21	0.21	0.26	0.33	0.42
(×100)	(0.125)	(0.131)	(0.131)	(0.141)	(0.154)

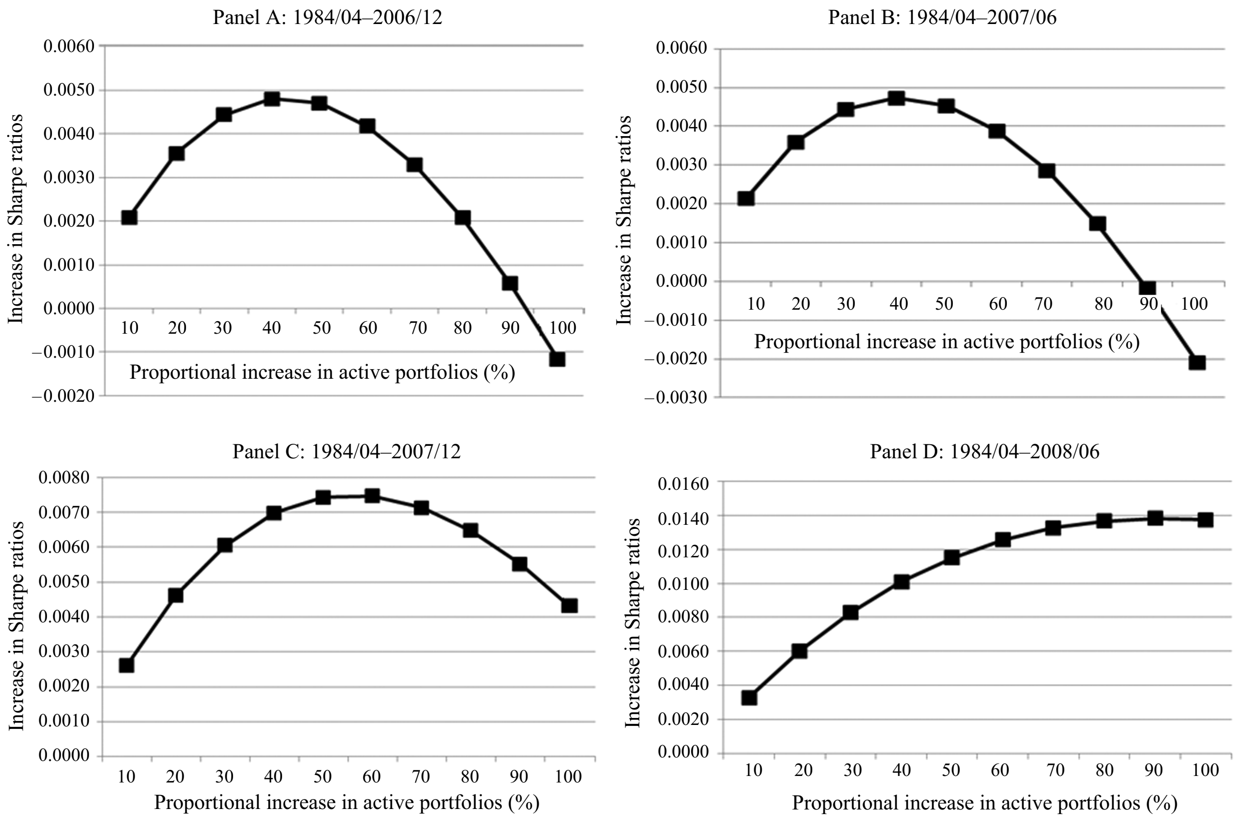
Notes. This table shows average Sharpe ratios for the active portfolio, benchmark index, and total fund portfolio of individual mutual funds. It also shows the average Sharpe ratio of a hypothetical fund that combines the benchmark index and 1.10 times the active portfolio. The analyses involve 2,273 distinct funds with at least two years of return history. We test the difference in the Sharpe ratios of the hypothetical and actual fund portfolios for each individual fund, following the robust inference method proposed by Ledoit and Wolf (2008), and report in parentheses the fraction of funds with significant improvements in Sharpe ratios at the 5% level. We use five sample periods: period (1), April 1984–December 2006; period (2), April 1984–June 2007; period (3), April 1984–December 2007; period (4), April 1984–June 2008; period (5), April 1984–December 2008.

As shown in Table 7, the average Sharpe ratio for each individual fund's active portfolio is lower than that of the fund's benchmark portfolio. By combining the active and passive portfolios, actively managed mutual funds on average achieve higher Sharpe ratios for their overall portfolios than those on their benchmarks or active portfolios. These results hold for the sample periods excluding the recent financial crisis in different ways (columns (1)–(4)). Even when we include the last six months in 2008 when the benchmark indexes plummeted (column (5)), on average, overall fund portfolios have Sharpe ratios that are 1% higher than those of the active portfolios.

To illustrate whether individual fund managers could achieve better performance by being more active, we construct hypothetical fund portfolios consisting of the benchmark portfolio and 1.10× the active portfolio. In other words, the managers of those hypothetical funds are forced to be more active with an extra 10% invested in each side of the (long–short) active portfolio. We compute the average Sharpe ratios for these hypothetical funds and examine the marginal gains from being more active. The results indicate that for an average fund in our sample, the increase in Sharpe ratio is less than 1% by being 10% more active. To assess the statistical significance of the difference in Sharpe ratios between the hypothetical and actual fund portfolios, we use the bootstrap-based technique proposed by Ledoit and Wolf (2008), which is robust to nonnormality of return

[14] The active portfolio return is computed as $R^{\text{active}}_{j,t+1} = \sum_{i=1}^{N_j} (w^j_{i,t} - w^{b_j}_{i,t}) \cdot R_{i,t+1}$, where $R^{\text{active}}_{j,t+1}$ is the return to fund j's active portfolio in month $t+1$, $w^j_{i,t}$ is the weight of stock i in fund j's portfolio in quarter t, $w^{b_j}_{i,t}$ is the weight of stock i in fund j's benchmark index in quarter t, and $R_{i,t+1}$ is the return on stock i in month $t+1$. According to this equation, overweighted stocks enter the long position of the active portfolio, and underweighted stocks enter the short position.

Figure 3 **Improvements in Sharpe Ratios by Being More Active**



Notes. This figure shows the average increase in Sharpe ratios for mutual funds with increasing proportional investments (from 10% to 100%) in the active portfolios. We use monthly excess fund returns to compute the Sharpe ratios, which are annualized by multiplying the ratio by the square root of 12. Panels A–D correspond the following four sample periods: April 1984–December 2006, April 1984–June 2007, April 1984–December 2007, and April 1984–June 2008.

distributions and has superior small-sample performance. Then we present the fraction of funds that could significantly improve the Sharpe ratio at the 5% level. The results indicate that for the majority of active funds, the improvement in Sharpe ratios is statistically insignificant.[15] Although less than 15% funds could achieve statistically significant enhancements in Sharpe ratios by becoming more active, the magnitude of the improvements is small. The intuition for the difference between fund-level and stock-level analyses lies in the fact that individual fund managers cannot form well-diversified portfolios that aggregate the overweighting and underweighting decisions of all active fund managers. For a typical fund manager who invests in a limited number of stocks, the higher idiosyncratic risk on the alpha-generating stocks in her active portfolio could discourage her from taking more aggressive positions in her active portfolio.

Finally, in Figure 3, we show the change in Sharpe ratios for an average fund when its manager increases its investment in the active portfolio proportionally from 10% to 100%. The results indicate an interesting inverted U-shaped relationship between the Sharpe ratio and the aggressiveness of investing in the active portfolio. The central message is that the improvement in Sharpe ratio is quantitatively small, even when the manager chooses an optimal combination of the benchmark and active portfolio.

4. Robustness Checks

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

[15] Following the insight of Gibbons et al. (1989), we also conduct a formal test for whether individual funds can achieve better performance by tilting their portfolios more toward the active portfolios. The idea is that if active fund managers combine active and passive portfolios to maximize the funds' Sharpe ratios, then in time-series regressions of monthly returns to the fund's active portfolio on the fund's total excess return, the intercepts should be statistically indistinguishable from zero. A significantly positive intercept would indicate that the fund could perform better by being more active. The results indicate that only 11%–15% of all funds in our sample could have achieved significantly higher in-sample Sharpe ratios by tilting more aggressively toward their active portfolios (t-statistics of the intercepts above 1.96).

4.1. Alternative Measures of *DFB*

We have included 19 stock indexes widely used by practitioners as our primary universe of performance benchmarks. We also 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. With these specifically tailored benchmark indexes, we are able to show qualitatively similar results.

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 1 if the stock is overweighted by the fund and 0 otherwise. Then we average this indicator variable for all funds whose investment comprises that stock, as in Equation (2). This new measure, DFB^{alt}, captures the fraction of funds that overweight the stock. It also can be viewed as polling each fund manager to vote for stocks that they perceive as future winners based on their portfolio weighting decisions. A stock receives a strong buy recommendation if the majority of the funds polled are bullish about the stock; it receives a strong sell if the majority of the funds are bearish about it:

$$DFB^{\mathrm{alt}}_{i,t} = \sum_{j=1}^{N_i} Indicator(w^j_{i,t} - w^b_{i,t} > 0)/N_i. \qquad (3)$$

We are able to show that DFB^{alt} is a reliable predictor of future stock returns.

4.2. Preferential Allocations of IPOs

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

5. Conclusions

Despite the consensus view that active mutual funds on average fail to outperform passive benchmarks, we find a high investment value of the consensus wisdom of active mutual funds. In particular, stocks that are heavily overweighted by active funds relative to their benchmark indexes perform substantially better than their underweighted counterparts. This outperformance is greater in stocks with more firm-specific information, as well as in those with fewer active mutual funds that compete for private information. The large premium dissipates quickly as the consensus view becomes publicly available. The results thus are consistent with the notion that informed investing by active mutual funds enhances the informativeness of stock prices.

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

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2013.1847.

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