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Investor Sentiment and Mutual Fund Strategies

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Abstract

We show that mutual funds employ portfolio strategies based on market sentiment. We build a proxy for the degree of a fund's sentiment beta (or FSB). The low-FSB funds outperform high-FSB funds, even after controlling for standard risk factors and fund characteristics. This effect is sizable and delivers a net-of-risk performance of 3.8% per year. Funds with a lower FSB follow more idiosyncratic strategies, suggesting that FSB is a deliberate, active choice of the fund manager. A sentiment contrarian strategy leads to high flows due to its superior performance, whereas a sentiment catering strategy fails to attract significant investor flows.

I. Introduction

Recent advances in behavioral finance have shown that stock prices are affected by "sentiment." Sentiment creates cross-sectional variations in returns across stocks (Baker and Wurgler (2006)). When investor sentiment is high, the low-sentiment-beta stocks (i.e., the stocks with negative loading on sentiment) are undervalued and their subsequent returns are higher. This suggests, and we confirm in our sample, that low-sentiment-beta stocks significantly outperform high-sentiment-beta stocks. This also suggests that an ideal trading strategy for asset managers interested in maximizing performance is to invest mostly in low-sentiment-beta stocks. Consistent loading on low-sentiment-beta stocks should generate superior performance, as it greatly outperforms conditional on high market sentiment and does not greatly underperform conditional on low market sentiment.

This strategy would be even more efficient if asset managers were not only able to identify the degree of sentiment loading of the stocks (i.e., whether they are high- or low-sentiment-beta stocks) but also able to predict the degree of market sentiment. We expect mutual fund managers to be ideally placed to take advantage of this feature, as they have access to the flows of the investors in the funds and

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can use this information to determine which stocks are more sensitive to market sentiment (e.g., Frazzini and Lamont (2008)). Indeed, a fund management company can timely observe flows detailed at the investor level and is able to learn from the behavior (i.e., flows in and out) of the investors in the fund. This sizable amount of privileged information it can rely on to detect sentiment provides a useful vantage point vis-à-vis the market. A clear example of the use of clients' trading behavior to detect current investor sentiment is the creation of the investor sentiment index by TD Ameritrade (Horowitz (2013)).

These observations beg the question of whether the mutual fund industry exploits market sentiment. In this article, we answer this question by focusing on a sample of U.S. mutual funds from 1984 to 2005. We identify stocks as a function of their current loading on sentiment and use fund portfolio holdings to identify the strategies of mutual funds as a function of investor sentiment. The null hypothesis is that investor sentiment has no effect on the portfolio management of mutual funds. Our alternative hypotheses emerge from two different potential effects that sentiment may have on the strategies adopted by mutual fund managers. Our first alternative hypothesis is that fund managers cater to investor sentiment, loading on high-sentiment-beta stocks to attract flows (Catering Strategy, Hypothesis 1). There is now ample evidence that investors observe the assets in which the funds invest and are attracted by funds that invest in stocks that attract more investor attention (Solomon, Soltes, and Sosyura (2014)). The second alternative hypothesis is that funds bet against investor sentiment in the hope that the long-term benefits from superior performance outweigh the short-term catering effects (Contrarian Strategy, Hypothesis 2). The third alternative hypothesis is based on an equilibrium argument in which both kinds of strategies prevail among different funds at the same time. That is, some funds cater to investor sentiment to attract flows in the short run, whereas other funds choose to bet against investor sentiment to generate performance that will lead to high flows in the long run (Mixed Equilibrium, Hypothesis 3). A famous example of the choices a fund manager might face is the one faced by Warren Buffet during the Internet boom of the late 1990s. Buffet, who might be considered a contrarian fund manager in this context, was criticized by many for not holding Internet stocks in his portfolio. He countered by claiming that technology stocks were overvalued. He wrote in his year 2000 annual letter to the shareholders of Berkshire Hathaway: "Far more irrational still were the huge valuations that market participants were then putting on businesses almost certain to end up being of modest or no value. Yet investors, mesmerized by soaring stock prices and ignoring all else, piled into these enterprises" (Buffett (2001), p. 14). Some of the striking examples of catering funds around the Internet bubble are WWW Internet Fund, NetNet Fund, and Internet Fund. These funds were investing in Internet stocks precisely when there was high demand for these stocks from investors. The investment philosophy of NetNet Fund was summarized by its manager Paul Cook as follows: "Any company we feel will benefit from using Internet technology, whether in a marketing or distribution format, is up for inclusion in the fund" (Lee (1998)).

The three hypotheses have distinct predictions in terms of performance and flows for mutual funds. The catering strategy hypothesis predicts that investors observe the holdings of the funds and therefore the funds strategically choose stocks that investors like, regardless of their performance implications. In doing so, the funds receive large inflows disproportionate to their performance. The contrarian strategy hypothesis predicts that funds invest in low-sentiment-beta stocks in order to generate high future performance. The mixed equilibrium hypothesis predicts that both kinds of funds coexist; the catering funds receive higher inflows in the short run despite poor performance, whereas the contrarian funds generate higher performance and receive high flows in the long run. This implies no overall link between sentiment and fund strategies. However, we expect a direct relation between strategies, when implemented, and fund performance.

Our results allow us to reject the explicit catering hypothesis for all of the funds and support the contrarian hypothesis *for the funds that do load on sentiment*. However, overall, there is not such a thing as a unique behavioral strategic reaction to sentiment by all of the mutual funds. This provides more credence to the mixed equilibrium hypothesis.

We start the empirical analysis by defining the sentiment beta of stocks on the basis of the Baker and Wurgler (2006), (2007) methodology. Then, for each fund, we identify its sentiment beta by aggregating the sentiment beta of its stock positions. Once funds are defined in terms of their fund sentiment beta (FSB), we use FSB to explain fund performance. For most of the analysis, we divide the funds into five quintiles based on their FSBs. Funds in quintile 1 have negative FSBs and are likely to be the ones playing a contrarian strategy. Funds in quintile 5 have positive FSBs and are likely to be the ones playing a catering strategy.

We document a strong negative relation between fund FSB and fund performance. Low-FSB funds outperform high-FSB funds, even after controlling for the standard risk factors and fund characteristics. By creating portfolios sorted on the basis of the FSB, we show that the low-FSB funds always deliver a higher performance than the high-FSB funds. Low-FSB funds (quintile 1) outperform high-FSB funds (quintile 5) by 31 basis points (bps) per month (3.8% per year) in the case of 4-factor alphas calculated on excess returns. These results are confirmed in a multivariate analysis that controls for fund- and family-specific characteristics (i.e., fund and family size, fund age, portfolio turnover, expense ratio, total load fees, flows, and volatility of flows in the prior 12 months). This holds across different measures of performance (gross and net return, net-of-style return, market-adjusted return, capital asset pricing model (CAPM), and 4-factor alpha), as well as for all of the different econometric specifications: portfolios, panel, and Fama–MacBeth (1973).

The effect is larger as well as statistically stronger when the beginning-of-month sentiment is high. In these months, low-FSB funds outperform high-FSB funds by 48 bps per month (5.8% per year) in the case of 4-factor alphas calculated on excess returns. These results are in line with Stambaugh, Yu, and Yuan (2012), who show that most of the predictability of sentiment comes on the short side: When sentiment is high, it's particularly important to maintain low exposure to this sentiment to get out of the way of the eventual crash.

Next, we ask whether the FSB–performance relationship is just due to a passive negative loading on the market. In line with Amihud and Goyenko (2013), we build a proxy for active management based on the tracking error of the fund.

Funds that display a higher tracking error, and therefore have a lower explanatory power of the factor model, are the ones that are less likely to follow a conventional or passive investment strategy. We show that FSB is positively related to R^2. Funds with lower FSBs follow more idiosyncratic strategies. A 1-standard-deviation-lower degree of FSB (style-adjusted FSB) translates into a reduction of 0.04 (0.03) in R^2. Because more than 90% of all funds have an R^2 between 0.78 and 0.99 (i.e., within a small range of 0.21), a change of 0.04 in R^2 is quite significant. This suggests that lower FSB is not the outcome of a conventional or passive investment strategy, but the deliberate, active choice of the fund manager. Given that active management has been interpreted as information-based trading, this would suggest that lower FSB is enacted by better-informed funds.

Finally, we measure the relative effectiveness of catering and contrarian strategies. Although a contrarian strategy is likely to produce better long-term returns, maximizing returns is not necessarily the primary objective of funds. Ultimately, funds are more interested in maximizing the total assets under management, irrespective of how these assets are attracted. Therefore, we look at the flow–performance relationship, in which we measure the effects of catering strategy and contrarian strategy on flows. We include FSB and sentiment-related performance as explanatory variables for fund flows. How does the market react to the performance related to sentiment? It may be that investors would react differently, and less, to sentiment-related performance. We investigate this issue by relating fund flows to the performance of the funds, separately reporting the part of the performance related to sentiment strategies. We therefore estimate the standard flow–performance relationship, including performance and its convex relation to flows (Sirri and Tufano (1998)), separately identifying the part that is attributable to sentiment exposure, and we assess how investors react to it. We find that investors react to it in a nonlinear way: Higher exposure is interpreted as higher performance and leads to disproportionately more inflows. The flow–performance sensitivity corresponding to the performance attributable to FSB-generated performance is roughly equal to half that due to the overall performance of the fund! However, investors do not seem to directly react to FSB. In other words, FSB does not directly affect flows, and its effect is felt only through its effect on performance. This result does not support the catering hypothesis and supports the contrarian strategy hypothesis. Although this holds overall, it is possible that for some funds the results differ, as the mixed hypothesis would suggest.

Overall, these results trace the way investors interpret a specific type of outperformance, and whether funds sort across sentiment-beta loadings so as to equilibrate the marginal profits to taking different approaches, given how investors interpret performance. In the end, the evidence points in the direction of funds deliberately using sentiment to increase their performance and therefore to indirectly boost their flows.

This article contributes to literature on fund performance and window-dressing of disclosed portfolios by fund managers. We contribute by focusing on how mutual fund managers react to sentiment, optimally exploiting it to maximize performance. One article similar to ours is that by Brunnermeier and Nagel (2004).

They show that during the bubble, hedge funds heavily invested in technology stocks, effectively riding the bubble until the end. In our words, this would correspond to hedge funds loading up on high-sentiment stocks and then timely correcting as sentiment switches.

Second, we contribute to the literature on sentiment (Baker and Wurgler (2006), (2007)) by providing insight on how a major class of arguably rational investors, the mutual fund managers, exploits market sentiment. It is interesting to note that our results also suggest that, in equilibrium, if some funds deliberately maintain low sentiment exposure, this would be consistent with De Long, Shleifer, Summers, and Waldmann's (1990) argument that noise trader risk is a limit to arbitrage. In our case, fund behavior may be considered as such.

II. Data and Main Variables

A. The Data Sources

The primary data source is the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database for the period from Jan. 1984 to Dec. 2005. We extract data on mutual fund monthly returns, total assets under management, and annual fund characteristics (e.g., expense ratio, load fees, starting date of the fund) for U.S. equity funds from the CRSP Mutual Fund Database and Morningstar Principia Database. We define equity funds as those funds for which the reported percentage of total assets invested in equities is above 80%. We limit our analysis to actively managed U.S. equity funds that are more than 1 year old and have at least $15 million in assets under management. We take the mutual funds holdings data from Thomson Reuters Mutual Fund Holdings Database. For most of our sample period, mutual funds were required to report their holdings semiannually. A large number of funds in our sample reported their holdings every quarter. We impute the holdings for nonreporting months using the last available holdings for the fund, assuming that the fund continues to hold the same portfolio since the last reporting date. We use the Morningstar-style classification to identify the investment style of funds. Appendix A provides further details on the sample selection.

We aggregate multiple classes of the same fund. Although multiple-share classes are listed as separate funds in the CRSP, they have the same pool of securities, the same portfolio manager, and the same returns before expenses and loads. We aggregate data on different share classes of a fund in a month to create a single fund observation, for which the total net assets (TNA) is the sum of the TNAs of all share classes, and age is the age of the oldest share class. Expense ratio, load, turnover, and return for the new observation are calculated as the TNA-weighted average of the corresponding items of all share classes.

B. Our Measure of Fund Sentiment Beta

We construct the measure of FSB as follows. First, we define the sentiment beta of each stock. Then, we aggregate it at the fund level using the weight of each stock in the fund's portfolio.

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1. Sentiment Beta of Stocks

We define the sentiment beta of stock i in month t by following Baker and Wurgler (2006), (2007). We first run the following regression using 36 months of data preceding the current month:

$$(1) \qquad R_{it} - R_{ft} = a + b_1 \mathrm{MKTRF}_t + b_2 \mathrm{SMB}_t + b_3 \mathrm{HML}_t + b_4 \mathrm{UMD}_t + b_5 \mathrm{SENTIMENT}_{t-1},$$

where R_{it} is the return of stock i for month t; R_{ft} is the risk-free rate of return for month t; MKTRF, SMB, and HML are the 3 Fama–French (1993) factors; and UMD is the Carhart (1997) momentum factor for the respective month (4 factors). SENTIMENT is the index of investor sentiment, obtained from Wurgler's Web site (http://people.stern.nyu.edu/jwurgler/). The coefficient of SENTIMENT is our measure of the sentiment loading/beta of the ith stock for month t.

Next, we rank stocks into 5 quintiles based on their sentiment betas. We calculate the equal-weighted and value-weighted average return of the stocks in each portfolio. The results are reported in Table 1. The time-series average of portfolio returns is reported in Panel A. We report the time-series average of portfolio returns for all months combined as well as separately for months where SENTIMENT is negative and months where SENTIMENT is positive. The average sentiment beta varies from -0.09 for quintile 1 to 0.08 for quintile 5, and is around 0 for quintile 3. We refer to the quintile 1 (quintile 5) stocks either as lowest-sentiment-beta (highest-sentiment-beta) stocks or as negative-sentiment-beta (positive-sentiment-beta) stocks and to the stocks in quintiles 2–4 as zero-beta stocks.

The equal-weighted returns show that both the negative- and the positive-sentiment-beta stocks perform worse than the zero-sentiment-beta stocks. In terms of value-weighted returns, we see a negative relationship between sentiment beta and performance: The excess return of negative-sentiment-beta stocks is 77 bps per month (9.24% per year) and that of positive-sentiment-beta stocks is 42 bps per month (5.04% per year). We conclude that negative-sentiment-beta stocks outperform positive-sentiment-beta stocks on average.

Then, we separate the 264 months into two subsamples: the months where beginning-of-month sentiment is negative and the months where beginning-of-month sentiment is positive. In the negative-sentiment months, extreme-sentiment-beta stocks, both negative and positive, outperform zero-beta stocks. In the positive-sentiment months, extreme-sentiment-beta stocks, both negative and positive, underperform zero-beta stocks (Baker and Wurgler (2006), (2007)). More important, negative-beta stocks outperform positive-beta stocks in both of the subsamples.

Next, we analyze the risk-adjusted performance. We regress the monthly value-weighted (equal-weighted) returns of the 5 sentiment-beta-based portfolios on 4 factors, and report the results in Panel B (Panel C) of Table 1. The intercept in each regression is the alpha of the portfolio. For value-weighted returns, negative-sentiment-beta stocks outperform positive-sentiment-beta stocks by 54 bps (6.48% per year). For equal-weighted returns, negative-sentiment-beta stocks outperform positive-sentiment-beta stocks by 37 bps (4.44% per year).

TABLE 1

Stock Sentiment Beta and Performance

Table 1 reports the relationship between stock sentiment beta and stock returns. For each month T, stock sentiment beta is calculated as the coefficient of SENTIMENT in the following regression based on months $T-1$ to $T-36$: $R_{it}-R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + b_5\text{SENTIMENT}_{t-1}$, where MKTRF, SMB, and HML are the Fama–French (1993) factors; UMD is the Carhart (1997) momentum factor; and SENTIMENT is the sentiment index. We rank stocks into 5 quintiles based on their sentiment betas. We calculate the equal-weighted and value-weighted average returns of the stocks in each portfolio. The time-series average of portfolio returns is reported in Panel A. We report the time-series average of portfolio returns for all months combined as well as separately for months where beginning-of-month SENTIMENT is negative and months where beginning-of-month SENTIMENT is positive. We regress equal-weighted (value-weighted) portfolio returns on the Fama–French factors and the Carhart momentum factor, and report the results in Panel B (Panel C). Alpha is the intercept of the regression. MKTRF, SMB, HML, and UMD represent the coefficients of the respective factors in the regression. * and ** in Panels B and C indicate statistical significance at the 5% and 1% levels, respectively.

		All Months (1984–2005)		Negative-SENTIMENT Months		Positive-SENTIMENT Months	
Sentiment-Beta Quintiles	Average Sentiment Beta	Equal-Weighted Returns	Value-Weighted Returns	Equal-Weighted Returns	Value-Weighted Returns	Equal-Weighted Returns	Value-Weighted Returns
Panel A. All Months							
1	−0.0924	0.68	0.77	1.70	1.80	−0.43	−0.35
2	−0.0256	0.86	0.73	1.52	1.22	0.13	0.19
3	−0.0015	0.84	0.74	1.35	1.17	0.27	0.26
4	0.0218	0.80	0.68	1.41	1.33	0.14	−0.04
5	0.0815	0.65	0.42	1.69	1.49	−0.50	−0.74

Sentiment-Beta Quintiles	Alpha	MKTRF	SMB	HML	UMD
Panel B. Value-Weighted Returns, Regression $R_{it}-R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + e_t$					
1	0.3461*	1.0865	0.1417	−0.3518	−0.1637
2	0.0485	0.9595	−0.0997	0.0210	0.0732
3	0.0504	0.9598	−0.1605	0.1794	0.0065
4	0.0422	1.0210	−0.1067	0.1311	−0.0817
5	−0.1927	1.1874	0.3189	−0.1542	−0.1148
Panel C. Equal-Weighted Returns, Regression $R_{it}-R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + e_t$					
1	0.2741	0.9504	0.9926	0.1232	−0.3318
2	0.2456*	0.8967	0.6175	0.3543	−0.1451
3	0.1894*	0.8790	0.5440	0.4316	−0.1211
4	0.1678*	0.9271	0.6634	0.4413	−0.1840
5	0.0966	1.0545	1.0902	0.1516	−0.2631

Given that Baker and Wurgler (2006), (2007) show that the sentiment-sensitive stocks underperform following high-sentiment periods and outperform following low-sentiment periods, the next step is to study the relationship between risk-adjusted portfolio returns and market sentiment in different sentiment periods. We use a piecewise linear regression framework. For each quintile portfolio, we estimate the piecewise linear regression:

$$\text{(2)} \qquad \begin{aligned} \text{PERFORMANCE}_{q,t} \quad &= \\ &(1-d)\times(a_{\text{LOW\_SENT}} + b_{\text{LOW\_SENT}}\text{SENTIMENT}_{t-1}) \\ &+ d\times(a_{\text{HIGH\_SENT}} + b_{\text{HIGH\_SENT}}\text{SENTIMENT}_{t-1}) + e_t, \end{aligned}$$

where $\text{PERFORMANCE}_{q,t}$ $(q = 1, 2, 3, 4, 5)$ is the monthly performance of the qth stock quintile portfolio. SENTIMENT is the market sentiment for the month, and d is equal to 1 if SENTIMENT is positive and 0 if SENTIMENT is negative. The threshold value of d is chosen to be 0 in each case; therefore the continuity restriction implies $a_{\text{LOW\_SENT}} = a_{\text{HIGH\_SENT}}$ in each regression. Because we want to estimate the effect of sentiment on return after controlling for the 4 factors, we use the Frisch–Waugh (1933) theorem to first partial out the effect of the 4 factors from the portfolio returns and the market sentiment.

We report the results in Table 2. Columns 1–5 present the results for 5 sentiment-beta quintile portfolios. Column 6 presents the results for a portfolio that is long on stocks in portfolio 1 and short on stocks in portfolio 5 at the beginning of every month. This specification is the same as the one by Mitchell and Pulvino (2001), and, in the same spirit, it shows the effect of sentiment on return in two regimes, the low-sentiment regime and the high-sentiment regime. Because of the nonlinear relationship between sentiment and stock returns, the intercepts cannot be interpreted as excess returns.

TABLE 2

Piecewise Linear Regression: Stock Return versus Sentiment

Table 2 reports the results of piecewise linear regression of excess returns of sentiment-beta-based stock portfolios on market sentiment, controlling for the 3 Fama–French (1993) factors and the Carhart (1997) momentum factor:

$$\begin{aligned} \text{PERFORMANCE}_{q,t} &= (1-d)(a_{\text{LOW\_SENT}} + b_{\text{LOW\_SENT}}\text{SENTIMENT}_{t-1}) \\ &\quad + d(a_{\text{HIGH\_SENT}} + b_{\text{HIGH\_SENT}}\text{SENTIMENT}_{t-1}) + e_t, \end{aligned}$$

where $\text{PERFORMANCE}_{q,t}$ ($q = 1, 2, 3, 4, 5$) is the monthly return of the qth sentiment-beta quintile portfolio. SENTIMENT is market sentiment for the month, and d is equal to 1 if SENTIMENT is positive and 0 if SENTIMENT is negative. The threshold value of d is chosen to be 0 in each case; therefore the continuity restriction implies $a_{\text{LOW\_SENT}} = a_{\text{HIGH\_SENT}}$ in each regression. Because we want to estimate the effect of sentiment on return after controlling for the Fama–French (1993) and Carhart (1997) momentum factors, we use the Frisch–Waugh (1933) theorem to first partial out the effect of the 4 factors from the portfolio returns and the market sentiment. Quintile 1 (5) is the portfolio of stocks with lowest (highest) FSB. Columns 1 to 5 give results for portfolios 1 to 5, respectively. Long–short portfolio 1-5 is formed by buying stocks in portfolio 1 and selling stocks in portfolio 5 at the beginning of every month. The sample period is from Jan. 1984 to Dec. 2005, representing a total of 264 months. The t-statistics are given in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

	Dependent Variables					
Independent Variables	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Long–Short Portfolio 1-5
$a_{\text{LOW\_SENT}}$	−0.5482*	−0.2051	−0.0795	0.1746	0.3455	−0.8937*
	(−2.13)	(−1.63)	(−0.84)	(1.58)	(1.42)	(−2.31)
$b_{\text{LOW\_SENT}}$	−0.9454	−0.0801	0.0455	0.2051	0.4334	−1.3788
	(−1.76)	(−0.31)	(0.23)	(0.89)	(0.85)	(−1.70)
$b_{\text{HIGH\_SENT}}$	2.1324**	0.7978*	0.3094	−0.6794*	−1.3440	3.4764**
	(2.68)	(2.05)	(1.06)	(−1.99)	(−1.79)	(2.90)
No. of months	264	264	264	264	264	264
R^2	0.03	0.06	0.03	0.03	0.02	0.05

We see that in low-sentiment periods, the beta of the long–short portfolio on the sentiment is −1.38, statistically significant at the 10% level of significance but insignificant at the 5% level. The beta on the sentiment of the long–short portfolio in high-sentiment periods is 3.48 and statistically significant at the 1% level of significance. This implies that the return difference between the lowest- and highest-sentiment-beta portfolios increases by 0.35% per month (4.2% per year) if sentiment changes by 0.1 unit in high-sentiment periods. We recall that the sentiment index developed by Baker and Wurgler (2006), (2007) has mean equal to 0 and standard deviation equal to 1.

Is the sentiment beta persistent, or does it change over time? To answer this question, we report the transition frequencies of stocks across sentiment-beta quintiles in Table 3. For $k = 6$, 12, 24, and 36, the sentiment-beta quintiles for

TABLE 3

Persistence of Sentiment Beta of Stocks

Table 3 reports the transition frequencies of stocks across sentiment-beta quintiles. For $k = 6$, 12, 24, and 36, the sentiment-beta quintiles for each stock in months t and $t + k$ are recorded. The rows in the table represent the sentiment-beta quintile in month t, and the columns represent the sentiment-beta quintile in month $t + k$. Quintile rank 99 stands for the fraction of stocks that no longer exist after k months. Therefore, the entry in cell (i, j) represents the percentage of stocks belonging to quintile i in month t that move to quintile j in month $t + k$.

Panel A. 6-Month Transition Frequency

Quintile Rank in Month t	Quintile Rank in Month $t + 6$						
	1	2	3	4	5	99	Total
1	12.12	3.81	1.33	0.79	0.60	1.33	20.00
2	3.60	8.10	4.58	1.98	0.86	0.89	20.00
3	1.35	4.43	7.47	4.55	1.43	0.77	20.00
4	0.84	1.97	4.48	8.02	3.84	0.85	20.00
5	0.60	0.85	1.43	3.88	11.94	1.30	20.00

Panel B. 12-Month Transition Frequency

Quintile Rank in Month t	Quintile Rank in Month $t + 12$						
	1	2	3	4	5	99	Total
1	8.91	3.81	1.92	1.48	1.38	2.49	20.00
2	3.55	5.93	4.51	2.75	1.57	1.70	20.00
3	1.92	4.34	5.73	4.42	2.04	1.55	20.00
4	1.50	2.72	4.31	5.96	3.82	1.69	20.00
5	1.39	1.53	2.08	3.83	8.74	2.42	20.00

Panel C. 24-Month Transition Frequency

Quintile Rank in Month t	Quintile Rank in Month $t + 24$						
	1	2	3	4	5	99	Total
1	5.30	3.12	2.25	2.21	2.66	4.46	20.00
2	2.92	4.30	4.06	3.27	2.25	3.20	20.00
3	2.16	3.94	4.57	3.97	2.34	3.02	20.00
4	2.17	3.21	3.92	4.32	3.17	3.22	20.00
5	2.58	2.26	2.37	3.19	5.22	4.39	20.00

Panel D. 36-Month Transition Frequency

Quintile Rank in Month t	Quintile Rank in Month $t + 36$						
	1	2	3	4	5	99	Total
1	3.46	2.57	2.19	2.44	3.23	6.11	20.00
2	2.40	3.38	3.69	3.43	2.53	4.57	20.00
3	2.05	3.58	4.03	3.67	2.36	4.32	20.00
4	2.33	3.37	3.66	3.51	2.58	4.56	20.00
5	3.22	2.57	2.32	2.59	3.28	6.01	20.00

each stock in months t and $t + k$ are recorded. The rows in the table represent the sentiment-beta quintile in month t. Columns 1–5 represent the five sentiment-beta quintiles in month $t + k$ for the surviving stocks, whereas column 99 stands for the fraction of stocks that no longer exist after k months. Therefore, the entry in cell (i, j) represents the percentage of stocks belonging to quintile i in month t that move to quintile j in month $t + k$. There is no long-term persistence in stock sentiment beta, as is evident from Panel D. Out of every 20 stocks belonging to quintile 1 in month t, only 3.46 are still in quintile 1 after 36 months, whereas 3.23 stocks have moved to quintile 5. Similarly, out of every 20 stocks belonging to quintile 5 in month t, only 3.28 are still in quintile 5 after 36 months, whereas 3.22 stocks have moved to quintile 1. We conclude that stocks do not have consistently negative- or positive-sentiment beta. Also, stocks in extreme quintiles are more likely to remain in or move to extreme quintiles rather than move to zero-beta quintiles.

2. A Measure of Fund Sentiment Beta

The negative relationship between sentiment beta and stock performance suggests that investing in negative-sentiment-beta stocks would be a profitable strategy for mutual funds. We construct a proxy of the degree by which a fund loads on sentiment. We aggregate the sentiment beta of the stocks in the portfolio, by their representation in the portfolio. For each fund f and month t, our measure of FSB is:

$$\text{FSB}_t^f = \sum_{i=1}^{I} w_{i,t}^f \beta_{5i,t}, \tag{3}$$

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where $w^f_{i,t}$ is the portfolio weight in stock i of fund f in month t, and $\beta_{5i,t}$ is the estimated sentiment beta of stock i for month t estimated from equation (1).

An alternative method to calculate FSB could be to relate fund returns to FSB directly (i.e., run the regression of fund excess returns from the previous 36 months on 4 factors and sentiment, and use the coefficient of sentiment as a measure of FSB). This alternative method suffers from a serious drawback. It is based on fund returns coming from the portfolios of the previous 36 months. However, the stocks in these portfolios might have had very different sentiment betas from the stocks in the fund's current portfolio. Because the future returns of the fund will depend only on its current portfolio, we believe it is more appropriate to use the weighted average of the sentiment betas of the stocks in the current portfolio as a measure of FSB.

As a robustness check, we also calculate FSB using this method and measure the performance of fund quintile portfolios based on this alternative measure of FSB. The results are confirmed but the economic significance is lower: The low-FSB funds outperform the high-FSB funds by 7 bps per month (84 bps per year) in terms of net returns, and only 2 bps per month (24 bps per year) in terms of 4-factor alpha.

Panel A of Table 4 presents summary statistics for the sample of mutual funds used in this article. The summary statistics for different variables in this table are calculated based on the number of observations for which the data for the variable are available. The sample covers monthly observations from Jan. 1984 to Dec. 2005, representing a total of 264 months. During this period, the volume of assets under management, as well as the number of funds, has steadily increased over time. On average, over the whole sample period, the mutual fund families in the sample manage $802 billion in assets distributed over 2,031 funds. The corresponding figures for year 2005 are $1,780 billion (representing 36% of all equity funds) distributed over 1,099 mutual funds. The average fund in the sample period has assets worth $1.15 billion, charges 1.23% in total annual fees, and is 15 years old. The average family manages five equity funds and $5.7 billion in assets.

TOTAL_NET_ASSETS (TNA) is the sum of the net assets of different classes of the same fund. The average TNA of funds in our sample is $1,147 million, with a standard deviation of $4,116 million. The high standard deviation suggests that the funds in our sample have substantial variation in size. Therefore, we use the logarithm of TNA in our regressions. FAMILY_SIZE is defined as the sum of the TNAs of all other funds belonging to the same management company. We use log(FAMILY_SIZE) calculated as the log of 1 plus FAMILY_SIZE in the regressions. TURNOVER is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund in the previous year. The average fund turnover is 84% per year. AGE is the number of years since the fund was first offered. The average fund age is 15.17 years. EXPENSE_RATIO is the ratio of total investment that shareholders paid for the fund's operating expenses in the previous year. The average expense ratio of funds is 1.23% per year. TOTAL_LOAD is the sum of front load and rear load charged by the fund at the end of the prior year, expressed as a percentage of the money invested. Investors pay an average load of 2.36% per year.

TABLE 4

Summary Statistics of Mutual Funds in the Sample

Panel A of Table 4 reports summary statistics on fund characteristics for the sample of mutual funds used in this article. The sample covers monthly observations from Jan. 1984 to Dec. 2005, representing a total of 264 months. The number of distinct mutual funds in the sample is 2,031, and the total number of fund-month observations is 184,646. Total net assets (TNA) is the sum of the net assets of different classes of the same fund. FAMILY_SIZE is the log of 1 plus the sum of TNA of all other funds belonging to the same management company. TURNOVER is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund in the previous year. AGE is the number of years since the fund was first offered. EXPENSE_RATIO is the ratio of total investment that shareholders paid for the fund's operating expenses in the previous year. TOTAL_LOAD is the sum of front load and rear load charged by the fund at the end of previous year, expressed as a percentage of the money invested. NET_RETURN is the simple return received by the investors after fund expenses. GROSS_RETURN is net return plus monthly expense ratio, where monthly expense ratio is calculated as the annual expense ratio divided by 12. MARKET-ADJUSTED_RETURN is net return minus market return. Factor loadings of a fund for a month are obtained by running a time-series regression of fund excess return on market excess return (MKTRF) in the case of the CAPM, the 3 Fama–French (1993) factors (MKTRF, SMB, and HML) in the case of the 3-factor model, and 4 factors (3 Fama–French factors plus the Carhart (1997) momentum factor) in the case of the 4-factor model using past 36 months data. We require a minimum of 30 observations for a fund to estimate its factor loadings. CAPM_ALPHA, 3-FACTOR_ALPHA, and 4-FACTOR_ALPHA for the current month are calculated as the fund excess return minus the sum of the products of the relevant factor loadings with the current month factor realizations. Panel B reports summary statistics on FSB by style for funds within each major Morningstar style. FSB for a fund in a month is defined as the weighted average of the sentiment betas of the stocks in its portfolio, weighted by the value of its stock holdings. The sentiment beta of a stock is obtained by running a time-series regression of monthly fund excess returns on 3 Fama–French factors, the Carhart momentum factor, and monthly sentiment. The monthly sentiment data are based on Baker and Wurgler (2006) and were obtained from Wurgler's Web site (http://people.stern.nyu.edu/jwurgler/).

Panel A. Fund Characteristics

				Percentiles	
Variables	Mean	Median	Std Dev	1st	99th
TNA ($million)	1,146.75	226.06	4,116.74	17.03	17,734.80
log(TNA) ($million)	5.54	5.41	1.59	2.83	9.78
log(FAMILY_SIZE) ($million)	8.70	9.22	2.93	0.00	13.51
TURNOVER (% per year)	84.44	65.00	80.24	3.00	371.00
AGE (years)	15.17	9.17	15.12	1.42	67.33
EXPENSE_RATIO (% per year)	1.23	1.18	0.45	0.17	2.44
TOTAL_LOAD (% per year)	2.36	1.00	2.66	0.00	8.50
NET_RETURN (% per month)	0.93	1.17	5.21	−14.72	13.17
GROSS_RETURN (% per month)	1.04	1.27	5.21	−14.60	13.26
MARKET-ADJUSTED_RETURN (% per month)	−0.06	−0.13	2.89	−7.96	8.37
CAPM_ALPHA (% per month)	−0.07	−0.10	2.74	−7.74	7.64
3-FACTOR_ALPHA (% per month)	−0.10	−0.12	2.12	−5.87	5.91
4-FACTOR_ALPHA (% per month)	−0.12	−0.13	2.08	−5.87	5.67

Panel B. Fund Sentiment Beta by Style

				Percentiles	
Styles	Mean	Median	Std Dev	1st	99th
Large Blend	0.0012	0.0016	0.0049	−0.0113	0.0120
Large Growth	0.0009	0.0017	0.0064	−0.0179	0.0168
Large Value	0.0013	0.0017	0.0042	−0.0105	0.0111
Mid-Cap Blend	0.0003	0.0010	0.0081	−0.0252	0.0206
Mid-Cap Growth	0.0001	0.0004	0.0110	−0.0297	0.0326
Mid-Cap Value	0.0008	0.0009	0.0063	−0.0203	0.0146
Small Blend	0.0028	0.0036	0.0082	−0.0251	0.0208
Small Growth	0.0045	0.0051	0.0131	−0.0368	0.0401
Small Value	0.0018	0.0023	0.0069	−0.0182	0.0170
All funds	0.0015	0.0018	0.0077	−0.0210	0.0233

The average monthly NET_RETURN and GROSS_RETURN of the funds in our sample are 0.93% and 1.04%, respectively. CAPM_ALPHA, 3-FACTOR_ALPHA, and 4-FACTOR_ALPHA of a fund for a month are calculated by running a time-series regression of fund excess return on market excess return (MKTRF) for CAPM alpha, the 3 Fama–French (1993) factors (MKTRF, SMB, and HML) for 3-factor alpha, and 4-factor alpha using data from the past 36 months. FUND_ALPHA for the current month is obtained as the fund excess return minus the sum of the products of the factor loadings with the current-month factor realizations. The funds in our sample have, on average, −0.06% market-adjusted return, −0.07% CAPM alpha, −0.10% 3-factor alpha, and −0.12% 4-factor alpha per month.

In Panel B of Table 4, we report some descriptive statistics about the FSB of the funds across different styles. The funds that invest in small and growth stocks have higher average FSBs. Moreover, the within-style cross-sectional variation is higher for these funds. This variation will be exploited in our specifications, which are always conditional on style.

III. FSB and Fund Performance

We now relate FSB to fund performance. First, we test whether performance is related to the degree of FSB of the fund. Then, we analyze whether the relation between FSB and performance is persistent and whether it helps to forecast future performance.

A. Overall FSB–Performance Relationship

We start by documenting the relation between fund sentiment beta and fund performance. We consider both a portfolio-based approach and a multivariate analysis. We use the following as measures of performance: net return, style-adjusted return, gross return, market-adjusted return, CAPM alpha, and the 3-factor alpha, and 4-factor alpha of the different portfolios and also of the difference between portfolio 1 and portfolio 5. For each month, we sort all of the funds based on their degree of FSB at the beginning of the month and group them into five quintiles. We then proceed in two alternative ways. First, we construct the different measures of performance at the fund level, and then we average them out across all of the funds belonging to the same quintile. This method is the same as the one used by Fama and French (1993) to form stock portfolios based on size or beta. The portfolio performance is the equal-weighted mean of the return of the funds in the portfolios.

Alternatively, we construct the measures of performance directly for the portfolios of the funds. In the latter case, we construct five portfolios from the lowest (portfolio 1) to the highest (portfolio 5) degree of FSB. Then, we regress the portfolio returns (i.e., the equal-weighted mean of the returns of the funds in the portfolios) on the factors. We also form a long–short portfolio that buys low-FSB funds and sells high-FSB funds, and run a time-series regression of the returns of this long–short portfolio on the 4 factors to estimate alpha.

We calculate the alpha of fund i in month t, following the standard two-stage estimation method (e.g., Carhart (1997)). We first estimate the factor loadings of the fund by running the following regression using the past 36 months of returns:

$$(4) \qquad \begin{aligned} R_{it} - R_{ft} \quad = \quad & \alpha_i + b_i^{\text{MKTRF}}\text{MKTRF}_t + b_i^{\text{SMB}}\text{SMB}_t \\ & + b_i^{\text{HML}}\text{HML}_t + b_i^{\text{UMD}}\text{UMD}_t + \varepsilon_{it}. \end{aligned}$$

The estimated β_i^{MKTRF}, β_i^{SMB}, β_i^{HML}, and β_i^{UMD} are the factor loadings. Then, we calculate the monthly alpha of fund i as:

$$(5) \qquad \alpha_{iT} = (R_{iT} - R_{fT}) - (\beta_i^{\text{MKTRF}}\text{MKTRF}_T + \beta_i^{\text{SMB}}\text{SMB}_T + \beta_i^{\text{HML}}\text{HML}_T + \beta_i^{\text{UMD}}\text{UMD}_T).$$

We report the results for the first methodology (i.e., average values of performance across funds) in Table 5 and those for the second methodology (i.e., portfolio performance) in Table 6.

TABLE 5

Fund Sentiment Beta and Fund Performance

Table 5 reports the relation between fund FSB and fund performance. Quintile portfolios are formed every month by sorting funds based on their FSBs at the beginning of the month. Portfolio 1 (5) is the portfolio of funds with the lowest (highest) FSB. The table reports various measures of portfolio return using the equal-weighted mean of the return of the funds in the portfolios. NET_RETURN is the simple return received by the investors after fund expenses. STYLE-ADJUSTED_RETURN is fund return minus the average return of funds in the same style, where we have used Morningstar styles to classify funds into different styles. GROSS_RETURN is NET_RETURN plus monthly expense ratio, where monthly expense ratio is calculated as the annual expense ratio divided by 12. MARKET-ADJUSTED_RETURN is net return minus market return. Factor loadings of a fund for a month are obtained by running a time-series regression of fund excess return on market excess return (MKTRF) in case of CAPM, the 3 Fama–French (1993) factors (MKTRF, SMB, and HML) in case of 3-factor model, and 4 factors (3 Fama–French factors plus the Carhart (1997) momentum factor) in case of 4-factor model using past 36 months data. We require a minimum of 30 observations for a fund to estimate its factor loadings. CAPM_ALPHA, 3-FACTOR_ALPHA, and 4-FACTOR_ALPHA for the current month are calculated as the fund excess return minus the sum of the products of the relevant factor loadings with the current month factor realizations. The DIFF 1-5 row gives the difference in return between portfolio 1 and portfolio 5, and the last row gives the *t*-statistics for the significance of the difference. The sample period is from Jan. 1984 to Dec. 2005, a total of 264 month observations. Panel A reports the results for all months. Panels B and C report results for negative-sentiment months and positive-sentiment months, respectively. The *t*-statistics are given in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Portfolios	No. of Months	NET_RETURN	GROSS_RETURN	STYLE-ADJUSTED_RETURN	MARKET-ADJUSTED_RETURN	CAPM_ALPHA	3-FACTOR_ALPHA	4-FACTOR_ALPHA
Panel A. All Months								
1	264	1.19	1.29	0.09	0.14	0.06	0.07	0.02
2	264	1.04	1.13	0.02	−0.01	−0.03	−0.03	−0.04
3	264	0.96	1.05	−0.02	−0.08	−0.07	−0.08	−0.09
4	264	0.96	1.05	−0.02	−0.09	−0.09	−0.09	−0.10
5	264	0.83	0.93	−0.09	−0.22	−0.21	−0.14	−0.19
DIFF 1-5	264	0.36**	0.36**	0.19**	0.36**	0.27**	0.21**	0.22**
t-statistics		(3.21)	(3.21)	(3.52)	(3.21)	(2.82)	(2.84)	(3.71)
Panel B. Negative-Sentiment Months								
1	138	1.80	1.90	0.09	0.14	0.10	0.07	−0.00
2	138	1.62	1.71	−0.01	−0.04	−0.01	−0.03	−0.06
3	138	1.53	1.63	−0.06	−0.12	−0.07	−0.09	−0.10
4	138	1.59	1.68	−0.01	−0.07	−0.05	−0.07	−0.07
5	138	1.66	1.76	−0.03	0.00	−0.10	−0.13	−0.12
DIFF 1-5	138	0.14	0.14	0.11	0.14	0.20	0.19**	0.12*
t-statistics		(1.41)	(1.43)	(1.90)	(1.41)	(1.80)	(2.74)	(2.01)
Panel C. Positive-Sentiment Months								
1	126	0.52	0.62	0.10	0.14	0.02	0.08	0.05
2	126	0.41	0.50	0.05	0.03	−0.05	−0.03	−0.03
3	126	0.34	0.43	0.03	−0.04	−0.07	−0.06	−0.08
4	126	0.27	0.36	−0.03	−0.11	−0.13	−0.10	−0.12
5	126	−0.07	0.03	−0.16	−0.45	−0.34	−0.14	−0.27
DIFF 1-5	126	0.59**	0.59**	0.26**	0.59**	0.36*	0.22	0.32**
t-statistics		(2.91)	(2.90)	(2.98)	(2.91)	(2.18)	(1.68)	(3.13)

TABLE 6

Portfolios of Mutual Funds Formed on FSB

Table 6 reports the results of the regression of fund excess return (i.e., fund return minus risk-free return) of FSB portfolios on the 3 Fama–French (1993) factors and the momentum factor. In both cases, the results are given for all months as well as separately for negative-sentiment months and positive-sentiment months. Quintile portfolios are formed every month by sorting funds based on their FSBs at the beginning of the month. Quintile 1 (5) is the portfolio of funds with the lowest (highest) FSB. Columns 1 to 5 give results for portfolios 1 to 5, respectively. Long–short portfolio 1-5 is formed by buying funds in portfolio 1 and selling funds in portfolio 5 at the beginning of every month. Alpha is the intercept of the regression. The sample period is from Jan. 1984 to Dec. 2005, representing a total of 264 months. The *t*-statistics are given in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Independent Variables	Portfolios 1	2	3	4	5	Long–Short Portfolio 1-5
Panel A. All Months, Regression $R_{it} - R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + e_t$						
Alpha	0.0596	−0.0315	−0.0836*	−0.1156*	−0.2470**	0.3066**
	(0.83)	(−0.73)	(−2.15)	(−2.53)	(−3.16)	(2.72)
MKTRF	0.9851**	0.9642**	0.9622**	0.9768**	1.0302**	−0.0451
	(55.15)	(89.10)	(99.18)	(85.82)	(52.98)	(−1.60)
SMB	0.2598**	0.0761**	0.0358**	0.0765**	0.3161**	−0.0563
	(11.76)	(5.69)	(2.99)	(5.44)	(13.14)	(−1.62)
HML	−0.0642*	0.0272	0.0600**	0.0746**	0.0098	−0.0740
	(−2.42)	(1.69)	(4.15)	(4.40)	(0.34)	(−1.77)
UMD	0.0746**	0.0145	−0.0139	−0.0147	−0.0328	0.1074**
	(4.77)	(1.53)	(−1.64)	(−1.48)	(−1.93)	(4.36)
No. of Months	264	264	264	264	264	264
R^2	0.95	0.98	0.98	0.97	0.94	0.09
Panel B. Negative-Sentiment Months, Regression $R_{it} - R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + e_t$						
Alpha	−0.0947	−0.0842	−0.1266**	−0.0849	−0.1303	0.0356
	(−1.45)	(−1.96)	(−3.65)	(−1.88)	(−1.87)	(0.37)
MKTRF	1.0265**	0.9727**	0.9608**	0.9531**	0.9910**	0.0355
	(55.45)	(79.76)	(97.40)	(74.37)	(50.03)	(1.29)
SMB	0.3330**	0.1186**	0.1140**	0.1625**	0.4083**	−0.0752*
	(14.00)	(7.57)	(8.99)	(9.87)	(16.05)	(−2.13)
HML	−0.1800**	−0.1043**	−0.0474**	−0.0230	−0.0206	−0.1594**
	(−6.08)	(−5.35)	(−3.01)	(−1.12)	(−0.65)	(−3.62)
UMD	0.1103**	0.0388**	0.0299**	0.0373**	0.0273	0.0829**
	(6.45)	(3.44)	(3.29)	(3.15)	(1.49)	(3.26)
No. of Months	138	138	138	138	138	138
R^2	0.97	0.99	0.99	0.98	0.97	0.22
Panel C. Positive-Sentiment Months, Regression $R_{it} - R_{ft} = a + b_1\text{MKTRF}_t + b_2\text{SMB}_t + b_3\text{HML}_t + b_4\text{UMD}_t + e_t$						
Alpha	0.0982	−0.0614	−0.1120	−0.1967**	−0.3770**	0.4752*
	(0.77)	(−0.88)	(−1.77)	(−2.65)	(−2.67)	(2.28)
MKTRF	0.9607**	0.9601**	0.9621**	0.9884**	1.0481**	−0.0874
	(34.40)	(62.20)	(69.19)	(60.58)	(33.67)	(−1.91)
SMB	0.2513**	0.0879**	0.0260	0.0627**	0.2859**	−0.0346
	(7.04)	(4.45)	(1.46)	(3.01)	(7.18)	(−0.59)
HML	−0.0396	0.0774**	0.0911**	0.1060**	0.0140	−0.0537
	(−0.94)	(3.33)	(4.35)	(4.32)	(0.30)	(−0.78)
UMD	0.0657**	0.0063	−0.0287*	−0.0339*	−0.0554*	0.1211**
	(2.75)	(0.47)	(−2.41)	(−2.42)	(−2.08)	(3.09)
No. of Months	126	126	126	126	126	126
R^2	0.94	0.98	0.98	0.98	0.94	0.11

We start with the first methodology. In Panel A of Table 5, we report the results for the overall period, and in Panels B and C, we report the results broken down into negative-sentiment months and positive-sentiment months, respectively. The results show a strong negative relationship between fund performance and FSB. This relationship is monotonic across portfolios and is robust across alternative definitions of performance. The difference between low- and high-FSB funds is around 36 bps per month (4.3% per year) in the case of gross return, 36 bps per month (4.3% per year) in the case of net return, 27 bps per month (3.2% per year) in the case of CAPM alpha, 21 bps per month (2.5% per year) in the case of 3-factor alpha, and 22 bps per month (2.64% per year) in the case of 4-factor alpha. The difference in performance between low-FSB funds and high-FSB funds is higher when the beginning-of-month sentiment is positive: 12 bps per month (1.44% per year) 4-factor alpha in negative-sentiment months versus 32 bps per month (3.94% per year) in positive-sentiment months.

We then consider portfolio performance. We regress the returns of the FSB-based portfolios on the 4 factors. We report the results in Table 6. The dependent variable is the excess return. We also consider the gross-of-fee return. In the interest of brevity, we do not tabulate them, but they deliver similar results. The results show that low-FSB funds (quintile 1) outperform high-FSB funds (quintile 5) by 31 bps per month (3.7% per year). Most of this outperformance comes from the months when the beginning-of-month sentiment is positive. In these months, low-FSB funds outperform high-FSB funds by 48 bps per month (5.8% per year).

Next, we perform a multivariate analysis of the monthly returns. This allows us to control for a set of fund-specific characteristics that may be spuriously related to fund sentiment. These are the size of the fund, the size of the family the fund belongs to, the age of the fund, its portfolio turnover, the expense ratio and the total load fees it charges, and the flows it received as well as the volatility of flows in the prior 12 months. We also include the fund performance in the prior 12 months (i.e., a lagged measure of the fund performance). A detailed definition of the control variables is reported in Appendix B. We report the results in Table 7. In the interest of brevity, we report only the results based on the 4-factor alpha. The results for market-adjusted return, 1-factor alpha, and 3-factor alpha are consistent both economically and statistically with those reported for the 4-factor alpha. Columns 1–3 report the results based on the Fama–MacBeth (1973) specification with t-statistics adjusted for serial correlation using Newey–West (1987) lags of order 3. Columns 4–6 report the results based on a pooled specification that includes time dummies and standard errors cluster-corrected by fund. As a robustness check, we also estimate pooled regressions with standard errors cluster-corrected by family. The (unreported) results are similar to the displayed ones.

The results are consistent with the portfolio results and display a strong positive correlation between fund FSB and fund performance. This holds across all the specifications. It is also economically significant. A 1-standard-deviation-lower FSB relates to a 4-factor alpha that is 66 bps per year higher.[1] The effect is larger and statistically stronger when the beginning-of-month sentiment is positive. Then, a 1-standard-deviation-lower FSB relates to an annual 4-factor alpha that is 87 bps higher.

[1]One standard deviation of FSB is 0.0077. Therefore, a 1-standard-deviation-lower FSB is related to a 4-factor alpha that is 0.0077 times 7.0988%, or 5.5 bps per month, or 66 bps per year, higher.

TABLE 7

Regression of Fund Performance on FSB

Table 7 regresses various measures of fund performance on FSB at the beginning of the month and other control variables. The control variables are as explained in Appendix B. The dependent variable in the results reported in this table is the 4-factor alpha. The results for CAPM alpha and 3-factor alpha lead to the same conclusions and therefore are not reported. Columns 1–3 report results using the Fama–MacBeth (1973) regression, in which the *t*-statistics are adjusted for serial correlation using Newey–West (1987) lags of order 3 and are shown in parentheses. Columns 4–6 report results using pooled regression including time dummies, in which the *t*-statistics are cluster-corrected using clustering by fund and are shown in parentheses. The sample period is from Jan. 1984 to Dec. 2005, a total of 264 months. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

	Fama–MacBeth			Pooled		
Independent Variables	All Months 1	Negative Sentiment 2	Positive Sentiment 3	All Months 4	Negative Sentiment 5	Positive Sentiment 6
FSB	−7.0988**	−4.9923	−9.4060*	−14.2233**	−10.1577**	−16.1822**
	(−2.71)	(−1.68)	(−2.44)	(−9.60)	(−6.64)	(−7.97)
log(TNA)	−0.0184**	−0.0130	−0.0242*	−0.0232**	−0.0085	−0.0339**
	(−2.92)	(−1.85)	(−2.38)	(−4.80)	(−1.67)	(−4.74)
log(FAMILY_SIZE)	0.0096**	0.0048	0.0148**	0.0079*	0.0008	0.0143**
	(3.79)	(1.15)	(4.24)	(2.50)	(0.28)	(3.13)
TURNOVER	−0.0003	−0.0001	−0.0005	−0.0002	0.0000	−0.0004
	(−1.45)	(−0.45)	(−1.77)	(−1.32)	(0.07)	(−1.60)
AGE	−0.0009*	−0.0011*	−0.0006	−0.0007	−0.0009*	−0.0007
	(−2.26)	(−2.24)	(−0.94)	(−1.75)	(−2.02)	(−1.19)
EXPENSE_RATIO	−0.0626**	−0.0449*	−0.0821*	−0.0614**	−0.0469**	−0.0831**
	(−3.47)	(−2.09)	(−2.36)	(−3.71)	(−2.68)	(−3.12)
TOTAL_LOAD	−0.0016	−0.0031	0.0001	−0.0014	−0.0018	−0.0008
	(−0.69)	(−1.24)	(0.03)	(−0.58)	(−0.66)	(−0.22)
LAG_FLOW	0.0003	0.0003	0.0002	−0.0000	0.0000	−0.0001
	(0.77)	(0.61)	(0.81)	(−0.48)	(0.48)	(−0.66)
LAG_FUND_RET	0.0106**	0.0085*	0.0130**	0.0125**	0.0057**	0.0151**
	(3.99)	(2.60)	(3.41)	(15.19)	(5.57)	(14.49)
SIGMA_FLOW	−0.0010	−0.0011	−0.0010	0.0000	0.0000**	−0.0001
	(−0.74)	(−0.47)	(−0.50)	(0.54)	(5.80)	(−1.85)
Intercept	0.0241	0.0509	−0.0052	−1.3250**	−0.4825**	−1.3429**
	(0.27)	(0.60)	(−0.04)	(−7.41)	(−3.82)	(−7.22)
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	Yes	Yes	Yes
No. of obs.	156,469	82,433	74,036	156,469	82,433	74,036
R^2	0.17	0.16	0.18	0.08	0.06	0.10

B. Persistence and Predictability

The previous results show that low-FSB funds outperform high-FSB funds after controlling for risk factors and fund characteristics. However, it may be the case that poorly performing funds within the set of low-FSB funds are closed and the higher performance of low-FSB funds is just due to survivorship bias. To address this issue, we provide univariate statistics on survival rates of funds within different FSB quintiles. More specifically, we track the quintile portfolios formed each month for the following 12 months and construct the fraction of funds surviving in each of the following months. This delivers, for each of the following months from 1 to 12, a time series of the fraction of funds that survived up to that month.

In Table 8, we report the time-series average of the cross-sectional fraction of funds in a quintile portfolio that survived in the following months. This number is 1.00, by default, in month 1 and decreases with time. We see that the fraction

TABLE 8

Fraction of Funds Surviving in Future Months

Table 8 analyzes the survival rate of funds belonging to different FSB quintiles. Quintile portfolios are formed every month by sorting funds based on their FSBs at the beginning of the month. Portfolio 1 (5) is the portfolio of funds with the lowest (highest) FSB. The quintile portfolios formed each month are tracked for next the 12 months and the fraction of funds surviving in each of the future months is calculated. Corresponding to each future month from 1 to 12, we have a time series of the fraction of funds that survived up to that month. This table reports the time-series average of the fraction of funds in a quintile portfolio that are surviving in future months, for months 1 to 12. The sample period is from Jan. 1984 to Dec. 2005.

	Months											
Portfolios	1	2	3	4	5	6	7	8	9	10	11	12
1	1.00	0.99	0.98	0.98	0.97	0.96	0.95	0.95	0.94	0.93	0.93	0.92
2	1.00	0.99	0.99	0.98	0.97	0.97	0.96	0.96	0.95	0.94	0.94	0.93
3	1.00	0.99	0.99	0.98	0.97	0.97	0.96	0.96	0.95	0.94	0.94	0.93
4	1.00	0.99	0.99	0.98	0.97	0.97	0.96	0.96	0.95	0.95	0.94	0.93
5	1.00	0.99	0.98	0.98	0.97	0.96	0.96	0.95	0.94	0.94	0.93	0.93

of funds surviving in future months is almost the same for each quintile. By the end of 1 year, 92% of funds in quintile 1 survived, as compared with 93% in the other quintiles. The drop over time is also similar across quintiles. This suggests that survivorship bias is unlikely to be a reason for the superior performance of the low-FSB funds.

Next, we investigate the predictive power of fund FSB for future performance of funds at longer horizons, ranging from 1 to 12 months. We adopt a portfolio approach. For this purpose, every month, we construct portfolios by sorting funds based on their FSBs at the beginning of the month. Portfolio 1 (5) is the portfolio of funds with the lowest (highest) FSB. We then track the portfolios formed for the following 12 months and calculate the portfolio return for each of these 12 months. The portfolio return is the mean return of the funds in the portfolio. This creates a time series of portfolio returns corresponding to each future month from 1 to 12. Then, corresponding to each month, we regress the portfolio returns on the 4 factors. Alpha is defined as the intercept of the time-series regression in each case.

We report the results in Table 9. Rows 1–5 report the alphas for quintiles 1–5, respectively. Row Long–Short Portfolio 1-5 gives the alpha for a long–short portfolio formed by buying funds in portfolio 1 and selling funds in portfolio 5. The results show that low-FSB funds have higher alphas in the following 12 months. This difference in performance is statistically significant in each of the following 7 months. It corresponds to 32 bps for the next month and goes down to 20 bps in month 7. The cumulative 4-factor alpha for 12 months is 236 bps (2.36%). In other words, a portfolio long on low-FSB funds and short on high-FSB funds has an alpha of 2.36% if held for 1 year.

Overall, these findings show that the funds that load negatively on market sentiment (i.e., display low FSB) enjoy higher performance, and this higher performance is not just a fluke, but persists over time. We now try to assess which type of investment vehicle is more likely to play this strategy. We look at whether persistence is related to the size of the family. A more persistent relationship suggests family coordination as opposed to the case of temporary behavior, potentially determined by the fund manager, induced, for example, by the need to time the benchmark or compete in a tournament.

TABLE 9

Prediction of Future Performance

Table 9 reports the results of the analysis of the predictive power of FSB for the future performance of funds at longer horizons ranging from 1 to 12 months. Quintile portfolios are formed every month by sorting funds based on their FSBs at the beginning of the month. Portfolio 1 (5) is the portfolio of funds with the lowest (highest) FSB. The quintile portfolios formed each month are tracked for the next 12 months, and the portfolio return is calculated for each of these 12 months. Portfolio returns are calculated as the mean return of funds in the portfolio. This creates a time series of portfolio returns corresponding to each future month from 1 to 12. Corresponding to each month, portfolio excess return is regressed on the 4 factors (3 Fama–French (1993) factors and the momentum factor). Alpha is defined as the intercept of the time-series regression in each case. Rows 1 to 5 give alphas for quintiles 1 to 5, respectively. Row Long–Short Portfolio 1-5 gives the alpha for a long–short portfolio formed by buying funds in portfolio 1 and selling funds in portfolio 5. The *t*-statistics are given in parentheses. The sample period is from Jan. 1984 to Dec. 2005, representing a total of 264 months. The *t*-statistics are given in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

	Months											
Portfolios	1	2	3	4	5	6	7	8	9	10	11	12
1	0.07	0.05	0.05	0.03	0.04	0.04	0.02	0.01	–0.02	–0.02	–0.05	–0.08
	(1.00)	(0.83)	(0.68)	(0.46)	(0.65)	(0.69)	(0.32)	(0.13)	(–0.43)	(–0.44)	(–0.92)	(–1.50)
2	–0.02	–0.02	–0.01	–0.03	–0.05	–0.06	–0.05	–0.06	–0.05	–0.05	–0.05	–0.07*
	(–0.52)	(–0.39)	(–0.25)	(–0.70)	(–1.31)	(–1.63)	(–1.47)	(–1.60)	(–1.29)	(–1.61)	(–1.56)	(–2.19)
3	–0.08*	–0.07	–0.05	–0.04	–0.05	–0.06	–0.07*	–0.07	–0.07	–0.06	–0.06	–0.05
	(–2.04)	(–1.91)	(–1.35)	(–0.98)	(–1.41)	(–1.69)	(–2.05)	(–1.96)	(–1.74)	(–1.67)	(–1.55)	(–1.46)
4	–0.11*	–0.10*	–0.11*	–0.12**	–0.11*	–0.09*	–0.09*	–0.11*	–0.12*	–0.11*	–0.12*	–0.09*
	(–2.47)	(–2.28)	(–2.45)	(–2.64)	(–2.53)	(–2.11)	(–2.00)	(–2.32)	(–2.42)	(–2.37)	(–2.59)	(–2.08)
5	–0.25**	–0.23**	–0.22**	–0.21*	–0.19*	–0.18*	–0.19*	–0.19*	–0.17*	–0.16*	–0.15	–0.12
	(–3.21)	(–2.85)	(–2.82)	(–2.51)	(–2.34)	(–2.25)	(–2.36)	(–2.35)	(–2.13)	(–2.00)	(–1.95)	(–1.58)
Long–Short	0.32**	0.28*	0.27*	0.23*	0.23*	0.22*	0.20*	0.19	0.15	0.13	0.10	0.04
Portfolio 1-5	(2.87)	(2.55)	(2.41)	(2.09)	(2.12)	(2.14)	(2.04)	(1.96)	(1.50)	(1.39)	(1.09)	(0.48)

To address this issue, we study the degree of persistence of FSB. Each month, we divide the funds into two groups according to whether the FSB is above median or below median in the cross section of funds in the month. We then define the ratio (R) as the difference between the numbers of times the fund is above median minus the number of times the fund is below median over the total number of months for which fund data are available. A high (low) value of R means the fund has a low (high) degree of FSB in most of the months. We also define a style-adjusted R as the difference between the R of the fund and the average R of all funds in the same style, where the Morningstar-style classification is used to identify the style of the fund.

We call "persistence ratio" the absolute value of R. The style-adjusted persistence ratio of a fund is defined as the persistence ratio of the fund minus the average persistence ratio of all funds in the same style. We use the Morningstar-style classification to identify the style of the fund. The value of the persistence ratio for a fund is high if the fund has either a high or low degree of sentiment in most of the months. We then regress the ratio as well as the persistence ratio on the number of funds of the family and fund characteristics.

We report the results in Panel A of Table 10. The results show that the ratios, as well as the style-adjusted ratios, are negatively related to the number of funds of the family. This is not only statistically significant, but also economically relevant. A 1-standard-deviation-*smaller* family corresponds to a 5.44% (5.44%) higher ratio (style-adjusted ratio) and to a 3.31% (3.54%) higher degree of persistence in the case of the absolute ratio (style-adjusted absolute ratio). The results are consistent with the previous ones and show that not only is low FSB a small-family choice, but also that it is a time-persistent choice. As a robustness

TABLE 10

Persistence of FSB and Family Affiliation

Panel A of Table 10 reports the results of an analysis of the persistence of FSB for the mutual funds in our sample. For each month the funds are divided into two groups according to whether the fund's FSB is below median or above median in the cross section of funds in that month. For each fund, ratio R is defined as the ratio of the number of times the fund is above median minus the number of times the fund is below median divided by the total number of months for which fund data are available. A high (low) value of R means the fund has low (high) FSB in most of the months. The style-adjusted R of a fund is defined as the R of the fund minus the average R of all funds in the same style, where the Morningstar style classification is used to identify the style of the fund. The persistence ratio is defined as the absolute value of R. The style-adjusted persistence ratio of a fund is defined as the persistence ratio of the fund minus the average persistence ratio of all funds in the same style, where the Morningstar-style classification is used to identify the style of the fund. The value of the persistence ratio for a fund is high if the fund has either high FSB in most of the months or low FSB in most of the months. In the first two regressions, R is regressed on fund characteristics. In the last two regressions, persistence ratio, the absolute value of R, is regressed on fund characteristics. The *t*-statistics are cluster-corrected using clustering by fund. * and ** indicate statistical significance at the 5% and 1% levels, respectively. Panel B reports the transition frequencies of mutual funds across FSB quintiles. For each mutual fund in our sample that survives for at least 36 months, its FSB quintiles in months *t* and *t* + 36 are recorded. The rows in the table represent the FSB quintile in month *t*, and the columns represent the FSB quintile in month *t* + 36. Therefore, the entry in cell (*i*, *j*) represents the percentage of funds belonging to quintile *i* in month *t* that moved to quintile *j* in month *t* + 36.

Panel A. Persistence

Independent Variables	R	Style-Adjusted R	Persistence Ratio	Style-Adjusted Persistence Ratio
	1	2	3	4
log(FAMILY_SIZE)	0.23**	0.23**	0.14**	0.15**
	(4.05)	(4.00)	(4.30)	(4.63)
log(TNA)	−2.34*	−2.37*	−3.70**	−3.79**
	(−2.20)	(−2.28)	(−6.24)	(−6.48)
TURNOVER	−0.01	−0.01	−0.02*	−0.02*
	(−0.85)	(−1.03)	(−2.38)	(−2.45)
AGE	0.33**	0.30*	−0.61**	−0.57**
	(2.59)	(2.41)	(−8.70)	(−8.26)
EXPENSE_RATIO	−6.16	−5.07	5.14**	4.55*
	(−1.80)	(−1.53)	(2.68)	(2.44)
TOTAL_LOAD	0.56	0.27	−0.75*	−0.70*
	(0.88)	(0.44)	(−2.11)	(−2.03)
LAG_FLOW	−0.01	−0.01	0.01*	0.01*
	(−1.12)	(−1.19)	(2.08)	(2.18)
LAG_FUND_RET	−0.32*	−0.24	0.09	0.05
	(−1.99)	(−1.55)	(0.99)	(0.56)
SIGMA_FLOW	0.00	0.00	−0.01	−0.01
	(0.36)	(0.41)	(−1.36)	(−1.37)
Intercept	17.38*	15.17*	71.00**	18.71**
	(2.01)	(2.05)	(14.67)	(4.50)
Style dummies	Yes	No	Yes	No
No. of obs.	1,910	1,910	1,910	1,910
R^2	0.07	0.02	0.13	0.11

Panel B. Transition Frequencies

	FSB Quintile in Month *t* + 36				
FSB Quintile in Month *t*	1	2	3	4	5
1	26.83	17.91	16.82	17.23	21.21
2	18.10	22.65	22.72	21.65	14.87
3	15.88	22.94	24.93	22.29	13.97
4	15.61	21.38	21.88	23.23	17.90
5	19.07	14.77	15.90	19.87	30.39

check, in Panel B we provide the transition frequencies of mutual funds across FSB quintiles. For each mutual fund in our sample that survives for at least 36 months, its FSB quintiles in months *t* and *t* + 36 are recorded. The rows in the table represent the FSB quintile in month *t* and the columns represent the FSB quintile in month *t* + 36. Therefore, the entry in cell (*i*, *j*) is the percentage of

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funds belonging to quintile i in month t that moved to quintile j in month $t+36$. We see that there is stability in the persistence and transition.

Overall, the findings thus far suggest that the funds with lower FSBs deliver higher net-of-risk performance and support the contrarian strategy hypothesis. They also show that this is not due to loading on liquidity risk, but to an active strategy. As we argued, this behavior may represent a deliberate risk-taking strategy that allows the funds to deliver better (gross-of-sentiment risk) performance by loading up on sentiment risk. Unreported results show that fund sentiment is not related to portfolio illiquidity. Indeed, it may be the case that FSB is related to tilting the portfolio as a function of liquidity. However, if we control for illiquidity the previous results hold. The next question is whether a low-FSB strategy involves active management or is only a passive strategy.

IV. Is FSB Actively Managed?

Low-FSB funds outperform high-FSB funds. The goal of this section is to investigate whether low FSB is a passive strategy or involves the active management of the fund. We proceed in two steps. First, we directly assess the degree of active management of the low-FSB funds. Then, we study how FSB-induced performance is related to the current level of market sentiment.

A. FSB and Active Management

We start by looking at "active management" and ask whether there is a relationship between the degree of FSB of the fund and its "activity." We conjecture that low-FSB funds are more active in rebalancing their portfolios and track less closely the benchmark. This can be done by engaging in more idiosyncratic strategies and specific stock picking.

To test this hypothesis, following Amihud and Goyenko (2013), we focus on the tracking error of the fund. This is constructed using the R^2 of the benchmark-factor model. It has been shown that funds that display a higher tracking error, and therefore a lower explanatory power of the factor model, are those that are less likely to follow a conventional or passive investment strategy. If, as we argued, lower FSB is related to risk taking, we expect a negative relation between the FSB and its tracking error and a positive relation between FSB and R^2.

Each month, we construct the R^2 for each fund as the R^2 of the regression of the fund excess return on the 4 risk factors using the prior 36 months of data. Following Amihud and Goyenko (2013), we use a logistic transformation of R^2 defined as follows: $\text{TR}^2 = \log[\sqrt{R^2}/(1-\sqrt{R^2})]$. The distribution of TR^2 is more symmetric and well behaved than that of R^2. Then, we perform yearly regressions of TR^2 on fund sentiment.[2] Other fund characteristics and style dummies using Morningstar fund styles are included.

[2]Because R^2 is calculated using the prior 36 months of data, the R^2 values of a fund in successive months are highly correlated. We therefore consider the R^2 only at an annual frequency. In other words, we perform Fama–MacBeth (1973) regressions based on yearly cross sections in which the dependent variable is the TR^2 obtained by regressing the monthly fund excess returns on the 4 factors using monthly data of the current year and the previous 2 years. On average, TR^2 has a mean of 3.07 and standard deviation of 0.83.

We report the results in Table 11. In specifications 1–3, the main independent variable is FSB, whereas in specifications 4–6, the main independent variable is the style-adjusted FSB (i.e., the FSB of the fund net-of-average FSB of the style the fund belongs to). Style dummies are not included in regressions 4–6. The results display a strong positive correlation between FSB and TR^2. Funds with lower FSB follow more idiosyncratic strategies. This holds both for FSB and its net-of-style value. The economic significance is quite relevant.[3] A 1-standard-deviation-lower degree of FSB (style adjusted) translates in a reduction of 0.04 (0.03) in R^2. Because more than 90% of funds have an R^2 between

TABLE 11

Fund Sentiment and R^2

Table 11 reports the results of regressions of TR^2 on FSB and other fund characteristics, where TR^2 is the logistic transformation of R^2. R^2 for a fund-month is defined as the R^2 from a regression of fund excess return on the 4 factors (3 Fama–French (1993) factors and the momentum factor) using data from the past 3 years. The control variables are as explained in Appendix B. In columns 1–3, TR^2 is regressed on FSB and other fund characteristics including style dummies, using Morningstar fund styles. In columns 4–6, TR^2 is regressed on style-adjusted FSB and other fund characteristics without including style dummies. STYLE-ADJUSTED_FSB is defined as the fund FSB minus the average FSB of all funds in the same Morningstar style. In the Fama–MacBeth (1973) regressions, the *t*-statistics are adjusted for serial correlation using Newey–West (1987) lags of order 3 and are shown in parentheses. In pooled regressions, time dummies are included and the *t*-statistics are cluster-corrected using clustering by fund or family. The sample period is from Jan. 1984 to Dec. 2005, a total of 22 years. These regressions are run on an annual basis (i.e., only one observation per fund per year). * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Independent Variables	Fama–MacBeth 1	Pooled 2	Pooled 3	Fama–MacBeth 4	Pooled 5	Pooled 6
FSB	6.5370**	6.3019**	6.3019**			
	(3.01)	(5.58)	(5.11)			
STYLE-ADJUSTED_FSB				5.0356**	5.0749**	5.0749**
				(2.77)	(3.89)	(3.38)
log(TNA)	0.0417**	0.0219*	0.0219	0.0467**	0.0246*	0.0246*
	(3.29)	(2.03)	(1.74)	(3.23)	(2.21)	(2.02)
log(FAMILY_SIZE)	0.0367**	0.0422**	0.0422**	0.0386**	0.0480**	0.0480**
	(6.87)	(6.62)	(5.66)	(6.31)	(7.20)	(6.39)
TURNOVER	−0.0014**	−0.0010**	−0.0010**	−0.0014**	−0.0010**	−0.0010**
	(−5.25)	(−5.15)	(−3.63)	(−5.47)	(−5.13)	(−3.79)
AGE	−0.0015	−0.0030**	−0.0030*	−0.0002	−0.0007	−0.0007
	(−0.97)	(−2.73)	(−2.46)	(−0.14)	(−0.61)	(−0.56)
EXPENSE_RATIO	−0.2560**	−0.2586**	−0.2586**	−0.3224**	−0.3523**	−0.3523**
	(−6.41)	(−7.36)	(−5.33)	(−6.23)	(−9.50)	(−6.97)
TOTAL_LOAD	0.0029	0.0026	0.0026	0.0097	0.0096	0.0096
	(0.43)	(0.49)	(0.39)	(1.20)	(1.65)	(1.25)
LAG_FLOW	−0.0008**	−0.0004**	−0.0004**	−0.0010**	−0.0004**	−0.0004**
	(−3.24)	(−4.87)	(−4.44)	(−3.68)	(−4.34)	(−4.06)
LAG_FUND_RET	−0.0005	−0.0061**	−0.0061**	−0.0036	−0.0076**	−0.0076**
	(−0.13)	(−10.89)	(−9.78)	(−0.68)	(−12.84)	(−11.33)
SIGMA_FLOW	0.0049*	−0.0000*	−0.0000*	0.0058*	−0.0000	−0.0000
	(2.49)	(−2.20)	(−2.15)	(2.08)	(−1.03)	(−1.02)
Intercept	2.6395**	2.6343**	2.6343**	2.9201**	3.0705**	3.0705**
	(25.09)	(28.77)	(24.53)	(21.65)	(40.81)	(31.85)
Style dummies	Yes	Yes	Yes	No	No	No
Time fixed effects	No	Yes	Yes	No	Yes	Yes
Cluster	No	Fund	Family	No	Fund	Family
No. of obs.	13,098	13,098	13,098	13,098	13,098	13,098
R^2	0.20	0.39	0.39	0.20	0.31	0.31

[3]Because $TR^2 = \log[\sqrt{R^2}/(1 - \sqrt{R^2})]$, we can write $R^2 = [1 + \exp(-TR^2)]^{-2}$. Therefore, a 1-standard-deviation-higher-degree of FSB (style adjusted) translates in a change of 0.50 (0.39) in TR^2, which is equivalent to a reduction of 0.04 (0.03) in R^2.

0.78 and 0.99 (i.e., within a small range of 0.21), a change of 0.04 in R^2 is quite significant. These results suggest that lower FSB is related to funds engaging in idiosyncratic stock-picking strategies. Our results are in line with a direct relation between performance and R^2, as predicted by Amihud and Goyenko (2013).

B. FSB and Conditional Performance

Another way of assessing whether there is active management with respect to the market is asking whether the relation between fund return and FSB depends on market sentiment in a nonlinear fashion. In other words, we want to know whether low-FSB funds engage in sentiment timing, loading negatively on sentiment when sentiment is high in the market, and betting on sentiment reversal, and therefore loading on the related sentiment risk. To study the dependence of return of FSB quintile portfolios on market sentiment under different sentiment periods, we use a piecewise linear regression framework. For each quintile portfolio, we estimate the piecewise linear regression of portfolio return on market sentiment:

$$
\begin{aligned}
(6) \qquad \text{PERFORMANCE}_{q,t} \quad = & \\
& (1-d) \times (a_{\text{LOW\_SENT}} + b_{\text{LOW\_SENT}}\text{SENTIMENT}_{t-1}) \\
& + d \times (a_{\text{HIGH\_SENT}} + b_{\text{HIGH\_SENT}}\text{SENTIMENT}_{t-1}) + e_t,
\end{aligned}
$$

where $\text{PERFORMANCE}_{q,t}$ ($q = 1, 2, 3, 4, 5$) is the monthly performance of the qth FSB quintile portfolio. SENTIMENT is the level of market sentiment for the month, and d is equal to 1 if SENTIMENT is positive and 0 if SENTIMENT is negative. The threshold value of d is chosen to be 0 in each case; therefore the continuity restriction implies $a_{\text{LOW\_SENT}} = a_{\text{HIGH\_SENT}}$ in each regression. Because we want to estimate the effect of sentiment on return after controlling for the 4 factors, we use the Frisch–Waugh (1933) theorem to first partial out the effect of the 4 factors from the portfolio returns and the market sentiment.

We report the results in Panel A of Table 12. Columns 1–5 present the results for 5 FSB quintile portfolios. Column 6 presents the results for a long–short portfolio formed by buying funds in portfolio 1 and selling funds in portfolio 5 at the beginning of every month. As we argued earlier, because of the nonlinear relationship between sentiment and fund returns, the intercepts in these regressions cannot be interpreted as excess returns. The sentiment beta is insignificant for all portfolios in low-sentiment periods. In high-sentiment periods, the sentiment beta for the low-FSB portfolio is equal to 1.09 and statistically significant. The sentiment beta for all the other portfolios is statistically insignificant. The sentiment beta of the long–short portfolio is insignificant in low-sentiment periods but positive and statistically significant in high-sentiment periods. The sentiment beta is 1.32 for the long–short portfolio in the high-sentiment period. This implies that the return difference between the low-FSB portfolio and the high-FSB portfolio increases by 13.2 bps per month if sentiment changes by 0.1 standard deviation in high-sentiment periods.

We perform similar analysis for holding returns of funds and report the results in Panel B of Table 12. The results are consistent with those for net returns.

Overall, both the results on active trade and the results on conditional performance can be interpreted as evidence that low-FSB funds are informed. Also, the

TABLE 12

Piecewise Linear Regression: Fund Return versus Sentiment

Panel A of Table 12 reports the result of piecewise linear regression of fund excess return of FSB portfolios on market sentiment, controlling for the 3 Fama–French (1993) factors and the momentum factor:

$$\text{PERFORMANCE}_{q,t} = (1-d)(a_{\text{LOW\_SENT}} + b_{\text{LOW\_SENT}}\text{SENTIMENT}_t) + d(a_{\text{HIGH\_SENT}} + b_{\text{HIGH\_SENT}}\text{SENTIMENT}_t) + e_t,$$

where $\text{PERFORMANCE}_{q,t}$ ($q = 1, 2, 3, 4, 5$) is the monthly return of the qth FSB quintile portfolio. SENTIMENT is market sentiment for the month, and d is equal to 1 if SENTIMENT is positive and 0 if SENTIMENT is negative. The threshold value of d is chosen to be 0 in each case; therefore the continuity restriction implies $a_{\text{LOW\_SENT}} = a_{\text{HIGH\_SENT}}$ in each regression. Because we want to estimate the effect of sentiment on return after controlling for the Fama–French (1993) and momentum factors, we use the Frisch–Waugh (1933) theorem to first partial out the effect of the 4 factors from the fund portfolio returns and the market sentiment. Quintile 1 (5) is the portfolio of funds with the lowest (highest) FSB. Columns 1 to 5 give results for portfolios 1 to 5, respectively. Column Long–Short Portfolio 1-5 gives the result for a long–short portfolio formed by buying funds in portfolio 1 and selling funds in portfolio 5 at the beginning of every month. The sample period is from Jan. 1984 to Dec. 2005, representing a total of 264 months. The t-statistics are given in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

	Dependent Variables					
Independent Variables	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Long–Short Portfolio 1-5
Panel A. Fund Net Returns						
$a_{\text{LOW\_SENT}}$	−0.2799*	−0.0801	−0.0083	−0.0005	0.0610	−0.3409*
	(−2.57)	(−1.21)	(−0.14)	(−0.01)	(0.52)	(−2.04)
$b_{\text{LOW\_SENT}}$	−0.3070	−0.0086	0.0663	−0.0654	−0.2160	−0.0910
	(−1.35)	(−0.06)	(0.52)	(−0.44)	(−0.88)	(−0.26)
$b_{\text{HIGH\_SENT}}$	1.0891**	0.3116	0.0323	0.0021	−0.2374	1.3265*
	(3.24)	(1.52)	(0.17)	(0.01)	(−0.65)	(2.56)
No. of months	264	264	264	264	264	264
R^2	0.08	0.04	0.01	0.00	0.04	0.10
Panel B. Fund Holding Returns						
$a_{\text{LOW\_SENT}}$	−0.3146*	−0.0656	0.0266	0.0363	0.0847	−0.3993*
	(−2.33)	(−0.77)	(0.35)	(0.43)	(0.66)	(−2.09)
$b_{\text{LOW\_SENT}}$	−0.3990	−0.0089	0.0969	−0.0237	−0.2750	−0.1240
	(−1.41)	(−0.05)	(0.60)	(−0.13)	(−1.03)	(−0.31)
$b_{\text{HIGH\_SENT}}$	1.2242**	0.2552	−0.1036	−0.1413	−0.3296	1.5538**
	(2.93)	(0.96)	(−0.44)	(−0.54)	(−0.83)	(2.63)
No. of months	264	264	264	264	264	264
R^2	0.06	0.02	0.00	0.01	0.06	0.10

evidence of conditional performance suggests sentiment timing, a strategy that requires fund managers to be informed. Unreported robustness checks confirm the extra performance to be due to sentiment exposure.

V. Sentiment-Related Strategies and Fund Flows

The previous results suggest that low FSB helps managers to boost performance. In a rational world, therefore, it might seem that the contrarian strategy of low FSB is the optimal strategy for mutual funds. However, the objective of a fund manager is not necessarily improving fund performance but maximizing fund flows. Some funds may consider it optimal to attract flows using other methods rather than performance. One such strategy is the catering strategy that involves holding those stocks in a portfolio that will attract investors. The funds following a catering strategy will hold high-sentiment-beta stocks and therefore will have high FSB. Of course, some funds may adopt a contrarian strategy whereas others may follow a catering strategy at the same time.

A sentiment-related contrarian strategy requires loading on stocks with low sentiment exposure. Would this affect the way the market reacts to the performance? Can investors discern the fund performance that is due to its loading on low-sentiment stocks? Will investors over- or underreact to sentiment-related performance? It may be that investors would react differently, and less, to sentiment-related performance. We now directly look at how investors react to it, by relating fund flows to the performance of the funds, separately reporting the part of "performance" due to the sentiment risk. We also look at the effect of catering strategy on flows by including FSB as an explanatory variable in the flow regressions.

More specifically, we estimate the standard flow–performance relationship, including performance and its convex relation to flows (Sirri and Tufano (1998)), separately identifying the one that is attributable to sentiment. We proceed as follows. We estimate a 4-factor alpha model as the intercept in a regression of fund return on the 4 factors. Then, we estimate an "extended model" as the intercept in a regression of fund return on the 4 factors and sentiment. In the case of sentiment, we also include the square of the sentiment variable to control for the fact that sentiment affects performance in a nonlinear manner. We define the sentiment-related performance as the difference between the 4-factor alpha (α4), and the alpha of the extended model (αE). This is the part of the alpha that is attributable to sentiment (αS).

Following Sirri and Tufano (1998), we define the fund's performance rank variables RANK_4, RANK_E, and RANK_S, corresponding to α4, αE, and αS, respectively, as the fractional rank of the fund in the cross section of funds on a scale of 0 to 1. Corresponding to the 4-factor alpha (α4), we define the following variables: LOW_PERF_4 = min(0.2, RANK_4), MID_PERF_4 = min(0.6, RANK_4 − LOW_PERF_4), and HIGH_PERF_4 = RANK_4 − (LOW_PERF_4 + MID_PERF_4). Corresponding to the extended model alpha (αE), we define the following variables: LOW_PERF_E = min(0.2, RANK_E), MID_PERF_E = min(0.6, RANK_E − LOW_PERF_E), and HIGH_PERF_E = RANK_E − (LOW_PERF_E + MID_PERF_E). Similarly, corresponding to the sentiment-related part (αS), we define the following variables: LOW_PERF_S = min(0.2, RANK_S), MID_PERF_S = min(0.6, RANK_S − LOW_PERF_S), and HIGH_PERF_S = RANK_S − (LOW_PERF_S + MID_PERF_S). The coefficients of these piecewise decompositions of ranks represent the performance sensitivity of flows to different levels of performance.

We report the results in Table 13. The dependent variable is the annual flow in all of the regressions. In columns 1 and 2, we consider a Fama–MacBeth (1973) specification, whereas in columns 3 and 4, we consider a pooled regression. Columns 1 and 3 represent standard flow–performance regressions as used by Sirri and Tufano (1998). The results are consistent with those of Sirri and Tufano. In line with the literature, we document a convex flow–performance sensitivity, significantly higher at higher performance levels. In columns 2 and 4, we decompose the total performance (αE) into the 4-factor alpha (α4) and the sentiment-related part (αS), and include the corresponding rank variables as independent variables. The results show that investors react to the sentiment-related performance in a nonlinear way: Higher exposure to sentiment leads to disproportionately more inflows. The results are robust across different specifications and

TABLE 13

Performance Due to FSB and Fund Flows

Table 13 estimates an "extended model" alpha as the intercept in a regression of fund return on the 4 standard factors (MKTRF, SMB, HML, and UMD) and sentiment. In the case of sentiment, we also include the square of the sentiment variable to control for the fact that sentiment affects performance in a nonlinear manner. We define the sentiment-related performance as the difference between the 4-factor alpha ($\alpha 4$) and the alpha of the extended model (αE). This is the part of alpha that is attributable to sentiment (αS). We define the fund's performance-rank variables, RANK_4, RANK_E, and RANK_S, corresponding to $\alpha 4$, αE, and αS, respectively, as the fractional rank of the fund in the cross section of funds on a scale of 0 to 1. Corresponding to the 4-factor alpha, we define the following variables: LOW_PERF_4 = min(0.2, RANK_4), MID_PERF_4 = min(0.6, RANK_4 − LOW_PERF_4), and HIGH_PERF_4 = RANK_4 − (LOW_PERF_4 + MID_PERF_4). Corresponding to the extended model, we define the following variables: LOW_PERF_E = min(0.2, RANK_E), MID_PERF_E = min(0.6, RANK_E − LOW_PERF_E), and HIGH_PERF_E = RANK_E − (LOW_PERF_E + MID_PERF_E). Similarly, corresponding to αS, we define the following variables: LOW_PERF_S = min(0.2, RANK_S), MID_PERF_S = min(0.6, RANK_S − LOW_PERF_S), and HIGH_PERF_S = RANK_S − (LOW_PERF_S + MID_PERF_S). The coefficients of these piecewise decompositions of fractional ranks represent the performance sensitivity of flows at different levels of performance. Annual flows to funds are regressed on performance measures based on the performance of funds in the previous year. In Fama–MacBeth (1973) regressions, the *t*-statistics are adjusted for serial correlation using Newey–West (1987) lags of order 3. In pooled regressions, time dummies are included and the *t*-statistics are cluster-corrected using clustering by fund. The sample period is from Jan. 1984 to Dec. 2005. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Independent Variables	Fama–MacBeth		Pooled	
	1	2	3	4
FSB	−430.62**	−1,036.58	−257.43*	−269.95*
	(−2.94)	(−1.70)	(−2.25)	(−2.30)
LOW_PERF_E	33.39*		49.76**	
	(2.48)		(4.97)	
MID_PERF_E	24.99**		28.16**	
	(7.34)		(8.92)	
HIGH_PERF_E	192.14**		242.72**	
	(3.76)		(9.46)	
LOW_PERF_4		120.09**		88.46**
		(3.90)		(7.14)
MID_PERF_4		18.71		34.17**
		(1.11)		(9.90)
HIGH_PERF_4		210.99**		187.74**
		(5.16)		(7.46)
LOW_PERF_S		76.30**		43.11**
		(3.33)		(2.85)
MID_PERF_S		8.76		16.08**
		(0.82)		(4.76)
HIGH_PERF_S		98.27**		84.55**
		(3.71)		(4.40)
log(TNA)	−3.56**	−4.20**	−4.23**	−4.26**
	(−4.11)	(−5.71)	(−7.12)	(−7.10)
log(FAMILY_SIZE)	1.88**	1.84**	1.85**	1.83**
	(3.71)	(3.79)	(5.74)	(5.62)
TURNOVER	0.02	−0.03	0.01	0.01
	(1.22)	(−0.58)	(0.43)	(0.71)
AGE	−0.18**	−0.27**	−0.24**	−0.23**
	(−3.80)	(−3.16)	(−6.34)	(−5.99)
EXPENSE_RATIO	5.83	5.94	2.55	3.35
	(1.39)	(1.53)	(1.33)	(1.74)
TOTAL_LOAD	0.22	0.14	0.39	0.37
	(0.74)	(0.43)	(1.44)	(1.35)
Intercept	−7.42	−30.86**	−6.78	−30.41**
	(−1.11)	(−4.23)	(−1.11)	(−4.54)
Style dummies	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes
No. of obs.	10,464	10,464	10,464	10,464
R^2	0.22	0.23	0.12	0.11

both for pooled and Fama–MacBeth (1973) specifications. Also, in terms of economic significance, the effect is very sizable. The flow–performance sensitivity corresponding to the performance attributable to FSB-generated performance is roughly equal to half that due to the overall performance of the fund. This holds across the different measures of performance. For the catering hypothesis to be true, we expect the coefficient of FSB to be positive. However, it is not only negative but also significant in some regression specifications. Statistically, there is strong evidence in support of the contrarian strategy hypothesis but none in favor of the catering strategy hypothesis. However, we should be careful in interpreting these results. The results do not rule out the possibility of contrarian strategy; they merely suggest that even if there are funds that follow contrarian strategy they are not successful in attracting flows.

More important, these results show that FSB holding by itself does not attract flows, rejecting the catering hypothesis. Overall, these findings show that sentiment loading is a way for funds, especially the ones affiliated with smaller families, to generate performance. The market positively reacts to it. The interpretation we have taken thus far is that this is a genuine performance-enhancing strategy used by managers who properly exploit sentiment, likely using the information they derive from their flows. However, the fact that not all of the funds pursue a contrarian strategy lends credence to the possibility of the mixed equilibrium hypotheses.

There is, however, another potential explanation. If sentiment proxies for some sort of risk, fund managers would effectively load up on this exposure. In this case, the fund managers load up on sentiment risk and deliver a higher return but camouflage it as performance. Indeed, given that this risk would be related to the overall mood of the investors in the market, investors would be less aware of such a risk or less sensitive to it. They would therefore react positively to the higher returns generated by the sentiment-driven strategy, even if these would just be a remuneration for higher risk. In this case, we would interpret the later results on flows simply as the market not recognizing the existence of sentiment risk and remunerating sentiment risk taking as performance. These findings suggest that funds load on sentiment risk to create "fake" performance.

Of course, this would be inconsistent with standard literature (e.g., De Long et al. (1990)) arguing that the high-sentiment-beta stocks are the risky ones that deserve higher returns. Baker and Wurgler (2006) show that sentiment affects the cross section of stock returns, but do not explicitly show that it is a priced factor. Nor has the literature reached a conclusion on this topic. We therefore do not endorse this view and tentatively conclude that the results paint a consistent picture of funds exploiting sentiment-driven trading strategies.

VI. Conclusion

We study the strategies of mutual funds as a function of investor sentiment. We consider three alternative hypotheses. Our first alternative hypothesis is that fund managers cater to investor sentiment, loading on high-sentiment-beta stocks to attract flows (the catering strategy). The second alternative hypothesis is that funds may choose to bet against investor sentiment in the hope that the long-term benefits from superior performance outweigh the short-term catering effects (the contrarian strategy). Our third hypothesis is based on an equilibrium argument in which both kinds of strategies prevail among different funds at the same time. That is, some funds cater to investor sentiment to attract flows in the short run, whereas other funds choose to bet against investor sentiment to generate performance, which will lead to high flows in the long run. We find strong evidence in support of the contrarian hypothesis. Using both portfolio and multivariate analysis, we show that low-FSB funds outperform high-FSB funds, even after controlling for the *standard* risk factors and fund characteristics.

We show that the FSB–performance relationship is not just due to a passive negative loading on the market. In line with Amihud and Goyenko (2013), we build a proxy for active management based on the tracking error of the fund. Funds with lower FSB follow more idiosyncratic strategies, suggesting that low FSB is not the outcome of a conventional or passive investment strategy, but the deliberate active choice of the fund manager. Given that active management has been interpreted as information-based trading, this would suggest that the strategy of lower FSB is enacted by more informed funds. Funds are rewarded for the performance attributable to FSB in a nonlinear way: Higher exposure to low-sentiment-beta stocks leads to disproportionately more inflows. The flow–performance sensitivity corresponding to the performance attributable to FSB-generated performance is roughly equal to half that due to the overall performance of the fund. This suggests that the sentiment contrarian funds succeed in their strategy of attracting flows based on their performance. Finally, the flow–performance results do not necessarily rule out the existence of catering funds; they merely suggest that a catering strategy is not significantly effective in attracting flows.

Appendix A. Data Sources and Sample Selection

We start with the mutual funds in the CRSP Survivor-Bias-Free U.S. Mutual Fund Database covering the period from Jan. 1984 to Dec. 2005. We focus our analysis on U.S. domestic equity mutual funds. Specifically, we include a fund in our sample if its Strategic Inside mutual fund objective code (si_obj_cd) is in (AGG, FLX, GMC, GRI, GRO, ING, SCG), or its Wiesenberger mutual fund objective code (wbrger_obj_cd) is in (G, G-I, GIS, G-S, GCI, I-G, I-S-G, MCG, SCG, AGG, GRI, GRO, LTG), or its Lipper mutual fund objective code (lipper_obj_cd) is in (G, GI, LCCE, LCGE, LCVE, LSE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, SG). We want to focus on equity funds. Therefore, we include only those funds that have more than 80% of their holdings in domestic stocks. We exclude funds that have less than $15 million in assets under management. We also exclude funds that are less than 1 year old.

We aggregate data on different share classes of a fund in a month to create a single fund observation. For the new observation, the TNA is the sum of the TNAs of all share classes, and age is the age of the oldest share class. Expense ratio, load, turnover, and return for the new observation are calculated as the weighted average of the corresponding figures of all share classes, the weights being the lagged TNAs of the share classes.

We take the mutual funds holdings data from the Thomson Reuters Mutual Fund Holdings Database. For most of our sample period, mutual funds were required to report their holdings semiannually. A large number of funds in our sample reported their holdings every quarter. We impute the holdings for nonreporting months using the last available holdings for the fund, assuming that the fund continues to hold the same portfolio since the last reporting date. The Thomson Reuters database reports the number of stocks and price of the stock. We use CRSP Monthly Stock Data for the monthly returns of stocks. We use CRSP Daily Stock Data to calculate our liquidity measures. We use the Morningstar-style classification from Morningstar Principia to identify the investment style of funds.

Appendix B. Definitions of Variables

FSB. Fund sentiment beta (FSB) for a fund in a month is defined as the weighted average of the sentiment betas of the stocks in its portfolio, weighted by the value of its stock holdings. The sentiment beta of a stock is obtained by running a time-series regression of monthly fund excess returns on 3 Fama–French (1993) factors and the Carhart (1997) momentum factor and monthly sentiment. The monthly sentiment data are based on Baker and Wurgler (2006) and were obtained from Wurgler's Web site (http://people.stern.nyu.edu/jwurgler/).

STYLE_ADJUSTED_FSB. The style-adjusted FSB of a fund is defined as the fund FSB minus the average FSB of all funds in the same Morningstar style.

TNA. The sum of the net assets of different classes of the fund.

log(TNA). The log of TNAs of the fund at the end of the previous month.

log(FAMILY_SIZE). The log of 1 plus the sum of TNAs of all other funds belonging to same management company at the end of the previous month.

TURNOVER. Minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNAs of the fund in the previous year.

AGE. Number of years since the fund was first offered.

EXPENSE_RATIO. Ratio of total investment that shareholders paid for the fund's operating expenses in the previous year.

TOTAL_LOAD. Sum of front load and rear load charged by the fund at the end of the previous year, expressed as a percentage of the money invested. Front load is the fee charged by the fund when an investor joins the fund. Rear load is the fee charged by the fund when an investor withdraws from the fund.

LAG_FLOW. Net flow of new investments in the fund in last 12 months, as a percentage of TNAs at the beginning of that period. Mathematically, $\text{LAG\_FLOW}_t = \text{TNA}_{t-1} - (1 + R_{t-13,t-1}) \times \text{TNA}_{t-13}/\text{TNA}_{t-13}$, where TNA_{t-1} and TNA_{t-13} are TNAs of the fund at the end of month $t-1$ and month $t-13$, respectively, and $R_{t-13,t-1}$ is the net return of the fund from the end of month $t-13$ to the end of month $t-1$.

SIGMA_FLOW. Standard deviation of net monthly flows in last 12 months.

NET_RETURN. Investor return per share net of fund expenses for a month as reported in CRSP mutual fund database.

GROSS_RETURN. The gross return of a fund for a month is its net return plus $1/12$ of its annual expense ratio.

STYLE-ADJUSTED_RETURN. The style-adjusted return of a fund is defined as fund net return minus the average return of funds in the same style.

MARKET-ADJUSTED_RETURN. The market-adjusted return of a fund for a month is its net return minus the return of the market for the month.

4-FACTOR_ALPHA. The 4-factor alpha for current month is calculated as the fund excess return minus the sum of the products of the factor loadings with the current-month factor realizations, as in Carhart (1997). The factor loadings for the fund are calculated by running a time-series regression of fund excess return on the 4 factors (3 Fama–French (1993) factors plus the momentum factor) using data from the past 36 months.

3-FACTOR_ALPHA. Three-factor alpha is calculated using same method as for 4-factor alpha except that only 3 factors, MKTRF, SMB, and HML, are used to calculate 3-factor alpha.

CAPM_ALPHA. CAPM alpha is calculated using same method as for 4-factor alpha except that only 1 factor, MKTRF, is used to calculate CAPM alpha.

LAG_FUND_RET. Fund return in past 12 months, calculated by compounding the total returns of the past 12 months.

FUND_R^2. R^2 for a fund in month t is defined as the R^2 of the regression of fund excess return on Fama–French (1993) factors and the momentum factor using the past 36 months of observations.

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