Cullen, G., Gasbarro, D., Monroe, G.S. and Zumwalt, J.K. (2011) Investor sentiment and momentum and contrarian trading strategies: Mutual fund evidence. In: 24th Australasian Finance and Banking Conference, 14 - 16 December, Sydney, NSW, Australia.

Investor sentiment and momentum and contrarian trading strategies: Mutual fund evidence.

Grant Cullen[a], Dominic Gasbarro[a], Gary S. Monroe[b,*], J. Kenton Zumwalt[c]

[a]*Murdoch Business School, Murdoch University, Murdoch, WA 6150, Australia*

[b]*School of Accounting, University of New South Wales, Sydney, NSW 2052, Australia*

[c]*Department of Finance and Real Estate, Colorado State University, Fort Collins, CO 80523, USA*

ABSTRACT

Stocks with high sentiment betas are more sensitive to investor sentiment, with more subjective valuations. We contend that sentiment beta also captures the duration of mispricing. Accordingly, stocks with high (low) sentiment betas provide opportunities for momentum (contrarian) traders. We form hypothetical zero investment portfolios of high (low) sentiment betas stocks, and show that momentum profits decompose to reveal positive (negative) serial correlation of idiosyncratic returns, that contribute to momentum (contrarian) profits. Furthermore, actual mutual funds identified as momentum (contrarian) traders hold stocks with higher (lower) sentiment betas. Additionally, funds adjust sentiment betas to enhance performance as sentiment changes.

JEL classification: G2, G11, G14, G23

Keywords: Investor sentiment, Momentum, Contrarian, Mutual fund

---

* Corresponding author at: Tel.: +61 2 9385 6443; fax: +61 2 9385 5925.

E-mail addresses: g.cullen@murdoch.edu.au (G. Cullen), d.gasbarro@murdoch.edu.au (D. Gasbarro), g.monroe@unsw.edu.au (G. Monroe), Kent.zumwalt@business.colostate.edu (K. Zumwalt).

Investor sentiment and momentum and contrarian trading strategies: Mutual fund evidence

1. Introduction

The opportunity to profit from momentum or contrarian trading relies on stocks being mispriced. Baker and Wurgler (2007) show that the degree of mispricing is related to the stock's sentiment beta.[1] We extend their analysis using the Jegadeesh and Titman (1995) decomposition of momentum[2] profits over different return intervals, for stocks partitioned according to their sentiment beta. The direction of stock price reaction to firm specific events varies with sentiment beta and return interval, from which we infer an association between stock sentiment betas and the duration of stock mispricing. Accordingly, we contend that stock sentiment betas can be used to identify stocks that are predisposed to momentum or contrarian, trading strategies.

According to Jegadeesh and Titman (1995), stocks with positive (negative) serial correlation of their idiosyncratic returns contribute positively (negatively) to the momentum profits of the hypothetical zero investment stock portfolios. We use the Jegadeesh and Titman (1995) method to decompose momentum profits of portfolios formed over one-, two-, three- and four-month formation and holding periods. For one-month formation and holding periods, we find that stock idiosyncratic returns are negatively serially correlated, consistent with Jegadeesh and Titman (1995), but become

[1] Sentiment beta quantifies a stock's price response to investor sentiment that is measured by Baker and Wurgler's (2007) sentiment changes index. High (low) values of the sentiment changes index indicate that investors are becoming more optimistic (pessimistic).

[2] Jegadeesh and Titman (1995) decompose contrarian profits. However, momentum and contrarian profits differ only in sign.

positively correlated when we extend the period, consistent with Jegadeesh and Titman (1993). However, over longer holding periods, the serial correlation of stock idiosyncratic returns, used by Jegadeesh and Titman (1995) to measure over-reaction to firm specific events, remains negative in low sentiment beta stocks.[3] Notably, we find that over the three-month return horizon, stocks with high sentiment beta have, on average, positive serial correlations while stocks with low sentiment betas have negative serial correlations.

We conjecture that stocks with positive (negative) serial correlation of idiosyncratic returns adjust to their intrinsic value more slowly (quickly) because they are harder (easier) to value and arbitrage. According to Baker and Wurgler (2007), stocks that are harder (easier) to value and arbitrage have high (low) sentiment betas. Therefore, as we find over a three-month interval, stocks with high (low) sentiment betas, should have positive (negative) serial correlation of their idiosyncratic returns, which make them candidates for momentum (contrarian) trading. Fortuitously, most mutual funds report their stock holdings quarterly, and this presents the ideal opportunity to extend insights we obtain from hypothetical stock portfolios to real mutual fund portfolios over the same time-frame.

The extant literature does not provide a suitable method for statistically identifying mutual funds that engage in momentum or contrarian trading in a given fund-quarter. We overcome this deficiency by adapting a method that uses fund holdings to reveal trading preferences for stocks with particular attributes. Based on the reasoning

---

[3] Jegadeesh and Titman (1995) attribute the negative correlation of idiosyncratic returns that are measured over a one week horizon to liquidity, short-term price pressures and bid-ask spread. However, this does not adequately explain the negative correlation of low sentiment beta stocks over longer return intervals, as these stocks tend to be larger and more actively traded (by value) and, therefore, less likely to be affected by these factors than high sentiment beta stocks.

that the success of momentum or contrarian trading strategies relies on identifying mispriced stocks, we calculate sentiment betas to identify stocks predisposed to mispricing. We observe strong preferences for momentum funds to hold stocks with high sentiment betas and for contrarian funds to hold the opposite. Therefore, mutual funds exhibit preferences that are consistent with our contention that stocks with high (low) sentiment betas return to their intrinsic value more slowly (quickly), and in the medium term present momentum (contrarian) trading opportunities.

When they engage in momentum or contrarian trading, mutual funds that hold stocks with the preferred sentiment beta are presumed to have a pecuniary motivation that will translate to better fund performance. However, investor sentiment also affects fund performance, and does so differentially depending on the fund's sentiment beta. While the latter effect is dominant, fund returns provide some evidence of the motivation behind momentum or contrarian funds choosing to hold stock portfolios with particular sentiment betas.

We show that the effect of investor sentiment on fund returns is consistent with the effect on stock returns established by Baker and Wurgler (2007). That is, funds with high (low) sentiment beta stock portfolios experience better performance following periods of low (high) investor sentiment. More directly, as investor sentiment increases (decreases), funds with high (low) sentiment betas experience better returns over the same period. We also examine changes to the fund's (portfolio) sentiment betas caused by the trades they make in a quarter. Consistent with our expectation, more funds increase their sentiment beta following low investor sentiment, or when investor sentiment increases. Following sentiment highs, or when sentiment falls, more funds decrease their sentiment beta. On average, funds that make changes to their portfolios' sentiment beta in the same period that sentiment changes occur receive a performance dividend, suggesting that some funds are able to correctly predict sentiment changes, rather than merely responding to them.

In Section 2 we discuss the development of our hypotheses. Section 3 describes the data and outlines our research procedure. Initially, in Section 4, we examine the returns of hypothetical portfolios of stocks and perform Jegadeesh and Titman's (1995) decomposition of contrarian profit. Later, we investigate whether mutual fund holdings and trades align with expectations gleaned from our examination of stocks. In section 5 we consider whether this is reflected in fund returns. The summary and conclusions of this research are presented in Section 6.

2. Empirical predictions and related literature

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 literature attributes the success of momentum strategies to under-reaction to information (Chan, Jegadeesh and Lakonishok (1999), Hong, Lim and Stein (2000)), or to over-reaction (Jegadeesh and Titman (1993, 2001)). Momentum trading may also assist continued mispricing (De Long, Shleifer, Summers and Waldmann (1990)). According to Jegadeesh and Titman (2001) contrarian profits are the eventual outcome of stock price over-reaction, while Lo and MacKinlay (1990) attribute a portion of short-term contrarian profits to delayed reaction to common factors.

A number of studies suggest that momentum profits are available in the short term, whereas contrarian profits are available when mispricing is resolved. These studies include De Long, Shleifer, Summers and Waldmann (1990), Conrad and Kaul (1998), and Jegadeesh and Titman (2001). Other studies suggest that stock attributes influence their suitability for momentum or contrarian trading. Jegadeesh, Kim, Krische and Lee (2004), Sagi and Seasholes (2007) and Baik, Faber and Petroni (2009) associate various stock attributes with enhanced momentum profits. Lakonishok, Shleifer and Vishny (1994), Piotroski (2000) and Chan and Lakonishok (2004) show that consideration of stock attributes can improve contrarian profits.

For a stock that has deviated from its intrinsic value, potential momentum and contrarian trading opportunities depend not only on the time-frame, but also on various stock attributes. Plausibly, the dependence of a successful trading strategy on both time and stock attributes jointly originate from the duration of a stock's mispricing. That is, over a particular time horizon, stocks that return to intrinsic value more slowly (quickly) are preferred for momentum (contrarian) trading.

Baker and Wurgler (2007) also demonstrate market inefficiency by finding predictability in stock returns. Specifically, investor sentiment affects stocks mispricing, with mispricing greatest for high sentiment beta stocks. These stocks tend to be smaller and more volatile and therefore difficult to value and arbitrage. We conjecture that stocks that are difficult to value and arbitrage will have longer departures from their intrinsic value. In contrast, low sentiment beta stocks are easier to value and arbitrage, and deviations from their intrinsic value should be smaller and of shorter duration.

Sentiment beta measures a stock's price sensitivity to investor sentiment. Baker and Wurgler (2007) create portfolios based on stock volatility, and regress their monthly returns on their index of sentiment changes, and interpret the gradient as the portfolio's sentiment beta. Glushkov (2006) calculates sentiment betas for each stock using time series regressions of the stock returns on a sentiment index he constructs.[4] Like Baker and

[4] Unlike Baker and Wurgler (2007), Glushkov (2006) calculates sentiment betas on a stock-by-stock basis, and does so by regressing stock returns on a Fama and French (1995) three-factor model augmented by a Pastor and Stambaugh (2003) liquidity factor and an index of investor sentiment change.

Wurgler (2007), Glushkov (2006) finds sentiment betas are negatively related to stock capitalization and positively related to volatility. Furthermore, Glushkov (2006) supports the view that high (low) sentiment beta stocks are more (less) difficult to value and arbitrage.

By extension, calculating a sentiment beta for each stock provides an indication of the duration of mispricing associated with the stock. That is, individual stocks identified as having a high (low) sentiment beta should return to their intrinsic value more slowly (quickly). Stocks with prolonged (brief) departures from their intrinsic value, should, with the appropriate choice of return measurement interval, exhibit positive (negative) serial covariance of their idiosyncratic returns. Moreover, we expect that over some return intervals, stocks with high sentiment betas that exhibit positive serial covariance of their idiosyncratic returns will coexist with low sentiment beta stocks with negative serial covariances.

Jegadeesh and Titman (1995) also consider the serial covariance of stock idiosyncratic returns, but do so in the context of momentum or contrarian trading strategies. Stocks with positive (negative) covariances contribute to momentum (contrarian) profits. Noting our earlier argument that over a given time horizon, the stocks preferred for momentum (contrarian) trading return to intrinsic value more slowly (quickly), it follows that stocks suitable for momentum (contrarian) trading should therefore have high (low) sentiment betas. Furthermore, we should be able to select this time horizon from the return interval where stocks with high sentiment betas exhibiting positive serial covariance of idiosyncratic returns, and those with low sentiment betas and negative serial covariance, coexist.

The standard procedure for assessing momentum or contrarian trading opportunities is by creating hypothetical zero investment, winner minus loser portfolios. This procedure is commonly employed by examining portfolio returns using a variety of formation and holding periods.[5] However, as Conrad and Kaul (1998) demonstrate, procedures that rely on the purchase of winners and sale of losers generate apparent momentum profits in the absence of stock mispricing. Nonetheless, if high (low) sentiment betas are able to identify stocks predisposed to momentum (contrarian) trading strategies, then differences in the performance of winner minus loser portfolios partitioned by sentiment beta should emerge. Insights regarding the role of sentiment beta in momentum and contrarian trading obtained from hypothetical portfolios, however, cannot be generalized to actual mutual funds. First, the creation of hypothetical portfolios ignores transaction costs that reduce the profitability of trading strategies,[6] particularly when portfolio rebalancing is more frequent. Second, mutual funds hold positive investment portfolios. Accordingly, the question of whether sentiment beta can inform momentum or contrarian trading in actual mutual funds remains to be addressed.

If sentiment beta can be used to identify stocks that are most suitable for momentum or contrarian trading, then funds employing these strategies should exhibit preferences with respect to sentiment beta. That is, with the appropriate choice of trading horizon, mutual funds exhibiting momentum (contrarian) trading would hold high (low) sentiment beta stocks. However, to investigate whether actual mutual funds that use these trading strategies have preferences with respect to sentiment beta, it is first necessary to identify such funds. Several studies investigate momentum trading by institutions. Before they test their measures of momentum trading for statistical significance, the studies either aggregate across funds (e.g. Gompers and Metrick (2001)), average over time (e.g. Grinblatt, Titman and Wermers (1995)), or aggregate across funds (e.g. Badrinath and

[5] For example Jegadeesh and Titman (1993) and Conrad and Kaul (1998).

[6] For example, Korajczyk and Sadka (2004) and Lesmond, Shill and Zhou (2004).

Wahal (2002)). Furthermore, Sias (2007) demonstrates that before aggregation or averaging occurs, the Grinblatt, Titman and Wermers (1995) measure of momentum (contrarian) trading is dominated by trading in the largest capitalization stocks. Therefore, the extant literature does not provide a measure that will statistically identify whether in a particular calendar quarter, a particular mutual fund has engaged in momentum or contrarian trading. We address this deficiency by adapting a procedure in Cullen, Gasbarro and Monroe (2010) and Cullen, Gasbarro, Monroe and Zumwalt (2011) that permits statistical testing of whether mutual fund trades exhibit preferences related to certain stock attributes in any fund-quarter.

Baker and Wurgler (2007) demonstrate that stock returns are predictable depending on the level of investor sentiment and the sentiment beta of the stock. They infer that high (low) sentiment precedes a decrease (increase) in sentiment to which stocks respond according their sentiment beta. Mutual funds might exploit this relation by altering their sentiment beta. In this event, we expect that mutual funds will decrease (increase) the sentiment beta of their portfolio when investor sentiment is high (low).

If mutual funds can predict changes in investor sentiment, then ahead of increasing (decreasing) sentiment, they would increase (decrease) their sentiment beta. Alternatively, mutual funds may respond to increasing (decreasing) sentiment by window dressing[7] where they buy (sell) stocks that have recently performed well (poorly). Since the high (low) sentiment beta stocks are the ones that should perform well (poorly) when sentiment increases, this would appear as if they were gaming sentiment. In either case, over a three-month period that sentiment increases (decreases), we expect funds to increase (decrease) their sentiment beta over the same period.

[7] See for example Lakonishok, Shleifer, Thaler, and Vishny (1991).

If sentiment betas are used in momentum (contrarian) trading strategies, and/or if these betas differentially affect stocks' responses to investor sentiment, then mutual fund performance will reflect trades based on sentiment betas. Since we contend that momentum (contrarian) traders benefit from using high (low) sentiment beta stocks, we expect that mutual funds using this strategy that hold high (low) sentiment beta stocks should receive a performance benefit. Mutual funds that hold portfolios of high (low) sentiment beta stocks should also earn higher returns when investor sentiment is low (high) or increases (decreases).

We consider whether mutual funds, do indeed, attempt to "game" sentiment beta. If they are able to predict an increase (decrease) in investor sentiment, and act to increase (decrease) the fund's sentiment beta, we expect that their performance should improve. However, if instead of predicting sentiment, they respond by window dressing, then no benefit will be evident.

3. Data description and method

3.1. Data description

To calculate stock sentiment betas, we use the monthly sentiment changes index developed by Baker and Wurgler (2007) and made available on Jeffrey Wurgler's website,[8] and stock return data from Center for Research in Security Prices (CRSP). 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

[8] 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 indexes 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.

reported on a quarterly basis, we infer transactions from the quarterly changes to the holdings while allowing for stock capitalization changes. Stock price and return data from CRSP are 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 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[9] 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.

3.2. Method

Using the Baker and Wurgler (2007) index of monthly investor sentiment changes, we calculate the sentiment beta for each stock. The stocks' sentiment betas are used first to rank stocks and allocate them to hypothetical quintile portfolios of increasing sentiment beta, and second to calculate the sentiment beta of actual mutual fund portfolios by weighting with the portfolio holdings. From the hypothetical portfolios, in the first instance, we further sort them by prior return, and in the second, perform the Jegadeesh and Titman (1995) decomposition of contrarian profits. These procedures are used with various formation and holding periods to explore the role of sentiment betas on the performance of hypothetical momentum and contrarian trading strategies.

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

Following the examination of the hypothetical portfolios, we use the "real world" mutual fund portfolios to investigate the role of sentiment beta in the use of momentum and contrarian trading strategies. We employ a procedure that identifies, with statistical confidence, individual funds that exhibit momentum/contrarian trading in a calendar quarter. We also consider the role of investor sentiment, and its association with the changes mutual funds make to their portfolios' sentiment beta, and whether there is a pecuniary incentive for funds to undertake the observed behaviors.

4. Momentum betas and returns

4.1. Descriptive statistics

In Panel A of Table 1 we partition stocks into quintiles of sentiment beta and report the averages of sentiment beta and the following stock attributes; market beta, return standard deviation, capitalization, and turnover, both value and proportion. Initially, our sample size is 1,219,090 stock-months, however, for consistency with Tables 2 and 3 the statistics we report in Panel B are based on 656,748 stock-months. This follows because for Table 3, we require each stock to have a continuous time series of 108 monthly returns to manage bias in the autocovariance estimates[10], particularly when these are converted to quarterly or four-month returns. Accordingly, we select the most recent 108 returns for each stock, and eliminate stocks with fewer observations. This creates a survivorship bias because of greater attrition in high sentiment beta stocks, however, comparison of panels A and B reveals qualitative similarity in the distribution of the various attributes.

In Panel B, the average sentiment beta of stocks in quintile 1 is negative, consistent with Baker and Wurgler's (2007) bond-like stocks. Notably, all other quintiles have positive average sentiment betas, while the beta of the highest quintile is considerably

[10] Jegadeesh and Titman (1995) also impose a data availability requirement for this reason.

greater than the absolute value of the first quintile. The traditional market beta increases monotonically across quintiles 1 to 5. In separate analyses, we find the correlation between sentiment beta and market beta to be 0.357.[11] Baker and Wurgler (2006) and Glushkov (2006) infer a positive relation between volatility (return standard deviation) and sentiment beta. We find that total risk (return standard deviation) follows a largely similar pattern, except that the minimum occurs in sentiment beta quintile 2. The higher total risk in quintile 1 is possibly consistent with flight-to-quality causing greater volatility in the negative sentiment beta, bond-like stocks.

In addition, in Panel B we standardize the market capitalization of stocks to recognize growth over time by dividing by the average market capitalization of all stocks in each corresponding month. Consistent with the expectation that low (high) sentiment beta stocks are easier (harder) to value and arbitrage, and also consistent with Baker and Wurgler (2006) and Glushkov (2006), stock market capitalization decreases monotonically. Market turnover (by value, standardized for market growth over time) and proportionate turnover (turnover divided by the number of shares outstanding) are greater for stocks with the highest sentiment betas, consistent with Glushkov (2006). Possibly, this reflects herding in these stocks. Stocks in the lowest sentiment beta quintile also have elevated turnover, consistent with increased demand for bond-like stocks, but due to the larger capitalization of these stocks, is most pronounced when turnover is measured by value.

As shown in Panel C, our sample contains 2450 distinct mutual funds, and 31,409 fund-quarters that meet our selection and data quality criteria. We calculate the weighted average sentiment beta for each portfolio of the 16,783 fund-quarters that remain after we

[11] 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.

match stock sentiment betas and fund returns. We also report the distribution of the change in a fund's weighted average sentiment beta over a trading quarter. 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 D 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.[12]

4.2. Stock level momentum and contrarian profit

4.2.1. Double sorted portfolios

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 traditional market beta. Similarly, we use the stock returns over the previous 60 months,[13] but use the sentiment changes in 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 returns, we create hypothetical portfolios of stocks. For each stock in our database, we select the most

[12] The mean of the sentiment changes index in our sample is similar to the Baker and Wurgler (2007) index that was standardized to have a mean of zero over their 40-year examination period. However, our standard deviation is lower than their unit variance as a consequence of using a 3-month moving average.

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

recent 108 consecutive monthly returns[14] within the period January 1991 – December 2005 creating a dataset of 656,748 stock-months. Each month, we form 25 portfolios by double sorting stocks first by sentiment beta and allocating these to quintiles, and second by prior return and also allocating these to quintiles. For prior return, we use, in turn, one-, two-, three-, and four-month formation periods, and equally weight the excess return[15] of the stocks in these portfolios over corresponding periods of one-, two-, three-, and four-months following portfolio formation. The resulting monthly series of one-, two-, three-, and four-month portfolio returns are averaged over time and are shown in Panels A, B, C and D of Table 2 respectively. Similar to Jegadeesh and Titman (1993), we calculate the average by pooling the overlapping time series of return measurement periods, for our two-, three- and four-month return series.

The right-hand column in each panel in Table 2 shows the profitability, on average, of the 'winner minus loser' (W-L) momentum strategy of purchasing prior return quintile 5 and selling return quintile 1. It is apparent that this varies within each panel according to sentiment beta, and across panels according to formation and holding period. The bottom row in each panel shows the averages across sentiment betas for each prior return quintile. This indicates the apparent profitability of a contrarian strategy when formation and holding period returns are measured over one and two months (Panels A and B). On average, a momentum strategy is also profitable when measured over three and four months (Panels C and D). In effect, we reveal the transition between the apparently profitable contrarian strategy based on weekly returns in Jegadeesh and Titman (1995)

[14] We balance the inclusion of stocks against the length of our time series. Our choice of 108 months achieves this goal and selects a similar dataset to the one we use for our decomposition of momentum profits.

[15] Excess returns are stock returns in excess of the value weighted market portfolio over the same period.

and the profitable momentum strategy based on six-month returns in Jegadeesh and Titman (1993).

Jegadeesh and Titman (1995) argue that the apparent success of the contrarian strategy using one-week portfolio formation and holding periods may be caused by short-term liquidity demands, price pressure and bid-ask bounce. These effects should diminish as the return measurement period increases. Consistent with this explanation, the return for the average sentiment beta, W-L portfolio increases from -0.0131 in Panel A to 0.0228 in Panel D as we move from one-month to four-month formation and holding periods. However, negative returns for the W-L portfolio persist in the lowest sentiment beta portfolios when moving from Panels A to C, and relative to the highest sentiment beta portfolios, continue to be lower in Panel D. These portfolios are comprised of stocks with low sentiment betas, which tend to be larger capitalization, with similar turnover (by value), and therefore are less susceptible to price pressure and bid-ask bounce effects.

The difference in the profitability of momentum strategies for portfolios with different sentiment betas indicated by the W-L column is particularly noteworthy in Panel C. A contrarian strategy using stocks in the second lowest sentiment beta quintile[16] yields an average profit of 0.39% over the three-month holding period, while a momentum strategy using stocks in the highest sentiment beta quintile produces a profit of 2.18%.[17] Both profits are statistically significant. This result provides initial support for our expectation that if high sentiment beta stocks deviate from their intrinsic value longer than

[16] The lowest sentiment beta quintile also indicates a profit for a contrarian trading strategy of 0.21%, however this value is not statistically significant.

[17] Observations where stock returns exceed 100% per month are removed. We note, however, that more severe winsorization will produce lower portfolio returns in the body of Table 2, but the pattern exhibited in the W-L column persists.

low sentiment beta stocks, the former may offer momentum trading opportunities, while the latter are more amenable to contrarian trading.[18]

[Insert Table 2]

4.2.2. Decomposition of momentum profits

The transition from contrarian profit to momentum profit with increasing formation and holding period, and the accompanying variation according to sentiment beta, is explored further using the Jegadeesh and Titman (1995) decomposition of momentum (contrarian) profit. We perform this decomposition using a two factor model of stock returns with contemporaneous and lagged factors. The common factors are the CRSP value-weighted index and Baker and Wurgler's sentiment changes index. We obtain monthly stock return and index series, but convert these into two-, three-, and four- month series commensurate with the various return intervals we wish to examine. For the sentiment changes index, this involves the moving average of two, three or four successive values respectively.

When we convert a stock's time series of monthly returns into two-month returns, we create two time-series with 54 observations that commence in adjacent months.

[18] For consistency with Table 3, we use the most recent 108 months of returns for each stock, and eliminate stocks with fewer observations. In separate tests, we do not truncate the time series at 108 months and obtain qualitatively similar results. However, the unavoidable requirement for a minimum number of time series observations in Table 3 imposes a possible survivorship bias. To assess this effect, we generate Panel C of Table 2 using different minimum observations. Consistent with survivors having higher average returns, in general, returns decline as we reduce this minimum. The greatest decline is experienced by the low prior performers and also by high sentiment beta stocks where survivorship is lower. Accordingly, we conclude that survivorship bias decreases the apparent profitability of the momentum strategy in high sentiment beta stocks, and increases the apparent profitability of the contrarian strategy.

Similarly, when we convert into three-month returns, we create three time series with 36 observations. For four-month returns, we create four time series, each with 27 observations. Separately, for each of the resultant ten sets of data, we model the returns of stock 'i' as

$$r_{i,t} = \alpha_i + \beta^t_{0,i}\,\mathrm{vwmr}_t + \beta^t_{1,i}\,\mathrm{vwmr}_{t-1} + \gamma^t_{0,i}\,\mathrm{ChSI}_t + \gamma^t_{1,i}\,\mathrm{ChSI}_{t-1} + \varepsilon_{i,t} \tag{1}$$

where α_i is the unconditional expected return of stock i, $\beta^t_{0,i}$ and $\beta^t_{1,i}$ are the sensitivities of stock i to the contemporaneous and lagged values of vwmr_t, the value-weighted market return, and $\gamma^t_{0,i}$ and $\gamma^t_{1,i}$ are the sensitivities of stock i to the contemporaneous and lagged values of ChSI_t, the average of successive values of the sentiment changes index, while $\varepsilon_{i,t}$ is the firm-specific component. Parallel to Jegadeesh and Titman (1995), we consider a momentum strategy where the portfolio weights of a stock are proportional to the deviation of its returns from the mean of all stocks in the previous period. The expected profit from this strategy decomposes as follows:

$$E(\pi) = \sigma^2_\alpha + \Omega + (\delta_\beta \sigma^2_{vwmr} + \delta_\gamma \sigma^2_{ChSI}) \tag{2}$$

where

$$\sigma^2_\alpha = \frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \overline{\alpha})^2 \tag{3}$$

$$\Omega = \frac{1}{N}\sum_{i=1}^{N}\mathrm{cov}(\varepsilon_{i,t}, \varepsilon_{i,t-1}) \tag{4}$$

$$\delta_\beta = \frac{1}{N}\sum_{i=1}^{N}(\beta_{0,i} - \overline{\beta}_0)(\beta_{1,i} - \overline{\beta}_1) \text{ and } \delta_\gamma = \frac{1}{N}\sum_{i=1}^{N}(\gamma_{0,i} - \overline{\gamma}_0)(\gamma_{1,i} - \overline{\gamma}_1) \tag{5}$$

Corresponding to the one, two, three or four month return interval being used, Equation (2) is generated either one, two, three, or four times. Where it is generated more than once, the decomposed returns are averaged. Table 3 reports this decomposition when returns are measured over one, two, three and four months in Panels A, B, C and D respectively. The first row in each panel in Table 3 is generated using the same stock-months selected for examination in Table 2. Subsets corresponding to the lowest and highest quintiles of sentiment beta are used to generate the second and third rows of Table 3, respectively.

[Insert Table 3]

Consistent with Table 2, the expected momentum profit (column 3) increases, moving from negative when returns are measured over one month in Panel A of Table 3 through to positive in Panel D when measured over four months. It should be noted, however, that while comparable, the definition of momentum profit in the Jegadeesh and Titman (1995) decomposition is not the same as the profit for the W-L portfolios shown in Table 2. In Table 3, the contribution of the cross-sectional variance of returns (column 4) to the expected momentum profit increases almost geometrically with return measurement period[19] as predicted by Conrad and Kaul (1998). As they demonstrate, this component of momentum profit would be expected even if stock prices followed a random walk, and the time-series of returns contained no information. Accordingly, our focus is on columns 5 to 7, since these relate to time-series market inefficiencies that are necessary for successful momentum and contrarian trading.[20]

---

[19] Expected profits arising from the cross-sectional dispersion of returns should increase with the square of the return measurement interval. Accordingly, in column 4, the corresponding values in Panels A, B, C, and D should increase by a factor of 1, 4, 9 and 16 respectively.

[20] Nonetheless, it is noteworthy that for all panels in column 4 of Table 3, the contribution of the cross-sectional variance of returns is lower for low sentiment beta stocks than for high sentiment beta stocks. This is likely because higher returns are expected from stocks with higher market betas, that are, in-turn, correlated with sentiment beta.

In Panel A, the decomposition of expected momentum profit shows that stock over-reaction to firm-specific events (column 5) is the dominant component, similar to Jegadeesh and Titman (1995) who used one-week returns. Furthermore, we find that over-reaction (omega = -0.00154) is greatest for high sentiment beta stocks, which tend to be speculative, with lower capitalization, a result also consistent with Jegadeesh and Titman (1995) who find that over-reaction decreases with firm size.

In all panels in Table 3, the omega for stocks in the low sentiment beta quintile is negative, indicating that the idiosyncratic component of their returns has, on average, negative serial covariance. In contrast, the serial covariance of this component of the returns of high sentiment beta stocks becomes positive and increases as return is measured over longer intervals. High sentiment beta stocks tend to be smaller and, therefore, more susceptible to liquidity demands, price-pressure, and bid-ask bounce causing negative serial covariance. Therefore, while these factors might explain the negative serial correlation of low sentiment beta stock idiosyncratic returns over short intervals, by symmetry, they cannot do so over longer intervals. Rather, over longer return intervals (Panels C and D), the negative omega for low sentiment beta stocks and positive omega for high sentiment beta stocks are more consistent with our hypothesis that unlike low sentiment beta stocks, high sentiment beta stocks have prolonged departures from their intrinsic value.

Equation (1) is a two factor model of stock returns. Similar to the one factor model in Jegadeesh and Titman (1995) that uses weekly returns, we find that for Panel A, the contribution of a delay in the stock's reaction to these common factors (columns 6 and 7) towards momentum profits is small relative to the impact of over-reaction to firm specific events (column 5). As the return interval increases to four months, moving towards Panel

D, the contribution of the delay in stock reaction varies, but remains a small proportion of expected momentum profits.

4.3. Momentum betas and fund level trading strategies

The evidence in the preceding section supports our contention that stock sentiment betas capture the duration of stock mispricing. However, the hypothetical zero investment stock portfolios used to demonstrate the availability of profitable momentum and contrarian trading strategies do not resemble the actual portfolios held by mutual funds. For example, Table 1 shows that mutual funds hold long positions in median number of 92 stocks, whereas for Table 2, the hypothetical W-L portfolios for each sentiment beta are created from an average of 230 stocks with offsetting short positions each month. Accordingly, we consider whether mutual funds use momentum and contrarian trading strategies to exploit stock mispricing that is indicated by the stocks' sentiment betas.

4.3.1. Identifying mutual funds that engage in momentum and contrarian trading

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 a 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.[21]

For each mutual fund, in each quarter, we create twenty ranked "prior performance buckets". Each of these is a stock portfolio of approximately equal value, to which we assign a measure of the bucket's prior performance (BucketPP). This measure is calculated by weighting the prior performance of each stock in the bucket by the stock's proportionate value. We perform 31,409 regressions, one for each fund-quarter between 1991 and 2005, using BucketPP as the independent variable. Like Cullen, Gasbarro and Monroe (2010), we use TradeValue as the dependent variable in these regressions as follows:

$$\text{TradeValue}_j = \alpha + \beta\,\text{BucketPP}_j + \varepsilon_j \qquad (6)$$

where

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

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

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

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

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

[21] 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.

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.[22]

Table 4 shows the results of these analyses. We find that 4777 fund-quarters have statistically negative momentum betas while 4702 fund-quarters have statistically positive momentum betas. Therefore, of the 31,409 fund-quarters in our dataset, 15.2% follow the contrarian trading strategy of re-balancing their portfolios away from recently better performing stocks towards recent poor performers. Momentum traders that follow the opposite strategy comprise 15.0% of fund quarters. These frequencies statistically exceed the expected frequency of 5% where funds trading randomly, with respect to stock prior return, may be mis-identified as either contrarian or momentum traders.

[Insert Table 4]

4.3.2. Fund sentiment betas and fund trading strategies

In view of the result in Panel C of Table 3 that zero investment naïve portfolios of low sentiment beta stocks contribute negatively (positively) to momentum (contrarian) profits, we expect real portfolios held by mutual funds pursuing a contrarian trading strategy will contain low sentiment beta stocks. Conversely, and in view of the result in Panel C of Table 3 that naïve portfolios of high sentiment beta stocks contribute positively to momentum profits, we expect mutual funds pursuing momentum strategies will hold high sentiment beta stocks.

[22] 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%.

We use the stock sentiment betas to calculate each fund's start-of-quarter sentiment beta ($FQSBeta_{t-1}$) by weighting the sentiment betas of the stocks held in the fund's portfolio by their proportionate values. Fund-quarters are ranked by $FQSBeta_{t-1}$ and allocated to quintile portfolios. The count of significantly negative and positive momentum betas in each quintile is determined to establish preferences for these attributes by the funds we identify as either contrarian or momentum traders.

Table 5 shows a near monotonic decrease in the number of fund-quarters with negative (contrarian) momentum betas with increasing quintiles of fund sentiment beta, while the number with positive momentum betas increases monotonically. For example, quintile 1 shows nearly twice as many negative as positive momentum betas while quintile 5 shows the reverse. Accordingly, we conclude that actual portfolios held by mutual funds exhibiting contrarian or momentum trading are consistent with expectations we derive from the examination of hypothetical portfolios.

[Insert Table 5]

4.4. Investor sentiment

Different mutual funds, report their holding on varying months of the year, such that the quarter over which we observe their trades also ends on varying months. We can obtain a measure of investor sentiment at the start or end of each quarter from Baker and Wurgler's (2007) non-orthogonolized monthly sentiment index (SI_t). However, to investigate how these trades relate to changes in investor sentiment over the same period we require a corresponding set of overlapping measures of three-month sentiment change ($SChI_{t+1}$). We generate this set by arithmetically averaging three successive values of Baker and Wurgler's (2007) non-orthogonolized monthly sentiment changes index, and moving these three-month averages forward, one month at a time.

4.4.1 Investor sentiment and stock level returns

Baker and Wurgler (2007) find a negative relation between the returns of bond-like stocks and their sentiment changes index, consistent with these stocks having a negative sentiment beta. Conversely, speculative stocks' returns are positively correlated with the sentiment changes index. Although we also use the same sentiment changes index, instead of first assembling stocks into portfolios, we calculate sentiment betas for each stock, and in the second column of Table 2, report the average for each sentiment beta quintile. Nonetheless, the lowest quintile of sentiment betas have, on average, small negative values, while the remaining sentiment beta quintiles have averages that become increasingly more positive, broadly consistent with Baker and Wurgler (2007).

In their analysis of how sentiment betas affect future stock returns, Baker and Wurgler (2007) partitioned the time-series into periods of high and low investor sentiment. We also partition the time-series, but instead create terciles of the sentiment changes index. Panel A records the lowest tercile (decreases) of contemporaneous sentiment changes index, while Panel B records the highest tercile (increases). By focusing on the second last column (Average) of Table 6, and therefore ignoring the partition by prior returns, we can observe the return in excess of the value-weighted market index for each quintile of sentiment beta. It shows that, on average, the excess returns of stocks in the low sentiment beta quintile are positive when sentiment decreases, and negative when sentiment increases. High sentiment beta stocks do the opposite. These results are broadly consistent with the seesaw diagram (figure 5) in Baker and Wurgler (2007) for highs and lows in investor sentiment levels respectively. The intuitive link is that investor sentiment highs and lows tend to precede, respectively, a decrease or increase in investor sentiment over the period in which stock return is measured.

[Insert Table 6]

Columns 2-6 of Table 6 are essentially a partitioning of the second last (average) column, discussed above, into prior return quintiles. In practice, they are derived by repeating the double sorting procedure we use to create the 25 portfolios in Panel C of Table 2. However, to create Panel A, we use the lowest tercile of the three-month average of sentiment changes index segments of the time-series, and create Panel B from the highest tercile. High sentiment beta stocks exhibit negative excess returns over the same quarter that sentiment declines, as noted above, but the quintile of poorest performers perform worst (-0.0490). When sentiment increases, the quintile of the best prior performers performs best (0.0601). This behavior is consistent with 'continuation' of return performance in high sentiment beta stocks. Corresponding reversals of performance in low sentiment beta stocks are less evident. When sentiment decreases, the worst performing stocks perform best (0.0481), but when sentiment increases, the average return of the best performing portfolio (-0.0276) is statistically indistinguishable from the return of the worst performer.

Table 6 provides an insight into possible alternative trading strategies available to mutual fund managers. One is for managers to 'game' sentiment by trading to alter the sentiment beta of their portfolio according to their expectations of how investor sentiment will change. However, the success of this strategy depends on the ability of managers to predict sentiment, which would appear from Baker and Wurgler (2007), to be predictable at investor sentiment high and lows. The W-L column, however, demonstrates that the success of hypothetical momentum and contrarian trading strategies involving zero investment portfolios is largely independent of investor sentiment, and therefore does not require forecasting ability. For example, unlike the "Average" column, comparison of the extreme sentiment beta quintiles in Panel A with those in Panel B, shows returns on the W-L portfolios that are similar.

4.4.2. Investor sentiment and fund level trading

Each fund's end-of-quarter weighted average sentiment beta ($FQSBeta_t$) is calculated using the same stock sentiment betas as the start-of-quarter sentiment beta, but with end-of-quarter proportions. By subtracting the start-of-quarter $FQSBeta_{t-1}$ from the end-of-quarter $FQSBeta_t$, we obtain the change in the fund's sentiment beta ($\Delta FQSbeta_t$) that 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.

Two cases are considered. First, we examine changes to fund sentiment betas in the quarter following high or low investor sentiment. Second, we examine changes in fund sentiment betas over the same quarter as investor sentiment changes. Changes to fund sentiment betas over the entire time-series that we examine are ranked and allocated to quintiles, such that quintile 1 in Table 7 contains fund-quarters where funds make the largest decrease in their sentiment beta. Quintile 5 contains those with the largest increases. The number of fund-quarters in each 'change in sentiment beta' quintile are crosstabulated against quarters where the sentiment index at the start of the quarter was in the lowest and highest tercile (columns 3 and 4), and also against quarters where the average sentiment changes index over the quarter was in the lowest and highest tercile (columns 6 and 7).

[Insert Table 7]

In Table 7, it is apparent from column 3 that following investor sentiment lows, a near monotonically increasing number of funds make larger increases (and fewer make larger decreases) to their sentiment beta. Following investor sentiment highs (column 4), the opposite occurs. This is consistent with fund managers gaming the expectation that investor sentiment will increase when sentiment is low, and that it will decrease when the level of sentiment is high. Evidence of this behavior is apparent from column 6 (7) where the sentiment changes index low (high) indicates decreasing (increasing) sentiment during a quarter. More funds make large decreases to their sentiment beta as sentiment declines (column 6), and more make large increases as sentiment increases (column 7). However, from this observation, we cannot distinguish funds that, within the quarter, alter their sentiment beta ahead of changes in sentiment from those that follow, perhaps window-dressing.

A fund may, through its trades during a quarter, alter its sentiment beta because of the level of investor sentiment and contemporaneous changes to sentiment as suggested in Table 7, but may also respond to its initial sentiment beta. To investigate these relations, we estimate:

$$\Delta \text{FQSBeta}_{jt} = a_0 + b_1 \text{FQSBeta}_{jt\text{-}1} + b_3 \text{SI}_{t\text{-}1} + b_4 \text{ChSI}_t + \varepsilon_{jt} \qquad (7)$$

where $\Delta\text{FQSBeta}_{jt}$ are changes to the fund's sentiment beta caused by trading, $\text{FQSBeta}_{jt\text{-}1}$ is the weighted average of the stock sentiment betas in the portfolio of fund j at the start of quarter t, $\text{SI}_{t\text{-}1}$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index at the start of quarter t, and SChI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with trading to change the sentiment beta of fund j.

Table 8 reports the results of this regression and shows that initial sentiment beta, initial sentiment index and sentiment changes index explain 28 percent of the change to fund sentiment betas over a quarter. The sign on the $\text{FQSBeta}_{jt\text{-}1}$ coefficient is statistically negative, consistent with mean reversion of the sentiment beta. Consistent with Table 7, the coefficients on SI_{t-1} and $SChI_t$ are statistically negative and positive respectively. Standardized coefficients show that the main influence on trades to (intentionally or unintentionally) alter the fund's sentiment beta is the fund's initial sentiment beta.

[Insert Table 8]

5. Fund level trading strategies and fund returns

Using hypothetical portfolios of stocks, we are, in Tables 2, 3 and 6, able to show that trading strategies using sentiment beta produce apparent return benefits. In Tables 5 and 7, we show that real mutual funds hold, and make changes to, the sentiment beta of their portfolios that are consistent with the motivations we identify. It remains for us to consider whether real mutual funds obtain an actual return benefit from this behavior.

Our analysis at the stock level shows that stock excess returns are a function of the interaction of investor sentiment and the stock's sentiment beta. Accordingly, in our examination of real mutual fund returns, in models (1), (2) and (3) of Table 9, we regress fund excess return on the sentiment index, fund sentiment beta, and their interaction as follows:

$$R_{jt+1} = a_0 + b_1 SI_t + b_2 FQSBeta_{jt} + b_3 FQSBeta_{jt} \times SI_t + \varepsilon_{jt} \quad (8)$$

where R_{jt+1} is the excess return of fund j in the quarter following classification of the fund as a momentum or contrarian trader, SI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index, and $FQSBeta_{jt}$ is the weighted average of the stock sentiment betas in the portfolio of fund j in quarter t. We perform this regression for funds we identify as contrarian and momentum traders in models (1) and (3) respectively, and for the remainder in model (2). The coefficients on the sentiment index and sentiment beta interaction terms ($FQSbeta_{jt}$ x SI_t) are all negative, significant at

1%. This indicates that when investor sentiment is low (high), funds with high (low) sentiment betas, on average, have higher returns in the following quarter. Therefore, we find that the relation between future stock returns and sentiment beta that Baker and Wurgler (2007) established in their seesaw diagram, also applies at the level of fund returns and fund sentiment betas.

[Insert Table 9]

Models (1) and (3) in Table 9 also demonstrate that the tendency of mutual funds following a contrarian (momentum) trading strategy to hold stocks with low (high) sentiment betas that is documented in Table 7 is a pecuniary response. To illustrate, we use their respective parameter estimates to compute the derivatives of excess return with respect to sentiment beta as Equations (9) and (10).

$$\frac{\partial R_{t+1}}{\partial FQSbeta_t} = 0.705 - 2.796 \times SI_t \tag{9}$$

$$\frac{\partial R_{t+1}}{\partial FQSbeta_t} = -0.482 - 3.809 \times SI_t \tag{10}$$

Equations (9) and (10) show fund returns are either positively or negatively related to the fund's sentiment beta depending on the level of investor sentiment. Figure 1 plots these relations over the observed range of SI_t (sentiment index), with each tick representing a one decile change.[23] It is apparent from Figure 1 that funds pursuing a momentum strategy increase their returns by holding portfolios with higher sentiment

[23] For illustrative purposes, we use deciles of sentiment index in Figure 1 to provide a sense of the distribution of this variable. In subsequent figures, we also use deciles for the variable on the x-axis for the same reason.

betas over a wider range of investor sentiment.[24] In contrast, contrarian funds increase their returns by having low sentiment betas over a wider range of investor sentiment.[25] Accordingly, we conclude that the predominance of mutual funds using a momentum (contrarian) trading strategy with high (low) sentiment betas, predicted by Panel C of Table 2 and observed in Table 6, is a response to pecuniary benefits for these funds over the widest range of investor sentiment.

[Insert Figure 1]

Our analysis in Table 6 concerns investor sentiment changes, rather than sentiment levels. Moreover, there is evidence in Tables 7 and 8 that funds alter their sentiment beta in response to sentiment changes. Accordingly, in models (4) to (6) of Table (9), we repeat the analysis of models (1) to (3) respectively, but instead examine the relation between fund returns and the interaction of fund sentiment beta and investor sentiment *changes* as follows:

$$R_{jt+1} = a_0 + b_1 SI_t + b_2 FQSBeta_{jt} + b_3 SChI_{t+1} + b_4 FQSBeta_{jt} \times SChI_{t+1} + \varepsilon_{jt} \quad (11)$$

where funds are classified as a momentum or contrarian traders in quarter t, R_{jt+1} is the excess return of fund j in quarter t+1, SI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index, $FQSBeta_{jt}$ is the weighted average of the stock sentiment betas in the portfolio of fund j at time t, and $SChI_{t+1}$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with the fund return. Consistent with Table 6, the coefficient on the

---

[24] For example, $\frac{\partial R_{t+1}}{\partial FQSbeta_t}$ is positive for all SI_t outcomes lower than 0.25, representing the lower six deciles of SI_t.

[25] For example, $\frac{\partial R_{t+1}}{\partial FQSbeta_t}$ is negative for all SI_t outcomes greater than -0.13, representing the upper seven deciles of SI_t.

interaction term $FQSbeta_{jt}$ x $SChI_{t+1}$ is statistically positive in all models. That is, the sensitivity of returns to fund sentiment beta $\left(\frac{\partial R_{t+1}}{\partial FQSbeta_{t}}\right)$ is positively related to $SChI_{t+1}$, which has values ranging from positive to negative. Accordingly, the performance of funds with high (low) sentiment betas improves when investor sentiment increases (decreases), as indicated by high (low) values of the sentiment changes index in Figure 2a.

[Insert Figures 2a and 2b]

However, unlike models (1) to (3) where returns are a function of information that is available ex-ante, in models (4) to (6), $ChSI_{t+1}$ is only known ex-post. Therefore, the relations cannot be used to predict returns. Instead, they bolster the implicit assumption that the source of the relation between investor sentiment level, stock sentiment betas, and subsequent stock returns is the subsequent change in investor sentiment. Intuitively, investor sentiment increases (decreases) tend to follow periods of low (high) investor sentiment, or as Baker and Wurgler (2007) note, "market crashes tend to occur in high sentiment periods".

The size and similarity of the $FQSbeta_{jt}$ x $SChI_{t+1}$ coefficients in models (4) to (6) of Table 9, show that the relation between fund returns and their sentiment beta is dominated by the response to changing investor sentiment rather than the trading strategy funds adopt. Using the parameter estimates in equation (11) to compute the derivatives of return with respect to sentiment changes index, minor differences emerge. Figure 2b shows that for funds with high sentiment betas, the returns of momentum traders are more sensitive to sentiment changes, while for low sentiment betas, contrarian traders have greater sensitivity. Therefore, unlike the hypothetical winner minus loser portfolios in the rightmost column in Table 6, the performance of real mutual funds that follow momentum and contrarian trading strategies are not less sensitive to changes in investor sentiment. This is expected since our criteria for classifying a real mutual fund as a momentum (contrarian) trader is only that they tilt their portfolios towards recent better (poorly) performing stocks through their trades in a quarter, which is a less onerous requirement than having to hold zero investment winner minus loser (loser minus winner) portfolios.

Mutual funds can trade to alter their sentiment beta. Table 6 identifies motives for doing so, and Table 7 confirms that funds change their sentiment in response to the level of investor sentiment and to investor sentiment changes. In Table (9) we establish that future fund returns are a function of the fund's sentiment beta and either the level of, or changes in, investor sentiment. By extension, if it were possible to predict changes to investor sentiment, funds may enhance their returns by altering their sentiment beta appropriately. We investigate the relation between fund performance and changes to their sentiment betas caused by the trades made by the fund in the same quarter, by estimating equation (12) below:

$$\begin{aligned} R_{jt} = {} & a_0 + b_1 SI_{t-1} + b_2 FQSBeta_{jt-1} + b_3 \Delta FQSBeta_{jt} + b_4 SChI_{t+1} \\ & + b_5 FQSBeta_{jt-1} \times SI_{t-1} + b_6 FQSBeta_{jt-1} \times SChI_t + b_7 \Delta FQSBeta_{jt} \times SI_{t-1} \\ & + b_8 \Delta FQSBeta_{jt} \times SChI_t + \varepsilon_{jt} \end{aligned} \qquad (12)$$

where R_{jt} is the excess return of fund j over the same quarter we examine changes to the fund's sentiment beta ($\Delta FQSBeta_{jt}$) caused by trading, SI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index, $FQSBeta_{jt-1}$ is the weighted average of the stock sentiment betas in the portfolio of fund j at the start of quarter t, and $SChI_t$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with trading to change the sentiment beta of fund j.

Model (4) of Table (10) shows that the effect of changing the fund's sentiment beta on fund returns is a complex relation that depends on the existing sentiment beta, the level of investor sentiment, and the contemporaneous change in investor sentiment. The signs on $\Delta FQSbeta_{jt}$ x SI_{t-1} and $\Delta FQSbeta_{jt}$ x $SChI_t$ are both significantly positive, indicating that by increasing its sentiment beta, a fund should contribute positively to its performance when investor sentiment at the start of the period is high, and when investor sentiment increases over the period. In model (3) the $\Delta FQSbeta_{jt}$ x SI_{t-1} coefficient remains similar when only the information regarding investor sentiment that was known at the start of the period we examine returns and trades, is included. The finding that a fund may improve its performance by increasing (decreasing) its sentiment beta when sentiment is high (low) is inconsistent with the behavior noted in Table 7 (columns (2) to (4)) where more funds decrease (increase) their sentiment beta when sentiment is high (low). However, not all periods of high (low) sentiment precede declines (increases) in sentiment, and possibly the gains (losses) from subsequent increases (declines) outweigh the losses (gains) that occur when they do.

The sign on the coefficient for $\Delta FQSbeta_{jt}$ x $ChSI_t$ in model (4) is consistent with the predominant behavior of mutual funds documented in Table 7 (columns (5) to (7)). That is, the predominant behavior of increasing (decreasing) a fund's sentiment beta in the same period that investor sentiment increases (decreases), is associated with higher contemporaneous fund returns. Notably, this result only becomes evident after we control for the fund's start-of-period sentiment beta, as the apparent result is reversed in model (2) when this control variable is omitted. Within the quarter we examine trading and returns, we are unable to determine whether fund managers pre-empt or respond to changes in investor sentiment when they make changes to their fund's sentiment beta. Nonetheless, it appears as though there is a pecuniary motive for changing the fund's sentiment beta in the direction of changes to investor sentiment.

6. Conclusions

We contend that the stock sentiment betas that Baker and Wurgler (2007) relate to the level of mispricing can be used to identify stocks that are predisposed to momentum or contrarian trading strategies. To support our contention, we perform the Jegadeesh and Titman (1995) decomposition of contrarian profits over one-, two-, three- and four-month formation and holding periods. Our results are consistent with both Jegadeesh and Titman (1995) and Jegadeesh and Titman (1993), and also demonstrate the transition from apparent short-term contrarian profits to momentum profits in the longer term. Furthermore, we show that contrarian profits are not exclusively explained by price over-reaction to firm specific events caused by liquidity, short term price pressures and bid-ask spread as they suggest. Rather, the sign on their measure of price reaction to firm specific events remains negative in low sentiment beta stocks as we examine longer holding periods. The sign on this measure becomes positive for high sentiment beta stocks. This is consistent with shorter (longer) duration of mispricing in easy (difficult) to value and arbitrage stocks.

To identify mutual funds employing momentum and contrarian trading strategies we develop a unique method that uses actual mutual fund trades. We find 15.0% of funds pursue a momentum trading strategy and 15.2% of funds are contrarian traders. Significantly, more momentum funds hold portfolios with higher sentiment betas, while more contrarian traders hold stocks with lower sentiment betas. Specifically, the ratio of contrarian to momentum traders decreases monotonically for increasing quintiles of sentiment beta. Therefore, actual mutual funds hold portfolios that exploit the feature of high (low) sentiment beta stocks that mispricing persists for longer (shorter) periods. The pecuniary motivation for funds to hold portfolios with high (low) sentiment betas while using a momentum (contrarian) strategy, however, is obscured by the strong relation between mutual fund returns and the interaction of investor sentiment and sentiment beta. Nonetheless, we find that the sensitivity of fund returns to the fund’s sentiment beta varies according to the level of investor sentiment and also whether the fund is a momentum or contrarian trader. In aggregate, our findings at stock and portfolio level, both hypothetical and real, support our contention that stock sentiment betas can be used to identify suitable stocks for momentum or contrarian trading.

Extending the analysis, we show that fund returns are greater when investor sentiment decreases (increases) for funds holding low (high) sentiment beta portfolios. This relation is consistent with the Baker and Wurgler's (2007) finding relating stock returns, stock sentiment betas and the level of sentiment, but revealed in a "real world" mutual fund context. Furthermore, we find that funds respond by altering their sentiment beta according to the level and changes in investor sentiment. Specifically, proportionately more funds increase (decrease) their sentiment beta when investor sentiment is low (high), and also when sentiment increases (decreases). Moreover, we find that funds improve their performance when they increase (decrease) their sentiment betas as investor sentiment increases (decreases), indicating that this behavior is likely motivated by pecuniary interests.

References

Badrinath, S.G., Wahal, S., 2002. Momentum trading by institutions. Journal of Finance 57, 2449–2477.

Baik, B., Farber, D.B., Petroni, K., 2009. Analysts' incentives and street earnings. Journal of Accounting Research 47, 45-69.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1679.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129–151.

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

Chan, L.K.C., Jegadeesh, N., Lakonishok, J., 1999. The profitability of momentum strategies. Financial Analysts Journal 55, 80-90.

Chan, L.K.C., Lakonishok, J., 2004. Value and growth investing: Review and update. Financial Analysts Journal 60, 71-86.

Chen, H.L., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. Journal of Financial and Quantitative Analysis 35, 343-368.

Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. Journal of Political Economy 105, 1167–1200.

Conrad, J., Kaul, G., 1998. An anatomy of trading strategies. Review of Financial Studies 11, 489-519.

Cullen, G.S., Gasbarro, D., Monroe, G.S., 2010. Mutual fund trades and the value of contradictory private information. Journal of Banking and Finance 34, 378-387.

Cullen, G.S., Gasbarro, D., Monroe, G.S., Zumwalt, J.K., 2011. Changes to mutual fund risk: Intentional or mean reverting?. Journal of Banking and Finance *forthcoming*.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. Journal of Finance 45, 379-395.

Elton, E.J., Gruber, M.J., Blake, C.R., Krasny, Y., Ozelge, S., 2010. The effect of holdings data frequency on conclusions about mutual fund behavior. Journal of Banking and Finance 34, 912-922.

Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. Journal of Finance 50, 131-155.

Glushkov, D., 2006. Sentiment beta. Working Paper. http://ssrn.com/abstract=862444.

Gompers, P.A., Metrick, A., 2001. Institutional investors and equity prices. Quarterly Journal of Economics 116, 229-259.

Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. American Economic Review 85, 1088-1105.

Hong, H., Lim, T., Stein, J.C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65-91.

Jegadeesh, N., Titman, S., 1995. Overreaction, delayed reaction, and contrarian profits. Review of Financial Studies 8, 973-993.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56, 699-720.

Jegadeesh, N., Kim, J., Krische, S.D., Lee, C.M.C., 2004. Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083-1124.

Korajczyk, R.A., Sadka, R., 2004. Are momentum profits robust to trading costs? Journal of Finance 59, 1039-1082.

Lakonishok, J., Shleifer, A., Thaler, R.,Vishny, R.W., 1991. Window dressing by pension fund managers, The American Economic Review 81, 227-231.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. Journal of Finance 49, 1541– 1578.

Lesmond, D.A., Shill, M., Zhou, C., 2004. The illusory nature of momentum profits. Journal of Financial Economics 71, 349-380.

Lo, A.W., MacKinlay, A.C., 1990. When are contrarian profits due to stock market-overreaction. Review of Financial Studies 3, 175-208.

Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Piotroski, J.D., 2000. Value investing: The use of historical financial statement information to separate winners from losers. Journal of Accounting Research 38, 1-41.

Sagi, J.S., Seasholes, M.S., 2007. Firm-specific attributes and the cross-section of momentum. Journal of Financial Economics 84, 389-434.

Sias, R.W., 2007. Reconcilable differences: Momentum trading by institutions. Financial Review 42, 1-22.

Table 1
Descriptive statistics.

Panel A. Stock attributes by quintile of sentiment beta (full sample) 1991-2005

	Quintile of sentiment beta				
Quintile average of:	1	2	3	4	5
Sentiment beta	-0.0167	0.0048	0.0186	0.0397	0.0946
Market beta	0.5021	0.6043	0.8510	1.2017	1.9566
Return standard deviation	0.1237	0.1001	0.1222	0.1625	0.2427
Stock capitalization	1.5875	1.4906	1.1808	0.9773	0.5522
Turnover (Value)	1.0657	1.0553	1.0489	1.3088	1.2918
Turnover (Prop)	0.0728	0.0623	0.0774	0.1051	0.1514

Panel B. Stock attributes by quintile of sentiment beta (108 months) 1991-2005

Sentiment beta	-0.0135	0.0035	0.0146	0.0314	0.0768
Market beta	0.4510	0.5579	0.7532	1.0588	1.6976
Return standard deviation	0.1163	0.0967	0.1130	0.1490	0.2279
Stock capitalization	2.0041	1.6645	1.2203	1.0381	0.9321
Turnover (Value)	1.3380	1.1415	1.0341	1.2487	1.8775
Turnover (Prop)	0.0722	0.0632	0.0731	0.0991	0.1509

Panel C. Fund descriptive statistics 1991-2005

	Mean	Median	Standard Deviation
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

Panel D. Market descriptive statistics 1991-2005

Value weighted market return (3-month)	0.0283	0.0333	0.0748
Sentiment changes index (3-month average)	-0.0016	0.0089	0.5532

Panel A reports the averages of the various stock attributes for each stock sentiment beta quintile from the full sample of 1,219,090 stock-months. Panel B reports the averages of the various stock attributes for each stock sentiment beta quintile from the reduced sample of 656,748 stock-months consistent with Tables 2 and 3. Stock capitalization is standardized for growth in market capitalization over time before averaging, 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. Panel C presents descriptive statistics for mutual funds and their associated trading periods. Panel D shows the distribution of three-month market returns and the three-month average of Baker and Wurgler's (2007) sentiment changes index.

Table 2
Stock excess return by past return and sentiment beta

Sentiment beta quintile		Average beta	Prior return quintile: Low 1	2	3	4	High 5	W-L
Panel A. Average excess one-month returns for entire time-series								
Low	1	-0.0137	0.0100	0.0043	0.0029	0.0008	-0.0033	-0.0133
			(0.0010)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0013)
	2	0.0034	0.0102	0.0036	0.0026	0.0005	-0.0032	-0.0134
			(0.0009)	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0012)
	3	0.0147	0.0076	0.0033	0.0022	0.0009	-0.0037	-0.0113
			(0.0010)	(0.0007)	(0.0006)	(0.0006)	(0.0008)	(0.0013)
	4	0.0315	0.0078	0.0033	0.0020	0.0004	-0.0038	-0.0116
			(0.0011)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0015)
High	5	0.0771	0.0097	0.0049	0.0021	-0.0010	-0.0062	-0.0159
			(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0019)
	Average	0.0226	0.0091	0.0039	0.0024	0.0003	-0.0040	-0.0131
Panel B. Average excess two-month returns for entire time-series								
Low	1	-0.0133	0.0111	0.0082	0.0033	0.0020	0.0024	-0.0087
			(0.0015)	(0.0010)	(0.0010)	(0.0010)	(0.0013)	(0.0020)
	2	0.0034	0.0094	0.0064	0.0039	0.0039	0.0020	-0.0074
			(0.0012)	(0.0009)	(0.0008)	(0.0008)	(0.0011)	(0.0016)
	3	0.0145	0.0086	0.0062	0.0058	0.0028	0.0015	-0.0071
			(0.0014)	(0.0010)	(0.0009)	(0.0009)	(0.0012)	(0.0018)
	4	0.0311	0.0063	0.0073	0.0036	0.0017	0.0049	-0.0014
			(0.0016)	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0021)
High	5	0.0759	0.0054	0.0039	0.0080	0.0050	0.0046	-0.0008
			(0.0020)	(0.0017)	(0.0016)	(0.0016)	(0.0018)	(0.0027)
	Average	0.0223	0.0082	0.0064	0.0049	0.0031	0.0031	-0.0051
Panel C. Average excess three-month returns for entire time-series								
Low	1	-0.0135	0.0090	0.0103	0.0052	0.0046	0.0069	-0.0021
			(0.0018)	(0.0013)	(0.0012)	(0.0012)	(0.0016)	(0.0024)
	2	0.0035	0.0093	0.0077	0.0091	0.0061	0.0054	-0.0039
			(0.0015)	(0.0011)	(0.0010)	(0.0010)	(0.0014)	(0.0020)
	3	0.0146	0.0037	0.0093	0.0093	0.0066	0.0091	0.0054
			(0.0017)	(0.0012)	(0.0011)	(0.0011)	(0.0015)	(0.0023)
	4	0.0314	-0.0007	0.0048	0.0054	0.0045	0.0204	0.0211
			(0.0020)	(0.0015)	(0.0014)	(0.0014)	(0.0018)	(0.0027)
High	5	0.0768	-0.0049	0.0028	0.0074	0.0080	0.0169	0.0218
			(0.0025)	(0.0021)	(0.0020)	(0.0020)	(0.0023)	(0.0034)
	Average	0.0225	0.0033	0.0070	0.0073	0.0060	0.0117	0.0085

Panel D. Average excess four-month returns for entire time-series

Low	1	-0.0134	0.0075	0.0121	0.0080	0.0060	0.0138	0.0063
			(0.0022)	(0.0015)	(0.0014)	(0.0014)	(0.0018)	(0.0028)
	2	0.0034	0.0084	0.0108	0.0096	0.0091	0.0137	0.0053
			(0.0018)	(0.0013)	(0.0012)	(0.0012)	(0.0016)	(0.0024)
	3	0.0145	0.0011	0.0113	0.0100	0.0116	0.0181	0.0170
			(0.0019)	(0.0014)	(0.0013)	(0.0013)	(0.0018)	(0.0026)
	4	0.0311	-0.0074	0.0054	0.0074	0.0133	0.0295	0.0369
			(0.0023)	(0.0018)	(0.0017)	(0.0017)	(0.0021)	(0.0031)
High	5	0.0760	-0.0163	0.0029	0.0086	0.0173	0.0324	0.0487
			(0.0029)	(0.0025)	(0.0024)	(0.0025)	(0.0028)	(0.0040)
	Average	0.0223	-0.0013	0.0085	0.0087	0.0115	0.0215	0.0228

Table 2 shows the mean excess returns of stocks that are double sorted into prior return and sentiment beta quintiles. W-L is prior return quintile 5 minus quintile 1. Stocks are separated by month prior to double-sorting. Excess returns are pooled over time before averaging. The portfolio formation and holding periods are both one-month, two-months and three-months for Panels A, B and C respectively. In Panel A, the 656,748 stock-periods are non-overlapping, but are overlapping in Panels B and C. Standard errors are shown in parentheses.

Table 3
Jegadeesh and Titman Decomposition of Momentum Profits

Sentiment Beta	N	Expected momentum (contrarian) profit E(π)	Cross-sectional variance of returns σ_{α}^{2}	Reaction to firm-specific events Ω	Timeliness of reaction to market $\delta_{\beta}\sigma_{vwmr}^{2}$	Timeliness of reaction to sentiment $\delta_{\gamma}\sigma_{SChI}^{2}$
Panel A. One-month return interval						
All	6178	-0.00055	0.00023	-0.00091	0.00003	0.00010
Low	1234	-0.00052	0.00014	-0.00071	0.00004	0.00002
High	1241	-0.00108	0.00039	-0.00154	-0.00001	0.00009
Panel B. Two-month return interval						
All	6002	0.00106	0.00107	-0.00019	-0.00002	0.00020
Low	1199	0.00045	0.00064	-0.00027	0.00006	0.00001
High	1205	0.00194	0.00185	0.00002	-0.00013	0.00029
Panel C. Three-month return interval						
All	6081	0.00302	0.00282	-0.00004	0.00025	0.00000
Low	1215	0.00138	0.00167	-0.00049	0.00024	-0.00004
High	1221	0.00543	0.00486	0.00046	0.00011	0.00000
Panel D. Four-month return interval						
All	6011	0.00564	0.00541	0.00020	-0.00023	0.00027
Low	1200	0.00317	0.00343	-0.00070	0.00022	0.00021
High	1206	0.01240	0.00902	0.00284	-0.00010	0.00063

Table 3 presents the Jegadeesh and Titman (1995) decomposition of momentum (contrarian) profit with two common factors – market and sentiment changes index according to: $\mathrm{E}(\pi) = \sigma_{\alpha}^{2} + \Omega + \delta_{\beta}\sigma_{vwmr}^{2} + \delta_{\gamma}\sigma_{SChI}^{2}$

"All" denotes the full sample using 656,748 overlapping stock-quarters representing 6081 time series of 108 months, "low" ("high") denotes the lowest (highest) quintile of sentiment beta stocks. Momentum (contrarian) profits are denoted by positive (negative) values of E(π). Momentum profits are based on a portfolio where the weight on each stock is determined by its prior period excess return. Negative (positive) values for Ω indicate over- (under-) reaction to firm specific events.

Table 4
Significant momentum betas - pooled count 1991-2005.

Trades	N	Binomial Critical Value	Momentum Beta Negative Count	Negative Percent	Positive Count	Positive Percent
Net	31,409	1660	4777	15.2***	4702	15.0***

Table 4 shows the number of statistically significant (10%, 2-tailed) momentum betas generated for each fund-quarter from: $TradeValue_j = \alpha + \beta \, BucketPP_j + \varepsilon_j$ where $TradeValue_j$ is the value of stocks in prior return 'bucket' j that are traded during a quarter, and $BucketPP_j$ is the value-weighted prior return of the stocks in 'bucket' j. 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 5

Significant momentum betas by quintile of fund-quarter sentiment betas 1991-2005.

Sentiment beta		Momentum beta		
Quintiles	Average	Negative	Positive	Ratio
Low 1	0.0040	1169	653	1.79
2	0.0116	1069	752	1.42
3	0.0174	918	928	0.99
4	0.0261	947	1069	0.89
High 5	0.0446	674	1300	0.52
Total		4777	4702	1.02

Table 5 crosstabulates the number of fund-quarters of contrarian or momentum trading by quintiles of ranked $FQSbeta_{jt}$. FQSbetas are calculated as a value-weighted average of the sentiment betas of the stocks held by a fund at the start of a quarter, and funds are allocated to quintiles each month. In any fund-quarter, contrarian (momentum) trading is identified from the betas in the regression: $\text{TradeValue}_j = \alpha + \beta\ \text{BucketPP}_j + \varepsilon_j$ that are statistically negative (positive). For each fund-quarter, TradeValue_j is the net value of the buy and sell trades in stocks allocated to 'bucket' j, and BucketPP_j is the value-weighted prior return of the stocks in the bucket.

Table 6

Partitioned time-series of stock excess returns by past return and sentiment beta

Sentiment beta quintile		Prior return quintile Low 1	2	3	4	High 5	Average	W-L
Panel A. Average excess three-month returns for low sentiment changes index quarters								
Low	1	0.0481	0.0476	0.0364	0.0343	0.0382	0.0409	-0.0099
		(0.0032)	(0.0023)	(0.0021)	(0.0022)	(0.0029)	(0.0012)	(0.0043)
	2	0.0302	0.0273	0.0270	0.0256	0.0232	0.0267	-0.0070
		(0.0027)	(0.0019)	(0.0018)	(0.0018)	(0.0024)	(0.0010)	(0.0036)
	3	0.0156	0.0203	0.0172	0.0187	0.0195	0.0183	0.0039
		(0.0030)	(0.0021)	(0.0019)	(0.0020)	(0.0026)	(0.0010)	(0.0040)
	4	-0.0039	0.0011	0.0020	0.0035	0.0208	0.0047	0.0247
		(0.0035)	(0.0027)	(0.0025)	(0.0026)	(0.0033)	(0.0013)	(0.0048)
High	5	-0.0490	-0.0273	-0.0278	-0.0275	-0.0214	-0.0306	0.0276
		(0.0043)	(0.0036)	(0.0034)	(0.0035)	(0.0038)	(0.0017)	(0.0057)
Panel B. Average excess three-month returns for high sentiment changes index quarters								
Low	1	-0.0284	-0.0242	-0.0235	-0.0273	-0.0276	-0.0262	0.0008
		(0.0031)	(0.0022)	(0.0020)	(0.0021)	(0.0026)	(0.0011)	(0.0040)
	2	-0.0097	-0.0115	-0.0102	-0.0166	-0.0139	-0.0124	-0.0042
		(0.0026)	(0.0019)	(0.0018)	(0.0018)	(0.0023)	(0.0009)	(0.0035)
	3	-0.0116	-0.0051	-0.0008	-0.0061	-0.0021	-0.0051	0.0095
		(0.0028)	(0.0021)	(0.0020)	(0.0020)	(0.0026)	(0.0010)	(0.0038)
	4	-0.0038	0.0037	0.0057	0.0048	0.0162	0.0053	0.0200
		(0.0035)	(0.0027)	(0.0025)	(0.0026)	(0.0032)	(0.0013)	(0.0047)
High	5	0.0405	0.0296	0.0365	0.0447	0.0601	0.0423	0.0196
		(0.0045)	(0.0039)	(0.0039)	(0.0038)	(0.0043)	(0.0018)	(0.0062)

Table 6 shows the mean excess returns of stocks that are double sorted into prior return and sentiment beta quintiles. W-L is prior return quintile 5 minus quintile 1. Stocks are separated by month prior to double-sorting. Excess returns are pooled over time before averaging. The portfolio formation and holding periods are both three-months. Panels A and B report the pooled average quarterly excess stock returns contemporaneous to the separations of the time-series of 626,810 overlapping stock-quarters into quarters with respectively, the lowest tercile of the index of sentiment change and highest tercile of the index of sentiment change. Standard errors are shown in parentheses.

Table 7

Change in fund sentiment beta ($\Delta FQSbeta_{jt}$) by Investor Sentiment: 1991-2005.

$\Delta FQSbeta_{jt}$		Sentiment index – start of period			Sentiment changes index – three-month average		
Quintile	Average	Low	High	Ratio	Low	High	Ratio
Low 1	-0.0086	1339	2676	0.50	3025	1414	2.14
2	-0.0022	1705	2200	0.78	2570	1575	1.63
3	-0.0006	2194	1806	1.21	2093	1899	1.10
4	0.0004	2589	1689	1.53	1577	2380	0.66
High 5	0.0034	2560	1764	1.45	1226	3046	0.40
Total		10,387	10,135		10,491	10,314	

Table 7 reports the number of fund-quarters in each quintile of ranked change in a fund's weighted average sentiment beta ($\Delta FQSbeta_{jt}$) over a trading period in the lowest and highest terciles of start-of-period sentiment index, and lowest (decreasing sentiment) and highest (increasing sentiment) terciles of the average change-in-sentiment index concurrent with the trading period

Table 8

Change in fund-quarter sentiment beta

Variable	Intercept	$FQSBeta_{jt-1}$	SI_{t-1}	$SChI_t$
Coefficient	0.002***	-0.140***	-0.000***	0.002***
t-statistic	(39.95)	(-97.30)	(-19.76)	(39.72)
N	30,297			
Adjusted R^2	0.281			

Table 8 reports the parameter estimates of the regression: $\Delta FQSBeta_{jt} = a_0 + b_1 FQSBeta_{jt-1} + b_3 SI_{t-1} + b_4 ChSI_t + \varepsilon_{jt}$ where $\Delta FQSBeta_{jt}$ are changes to the fund's sentiment beta caused by trading, $FQSBeta_{jt-1}$ is the weighted average of the stock sentiment betas in the portfolio of fund j at the start of quarter t, SI_{t-1} is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index at the start of quarter t, and $SChI_t$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with trading to change the sentiment beta of fund j.

*** indicates significance at the 1 percent level

Table 9
Fund excess return as a function of sentiment beta

	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.019***	0.002	-0.020***	0.010*	0.002	-0.018
	(2.77)	(0.64)	(-2.65)	(1.66)	(0.59)	(-2.61)
SI_t	0.073***	0.048***	0.052***	0.007	0.002	0.009*
	(9.73)	(12.21)	(5.62)	(1.42)	(0.62)	(1.68)
$FQSbeta_{jt}$	-0.482	-0.151	0.705**	-0.128	-0.119	0.751***
	(-1.49)	(-1.13)	(2.54)	(-0.46)	(-1.00)	(2.96)
$FQSbeta_{jt}$ x SI_t	-3.809***	-2.398***	-2.769***			
	(-7.79)	(-12.18)	(-7.13)			
$SChI_{t+1}$				-0.310***	-0.256***	-0.213***
				(-28.51)	(-48.45)	(-15.83)
$FQSbeta_{jt}$ x $SChI_{t+1}$				11.898***	11.308***	11.072***
				(21.22)	(47.24)	(21.46)
N	2565	11,711	2505	2565	11,711	2505
Adjusted R^2	0.041	0.015	0.019	0.255	0.183	0.159

The table presents the fund's excess return as a function of the interaction of fund sentiment beta with sentiment index and sentiment changes index in turn, based on the following regression: $R_{jt+1} = a_0 + b_1 SI_t + b_2 FQSBeta_{jt} + b_3 FQSBeta_{jt} \times SI_t + b_4 SChI_{t+1} + b_5 FQSBeta_{jt} \times SChI_{t+1} + \varepsilon_{jt}$, where R_{jt+1} is the excess return of fund j in the quarter following classification of the fund as a momentum or contrarian trader, SI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index, $FQSBeta_{jt}$ is the weighted average of the stock sentiment betas in the portfolio of fund j in quarter t, and $SChI_{t+1}$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with the fund return. We partition the data based on our statistical identification of the fund's trading strategy. Models (1) and (4) reflect fund-quarters where funds follow a contrarian trading strategy, while in Models (3) and (6) funds exhibit momentum trading. Models (2) and (5) are for the remainder. t-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively.

Table 10
Fund excess return as a function of change in sentiment beta.

	Model			
	(1)	(2)	(3)	(4)
Intercept	0.000	0.003	-0.004	-0.007***
	(0.05)	(1.43)	(-1.52)	(-3.15)
SI_{t-1}	0.023***	0.018***	0.050***	-0.004
	(10.39)	(7.89)	(15.90)	(-1.21)
$FQSbeta_{jt-1}$	0.012	0.130	0.158	0.332***
	(0.11)	(1.22)	(1.45)	(3.32)
$\Delta FQSbeta_{jt}$	-4.024***	0.394	-3.268***	1.352**
	(-5.74)	(0.56)	(-4.66)	(2.05)
$SChI_t$		-0.077***		-0.235***
		(-24.40)		(-53.96)
$FQSbeta_{jt-1}$ x SI_{t-1}			-1.921***	0.601***
			(-12.06)	(3.95)
$FQSbeta_{jt-1}$ x $SChI_t$				10.119***
				(50.25)
$\Delta FQSbeta_{jt}$ x $FQSbeta_{jt-1}$	135.685***	51.727***	116.244***	3.100
	(8.90)	(3.40)	(7.62)	(0.218)
$\Delta FQSbeta_{jt}$ x SI_{t-1}	6.245***	4.111***	3.338***	4.679***
	(14.43)	(8.83)	(6.76)	(9.64)
$\Delta FQSbeta_{jt}$ x $SChI_t$		-11.542***		4.241***
		(-18.90)		(6.56)
N	16,591	16,591	16,591	16,591
Adjusted R^2	0.028	0.069	0.036	0.196

The table presents the fund's excess return as a function of the interaction of fund sentiment beta and changes to fund sentiment betas over a quarter each with sentiment index and sentiment changes index in turn, based on the following regression:

$$R_{jt} = a_0 + b_1 SI_{t-1} + b_2 FQSBeta_{jt-1} + b_3 \Delta FQSBeta_{jt} + b_4 SChI_t$$
$$+ b_5 FQSBeta_{jt-1} \times SI_{t-1} + b_6 FQSBeta_{jt-1} \times SChI_t + b_7 \Delta FQSBeta_{jt} \times SI_{t-1}$$
$$+ b_8 \Delta FQSBeta_{jt} \times SChI_t + \varepsilon_{jt}$$

where R_{jt} is the excess return of fund j over the same quarter we examine changes to the fund's sentiment beta ($\Delta FQSBeta_{jt}$) caused by trading, SI_t is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment index, $FQSBeta_{jt}$ is the weighted average of the stock sentiment betas in the portfolio of fund j in quarter t, and $SChI_t$ is the Baker and Wurgler (2007) non-orthogonalized monthly investor sentiment changes index contemporaneous with trading to change the sentiment beta of fund j. t-statistics are in parentheses. ***, and ** indicate significance at the 1 and 5 percent levels respectively.

Figure 1
Sensitivity of fund return to fund sentiment beta as a function of sentiment index.

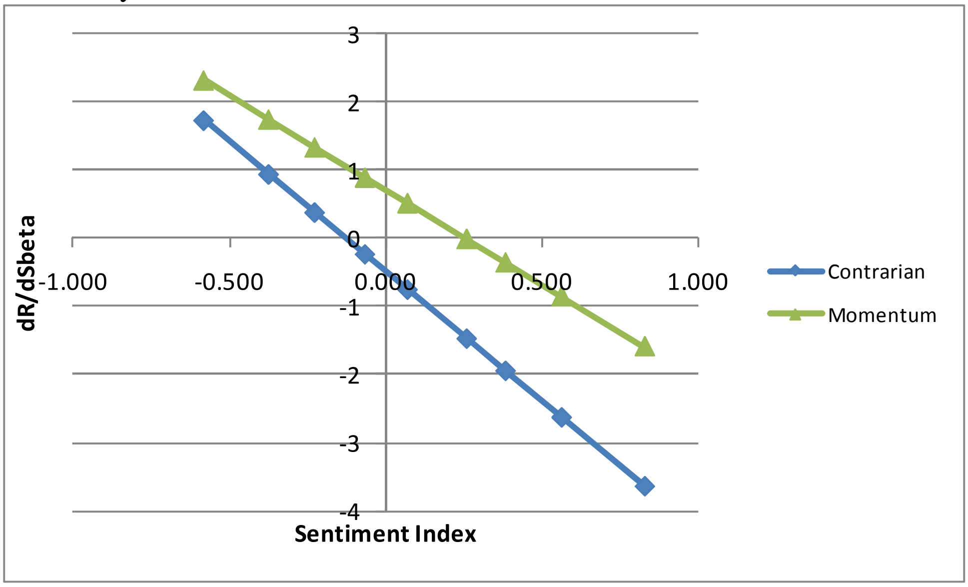

Figure 1 shows the sensitivity of fund return to fund sentiment beta ($\frac{\partial R_{t+1}}{\partial FQSbeta_t}$) as a function of the sentiment index at the start of the return measurement period for mutual funds exhibiting momentum and contrarian trading. Both momentum and contrarian funds benefit from having high sentiment betas for low values of the sentiment index, and from having low sentiment beta for high values of the sentiment index.

Figure 2a
Sensitivity of fund return to fund sentiment beta as a function of sentiment changes index.

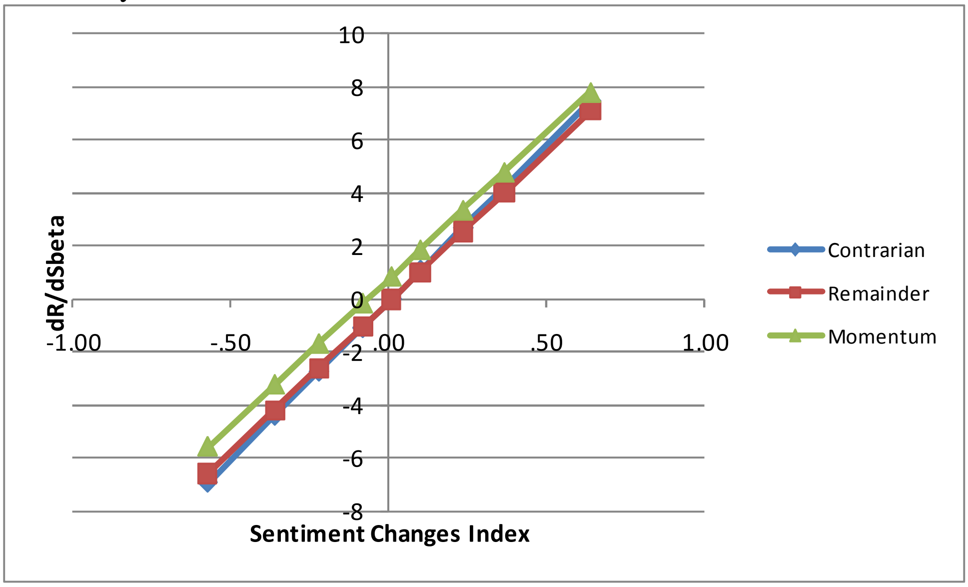

Figure 2b
Sensitivity of fund return to sentiment changes index as a function of fund sentiment beta.

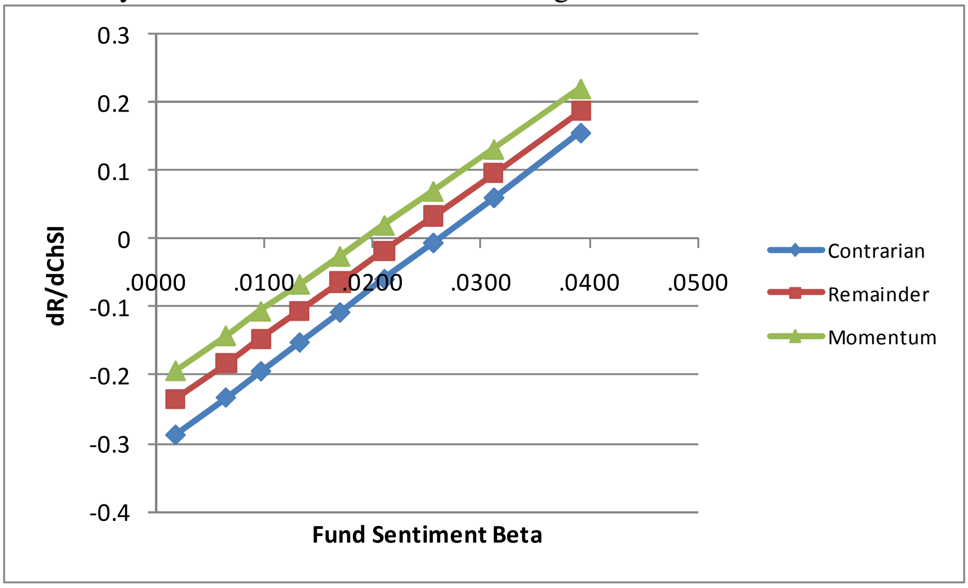

Figure 2a shows the sensitivity of fund return to fund sentiment beta ($\frac{\partial R_t}{\partial FQSbeta_{t-1}}$) as a function of the sentiment changes index at the start of the return measurement period. Figure 2b shows the sensitivity of fund return to the sentiment changes index ($\frac{\partial R_t}{\partial ChSI_t}$) as a function of fund sentiment beta. Both figures show that mutual funds benefit from having high sentiment betas when sentiment increases (high values of sentiment changes index).