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Investor sentiment and the performance of mutual funds pursuing momentum and contrarian trading strategies

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ABSTRACT

The success of mutual funds engaging in momentum and contrarian trading strategies is predicated on the identification of mispriced stocks. Stock investor sentiment betas capture salient characteristics that predispose stocks to mispricing. Funds engage in momentum and contrarian trading in equal proportions, but differ in the sentiment betas of the stocks in their portfolios. Momentum funds hold stocks with higher sentiment betas, and with a wider spread of betas compared to contrarian funds. Fund excess returns are strongly related to Baker and Wurgler's (2007) change in sentiment index, and the mean and spread of the sentiment betas of their stocks.

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1. Introduction

Both momentum and contrarian trading strategies have been shown to earn excess returns. These trading strategies are associated with superior performance even though momentum trading requires the purchase of past superior performing stocks (winners) and the selling of past losers while contrarian trading is based on the purchase of past losers and the selling of past winners. Neither strategy would generate excess returns in an efficient market since both rely on stock prices departing from their intrinsic value.

Baker and Wurgler (2006) find an association between investor sentiment and stock prices departing from their intrinsic values. Waves of positive and negative sentiment affect the stock market as a whole; however, individual stocks may be more or less responsive. The characteristics of a stock that affect the magnitude and duration of its mispricing, as a response to investor sentiment, are also likely to affect the efficacy of momentum or contrarian strategies in these stocks. Accordingly, the stock's sentiment beta, as a measure of its response to changing investor sentiment, may be used to proxy the characteristics that should be considered when selecting a stock for a momentum-based or contrarian-based trade.

Studies examining momentum and contrarian strategies commonly create hypothetical portfolios based on stocks' recent performances. However, little attention has been devoted to whether momentum and contrarian trading strategies are actually pursued by mutual funds. Moreover, by creating hypothetical portfolios, these studies only consider a subset of the issues that a professional fund manager may consider.

Specifically, when conducting a momentum or contrarian trade, a manager may consider the sentiment beta of the particular stock, and how this relates to the sentiment betas of the other stocks in the fund's portfolio. The impractical nature of continuously creating long-short portfolios based on prior performance suggests that actual momentum or contrarian strategies will involve far fewer stocks than are used to form hypothetical portfolios.

We use mutual fund holdings data to statistically identify funds that engage in momentum or contrarian trading. Based on the reasoning that the success of these trading strategies relies on identifying mispriced stocks, we calculate sentiment betas to proxy for characteristics that predispose stocks to mispricing. This allows us to investigate whether momentum or contrarian funds exhibit preferences for these characteristics. We observe strong preferences for momentum funds to hold stocks with high sentiment betas with a wide spread of betas in their portfolio, and for contrarian funds to hold the opposite. The preferred sentiment beta characteristics of momentum and contrarian fund portfolios are associated with enhanced return performance. Furthermore, we find that the sentiment beta characteristics of fund portfolios shape the fund's response to changing investor sentiment, and are able to explain one fifth of the variation in excess returns.

In Section 2 a brief review of the literature is presented. Section 3 describes the data and outlines our research procedure. We analyze the alignment of mutual fund trades with momentum and contrarian strategies and report how this is related to the sentiment beta characteristics of their portfolios and fund returns in Section 4. The summary and conclusions of this research are presented in Section 5.

2. Literature review and empirical predictions

In a survey of the trading strategies of German fund managers, Menkhoff and Schmidt (2005) report that momentum, contrarian and buy-and-hold strategies are all extensively used by these practitioners. Both strategies rely on the identification of stocks whose prices have departed from their intrinsic value, and neither would generate excess returns in an efficient market. Previous studies consider the efficacy of momentum and contrarian strategies, and we review this literature for its implications for market efficiency, and for mutual fund managers wishing to employ these trading strategies.

We also review the stream of literature that relates to the role of investor sentiment in asset pricing. This is pertinent because investor sentiment will only affect stock prices if price is able to deviate from the stock's intrinsic value. In the review, we compare the features cited in the sentiment literature that increase the sensitivity of stocks to sentiment with the stock characteristics that are associated with profitable momentum and contrarian trading opportunities.

2.1. Momentum trading strategies

The positive feedback trading model of De Long, Shleifer, Summers and Waldmann (1990) suggests that investors may earn profits from following a momentum strategy in the short-term and a contrarian strategy in the longer term. Although a stock may be mispriced, momentum trading may cause this mispricing to continue and even increase for an extended period. By creating decile portfolios from performance ranked stocks, Jegadeesh and Titman (1993) demonstrate that a strategy of purchasing recent winners will earn superior subsequent returns. They attribute this to stock prices over-reacting and deviating temporarily from their intrinsic values.

Moskowitz and Grinblatt (1999) show that momentum trading can be profitable, but ascribe the success of this strategy principally to industry momentum rather than the individual stocks. In fact, the purchasing of stocks from strongly performing industries and selling stocks from poorly performing industries subsumes individual stock momentum trading and is persistent. The industry component of the momentum strategy is examined by O'Neal (2000) over a quarterly and yearly basis, and although this trading strategy yields returns that exceed the market return, he finds its superiority significantly diminishes when risk is included.

Chan, Jegadeesh and Lakonishok (1999) also investigate momentum trading but consider the impact of earnings announcements and analysts' forecasts on returns. They show that a firm's positive (negative) earnings announcements lead to optimistic (pessimistic) expectations, but that analysts are slow to adjust their forecast to this new information. Therefore, the market does not respond quickly to new information, as assumed by efficient market theory, allowing short-term momentum strategies to be profitable. Hong, Lim and Stein (2000) support the price under-reaction explanation for momentum profits and, in particular, find that small stocks, and stocks with limited analyst coverage respond slowly to information.

In an update of their earlier research, Jegadeesh and Titman (2001) confirm the existence of profitable medium-term momentum trading but with price reversals after twelve months. These price reversals are consistent with the explanation of market over-reaction for their previous research finding, however, this may follow an initial under-reaction to new information and, therefore, is not inconsistent with Chan, Jegadeesh and Lakonishok (1999) or Hong, Lim and Stein (2000).

Subsequently, Jegadeesh, Kim, Krische, and Lee (2004) use market- and accounting-based stock characteristics to classify firms into glamour and value stocks, which may be useful in the stock selection process. Sagi and Seasholes (2007) show that the traditional momentum strategy can be enhanced by focusing on firms that possess both high growth in revenue and investment opportunities, and also have a low cost structure. Baik, Farber and Petroni (2009) perform a factor analysis of the Jegadeesh, Kim, Krische, and Lee (2004) stock characteristics and find glamour stocks are largely distinguished by high proportionate turnover and favorable long-term growth forecasts. This research underlines the importance of considering a number of characteristics that may predispose stocks to mispricing when implementing a momentum strategy.

2.2. Contrarian trading strategies

The profitability of contrarian strategies is commonly based on the notion of market over-reaction that is eventually corrected. As such, the opportunity for a contrarian profit is only inconsistent with a profitable momentum strategy if the source of the latter is based entirely on market under-reaction to information. Indeed, as noted by Jegadeesh and Titman (2001), the availability of contrarian profits is the eventual outcome of a market over-reaction to information, even if this is preceded by an initial delayed reaction.

When the time taken for the market to correct to the stock's intrinsic value is in the order of the sampling period, the availability of a contrarian profit is consistent with negative autocorrelation of stock prices. Lo and MacKinlay (1990) report that individual security returns are generally negatively autocorrelated but that portfolios of stocks and market indexes exhibit positive autocorrelation. However, they suggest that negative autocorrelation of stock returns is not necessary for a profitable contrarian trading strategy where poorly performing stocks exhibit low, but not necessarily negative returns. This follows because in the long-run, stocks will move in the same direction but at different speeds. In the short-term, one stock could move up relative to another providing an opportunity to transfer investment to one that had increased the least. According to Lo and MacKinlay (1990), this positive cross-autocorrelation of security returns is responsible for over half of the returns generated by contrarian strategies. They also report that, in general, returns of smaller stocks tend to lag those of the larger stocks.

Lakonishok, Shleifer and Vishny (1994) also provide evidence that contrarian strategies can outperform the market. However, unlike Lo and MacKinley (1990), they argue that the strategy is successful because investors consistently overestimate the value of glamour stocks relative to value stocks, resulting in "suboptimal" investor behavior.

Conrad and Kaul (1998) find that contrarian and momentum strategies are successful with similar frequency when portfolios are formed on the basis of prior stock returns and held for various periods. For holding periods of 3-12 months, the momentum strategy dominates, although this may be attributed to the manner in which the portfolio is formed. They find some evidence that contrarian trading produces profits over longer horizons. The efficacy of momentum and contrarian strategies is evaluated by Schiereck, DeBondt and Weber (1999) using German data. They report that both strategies outperform a strategy of buying and holding the market index and that the results are robust to differences in risk and firm size.

Value firms have high book-to-market ratios for a variety of reasons. Some firms deserve high ratios because financial distress results in low stock prices, while other firms do not warrant high ratios but their stock prices have been bid down due to overly pessimistic outlooks and may provide contrarian investment opportunities. Piotroski (2000) uses financial statement information to successfully differentiate between distressed firms and out-of-favor or neglected, but financially strong firms. He reports that financially healthy, high book-to-market firms generate higher returns and are characterized as small, thinly traded firms with limited analyst following.

Chan and Lakonishok (2004) confirm their earlier findings that value stocks outperform growth stocks, but report that during the late 1990s the relation deteriorated due to the technology bubble. They suggest that during that period investor over-optimism caused stock valuations in the technology industries to deviate from their intrinsic values.

2.3. Applied trading strategies

Both momentum and contrarian strategies have been the focus of numerous empirical studies and both appear to generate excess returns. Only a few studies consider the *actual* momentum and contrarian trading strategies that fund managers follow. Lakonishok, Shleifer and Vishny (1994) contend that institutional investors may favor glamour stocks because they appear to be "prudent" investments and because their time horizon is too short for the three to five years necessary for the value firms to rebound. Carhart (1997) examines the performance of mutual funds, but cautions that persistence in their performance may be due to the momentum of the stocks in the fund's extant portfolio rather than from momentum or contrarian trading. Similarly, Chen, Jegadeesh and Wermers (2000) examine the trades and stockholdings of mutual funds and also find that fund performance is driven by the extant portfolio holdings rather than the trades conducted by the fund managers. However, they report that the returns on the stocks purchased are greater than the returns on the stocks sold, and observe a momentum effect in that the past winners tend to outperform the past losers.

2.4. *Investor sentiment*

Baker and Wurgler (2006) examine the impact of investor sentiment on stock returns by creating an annual sentiment index. They find that stocks characterized by low capitalization and profitability, high volatility and growth may become relatively overvalued when market sentiment is high. Therefore, prices may deviate more from intrinsic value depending on the characteristics of the stocks and their response to market sentiment. Addressing this issue, Glushkov (2006) augments the Fama and French (1995) 3-factor model with the Pastor and Stambaugh (2003) liquidity factor and a sentiment index to calculate 'sentiment betas' for individual stocks. He finds that stocks with greater sensitivity to investor sentiment are characterized by lower capitalization and higher volatility, sales growth, turnover and analyst following.

In a subsequent study, Baker and Wurgler (2007) construct a monthly sentiment index, and use it to show that speculative stocks that are difficult to arbitrage exhibit lower average returns relative to safe, easy to arbitrage stocks following a month of high investor sentiment. In the month following low investor sentiment, this result is reversed. They posit that the characteristics that make stocks more speculative simultaneously make them more difficult to value and to arbitrage, and, therefore, more sensitive to investor sentiment. Similar to their earlier paper, the characteristics they identify include higher volatility and growth potential, and lower capitalization and profitability.

2.5. *Empirical predictions*

Successful momentum and contrarian trading strategies rely on the market being inefficient such that a stock's price can deviate from its intrinsic value. The stock characteristics cited in the literature that enhance returns include: capitalization, investment opportunities, growth in revenue, cost structure, risk, turnover, proportionate turnover, following by investment analysts, and whether it is a technology stock. These characteristics resemble those cited in the investor sentiment literature, namely: lower capitalization and profitability, and higher volatility and sales growth. Both sets include characteristics that increase the susceptibility of stocks to mispricing.

According to Baker and Wurgler (2007), speculative stocks that are harder to value become overvalued when investor sentiment is high, and undervalued when sentiment is low. That is, their values positively correlate with investor sentiment and therefore, have high sentiment betas. Such stocks cannot be easily arbitraged, providing momentum trading opportunities where, in the medium-term at least, speculative departures from intrinsic value may persist. [1]

Contrarian trading opportunities arise when stock prices over-react to information and return to intrinsic value. Stocks that can be more easily valued or more readily arbitraged will return to intrinsic value more quickly. As a consequence, in the medium term, the stock characteristics that provide profitable contrarian trading opportunities will be similar to those of stocks with low sentiment betas.

Accordingly, we expect that mutual funds that employ a momentum trading strategy will focus on stocks with high sentiment betas, while contrarian funds will focus on stocks with low sentiment betas. Furthermore, we expect that by focusing on stocks with sentiment betas appropriate to their trading strategy, mutual funds should improve their performance.

[1] It is likely that what constitutes a "medium-term" trading strategy will depend on the sampling frequency used to calculate the sentiment beta. We observe trades over a 3-month interval and use monthly returns to calculate the sentiment beta, but leave this as an area for further research.

3. Data description and method

3.1. Data description

We obtain the periodic stock holdings of all US equity mutual funds from Thomson Financial Services Ltd for the period January 1991 – December 2006. Since most holdings are reported on a quarterly basis, we infer transactions from the quarterly changes to the holdings while allowing for stock capitalization changes. Daily stock price and return data are obtained from Center for Research in Security Prices (CRSP) and used to calculate quarterly excess returns for the individual stocks before we combine these with the holdings data. The CRSP database is also the source of mutual fund returns, and these returns are matched with the Thomson's holdings data using Mutual Fund Links. To calculate stock sentiment betas, we use the monthly change in the sentiment index developed by Baker and Wurgler (2007) and made available on Jeffrey Wurgler's website.[2]

To ensure that our data covers most of the changes to a mutual fund's portfolio, we restrict our sample to funds with average equity holdings exceeding 80% and average cash holdings of less than 10% of fund investments. In a further restriction to limit data errors and omissions, we must be able to replicate[3] the value of the fund's net tangible assets (NTA) by using the stock holdings data and assuming start-of-quarter prices for the stock to remain in our sample.

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[2] Two sets of investor sentiment indexes are available at http://www.stern.nyu.edu/~jwurgler. The indexes have a correlation of 0.84 over the period of our study, and we use the sentiment index based on the first principal components of six non-orthogonalized sentiment proxies. Until recently, these index series finished in 2005, and we conclude our study accordingly.

[3] We allow a discrepancy of up to 10%, but exclude funds outside this range.

3.2. Method

Funds that preferentially purchase (sell) stocks that were recently better (poorer) performers follow a momentum trading strategy. A contrarian strategy involves the purchase (sale) of stocks that were recently poorer (better) performers. To identify whether a mutual fund is following either strategy in any quarter, we adapt the method in Cullen, Gasbarro and Monroe (2010) by ranking each stock held by a fund at the start of each trading quarter, by its return in the preceding quarter. We use this ranking to assign each fund's stocks to "prior performance buckets" before applying regression analysis to determine whether the stocks it trades during the quarter are related to the stocks' prior performance.[4]

Next, we calculate the sentiment beta for each stock using the index of monthly investor sentiment changes in Baker and Wurgler (2007). From these, we calculate three attributes for each of the mutual fund portfolios we examine. These are the fund's weighted average sentiment beta, weighted standard deviation of sentiment betas and the change in the fund's weighted average sentiment beta over the quarter in which we examine the fund's trades. We then crosstabulate decile portfolios based on these attributes with the trading strategies we have identified. Finally, we perform regression analysis to establish whether a fund's trading strategy and portfolio attributes, are associated with superior performance.

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[4] We acknowledge the Elton, Gruber, Blake, Krasny and Ozelge (2010) observation that approximately 20% of the within-quarter transactions are not observed with quarterly mutual fund holdings data. However, we balance sample size with frequency of observation to obtain 2450 funds and 31,409 fund-quarters in the period 1991 – 2005 in our study. This compares with 215 funds and 6432 fund-months in the Elton, Gruber, Blake, Krasny and Ozelge (2010) study over a similar period.

3.3. Assignment to prior performance buckets and regression analysis

To identify changes to a fund's asset portfolio that are consistent with momentum or contrarian trading, we rank stocks held by each fund at the start of a quarter by their return performance over the preceding quarter. Following Cullen, Gasbarro and Monroe (2010), we assemble these into twenty equal-value portfolios (prior performance buckets), and use the value-weighted prior performance of each bucket as a measure of the bucket's prior performance (BucketPR). We perform 31,409 regressions, one for each fund-quarter between 1991 and 2005, and use BucketPR as the independent variable. Like Cullen, Gasbarro and Monroe (2010), we use TradeValue as the dependent variable in these regressions as follows:

$$\text{TradeValue}_j = \alpha + \beta\,\text{BucketPR}_j + \varepsilon_j \tag{1}$$

where

$$\text{TradeValue}_j \equiv \sum_{i=1}^{n} \text{Value of stock}_i \text{ in prior performance bucket}_j \text{ traded;}$$

$$\text{BucketPR}_j \equiv \sum_{i=1}^{n} (\text{Stock prior performance}_i \times \frac{\text{Value stock}_i \text{ held}}{\text{Value prior performance bucket}_j \text{ held}});$$

$$\text{Stock prior performance}_i = \text{Quarterly excess return of stock } i\text{; and}$$

$$n = \text{number of stocks in prior performance bucket } j.$$

These regressions identify fund quarters in which there is an association between the value of stock traded and stock prior performance. A significantly positive (negative) coefficient, which we refer to as the "momentum beta", indicates the fund is making momentum (contrarian) trades while an insignificant regression coefficient indicates that the trades are neither momentum nor contrarian motivated. The cumulative binomial distribution is used to determine whether the count of significant momentum betas could have occurred by chance.[5]

We use three variations of the above procedure. In the first, we calculate "TradeValue_j" by including both the buy and sell trades in a quarter, and refer to the coefficient in Equation (1) as the "net" momentum beta. In the second, we include only the buy trades, while in the third we include only sell trades. We refer to these regression coefficients as "buy" momentum and "sell" momentum betas respectively. A contrarian trading strategy may be conducted by buying recent poor performers, or by selling recent superior performers, or both. Similarly, a momentum strategy may involve either buying winners or selling losers, or both. Buy and sell momentum betas for either contrarian or momentum traders, therefore, only indicate that a particular contrarian or particular momentum strategy was one that could be determined by examining either the funds' buy or sell trades in isolation.

3.4. Sentiment betas

3.4.1. Stock sentiment betas

We require stock sentiment betas to investigate how they might affect the relation between future return and the stock's previous performance. These sentiment betas are also required for us to derive various attributes of mutual fund portfolios that we wish to explore. We calculate sentiment betas for each stock using Baker and Wurgler's (2007) monthly "change in sentiment" index, in a procedure analogous to that for calculating the

[5] The number of regressions is used as the number of trials, the level of significance at which we find the coefficients to be positive (momentum) or negative (contrarian) is used as the probability of a success, and the critical number of successes corresponds to a cumulative binomial probability of 1%.

traditional market beta. Similarly, we use the stock returns over the previous 60 months,[6] but we use the change in sentiment index, over the same interval, in place of market returns. This procedure is repeated monthly, over the fifteen-year period of our study.

To investigate how stock returns relate to their sentiment beta and past return, each month, we form 25 hypothetical portfolios. We achieve this by double sorting stocks firstly by prior return and allocating these to pentiles, and secondly by sentiment beta and also allocating these to pentiles. We measure prior return over the three months preceding the month of portfolio formation, and calculate stock returns in excess of the value weighted market portfolio over the following three months. The pooled cross-section and overlapping return measurement periods are pooled to calculate average excess returns for each portfolio. This estimate of the mean is not biased through our use of overlapping time periods.

3.4.2 Fund sentiment betas

We use the stock sentiment betas to calculate each fund's start-of-quarter sentiment beta by weighting the sentiment betas of the stocks held in the fund's portfolio by their proportionate values. We also calculate each fund's end-of-quarter weighted average sentiment beta (FQSBeta) using the same stock sentiment betas with end-of-quarter proportions. By subtracting the start-of-quarter FQSBeta from the end-of-quarter FQSBeta, we obtain the change in the fund's sentiment beta (ΔSbeta) which we attribute to the trades conducted by the fund during the quarter. This procedure is analogous to that used by Chevalier and Ellison (1997) to calculate the change to fund return variances over each trading period. Another attribute that we wish to determine is the spread of sentiment betas of the stocks in a fund's portfolio. We calculate the standard deviation of

[6] We eliminate stocks without a minimum of 12 months of returns.

stock sentiment betas (SDFQSBeta), weighting each stock's sentiment beta by their end-of-quarter proportionate value in the portfolio.

In turn, fund-quarters are ranked by FQSBeta, SDFQSBeta and ΔSbeta, and allocated to decile portfolios. The count of significantly negative and positive momentum betas in each decile is determined to establish preferences for these attributes by the funds we identify as either contrarian or momentum traders. This is repeated for each procedure for identifying contrarian and momentum traders by using net, buy, and sell momentum betas in turn.

3.5. Fund returns

Annualized excess returns are calculated by subtracting the value weighted market return from the fund's return. Excess returns are determined for the three-month interval in which we examine the fund's trades, and are also calculated for the three-month interval following the trading quarter.

To test our expectation that by focusing on stocks with sentiment betas appropriate to the trading strategy, both momentum and contrarian funds should enhance future returns, multivariate regression analyses are conducted. We code the funds that have statistically significant momentum (contrarian) trades with corresponding momentum (contrarian) dummy variables. In addition to the dummy variables, we include multiplicative interaction terms between these dummy variables and sentiment beta characteristics of the funds' portfolios. Accordingly, we are able to determine whether these characteristics lead to different return outcomes if funds conduct either momentum or contrarian trades. Specifically, we include interactions between the dummy variables and FQSBeta, SDFQSBeta, and AbsΔSBeta. We use AbsΔSBeta, the absolute value of ΔSBeta, to distinguish large changes, both negative and positive, from small changes to the weighted average sentiment beta.

Chen, Jegadeesh and Wermers (2000) point out that the holdings of funds are associated with future return performance because winning (losing) funds tend to win (lose). Accordingly, we include the previous excess return as a control variable. Other control variables include the liquidity, turnover and size of the fund's portfolio.[7] Therefore, we use equation (2) to examine whether the sentiment beta characteristics of a fund's portfolio after it has engaged in either momentum or contrarian trading, have an effect on the fund's subsequent performance.

$$\begin{aligned} R_{jt+1} &= a_0 + b_1 MOM_{jt} + b_2 CON_{jt} + b_3 FQSBeta_{jt} + b_4 MOM_{jt} \times FQSBeta_{jt} + b_5 CON_{jt} \times FQSBeta_{jt} \\ &+ b_6 SDFQSBeta_{jt} + b_7 MOM_{jt} \times SDFQSBeta_{jt} + b_8 CON_{jt} \times SDFQSBeta_{jt} \\ &+ b_9 R_{jt} + b_{10} TO_{jt} + b_{11} Liq_{jt} + b_{12} Size_{jt} + \varepsilon_{jt} \end{aligned} \tag{2}$$

Equation (3) is used to examine whether changes to the fund's average sentiment beta, caused by contemporaneous momentum or contrarian trading, affect subsequent performance.

$$\begin{aligned} R_{jt+1} &= a_0 + b_1 MOM_{jt} + b_2 CON_{jt} + b_3 FQSbeta_{jt} + b_4 Abs\Delta Sbeta_{jt} + b_5 MOM_{jt} \times Abs\Delta SBeta_{jt} \\ &+ b_6 CON_{jt} \times Abs\Delta SBeta_{jt} + b_7 R_{jt} + b_8 TO_{jt} + b_9 Liq_{jt} + b_{10} Size_{jt} + \varepsilon_{jt} \end{aligned} \tag{3}$$

Where:

[7] We value-weight an adaption of the Amihud (2002) measure of stock illiquidity to measure the liquidity of a fund's portfolio. Liquidity and size are standardized to allow for growth over the sample period.

$$
\begin{aligned}
R_{jt+1} &= \text{excess return on fund j in interval } t+1; \\
MOM_{jt} &= \text{dummy variable for fund j with significant momentum trades in period t;} \\
CON_{jt} &= \text{dummy variable for fund j with significant contrarian trades in period t;} \\
FQSBeta_{jt} &= \text{value - weighted average of sentiment betas of stocks in fund j at time t;} \\
SDFQSBeta_{jt} &= \text{value - weighted standard deviation of sentiment betas of stocks in} \\
&\quad \text{fund j at time t;} \\
Abs\Delta SBeta_{jt} &= \text{absolute value of change in fund sentiment beta (FQSBeta)} \\
&\quad \text{from trades of fund j in period t;} \\
R_{jt} &= \text{excess return on fund j in period t;} \\
TO_{jt} &= \text{standardized portfolio turnover of fund j in period t;} \\
Liq_{jt} &= \text{standardized average portfolio liquidity of fund j at time t; and} \\
Size_{jt} &= \text{standardized capitalization of fund j at time t.}
\end{aligned}
$$

3.7. Change in sentiment index

We calculate excess fund returns over the three-month interval subsequent to the quarter in which we observe the trades we use to identify momentum and contrarian funds. For different funds, these quarters end on varying months throughout the year. To compare these excess returns with the change in investor sentiment index over the corresponding period, we arithmetically average three successive values of Baker and Wurgler's (2007) non-orthogonolized monthly change in sentiment index. These three-month averages are moved forward, one month at a time, to generate a set of overlapping measures of three-month change in sentiment ($ChSI_{t+1}$).

4. Momentum betas and returns

4.1. Descriptive statistics

Panel A of Table 1 shows the distributions of the three-month value-weighted market returns and the three-month moving averages of Baker and Wurgler's (2007) monthly change in sentiment index. The three-month averages are moved forward, one month at a time so that they overlap for consistency with our analyses that uses overlapping quarters of fund trades and returns. As shown in Panel B, our sample contains 2450 distinct mutual funds, and 31,409 fund-quarters that meet our selection and data quality criteria. The portfolios of the 16,783 fund-quarters that remain after we match stock sentiment betas and fund returns differ in the distribution of the sentiment betas of the stocks they contain. For each fund-quarter, we calculate the weighted average and the standard deviation of the stock sentiment betas. We report the distribution of these measures, and also the change in a fund's weighted average sentiment beta over a trading quarter in Panel B. It is apparent that funds differ in both the mean and spread of sentiment betas of the stocks they hold. Notably, changes to the portfolio sentiment betas caused by a fund's trading during a quarter, are close to zero on average, with a standard deviation of 0.0049.

[Insert Table 1]

Panel C of Table 1 shows the correlations between stock sentiment beta and other stock attributes for a pooled annual sample for the years 1991-2005. Stock sentiment beta correlates positively (0.387) with total risk, and also with the market beta (0.357)[8] suggesting common responses to various stock characteristics.[9] Consistent with the expectation that hard to value or difficult to arbitrage stocks are more likely to be mispriced, and, in contrast to market beta, sentiment beta is negatively correlated with market capitalization and analyst following. Market turnover (by value) and proportionate turnover (turnover divided by the number of shares outstanding) are positively correlated with the sentiment beta.

[8] This result is consistent with Baker and Wurgler (2007), who find a 0.32 correlation between the value-weighted market return and sentiment change index.

[9] Accordingly, the Jegadeesh and Titman (1993) finding that momentum strategies are more effective when they involve stocks with higher systematic risk supports our expectation with respect to stocks with high sentiment betas.

4.2. Stock level returns

On a monthly basis, we calculate returns for each stock over the preceding three months and returns in excess of the value weighted market portfolio over the subsequent three-month period. This provides us with 1,175,264 overlapping stock-quarters. We separate our dataset by time before double-sorting stocks into prior return and sentiment beta pentiles. The resultant 25 double-sorted portfolios for each month are pooled over time such that the pentile formation periods, and also the return measurement periods overlap. For each portfolio, the average of the excess returns over the three months following formation is and shown in Table 2. Panel B of Table 2 also shows the standard deviation of excess returns for each portfolio.

The bottom row of Panel A in Table 2 shows the averages across sentiment betas for each prior return pentile. Consistent with Jegadeesh and Titman (1993), this shows that, on average, a momentum strategy of purchasing prior return pentile 5 and selling return pentile 1 is profitable. However, it is apparent that profitable contrarian and momentum strategies are both available, on average, when sentiment beta is considered. For example, a contrarian strategy of purchasing stocks in the portfolio with both the lowest prior return and sentiment beta, while selling stocks with the highest prior return and sentiment beta would provide a return of 0.006 (= -0.006 – (-0.012)). Similarly, a momentum strategy holding the highest prior return and lowest sentiment beta stocks long while shorting the lowest prior return highest sentiment beta stocks would yield a profit of 0.015 (= -0.002 – (-0.017)).

[Insert Table 2]

Panel B of Table 2 demonstrates the practical difficulties associated with implementing either of these strategies when the spread of excess returns (standard deviation) over time and across stocks in each of the double-sort portfolios is considered.

In practice, funds hold a fraction of the number of stocks allocated to these hypothetical portfolios, and trade even fewer. Accordingly, while the "average fund" might generate a profit from contrarian and momentum strategies, based on past return and investor sentiment alone, a vast number of funds may experience substantial losses.

Panels C and D provide an insight into one source of variation in the excess returns experienced by the stocks in each of the 25 double-sorted portfolios. The data used to generate Panel A are separated by time into terciles of low, medium and high change in sentiment index over the same three-month intervals that the excess returns are measured. Panel C reports the average for each portfolio for 3-month periods of low change in sentiment index, while Panel D reports the averages for high change in sentiment index periods. As can be seen from these panels, portfolios with low sentiment betas, on average, outperform high sentiment beta portfolios during periods in which investor sentiment declines (lowest tercile of change in sentiment index), while this result is reversed when investor sentiment increases. Therefore, fund managers could enhance their returns by managing their portfolio's sentiment beta if they were also able to predict investor sentiment.

4.3. Fund level analyses

We perform 31,409 linear regressions to determine if there is a relation between the stocks' prior performances and the proportion of stocks traded by a fund during a quarter. Each regression is for one fund-quarter, and fund-quarters with momentum betas significant at the 10% level (2-tailed) are identified. Table 3 reports the pooled count and corresponding proportions over the fifteen-year period. A significant positive net momentum beta indicates that adjustments to a fund's portfolios during a period are consistent with a momentum trading strategy where recent superior performing stocks are purchased or underperforming stocks are sold, or both. A significant negative net momentum beta suggests funds are following a contrarian trading strategy. We repeat this procedure to determine whether funds exhibit momentum or contrarian trading only with respect to the stocks they buy, in the first instance, and then with respect to those they sell.

[Insert Table 3]

Momentum trading (positive net momentum betas) accounts for 15.0% of the fund-periods, while 15.2% of fund-periods exhibit contrarian trading (negative net momentum betas). Using the binomial distribution, we are able to determine that the frequency of the significant betas, both positive and negative, substantially exceeds that expected by random occurrence. Slightly reduced proportions of funds exhibit statistically significant momentum and contrarian trading when we focus exclusively stock purchases (buy momentum betas), followed by exclusive consideration of stock sales (sell momentum betas). Marginally more funds buy stocks using a contrarian strategy than using a momentum strategy, whereas the opposite is observed from the stocks that funds sell.

4.3.1. Fund sentiment beta sorts

For each fund, and for each quarter, we calculate three attributes of the funds' portfolio, which are based on the sentiment betas of the stocks in these portfolios. The first is the weighted average sentiment beta (FQSbeta) at the start of the quarter, while the second is the value-weighted standard deviation of sentiment betas (SDFQSbeta) at the start of the quarter. The third attribute is the change in the fund's FQSbeta (ΔSbeta) over the quarter obtained by subtracting the start-of-quarter FQSbeta from the end-of-quarter FQSbeta. Table 4 is obtained by pooling fund-quarters before ranking and allocating them to deciles according to each of these attributes in turn.

Panel A shows the crosstabulation of statistically significant momentum betas by FQSbeta decile. Negative (contrarian) and positive (momentum) net, buy and sell momentum betas are shown. We also provide the ratio of contrarian to momentum traders in columns 4, 7 and 10 for net, buy and sell momentum betas respectively. For the net momentum betas, this ratio ranges from 2.15 for the lowest FQSbeta decile to 0.45 for the highest FQSbeta. This occurs as the number of funds identified as contrarian traders decreases near monotonically while the number of momentum traders increases monotonically with increasing FQSbeta decile. Therefore, we conclude a preference for contrarian traders to hold portfolios with low average sentiment betas, and for momentum traders to hold high average sentiment betas.

Columns 5 – 7 (8 – 10) in Table 4 crosstabulate momentum betas by FQSbeta decile where the betas have been determined by statistically significant contrarian or momentum trading in relation to only stock purchases (sales) by a fund. The same overall pattern of contrarian traders tending to hold portfolios with low average sentiment betas and for momentum traders to hold high average sentiment betas is observed irrespective of how the trading strategy is established. Among funds that hold low sentiment beta stocks, the strategy with the highest prevalence is a contrarian strategy involving the purchase of recent poorly performing stock. Among funds that hold higher sentiment beta stocks, momentum strategies involving the sale of recent poorly performing stocks is most common. If the stocks that are held by these funds are representative of the stocks they trade, we might conclude that the most popular strategies involve poor recently performing stocks where low sentiment beta stocks are purchased, and high sentiment beta stocks are sold.

Panel B crosstabulates statistically significant momentum betas by SDFQSbeta decile, which are based on the spread of stock sentiment betas in fund portfolios. Near monotonic decreases in the number of contrarian traders and increases in the number of momentum traders is observed with increasing deciles. Accordingly, we conclude there is a preference for contrarian traders to hold portfolios with a narrow range of stock sentiment betas, and for momentum traders to hold portfolios with a larger spread. This is true irrespective of whether the trading strategies are determined by the net, buy, or sell momentum betas. However, the ratio of contrarian to momentum traders is greatest where funds have a narrow range of sentiment betas and execute these strategies by buying stocks, and lowest when funds with a wide range sell. Once again, the most popular trading strategies involve stocks that were recent poor performers, and these are purchased by contrarian funds with low spreads of sentiment betas and sold by momentum funds with a wide range.

In Panel C, the deciles are based on the changes to the fund sentiment betas over the quarter that trades are observed.[10] Decile 1 contains the fund-quarters with the most negative values of ΔSbeta, while decile 10 contains the most positive changes. Columns 4, 7 and 10 most clearly illustrate the predominance of contrarian traders making small changes (deciles 5 and 6) to sentiment beta while more momentum traders make large changes; both positive and negative. The same pattern is observed for net, buy, and sell momentum betas, but is most pronounced when the stock sales are used as the basis for determining the trading strategy.

In summary, Table 4 shows that the number of funds identified as following contrarian or momentum trading strategies varies as a function of FQSBeta, SDFQSBeta and ΔSbeta. More contrarian funds have stocks with low sentiment betas, with a relatively narrow spread, and make small changes to their sentiment beta when they trade. In

[10] The totals in Panel C differ from Panel A and Panel B because ΔSbeta requires matching of an additional time period, reducing the available fund-quarters to 30,298.

contrast, more momentum traders hold stocks with a wider range of sentiment betas, which are, on average, higher, and make larger changes when they trade. Accordingly, it is pertinent to question whether there is a performance dividend for contrarian and momentum traders through having these attributes. We address this question in the following section.

4.3.2 Multivariate analyses of trading strategy, sentiment betas and fund performance

Table 5 presents the results of the equation (2) and (3) regressions. The return measure is annualized excess return for the three-month intervals following the periods in which we identify momentum and contrarian trading strategies. Model (1) includes the momentum and contrarian dummy variables, the weighted average of the sentiment betas of the stocks in the fund's portfolio at the end of the trading period (FQSbeta), and multiplicative interactions between these terms. In view of the preferences exhibited in Panel A of Table 4 for momentum funds to have high FQSbetas, we expect momentum funds to exhibit higher returns when they have this attribute. Contrarian funds, in contrast, exhibited a preference for low FQSbetas. By symmetry, we expect contrarian funds to exhibit higher returns when they have low FQSbetas. Consistent with this expectation, the coefficient on MOM_{jt} x $FQSbeta_{jt}$ is significantly positive, and the coefficient on CON_{jt} x $FQSbeta_{jt}$ is negative.

[Insert Tables 5]

Model (2) in Table 5 considers the multiplicative interaction between the standard deviation of the sentiment betas of the stocks in the fund portfolios (SDFQSbeta) at the end of the trading period and the momentum and contrarian dummies. Reasoning that the preference shown in Panel B of Table 4 for momentum funds to have high SDFQSbetas, and contrarian funds to have low SDFQSbetas reflects an expectation of higher returns, we expect the coefficients on MOM_{jt} x $SDFQSbeta_{jt}$ and CON_{jt} x $SDFQSbeta_{jt}$, to be positive and negative respectively. We find weak empirical support for this expectation, however, only with the coefficient on MOM_{jt} x $SDFQSbeta_{jt}$.

The variables $FQSbeta_{jt}$ and $SDFQSbeta_{jt}$ are highly correlated.[11] Accordingly, when terms for their interactions with the momentum and contrarian dummy variables are entered together in Model (3), the coefficients on the $SDFQSbeta_{jt}$ interaction terms lose significance. The coefficients on $FQSbeta_{jt}$, however, suggest that an increase of one standard deviation of the range of FQSbetas, contributes 0.29%[12] annually to momentum fund excess returns. A decrease in FQSbeta by the same amount increases the excess returns of funds that follow a contrarian trading strategy by an economically significant 2.28%[13] annually. Therefore, we conclude that contrarian funds are able to increase their excess returns by holding stocks with lower average sentiment betas. Momentum funds improve their performance by holding stocks with a higher average sentiment beta, and may enhance this by having wider spread of sentiment betas.

Model (4) in Table 5 introduces the absolute value of changes to fund sentiment betas ($Abs\Delta Sbeta_{jt}$) that arise from the trades the funds conduct during a period[14], and the

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[11] The variables $FQSbeta_{jt}$ and $SDFQSbeta_{jt}$ have a correlation of 0.754, significant at the 1 percent level.

[12] As show in Table 1, one standard deviation of the FQSBeta is 0.0149. The return contribution is obtained by multiplying this by the sum of the coefficients on $FQSbeta_{jt}$ and MOM_{jt} x $FQSbeta_{jt}$ as follows: $0.0149x(-0.778+0.970)=0.0029$.

[13] $-0.0149x(-0.778-0.888)=0.0228$

[14] A fund may increase the absolute value of its weighted average sentiment beta by trading (buying or selling) stocks with high or low sentiment betas. However, funds with initially high or low average sentiment betas may also achieve an increase by trading stocks with moderate sentiment betas. Accordingly, it is not possible to make unambiguous inferences about the sentiment betas of the stocks traded by a fund using the coefficient on this term, or its interactions with the dummy variables.

multiplicative interaction of this term with the trading strategy dummies. This is motivated by our finding in Panel C of Table 4 that more momentum funds make larger changes to the weighted average sentiment beta of their portfolio, while fewer contrarian funds make large changes. We expect a positive coefficient on MOM_{jt} x $Abs\Delta Sbeta_{jt}$ and a negative coefficient on CON_{jt} x $Abs\Delta Sbeta_{jt}$ because the higher incidence of funds that change or avoid changing their sentiment beta while executing respective momentum or contrarian trading strategies may be associated with higher returns. We find empirical support for our expectation only with the coefficient on CON_{jt} x $Abs\Delta Sbeta_{jt}$, which is statistically negative at the 5% significance level. Therefore, we can conclude that, at least, contrarian traders that avoid making large changes to the sentiment beta of their portfolios outperform their peers that change their beta. The performance differential for each standard deviation of all sentiment beta changes that they differ is, on average, 0.46%[15] per annum.

The coefficients on the control variables are similar in magnitude and significance for all models in Table 5. They indicate that fund returns have positive serial correlation and that funds with greater turnover in their stock portfolio receive higher returns. Over the sample period, funds holding less-liquid portfolios perform better, while the size of the fund is not statistically related to fund performance.[16]

4.4 Sentiment changes and fund performance

The hypothetical portfolios of stocks in Panels C and D of Table 2 demonstrate an association between fund performance and the change in sentiment index which depends on the sentiment betas of the stocks in the portfolios. Stocks in the lowest sentiment beta

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[15] -0.0041x(1.723-2.836)=0.0046

[16] The inclusion of control variables reduces the number of observations from 16,783 to 16,367.

pentiles outperform stocks in high sentiment beta pentiles when investor sentiment decreases. In periods where investor sentiment increases and the change in sentiment index is in the highest tercile, the opposite is true. It is therefore appropriate to consider how actual fund returns relate to the change in sentiment index, and how this relation is affected by the sentiment beta of the fund portfolios.

Model (1) in Table 6 is generated by estimating Equation (4) using all fund-quarters in our sample as follows:

$$\begin{aligned} R_{jt+1} &= b_0 + b_1 ChSI_{t+1} + b_2 FQSbeta_{jt} + b_3 FQSbeta_{jt} \times ChSI_{t+1} \\ &\quad + b_4 SDFQSbeta_{jt} + b_5 SDFQSbeta_{jt} \times ChSI_{t+1} + \varepsilon_{jt} \end{aligned} \tag{4}$$

Where:

$$\begin{aligned} R_{jt+1} &= \text{excess return on fund j in interval } t+1; \\ ChSI_{t+1} &= \text{three month average of Baker and Wurgler's (2007)} \\ &\quad\ \text{monthly change in sentiment index ending at time } t+1; \\ FQSBeta_{jt} &= \text{value - weighted average of sentiment betas of stocks in fund j at time t; and} \\ SDFQSBeta_{jt} &= \text{value - weighted standard deviation of sentiment betas of stocks in fund j at time t.} \end{aligned}$$

The high r-square (0.202) indicates that fund excess returns have a strong contemporaneous association with the change in sentiment index.[17] Moreover, the relation between fund excess return and the change in sentiment index is a function of the mean and standard deviation of the sentiment betas of the stocks in the funds' portfolios. An insight into how the mean and standard deviation of fund sentiment betas affect the sensitivity of fund returns to changes in sentiment, is obtained by differentiating Equation (4) with respect to change in sentiment index as follows:

[17] We also estimate models using squared terms for change sentiment index, and include the same control variables used in Table 5. This improves the explanatory power and produces r-squares of 0.225, 0.299, and 0.192 for models corresponding to (1), (2) and (3) in Table 6. We present the simplified models for ease of exposition.

$$\frac{\partial \mathrm{R}}{\partial \mathrm{ChSI}} = \mathrm{b}_1 + \mathrm{b}_3 \mathrm{FQSbeta} + \mathrm{b}_5 \mathrm{SDFQSbeta} \tag{5}$$

Substituting in the parameters estimated for b_1, b_3 and b_5, we obtain:

$$\frac{\partial \mathrm{R}}{\partial \mathrm{ChSI}} = -0.39 + 7.589 \times \mathrm{FQSbeta} + 7.844 \times \mathrm{SDFQSbeta} \tag{6}$$

For funds holding stocks such that their FQSbetas and SDFQSbetas are close to the median values of 0.0170 and 0.0255 respectively, excess return is a decreasing function of change in sentiment index.[18] Therefore, funds with FQSbetas and SDFQSbetas close to the median should, on average, earn positive excess returns when sentiment decreases and negative excess returns when sentiment increases. This relation, however, is reversed when funds hold stocks with sentiment betas that are higher, on average, with greater spread, such as when the 70 percentile values of FQSbeta and SDFQSbeta are used in Equation (6).[19] Figure 1 illustrates how the relation between fund excess returns and change in sentiment index responds to changes in mean and standard deviation of portfolio sentiment betas.

[Insert Figure 1]

Four cases are illustrated in Figure 1. In the first, median values of FQSbeta and SDFQSbeta are used (MSB_MSDSB). In the second, FQSbeta is set to the 70-percentile value while SDFQSbeta remains at its median value (HSB_MSDSB). In the third, these are reversed (MSB_HSDSB), while in the fourth, both are set to 70-percentile values (HSB_HSDSB). Each tick on these lines corresponds to a decile value of change in

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[18] The median values of FQSbetas and SDFQSbetas are shown in Table 1. Substituting these into Equation (6) yields the gradient $\frac{\partial \mathrm{R}}{\partial ChSI} = -0.0609$.

[19] The 70-percentile values for FQSbetas and SDFQSbetas are 0.0256 and 0.0307 respectively. Substituting these into Equation (6) yields the gradient $\frac{\partial \mathrm{R}}{\partial \mathrm{ChSI}} = 0.0451$.

sentiment index.[20] Accordingly, the impact on fund excess return from an increase or decrease in the sentiment index of, for example, 2 deciles, may be assessed.

Models (2) and (3) in Table 6 are also generated by estimating Equation (4), but use only the fund-quarters we identify as trading with contrarian and momentum strategies respectively. The parameters estimated for these sub-groups resemble those estimated for the full sample, with similar behavior in the relation between fund excess return and the change in sentiment index. However, contrarian funds and momentum funds differ in the sensitivity of excess return to changes in investor sentiment for the same FQSbetas and SDFQSbetas. Generally, for lower FQSbetas and SDFQSbetas, contrarian fund excess returns are more negatively related to changes in investor sentiment than are momentum fund excess returns (Figure 2a). For higher FQSbetas and SDFQSbetas, momentum fund excess returns are more positively related to changes in investor sentiment (Figure 2b).

[Insert Figure 2]

5. Conclusions

We empirically confirm previous qualitative research and anecdotal reported behavior, which indicates that mutual fund managers follow both momentum and contrarian trading strategies. Our unique method uses actual mutual fund trades to identify managers that follow these strategies. We find 15.0% of funds pursue a momentum trading strategy and 15.2% of funds are contrarian traders. Identifying momentum and contrarian funds facilitates examination of the characteristics of their stock portfolios related to investor sentiment.

[20] The distribution of values for change in sentiment index averaged over three months is shown in Panel A of Table 1.

Fund managers may follow a momentum strategy by trading stocks with characteristics that predispose them to continued mispricing. Contrarian traders may trade mispriced stocks that will more rapidly revert to intrinsic value. Coincidentally, the investor sentiment literature identifies characteristics that render stocks hard to value and arbitrage, and therefore susceptible to mispricing. We proxy these characteristics by using Baker and Wurgler's (2007) sentiment index to calculate individual stock sentiment betas.

Consistent with the expectation that momentum funds depend on stocks deviating from their intrinsic value longer, we find that more momentum funds hold stocks with high sentiment betas. Conforming to the expectation that contrarian funds rely on timely reversion to stock intrinsic values, we find that contrarian funds hold stocks with lower sentiment betas. In addition to the average, we identify differences in the spread of stock sentiment betas and the change to the average beta over a quarter, that depend on the fund's trading strategy. Momentum funds have relatively wide spreads of sentiment betas, and make larger changes to their sentiment beta when they trade. In contrast, more contrarian traders hold stocks with a narrower range of sentiment betas and make smaller changes when they trade.

Momentum funds are able to increase their excess returns by holding stocks with higher average sentiment betas and may enhance this by having wider spread of sentiment betas. Contrarian funds improve their performance by holding stocks with a lower average sentiment beta, and when they avoid making large changes to the sentiment beta of their portfolio. Excess returns are strongly related, contemporaneously, to Baker and Wurgler's (2007) change in sentiment index. This relation is a function of the mean and standard deviation of the sentiment betas of the stocks in the funds' portfolios. Momentum and contrarian funds differ in the sensitivity of excess return to changes in investor sentiment. Compared to momentum funds, contrarian excess returns are more negatively related to changes in investor sentiment when they hold stocks with lower sentiment betas and with lower spread. For funds with stocks with higher betas and with wider spreads, excess returns of momentum funds are more positively related to changes in investor sentiment.

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Table 1

Descriptive statistics.

Panel A. Market descriptive statistics 1991-2005			
	Mean	Median	Standard Deviation
Value weighted market return (3-month)	0.0283	0.0333	0.0748
Change in sentiment index 3-month average	-0.0016	0.0089	0.5532
Panel B. Fund descriptive statistics 1991-2005			
Number of fund-quarters	31,409		
Number of fund-quarters with matching returns	16,783		
Number of funds	2450		
Number of stocks in portfolio	149	92	43
Portfolio weighted average sentiment beta	0.0192	0.0170	0.0149
Δ Portfolio weighted average sentiment beta	-0.0015	-0.0006	0.0049
AbsΔ portfolio weighted average sentiment beta	0.0030	0.0016	0.0041
Standard deviation portfolio sentiment beta	0.0271	0.0255	0.0103

Panel C. Stock attribute correlations 1991-2005							
	Sbeta	Mkt beta	Std Dev	Size	No. Analysts	Turnover (value)	Turnover (prop)
Sbeta	1						
Market beta	0.357	1					
Std Deviation	0.387	0.169	1				
Size	-0.126	0.268	-0.413	1			
No. Analysts	-0.014	0.285	-0.181	0.707	1		
Turnover (Value)	0.050	0.426	-0.170	0.877	0.700	1	
Turnover (Prop)	0.221	0.239	0.287	NS	0.107	0.277	1
N	37,257						

Panel A shows the distribution of three-month market returns and the three-month average of Baker and Wurgler's (2007) monthly change in sentiment index. Panel B presents descriptive statistics for mutual funds and their associated trading periods. Panel C reports the correlations between stock sentiment beta and other stock attributes for a pooled annual sample for the years 1991-2005. Sbeta is the sentiment beta for each stock, Market beta is the traditional market beta, Std Deviation is a stock's total risk, Size is standardized log of a stock's market capitalization, No. Analysts is the number of analysts providing earning forecasts in the month prior to the stock's annual reporting period, turnover (value) is the standardized market turnover of the stock multiplied by its price, and turnover (prop) is the stock's market turnover divided by the number of shares outstanding. All reported correlation coefficients are statistically significant at the 1% level. NS denotes "Not Significant".

Table 2
Stock excess return by past return and sentiment beta

Sentiment beta pentile		Prior return pentile Low 1	2	3	4	High 5	Average
Panel A. Average excess returns for entire time-series							
Low	1	-0.006	-0.014	-0.015	-0.018	-0.002	-0.011
	2	-0.013	-0.016	-0.018	-0.018	-0.005	-0.014
	3	-0.018	-0.017	-0.014	-0.017	-0.005	-0.014
	4	-0.016	-0.023	-0.020	-0.019	-0.004	-0.016
High	5	-0.017	-0.019	-0.020	-0.017	-0.012	-0.017
	Average	-0.014	-0.018	-0.017	-0.018	-0.005	-0.015
Panel B. Standard deviation of excess returns for entire time-series							
Low	1	0.459	0.283	0.275	0.266	0.366	0.330
	2	0.397	0.235	0.210	0.228	0.342	0.282
	3	0.394	0.252	0.280	0.235	0.359	0.304
	4	0.457	0.280	0.253	0.257	0.394	0.328
High	5	0.517	0.390	0.356	0.382	0.427	0.414
	Average	0.445	0.288	0.275	0.274	0.378	
Panel C. Average excess returns for low change sentiment index quarters							
Low	1	0.028	0.050	0.050	0.046	0.043	0.043
	2	0.012	0.054	0.055	0.050	0.034	0.041
	3	-0.007	0.038	0.051	0.045	0.018	0.029
	4	-0.044	0.015	0.033	0.025	-0.008	0.004
High	5	-0.083	-0.039	-0.027	-0.027	-0.054	-0.046
	Average	-0.019	0.023	0.032	0.028	0.007	0.014
Panel D. Average excess returns for high change sentiment index quarters							
Low	1	-0.025	-0.075	-0.077	-0.078	-0.040	-0.059
	2	-0.024	-0.079	-0.089	-0.086	-0.039	-0.063
	3	-0.021	-0.067	-0.077	-0.079	-0.016	-0.052
	4	0.022	-0.056	-0.067	-0.061	0.004	-0.031
High	5	0.064	0.006	-0.007	0.001	0.040	0.021
	Average	0.003	-0.054	-0.063	-0.060	-0.010	-0.037

Table 2 shows the quarterly excess returns of 1,175,264 overlapping stock-quarters that are double sorted into prior return and sentiment beta pentiles. Stocks are separated by month, prior to double sorting. Excess returns are pooled over time prior to calculating the average in Panel A and standard deviation in Panel B. Panels C and D report the pooled average quarterly excess stock returns contemporaneous to the separations of the time-series into quarters with respectively, the lowest tercile of change in sentiment index and highest tercile of change in sentiment index.

Table 3
Significant momentum betas - pooled count 1991-2005.

Trades			Momentum Beta			
		Binomial	Negative		Positive	
	N	Critical Value	Count	Percent	Count	Percent
Net	31,409	1660	4777	15.2***	4702	15.0***
Buy	31,409	1660	4190	13.3***	3694	11.8***
Sell	31,409	1660	3802	12.1***	4365	13.9***

Table 3 shows the number of statistically significant (10%, 2-tailed) momentum betas generated for each fund-quarter from: $\text{TradeValue}_j = \alpha + \beta\,\text{BucketPR}_j + \varepsilon_j$ where TradeValue_j is the value of stocks in prior return 'bucket' j that are traded during a quarter, and BucketPR_j is the value-weighted prior return of the stocks in 'bucket' j. We calculate "TradeValue_j" including, in turn, both buy and sell trades (Net), only buy trades (Buy), and only sell trades (Sell). Cumulative binomial distribution critical values reflect a 1% probability that a greater count occurs by chance.
*** indicates significance at the 1 percent level (two tailed).

Table 4

Significant momentum betas by decile of fund-quarter characteristics: 1991-2005.

Panel A. Weighted average of stock sentiment betas ($FQSbeta_{jt}$)

Decile	Net momentum beta Negative	Positive	Ratio	Buy momentum beta Negative	Positive	Ratio	Sell momentum beta Negative	Positive	Ratio
Low 1	619	288	2.15	574	212	2.71	416	355	1.17
2	655	297	2.21	580	207	2.80	456	284	1.61
3	468	363	1.29	397	309	1.28	384	329	1.17
4	484	420	1.15	417	403	1.03	441	365	1.21
5	445	497	0.90	400	400	1.00	372	447	0.83
6	477	509	0.94	385	368	1.05	403	465	0.87
7	470	504	0.93	403	413	0.98	412	450	0.92
8	446	560	0.80	361	415	0.87	376	528	0.71
9	411	600	0.69	359	473	0.76	317	537	0.59
High 10	302	664	0.45	314	494	0.64	225	605	0.37
Total	4777	4702	1.02	4190	3694	1.13	3802	4365	0.87

Panel B. Standard deviation of stock sentiment betas ($SDFQSbeta_{jt}$)

Decile	Net momentum beta Negative	Positive	Ratio	Buy momentum beta Negative	Positive	Ratio	Sell momentum beta Negative	Positive	Ratio
Low 1	611	304	2.01	559	225	2.48	422	388	1.09
2	629	307	2.05	555	205	2.71	458	314	1.46
3	549	379	1.45	500	254	1.97	438	404	1.08
4	487	446	1.09	403	319	1.26	393	422	0.93
5	405	453	0.89	373	346	1.08	345	411	0.84
6	373	561	0.66	337	514	0.66	349	438	0.80
7	431	521	0.83	358	442	0.81	387	461	0.84
8	483	580	0.83	375	457	0.82	357	482	0.74
9	434	547	0.79	390	418	0.93	338	491	0.69
High 10	375	604	0.62	340	514	0.66	315	554	0.57
Total	4777	4702	1.02	4190	3694	1.13	3802	4365	0.87

Panel C. Change in weighted average of stock sentiment betas ($\Delta Sbeta_{jt}$)

Decile	Net momentum beta Negative	Positive	Ratio	Buy momentum beta Negative	Positive	Ratio	Sell momentum beta Negative	Positive	Ratio
Low 1	347	647	0.54	314	473	0.66	249	571	0.44
2	402	504	0.80	340	395	0.86	347	493	0.70
3	440	425	1.04	375	315	1.19	383	427	0.90
4	500	373	1.34	401	300	1.34	425	377	1.13
5	557	327	1.70	469	293	1.60	446	325	1.37
6	536	316	1.70	403	263	1.53	472	313	1.51
7	515	323	1.59	451	276	1.63	396	348	1.14
8	481	381	1.26	454	295	1.54	393	366	1.07
9	432	511	0.85	436	412	1.06	318	405	0.79
High 10	401	717	0.56	400	549	0.73	258	559	0.46
Total	4611	4524	1.02	4043	3571	1.13	3687	4184	0.88

Table 4 crosstabulates the number of fund-quarters of contrarian or momentum trading by deciles of ranked $FQSbeta_{jt}$, $SDFQSbeta_{jt}$, and $\Delta Sbeta_{jt}$ in their respective Panels. In any fund-quarter, contrarian (momentum) trading is identified from the betas in the regression: $TradeValue_j = \alpha + \beta\, BucketPR_j + \varepsilon_j$ that are statistically negative (positive). Net, Buy, and Sell momentum betas correspond to respective variations where both buy and sell trades, only buy trades, and only sell trades are used to calculate $TradeValue_j$, and $BucketPR_j$ is the value-weighted prior return of the stocks in 'bucket' j.

Table 5
Fund excess return as a function of sentiment beta.

	Model			
	(1)	(2)	(3)	(4)
Intercept	0.477***	0.474***	0.478***	0.450***
	(16.62)	(16.49)	(16.58)	(16.09)
MOM_{jt}	-0.017**	-0.021	-0.012	-0.003
	(-2.15)	(-1.55)	(-0.82)	(-0.48)
CON_{jt}	0.011	0.012	0.002	0.008
	(1.54)	(0.90)	(0.14)	(1.51)
$FQSbeta_{jt}$	-0.787***	-0.735***	-0.778***	
	(-4.38)	(-4.45)	(-3.94)	
MOM_{jt} x $FQSbeta_{jt}$	0.822***		0.970**	
	(2.71)		(2.15)	
CON_{jt} x $FQSbeta_{jt}$	-0.632*		-0.888*	
	(-1.89)		(-1.81)	
$SDFPSbeta_{jt}$	-0.545**	-0.609**	-0.567*	
	(-2.17)	(-2.23)	(-1.90)	
MOM_{jt} x $SDFQSbeta_{jt}$		0.759*	-0.291	
		(1.71)	(-0.44)	
CON_{jt} x $SDFQSbeta_{jt}$		-0.433	0.512	
		(-0.89)	(0.71)	
$FQSbeta_{jt-1}$				-0.928***
				(-7.78)
$Abs\Delta Sbeta_{jt}$				1.723***
				(2.75)
MOM_{jt} x $Abs\Delta Sbeta_{jt}$				0.491
				(0.46)
CON_{jt} x $Abs\Delta Sbeta_{jt}$				-2.836**
				(-2.16)
R_{jt}	0.071***	0.071***	0.071***	0.073***
	(8.44)	(8.51)	(8.41)	(8.66)
TO_{jt}	0.018***	0.019***	0.018***	0.009
	(2.74)	(2.77)	(2.73)	(1.28)
Liq_{jt}	-0.470***	-0.468***	-0.470***	-0.453***
	(-19.77)	(-19.69)	(-19.78)	(-19.16)
$Size_{jt}$	0.008	0.010	0.008	0.005
	(0.44)	(0.51)	(0.41)	(0.29)
N	16,367	16,367	16,367	16,367
Adjusted R^2	0.034	0.033	0.034	0.033

Table 5 reports annualized excess returns that are calculated by subtracting the market return from the fund's return. We estimate:

$$
\begin{aligned}
R_{jt+1} = {} & a_0 + b_1 MOM_{jt} + b_2 CON_{jt} + b_3 FQSbeta_{jt} + b_4 MOM_{jt} \times FQSbeta_{jt} + b_5 CON_{jt} \times FQSbeta_{jt} \\
& + b_6 SDFQSbeta_{jt} + b_7 MOM_{jt} \times SDFQSbeta_{jt} + b_8 CON_{jt} \times SDFQSbeta_{jt} + b_9 R_{jt} + b_{10} TO_{jt} \\
& + b_{11} Liq_{jt} + b_{12} Size_{jt} + \varepsilon_{jt}
\end{aligned}
$$

for models (1), (2) and (3), and:

$$R_{jt+1} = a_0 + b_1 MOM_{jt} + b_2 CON_{jt} + b_3 FQSbeta_{jt} + b_4 Abs\Delta Sbeta_{jt} + b_5 MOM_{jt} \times Abs\Delta Sbeta_{jt}$$
$$+ b_6 CON_{jt} \times Abs\Delta Sbeta_{jt} + b_7 R_{jt} + b_8 TO_{jt} + b_9 Liq_{jt} + b_{10} Size_{jt} + \varepsilon_{jt}$$

for model (4). R_{jt+1} is annualized excess return on fund j in interval t+1, MOM_{jt} is a dummy variable for fund j with significant momentum trades in period t, CON_{jt} is a dummy variable for fund j with significant contrarian trades in period t, $FQSbeta_{jt}$ is weighted average sentiment beta of the stocks held by fund j at time t, $SDFQSbeta_{jt}$ is standard deviation of sentiment betas of the stocks held by fund j at time t, R_{jt} is annualized excess return on fund j in period t, TO_{jt} is portfolio turnover of fund j in period t, Liq_{jt} is standardized average portfolio liquidity of fund j at time t, $Size_{jt}$ is standardized capitalization of fund j at time t, and $Abs\Delta Sbeta_{jt}$ is the absolute value of the change in weighted average sentiment beta of fund j during period t.
***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.

Table 6
Fund excess return as a function of contemporaneous change in sentiment index.

	Model		
	(1) All fund-periods	(2) Contrarian	(3) Momentum
Intercept	-0.009**	-0.025**	-0.018
	(-2.08)	(-2.12)	(-1.52)
$ChSI_{t+1}$	-0.390***	-0.469***	-0.309***
	(-43.52)	(-19.80)	(-12.86)
$FQSbeta_{jt}$	-0.341**	-1.187***	0.649*
	(-2.28)	(-2.92)	(1.73)
$FQSbeta_{jt}$ x $ChSI_{t+1}$	7.589***	7.027***	8.283***
	(23.76)	(8.01)	(10.50)
$SDFQSbeta_{jt}$	0.636***	2.105***	0.143
	(2.87)	(3.54)	(0.26)
$SDFQSbeta_{jt}$ x $ChSI_{t+1}$	7.844***	9.721***	5.423***
	(16.15)	(7.29)	(4.62)
N	16,783	2565	2505
Adjusted R^2	0.202	0.273	0.165

Table 6 reports annualized excess returns that are calculated by subtracting the market return from the fund's return. We estimate equation:

$$R_{jt+1} = b_0 + b_1 ChSI_{t+1} + b_2 FQSbeta_{jt} + b_3 FQSbeta_{jt} \times ChSI_{t+1} + b_4 SDFQSbeta_{jt} + b_5 SDFQSbeta_{jt} \times ChSI_{t+1} + \varepsilon_{jt}$$

for models (1), (2) and (3). Model (1) includes all fund-periods in our sample, while we use only funds we identify as contrarian and momentum traders in models (2) and (3) respectively. $ChSI_{t+1}$ is change in sentiment index, $FQSbeta_{jt}$ is weighted average sentiment beta of the stocks held by fund j at time t, and $SDFQSbeta_{jt}$ is standard deviation of sentiment betas of the stocks held by fund j at time t.

***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.

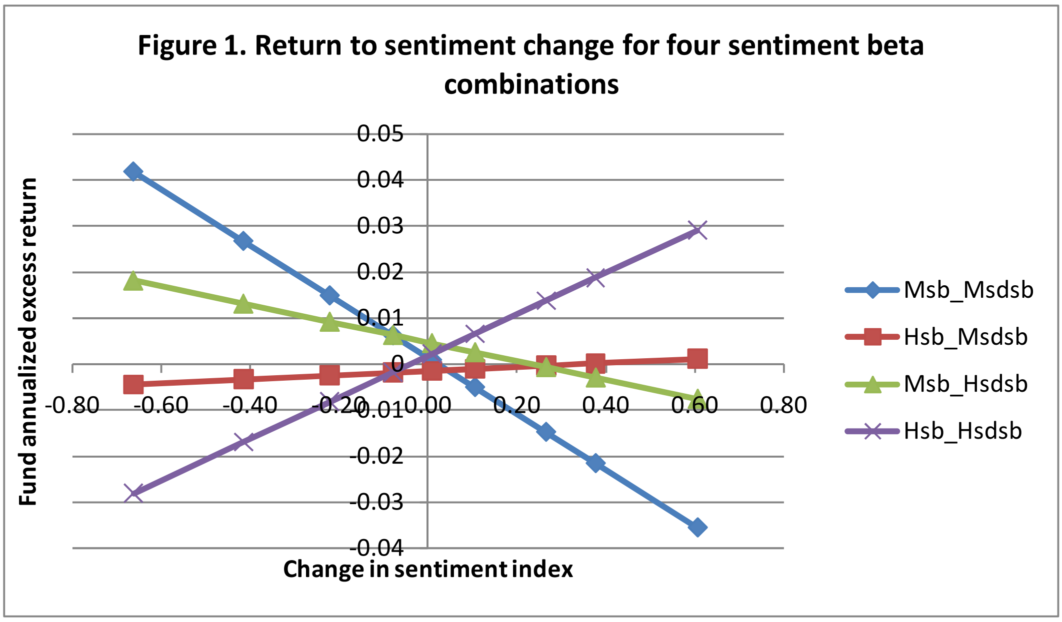
Figure 1. Return to sentiment change for four sentiment beta combinations
Fund annualized excess return
Change in sentiment index
Msb_Msdsb
Hsb_Msdsb
Msb_Hsdsb
Hsb_Hsdsb

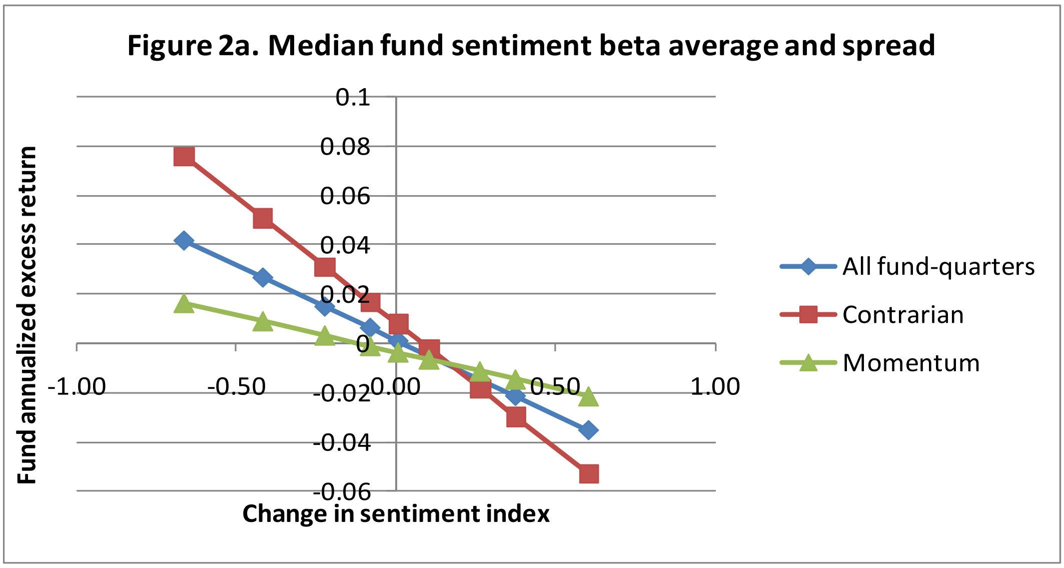
Figure 2a. Median fund sentiment beta average and spread
Fund annualized excess return
Change in sentiment index
All fund-quarters
Contrarian
Momentum

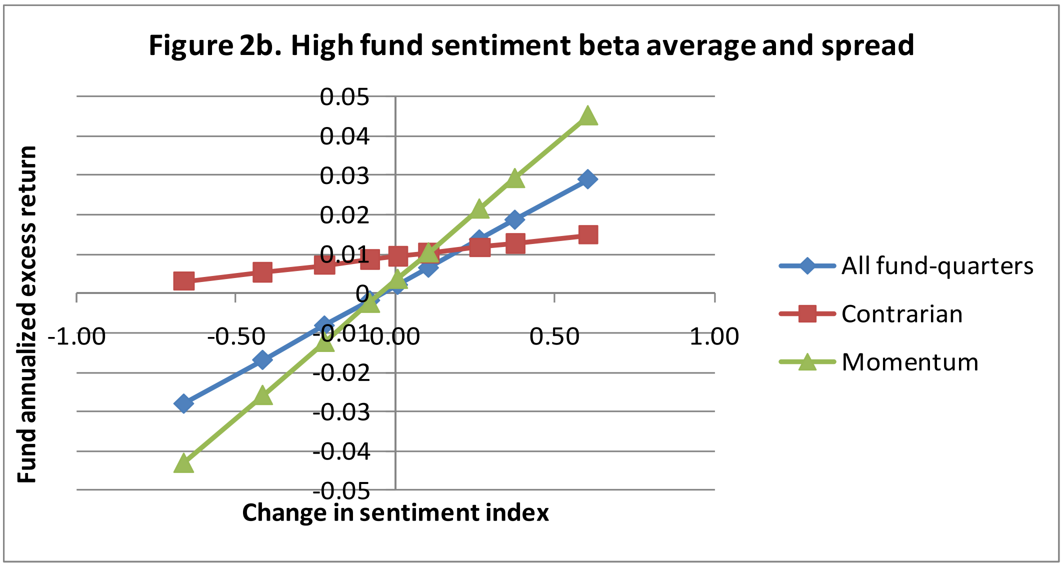
Figure 2b. High fund sentiment beta average and spread
Fund annualized excess return
Change in sentiment index
All fund-quarters
Contrarian
Momentum