SENTIMENT TRADING AND MUTUAL FUND PERFORMANCE

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Mutual funds employ different trading strategies when facing sentiment fluctuations. Using the exposure to sentiment changes as the sorting variable, I find that the funds with higher sentiment beta outperform funds with lower sentiment beta, even after adjusting risk factors and controlling for fund characteristics. The return spread between the two extreme deciles is sizable, delivering outperformance of 3.36% per year. This effect is stronger when the sentiment level is high, and the alpha is mainly generated during high sentiment periods. Further, I find that the timing ability could explain a large fraction of the outperformance. In addition, high sentiment beta funds managers deliberately choose unconventional strategies and exhibit higher managerial skills. My findings suggest that skilled mutual funds may engage in sentiment trading strategy, ride the sentiment bubble, and profit from sentiment fluctuations.

Keywords: Sentiment beta; Mutual fund; Sentiment trading

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1. Introduction

Investor sentiment is the crowd psychology in the market. It is an overall investors' attitude towards the market, revealed by the price levels and trading activities. In most cases, investor sentiment is seen as the irrational belief of naïve investors, which distorts the return-risk relation, drives up mispricing, and deters arbitrage activities. A vast volume of literature in both empirical and theoretical fields examines the impact of investor sentiment on the prices of different asset classes. This paper investigates the effect of sentiment variations on the institutional investor instead. To be precise, I study the impact of sentiment fluctuations on mutual fund performance and the coping trading strategies for the changes in sentiment.

Prior studies suggest that the influence of investor sentiment on asset price leads to return predictability across stocks (e.g., Baker & Wurgler 2006, 2007). During high sentiment periods, over-optimistic investors drive up the overvalued stock prices. When the investor sentiment calms down, the mispricing gets corrected, and the overpriced stock would subsequently have a low return. Therefore, a natural trading strategy is to trade against mispricing, especially when the sentiment level is high, and generate alpha from the following price correction. Since the overpriced stocks are more sensitive to sentiment changes than underpriced stocks, the arbitragers' exposures to sentiment fluctuations should be negative, because they short the overpriced stocks and long the underpriced stocks.

However, the uncertainty of sentiment changes reduces the arbitrager's willingness to trade against mispricing, resulting in larger price divergence from fundamental value (De Long *et al.* 1990a). Moreover, sophisticated investors are not always interested in arbitrage against mispricing. Dumas *et al.* (2009) prove that in the presence of market sentiment risk, the optimal equilibrium portfolio depends not only on the current level of mispricing but also on their judgment of the future sentiment level. In other words, sophisticated investors are likely to assess future sentiment changes when conducting risk arbitrage. De Long *et al.* (1990b) argue that if the noise traders follow positive-feedback strategies, sophisticated investors may time the mispricing and buy ahead of noise investors. Abreu and Brunnermeier (2002) show that due to the synchronization risk (i.e., investors become aware of mispricing sequentially), rational investors may choose to ride the bubble and delay arbitrage activities. In all cases, sophisticated investors should be able to time the market sentiment. And no matter whether sophisticated investors choose to delay arbitrage activities, ride the bubbles, or even trigger the bubble, their sentiment exposures would not necessarily be negative anymore.

Following these "rational arbitrage" models, this paper investigates whether mutual funds trade against or in the direction of sentiment-driven mispricing and the association between fund sentiment beta and mutual fund performance. I start the empirical work by estimating stock sentiment beta. Following Chen *et al.* (2021), I define the stock sentiment beta as the regression coefficient of sentiment changes rather than sentiment level. In the Intertemporal Capital Asset Pricing Model (I-CAPM hereafter), investors care about the risk both from market return and from the innovations in the state variables that help to forecast future returns. The intuition is that the changes in state variables deteriorate future investment opportunities and rational investors want to hedge against these risks. Therefore, if we believe that the investor sentiment is a market-wide risk source, the beta on changes in the sentiment should better capture the stock sentiment exposure. I first estimate individual stocks' sentiment beta by regressing stock return on sentiment changes and other risk factors. Then, I calculate the mutual fund sentiment beta as the value-weighted portfolio beta from the estimated stock sentiment beta, using the holding position as the weight.

My study focuses on mutual fund sentiment trading strategies, so I limit my sample to equity mutual funds that are actively managed, which consist of 502,323 fund-month observations covering January 1980 to December 2018. After sorting mutual funds into decile portfolios based on their sentiment beta, I find that the fund performance increases monotonically with sentiment beta. And the fund portfolio with the highest sentiment beta outperforms the portfolio with lowest sentiment beta. The return spread between the bottom and top decile are 0.33% (*t*-statistics=1.82) per month (3.96% per year). On the risk-adjusted basis, the CAPM-alpha spread gets even larger, at 0.42% (*t*-statistics=2.30) per month; the 3-factor-alpha and 4-factor-alpha are 0.35% (*t*-statistics=1.91) and 0.28% (*t*-statistics=1.52), respectively. I also perform a multivariate analysis to control for the fund characteristics and styles. Fama and MacBeth (1973) regression and panel regression confirm the positive relation between fund performance and sentiment beta. My results apply to both net and gross returns.

Since I focus on mutual fund performance and trading strategies, I do not conduct the detailed test about whether the sentiment risk is priced at the individual-stock level. First, the empirical evidence so far is still mixed; Second, theoretically, the sentiment risk premium varies depending on market conditions, and does not always deliver a positive premium. The key difference between individual stocks and mutual funds is that a mutual fund is an actively managed portfolio. Fund managers may employ dynamic trading strategies instead of a static buy-and-hold strategy. Thus, the mutual funds' sentiment-beta-return relation could be fundamentally different from that of individual stocks.

In addition, I decompose the fund performance into "Characteristic Selectivity" and "Characteristic Timing" abilities, following Daniel *et al.* (1997). I find that high sentiment beta funds' superior performance mainly arises from timing ability. For the fund portfolio with the highest sentiment beta, the CS measure is 0.29% (*t*-statistics=2.18) per quarter, and the CT measure is 2.01% (*t*-statistics =4.72) per quarter. The contribution from timing ability is almost 7 times higher than that from stock picking ability. For CS measure, the spread between the two extreme deciles is 0.28% (*t*-statistics =1.42); while for CT measure, the spread is 0.46% (*t*-statistics =3.42). The difference in market timing ability is much larger than that in stock picking ability. These results suggest that high sentiment beta funds outperform others because they are good at market timing rather than stock picking.

Although my mutual fund sentiment beta is the exposure to sentiment fluctuations, I am also interested in the role of sentiment level in the positive relation between sentiment beta and fund performance. I split the sample periods into high/low sentiment periods depending on whether the level of sentiment exceeds the sample median, and test whether the sentiment-beta-return relation behaves differently across high/low sentiment periods. In the portfolio sorts test, during high sentiment periods, the spreads of mutual funds' performance between the two extreme deciles are larger and more significant than the results estimated using the entire sample. In contrast, during low sentiment periods, all the spreads become statistically insignificant. In the multivariate analysis, the coefficients of the interaction term are significantly positive, suggesting that the relation between sentiment beta and fund performance is stronger when the sentiment level is high. In the CS and CT measures analyses, the results are similar. Specifically, when the sentiment level is high, both the CS and CT spreads between the two extreme deciles are large and significant; however, when the sentiment level is low, the spreads become insignificant.

Various lines of evidence in the sub-period analysis conclude that the positive relation between sentiment beta and fund performance is stronger during high sentiment periods. This result contradicts the conventional wisdom that institutional investors arbitrage against sentiment-driven mispricing. My empirical evidence seems consistent with "rational speculation" theories (De Long *et al.* 1990a, b; Abreu & Brunnermeier 2002, 2003; Dumas *et al.* 2009), which predict that rational investors tend to ride the bubble. So far, the empirical findings suggest that my conjecture about sentiment timing activities at least is not beyond the realms of possibility.

Further, I explore mutual funds' trading behaviors. I calculate the correlation coefficient between mutual funds' holding position changes and the stock mispricing score developed by Stambaugh *et al.* (2015). A negative correlation coefficient suggests that mutual funds trade against mispricing; if the coefficient is positive, then it means that mutual funds trade in the same direction as mispricing. In my context, not surprisingly, the correlation coefficients of fund portfolios are mostly negative. However, the funds with the highest sentiment beta have positive (not significant) correlation coefficients during high sentiment periods, consistent with Abreu and Brunnermeier (2002). Rational investors would not arbitrage against mispricing immediately. Instead, they may choose to ride the bubble and delay arbitrage activities.

Finally, I test whether the superior performance of high sentiment beta funds originates from managerial skills. Following Amihud and Goyenko (2013), I use the R-square as the proxy for active management skills. Low-skill fund managers tend to track the conventional strategies. Thus their performance could be better explained by the factor models. My results present a strongly negative relation between fund sentiment-beta and R-square. In particular, one unit increase in sentiment beta leads to a reduction of 0.069 (*t*-staticitc=3.96) in R-square. The magnitude of reduction is economically meaningful. This finding suggests that the outperformance of high sentiment beta funds is not from conventional strategies but active, deliberately chosen strategies.

My study contributes to the literature in several ways. First, I document a new source of mutual fund performance. Using the holdings data, several existing studies show that funds deviate from their benchmark (Cremers & Petajisto 2009; Petajisto 2013) or market-cap-weighted portfolios (Doshi *et al.* 2015) perform better. Other papers investigate the information difference between funds' actual and holding-based returns. For instance, funds with higher active shares (Kacperczyk *et al.* 2008) or lower risk-shifting levels (Huang *et al.* 2011) perform better in the future. My paper provides new evidence that fund sentiment beta contributes to mutual fund performance. The empirical results show that beyond the traditional wisdom, in which institutional investors perform the socially useful function of trading against sentiment-driven mispricing, mutual funds can profit from timing the changes in sentiment.

Second, my study about how the exposure to sentiment changes affects the fund performance and trading strategies contributes to the field of bubble-riding studies. K. Brunnermeier and Nagel (2004)document that some institutional investors do not act as arbitragers during the technology bubble. They ride the bubble, capture the upturn, and time the crash. A more recent similar work is Chen *et al.* (2021), which show that some skilled hedge fund managers are able to time the investor sentiment and generate alpha from the sentiment trading strategy. My work extends the findings of Chen *et al.* (2021) to the mutual fund industry. Notably, I find that mutual funds with high sentiment beta outperform others. This superior performance originates from managerial skills, especially timing skills. Moreover, using the holding data, I find that funds with the highest sentiment beta do not arbitrage against mispricing immediately. Instead, they may choose to ride the bubble and delay arbitrage activities. This finding is consistent with the prediction of Abreu and Brunnermeier (2002).

The rest of this paper is organized as follows. I describe the data sample and main variables in section 2. In section 3, I report the main results. Section 4 discusses the role of sentiment level. In section 5, I present the evidence of sentiment trading strategy from the holding position changes. Section 6 discusses the skill-based explanation. Section 7 concludes.

2. Related Literature

This section briefly reviews the related literature on mutual fund performance predictors and investor sentiment research.

2.1 Fund performance predictors

A central question of mutual fund research is whether I could distinguish the funds with positive alpha from those with negative alpha ex-ante. Many studies have investigated various theoretically and intuitively motivated variables to predict fund future performance. Some studies use past fund returns to forecast fund future alpha (Hendricks et al. 1993; Carhart 1997; Mamaysky et al. 2007), while others focus on holding-based information, which is more closely related to my fund sentiment beta measure.

Several papers focus on the extent to which funds deviate from their benchmarks. For instance, using holdings data, Cremers and Petajisto (2009) propose the active share, which is the absolute difference between the weights of portfolio holdings and the weights of benchmark index holdings, and show that it predicts future fund returns. Similarly, Doshi et al. (2015) find active weight, representing the absolute difference between the value weights and actual weights of portfolio holdings, captures managerial skill. In both cases, funds that deviate from the benchmark or market-cap-weighted portfolio perform better, indicating that fund managers who are more willing to make stock-specific bets exhibit skills.

Yet other papers compare the information difference between funds' own return and funds' holding-based return. Kacperczyk et al. (2008) proxy the unobserved actions of funds by the return difference between the actual returns and the holding-based return and show that the return gap predicts fund performance. Huang et al. (2011) propose a measure of risk-shifting proxied by the difference between holding-based return volatility and actual return volatility. They show that funds with higher risk-shifting levels perform poorly in the future.

Other studies also use fund holdings data to construct varieties of fund characteristics that have been proved to be related to fund future performance, such as momentum (Grinblatt et al. 1995), growth (Chan et al. 2002), and industry concentration (Kacperczyk et al. 2005).

All of these large-scale fund-performance-predictor studies contribute to the understanding of identifying the funds with positive alpha ex-ante and whether fund managers exhibit skills. And my study adds to this strand of literature by documenting a new fund-performance-predictor.

2.2 Mutual fund and sentiment-induced mispricing

A widely held traditional assumption believes that retail investors are more likely to be responsible for sentiment-induced mispricing, while more sophisticated institutional investors are more likely to act as arbitragers and correct the mispricing. In line with this assumption, several empirical works document that various anomalies are stronger among stocks with less institutional ownership (Nagel 2005; Campbell *et al.* 2008; Conrad *et al.* 2014; Stambaugh *et al.* 2015).

However, sophisticated investors are not always interested in arbitrage against mispricing. For instance, De Long *et al.* (1990a) show that the presence of noise traders in the market may make arbitrage activities risky. Sophisticated investors are unwilling to trade against mispricing in some cases, resulting in a larger price divergence from fundamental value. De Long et al. (1990b) further show that if the noise traders follow positive-feedback strategies, sophisticated investors may even time the mispricing, buy ahead of noise investors, and exploit profit from ridding bubble. Moreover, Abreu and Brunnermeier (2002) show that due to the synchronization risk (i.e., investors become aware of mispricing sequentially), rational investors may choose to ride the bubble and delay arbitrage activities. Abreu and Brunnermeier (2003) show that the synchronization risk, together with the investors' incentive to time the market, results in the substantial persistence of bubbles. Dumas et al. (2009) prove that in the presence of market sentiment risk, the optimal equilibrium portfolio depends not only on the current level of mispricing but also on their judgment of the future sentiment level. In all these theoretical model, sophisticated investors do not engage in arbitrage activities immediately and show some willingness to time the market sentiment to exploit capital gains in the short run.

In line with the rational speculation theories, several recent empirical papers find that institutional investors may contribute to the deviation of stock price from the fundamental value. Edelen *et al.* (2016) show that institutional investors have a strong tendency to buy stocks classified as overvalued (the short leg of anomalies) and make a profit at a quarterly horizon. Jang and Kang (2019) find that institutional investors may not always trade against mispricing but ride the bubbles and time the crashes of individual stocks. In terms of sentiment-related trading strategies, DeVault *et al.* (2019) provide evidence that the prevalent sentiment metrics capture the demand shocks of institutional investors rather than individual investors. Chen *et al.* (2021) find that hedge funds with high sentiment beta outperform others and exhibit sentiment timing skills. For mutual funds, the empirical evidence is still mixed. Massa and Yadav (2015) show that mutual funds with low sentiment beta outperform others and generate alpha from betting against sentiment-introduced mispricing. However, Chue and Mian (2021) find that fund managers choose to reduce active stock selection and trace their benchmark more closely during the high sentiment period, indicating that fund managers deliberately ride the sentiment bubble. My empirical findings also suggest that mutual fund managers exhibit timing skills and exploit profit from sentiment fluctuations.

3. Data and Main Variable

3.1 Mutual Funds

The main data source is the Centre for Research in Security Prices (hereafter CRSP) Survivor Bias-Free Mutual Fund Database. I extract the monthly fund returns, total net assets under management (hereafter TNA), and other fund characteristics (e.g., expense ratio, turnover ratio, total load fees, fund starting date, etc.) from this database. From Thomson Reuters Mutual Fund Holdings Database, I obtain the holding shares and stock identifier, which allow us to link to CRSP equity files and compute the market value of each stock's holding position. Most funds in my sample period report their holding positions quarterly, and others report semiannually. For non-reporting months, I assume the funds continue to hold the same portfolios from the last reporting date to the next. Further, I link these two databases by using the MFLINKS file from the Wharton Research Data Services.

Many funds in my sample have multiple-share classes. Although these multiple-share classes are listed as separate funds in CRSP, I aggregate them into a single fund. The reason is that such separated classes typically have the same fund manager, the same pool of assets, and consequently have the same raw return before expenses. The new aggregated single fund's TNA is the sum of the TNA of all share classes. The other fund characteristics are the TNA-Weighted average of corresponding characteristics of all share classes.

Since this study focuses on mutual funds' sentiment bubble riding behaviors, I limit my sample to actively managed U.S. domestic equity funds, of which the data is most reliable and complete. I rule out international, balanced, sector, bond, money market, and index funds. Since the funds' style categories variables in datasets may not fully reflect funds' investment objects, I further rule out the funds that hold less than 80% of net asset in equity during their lifetime. To eliminate the upward biased return among small funds ELTON *et al.* (2001), I exclude funds with TNA of less than 15 million USD. Moreover, Evans (2010) finds that the funds in incubation outperform others; however, this outperformance disappears when they are opened to the public. To eliminate this incubator bias, I also remove the fund return during the incubation period (18 months). Finally, I drop the fund observations with missing names in CRSP, following Cremers and Petajisto (2009).

Table 1 Panel A reports the summary statistics of the mutual fund sample used in this paper. The sample period starts from January 1980 to December 2018, covering 456 months. My sample consists of 502,323 fund-month observations and 3009 distinct mutual funds. During this sample period, each fund's average asset under management and the number of mutual funds have increased steadily over time. In January 1980, the number of mutual funds in the sample is 148. These mutual funds managed $177 billion of assets; in December 2018, the corresponding figures are 1289 mutual funds managed $2052 billion of assets.

The Total-Net-Asset (TNA) is the sum of total-net-asset of different classes of the same fund. The average TNA in my sample is 1382.89 million, with a standard deviation of 5770.02 million. This high standard deviation implies wide variations in fund size; therefore, I use the logarithm of TNA in my regression model. Similarly, FAMILY_TNA is the sum of TNA of different funds belonging to the same asset management company; and the log(FAMILY_TNA) is the logarithm of Family-TNA. TURN_OVER is the average aggregated sales and purchases of securities divided by the average TNA in the previous year. The yearly turnover rate of the average mutual fund is 82.72%. AGE is the length of time since the mutual fund was first offered. The average age of mutual funds in my sample is 11.39 years. EXPENSE_RATIO is the percent of the total investment that a fund charges for management in the previous year. The average expense ratio in my sample is 1.22% per year. TOTAL_LOAD, a percent of the investment paid to the mutual fund, is the sum of front-load and rear-load in the previous year. Among my sample, the average total-load is 2.83%.

NET_RETURN is the CRSP reported monthly net return after fund expense, and GROSS_RETURN is the sum of monthly net return and expense ratio. My sample's average monthly net return and gross return are 0.70% and 0.79%, respectively. CAPM_ALPHA is calculated by running 36-month rolling window regression of fund monthly excess return on the market factor (MKTRF). Similarly, 3_FACTOR_ALPHA is calculated by running a regression on Fama-French 3 factors (MKTRF, SMB, HML) (Fama & French 1992); and 4_FACTOR_ALPHA is calculated by running a regression on Fama-French-Carhart 4 factors (MKTRF, SMB, HML, UMD) (Carhart 1997). Among my sample, the average fund has 0.09% CAPM alpha, 0.07% 3-factor alpha, and 0.05% 4-factor alpha, respectively.

3.2 Mutual Fund Sentiment Beta

Following the literature, I adopt the widely-used Baker-Wurgler sentiment index to measure investor sentiment in the empirical tests. Baker and Wurgler (2006) (BW hereafter) construct a proxy for investor sentiment by extracting the first principle component of the following six measures: the closed-end fund discount, the market turnover of New York Stock Exchange (NYSE), the number of initial public offerings (hereafter IPOs), the average first-day return on IPOs, the equity share of new issuances, and the dividend premium. Baker and Wurgler (2006) show that their sentiment index could predict future stock return in the cross-section; the possible mechanism might be the price correction related to sentiment-driven mispricing.

Following Chen *et al.* (2021), I define the stock sentiment beta as the regression coefficient of sentiment index changes rather than sentiment index level (Massa & Yadav 2015). Market sentiment is investors' overall attitude towards the market, revealed by the price level and trading activities. It is a market-wide phenomenon and substantially impacts cross-sectional stock returns. Rational investors will construct their portfolio based on the public-known current sentiment level and also their projection of future sentiment levels. In a nutshell, the change in sentiment index (the difference between current and future sentiment levels) matters.

Theoretically, when investment opportunities vary with state variables over time, the multifactor asset pricing models (Merton 1973; Campbell 1992, 1996; Ross 2013) predict that the risk premia are associated with the conditional covariance between the returns and changes of state variables. I-CAPM proves that: if investors are more risk-averse than log utility, they should care about the risk both from market return and from the innovations in the state variables that help to forecast future returns. The intuition is that the changes in state variables impair future investment opportunities and rational investors want to hedge against these risks. Therefore, if we believe that the investor sentiment is a kind of market-wide risk, the beta on its changes should better capture the stock sentiment exposure.

Specifically, I estimate each stock's sentiment beta by regressing stock excess return on the sentiment changes while controlling for standard risk factors. In each month, for each stock, I perform the following 36-month rolling window regression:

$$r_{i,t} = \alpha + \beta_{i,t}^{s} \Delta sentiment_t + \beta^{'} f_t + \varepsilon_t \tag{1}$$

where $r_{i,t}$ is the mutual fund's monthly excess return in excess of 1 month T-bill rate; $\Delta sentiment_t$ is the changes in sentiment index; f_t is the factor vector of Fama-French 3 factors (MKTRF, SMB, HML). I use rolling window regression to allow for time-varying mutual fund sentiment beta. In month *t*, the rolling window covers from *t*-35 month to *t* month.

Next, I construct the mutual fund sentiment beta from stock sentiment beta. Using the last report day mutual fund holding data, I calculate the value-weighted portfolio beta as the fund's sentiment beta. Specifically, for f fund in month *t*, I computed mutual fund sentiment beta as follows:

$$Fund\_Sentiment\_Beta_t^f = \sum_{i=1}^{I} w_{i,t}^f \beta_{i,t}^s \tag{2}$$

where $Fund\_Sentiment\_Beta_t^f$ is the sentiment beta of fund f in month *t*, $w_{i,t}^f$ is the holding weight of stock *i* in month *t* of fund *f* (I assume the holding position do not change since last report day), $\beta_{i,t}^s$ is the sentiment beta of stock *i* in month *t* estimated from rolling window regression.

Kacperczyk et al. (2008) provide evidence that the unobserved actions (i.e., the investment activities that investors can not observe from disclosed holding data) of mutual fund managers could predict future performance. Naturally, considering these unobserved actions, an alternative way to estimate the fund sentiment beta is to directly run a 36-month-rolling window regression of fund excess return on sentiment changes and common risk factors. However, this alternative method might suffer from severe drawbacks. First, unlike stocks' sentiment beta, which could be relatively steady over time, mutual funds' sentiment loading could change radically with their investment strategies. Then the estimated fund sentiment beta could be biased from time series regression. Second, the fund return I used in the rolling window regression comes from the holding position of the previous 36 months. These historical positions might be very different from the funds' current position. On the contrary, the holding position revealed in the last report day could be closer to the current position. Therefore, I believe it is more appropriate to estimate mutual fund sentiment beta by aggregating holding stocks' sentiment beta.

In my sample, both the mean and median of Fund_Sent_Beta are close to 0. This result is consistent with our expectations. In the market, an average fund's sentiment beta should be zero. The standard deviation is 0.04, which is relatively small. One possible explanation is that mutual funds, in fact, are portfolios of stocks. Different sentiment beta levels of different stocks in the same mutual funds may cancel out each other, resulting in little variation in fund sentiment beta. In Panel B, Table 1, I present the correlation matrix of variables. The correlation coefficients between Fund_Send_Beta and performance measures (i.e., NET_RETURN, GROSS_RETURN, CAPM_ALPHA, 3_FACTOR_ALPHA, 4_FACTOR_ALPHA) are all positive.

4. Baseline Results

I now examine the relation between sentiment beta and mutual fund performance. First, I use portfolio sorts to test whether sentiment beta could predict fund performance in 1 month following portfolio formation. I also investigate the effect of sentiment beta on mutual funds over a more extended holding period (3, 6, 9, 12 months). Second, I perform Fama and MacBeth (1973) regression and panel regression of fund alpha on sentiment beta controlling for fund characteristics and style dummies. Third, I study the relation between sentiment beta and fund managers' "characteristics selectivity" and "characteristics timing" ability, following Daniel et al. (1997).

4.1 Portfolio Sorting

In this section, I use portfolio sorts to test the relation between sentiment beta and fund performance. Each month I construct 10 equal-weighted portfolios of mutual funds based on the fund sentiment beta estimated from the holding position. These portfolios are rebalanced monthly. I then track the fund returns over the following one month and generate a monthly decile portfolios return time series. Further, I estimate portfolios' alpha by running a time-series regression of the decile portfolios' excess return on standard risk factors (market factor, 3 factors, and 4 factors).

Table 2 presents the return and alpha of mutual fund decile portfolios sorted by sentiment beta. The results in Panel A rely on net-off-fee returns. For portfolio 10 (i.e., the fund portfolio with highest sentiment beta), the average net return, the excess net return, CAPM-alpha, 3-factor-alpha, and 4-factor-alpha are 1.18%, 0.84%, 0.52%, 0.50% and 0.43% per month, respectively; while for portfolio 1 (i.e., the fund portfolio has the lowest sentiment beta), these numbers are 0.85%, 0.50%, .010%, 0.15%, and 0.15%. Obviously, portfolio 10 outperforms portfolio 1 in terms of return and alphas. Both the return and excess return spread between the bottom and top decile are 0.33% (*t*-statistics=1.82) per month. On the risk-adjusted basis, the CAPM-alpha spread gets even larger, at 0.42% (*t*-statistics=2.30) per month; the 3-factor-alpha and 4-factor-alpha are 0.35% (*t*-statistics=1.91) and 0.28% (*t*-statistics=1.52), respectively. Moreover, both the portfolio returns and alphas increase monotonically with sentiment beta. Thus, portfolio sorting results indicate that before and after adjusting for standard risk factors, mutual fund performance is significantly positively related to sentiment beta.

Net return is the payoff to mutual fund investors, while gross return is the profit that mutual funds earn from the market. Compared to gross return, after-fee-net-return might be less closely related to arbitrage profit. This could be problematic if the fee charged by mutual funds is related to sentiment beta. Therefore, to address this problem, in Panel B, I also present the results relying on gross returns.

The average gross return, the excess gross return, CAPM-alpha, 3-factor-alpha, and 4-factor-alpha of portfolio 10 are 1.29%, 0.94%, 0.62%, 0.60% and 0.54% per month, respectively; while for portfolio 1, these numbers are 0.95%, 0.60%, 0.20%, 0.26%, and 0.26%. Fund portfolio with highest sentiment beta outperforms portfolio with lowest sentiment beta in terms of gross return and alpha. Both the return and excess return spread between the two extreme deciles are 0.34% (*t*-statistics=1.84) per month. On the risk-adjusted basis, the CAPM-alpha spread gets even larger, at 0.43% (*t*-statistics=2.32) per month; the 3-factor-alpha and 4-factor-alpha are 0.35% (*t*-statistics=1.93) and 0.28% (*t*-statistics=1.54), respectively. Thus, the results relying on gross return also lead to the same inference that mutual fund performance and sentiment beta are significantly positively related. Since the results based on net return and gross return are pretty similar, from now on, the following analysis will only rely on net return for brevity.

Next, I further examine sentiment beta's effect on mutual fund performance over a longer holding period. Specifically, each month, I form the equal-weighted decile portfolios based on sentiment beta and hold these portfolios for 3, 6, 9, 12 months, respectively. I track the fund performance over different time horizons and generate 4 time series of portfolio holding period returns. Similarly, I estimate portfolios' alpha by running a time-series regression of the decile portfolios' excess return on corresponding risk factors. Take the 3 months holding period case as an example, the corresponding risk factors are calculated as factors' 3 months cumulative returns.

Panel A of Table 3 reports the fund performance over 3 months after portfolio construction. The spreads of net return and excess net return between the bottom and top deciles are 1.90% (*t*-statistics=1.94). If I convert it into the annual rate, the spread per year is 7.60%, which is economically substantial. The CAPM-alpha, 3-factor-alpha and 4-factor-alpha are 2.18% (*t*-statistics=2.27), 2.08% (*t*-statistics=2.01) and, 1.95%

(t-statistics=1.76), respectively. Panel B presents the fund performance over 6 months after portfolio construction. The spreads of net return and excess net return between two extreme deciles are 1.76% (t-statistics=2.67), which means the spread per year is 3.52%. The CAPM-alpha, 3-factor-alpha and 4-factor-alpha are 2.03% (t-statistics=2.92), 1.05% (t-statistics=1.61) and, 0.99% (t-statistics=1.39), respectively. Panel C shows the fund performance over 9 months after portfolio construction. The spreads of net return and excess net return are 2.27% (t-statistics=2.66), which means the spread per year is 3.03%. The CAPM-alpha, 3-factor-alpha and 4-factor-alpha are 2.84% (t-statistics=3.12), 1.03% (t-statistics=1.25) and, 1.06% (t-statistics=1.15), respectively. Panel D shows the fund performance over 12 months after portfolio construction. The spreads of net return and excess net return are 1.90% (t-statistics=1.87). The CAPM-alpha, 3-factor-alpha and 4-factor-alpha are 2.17% (t-statistics=1.94), -0.18% (t-statistics=-0.17) and, 0.20% (t-statistics=0.16), respectively. The net return and CAPM-alpha spreads are still slightly significant even after 12 months; the 3-factor-alpha and 4-factor-alpha dacay to an insignificant level. Although the annual return spread attenuates when the holding periods get longer, The sentiment beta displays a fair amount of persistency on performance predictability. Most of the performance spread is significant until I extend the holding period to 12 months.

In sum, my portfolio sorts results are consistent across different specifications. Mutual fund performance increases monotonically with sentiment beta, and most spreads between two extreme deciles are statistically and economically significant.

4.2 Multivariate Analysis

I perform a multivariate analysis of the mutual fund alpha to control for known determinants of fund performance, including fund characteristics and style dummies. The regression model is as follows:

$$Performance_{t+1}^{f} = \lambda_0 + \lambda_1 \beta_t^{f} + \lambda' X_t^{f} + \varepsilon_{t+1}^{f} \qquad (3)$$

where $Performance_{t+1}^{f}$ is the f fund's performance, which is measured by excess return, CAPM-alpha, 3-factor-alpha, and 4-factor-alpha in month *t+1* times 100. β_{t}^{f} is f fund's estimated sentiment beta in month *t*. The control variables are predetermined mutual fund characteristics, including the logarithm of TNA, the logarithm of fund family size, the turnover rate in the previous year, fund age, total load, lag fund flow, the standard deviation of fund flow during the last year, and the fund style dummies.

Table 4 Panel A presents Fama and MacBeth (1973) regression results. Columns (2), (4), (6), and (8) control the style dummies, while columns (1), (3), (5), and (7) do not. Panel B reports the results from panel regression. All columns control the time fixed effect, and only columns (2), (4), (6), and (8) control the style dummies.

In Fama and MacBeth (1973) regression results, all the coefficients on fund sentiment beta are positive, and half of them (columns (3), (4), (7), and (8)) are significant at 1% significance level. In panel regression results, all the coefficients of fund sentiment beta are positive and significant. Across all different specifications, the coefficients of fund sentiment beta are positive and statistically significant. Moreover, the coefficients are also economically significant. For instance, in Panel A column (8), one unit increase in sentiment beta could lead to a 0.314% increase in 4-factor-alpha per month.

In sum, the multivariate analysis based on Fama and MacBeth (1973) regression and panel regression states the strong positive relation between mutual fund sentiment and fund performance. These results are consistent with portfolio sorts results.

4.3 DGTW Decomposition

Daniel et al. (1997) (DGTW hereafter) developed a method to decompose mutual fund performance into "Characteristic Selectivity" (CS hereafter) and "Characteristic Timing" (CT hereafter) abilities. They first construct 5×5×5=125 benchmarks along the dimensions of size, book-to-market ratio, and momentum. Then they match the stocks held by mutual funds based on these three characteristics. The month *t* CS measure is defined as follows:

$$CS_t^f = \sum_{i=1}^{N} \omega_{i,t-1}^f (r_{i,t} - r_t^{bi,t-1}) \tag{4}$$

where CS_t^f is the CS measure of fund *f* in month *t*. $\omega_{i,t-1}^f$ is the fund *f*'s holding position weight on stock *i* at the end of month *t*-1. $r_{i,t}$ is the stock *i*'s return in month *t*. $r_t^{bi,t-1}$ is the month *t* return of the benchmark, which is matched to stock *i* during month *t*-1. I use the most recent available holding data to estimate the holding weight of stock *i* in month *t*-1. A positive CS measure means the stocks held by the mutual fund outperform their corresponding benchmarks, suggesting that the mutual fund manager has additional stock picking ability.

Since the expected return of size premium, value premium, and momentum strategies varies over time. Some fund managers may exploit this pattern and time the styles. Daniel et al. (1997) also developed a measure to proxy this timing ability, The month *t* CT measure is defined as follows:

$$CT_t^f = \sum_{i=1}^{N} (\omega_{i,t-1}^f r_t^{bi,t-1} - \omega_{i,t-13}^f r_t^{bi,t-13}) \tag{5}$$

where CT_t^f is the CT measure of fund *f* in month *t*. $\omega_{i,t-13}^f$ is the fund *f*'s holding position weight on stock *i* in month *t*-13. $r_t^{bi,t-13}$ is the month *t* return of the benchmark, which is matched to stock *i* in month *t*-13.

For instance, at time *t*-1, a fund manager successfully forecasted the strong size premium at time *t* and increased its weight on small stocks. Then the CT measure of this fund at time *t* would be positive.

Each quarter, I first conduct the DGTW decomposition for each fund. Then I computed the equal-weighted average of CS and CT measures for decile portfolios. Thus, I generate the time series of CS and CT for decile portfolios.

Table 5 reports the results of DGTW decomposition. For portfolio 10 (i.e., the fund portfolio with highest sentiment beta), the CS measure is 0.29% (*t*-statistics=2.18) per quarter, and the CT measure is 2.01% (*t*=4.72) per quarter; while for portfolio 1 (i.e., the fund portfolio has the lowest sentiment beta, the CS measure is 0.01% (*t*-statistics=0.08) per quarter, and the CT measure is 1.55% (*t*=3.98) per quarter. The decile with the highest sentiment beta outperforms the decile with the lowest sentiment beta. The spread of CS measure is 0.28% (*t*-statistics=1.42), and of CT measure is 0.46% (*t*=3.42), suggesting that the outperformance of high sentiment beta funds mainly comes from the timing ability.

In sum, the DGTW decomposition results are consistent with those from portfolio sorts and regressions. Both CS measure and CT measure increase monotonically with sentiment beta. However, only the spread of CT measure is statistically significant. The small CS spread and big CT spread imply that high sentiment beta funds are good at market timing rather than stock picking.

These results may partially explain the pattern in Table 2: the spreads of return and CAPM-alpha are significant, while the spread of 4-factor-alpha is not significant enough. The sentiment-bubble-riding and momentum strategies are timing strategies, and these two are inevitably positively correlated. Therefore, once we adjust the alpha for the momentum factor, the spread between the two extreme deciles declines.

5. The Role of Sentiment Level

5.1 Portfolio Sorting

A natural way to access mutual funds' sentiment timing activities is by testing whether some mutual funds increase sentiment loading during high sentiment periods, ride the sentiment bubbles, and get higher returns from sentiment timing. In other words, I could first examine whether the outperformance becomes stronger when the sentiment level is high. Although my sentiment beta is the exposure to sentiment fluctuations, I am also interested in sentiment level's role in the positive relation between sentiment beta and fund performance. Following the literature, I split each month into high/low sentiment periods depending on whether the sentiment level exceeds the sample median or not.

Table 6 reports the different fund performance patterns during high and low sentiment periods. In the high sentiment level period subsample, the return and alpha spreads between the two extreme deciles become even more significant than those in the whole sample. The spreads of excess net return, CAPM-alpha, 3-factor-alpha and 4-factor-alpha are 0.65% (*t*-statistics=2.54), 0.71% (*t*-statistics=2.30), 0.35% (*t*-statistics=1.94), and 0.25% (*t*-statistics=1.72), respectively. However, during low sentiment periods, all the spreads become insignificantly. In a nutshell, the positive relation between sentiment beta and fund performance only holds when the sentiment level is high. And undoubtedly, during high sentiment period, this positive relation is much stronger than during low sentiment period.

5.2 Multivariate Analysis

I perform a similar multivariate analysis by adding an interaction term between the sentiment level dummy and fund sentiment beta. The regression model is as follows:

$$Performance_{t+1}^{f} = \lambda_0 + \lambda_1 D_t + \lambda_2 \beta_t^{f} + \lambda_3 \beta_t^{f} * D_t + \lambda^{'} X_t^{f} + \varepsilon_{t+1}^{f} \qquad (6)$$

where D_t is the sentiment level dummy in month *t*. D_t equal to 1 when sentiment level is higher than sample median and 0 otherwise. $\beta_t^f * D_t$ is the interaction term. Thus, the coefficient of interest is λ_3.

Table 7 reports the Fama and MacBeth (1973) regression results with and without controlling for style dummies. The coefficients before the interaction term are positive and statistically significant (columns (3), (4), (5), (6), (7), and (8)). The result implies that the positive relation between sentiment beta and fund performance is stronger when the sentiment dummy equals 1 (high sentiment periods).

5.3 DGTW Decomposition

Further, I also examine the CS and CT measures during high and low sentiment periods, respectively. Table 8 presents the CS and CT results of the decile portfolios conditional on market sentiment level. When the sentiment is high, the CS and CT spreads between the two extreme deciles are 0.57% (t-statistics=1.94), and 0.68% (t-statistics=3.62), respectively. While during low sentiment periods, both the CS and CT spreads become insignificant. When the market sentiment level is high, the mutual funds with higher sentiment beta display significantly better stock picking and market timing skills.

To summarize, various lines of evidence come to the same conclusion that the positive relation between sentiment beta and fund performance is stronger during high sentiment periods. The outperformance of high sentiment beta funds is mainly generated during high sentiment periods.

These empirical findings contradict the traditional wisdom that institutional investors play the socially useful role of arbitrager when facing sentiment-induced mispricing. If this is the case, we should observe the outperformance generated following high sentiment periods when mispricing gets corrected rather than during high sentiment periods when sentiment-induced mispricing is severe. So far, my empirical findings imply that my conjecture about sentiment timing activities at least is not beyond the realms of possibility.

6. Evidence from The Change of Mutual Fund Holding Position

In the conventional wisdom, institutional investors, such as mutual funds, profit from arbitrage activities. They trade against mispricing, buy the undervalued stocks, short the overpriced ones, and get alpha from the subsequent price correction process. This view suggests that superior performance should come after high sentiment periods (i.e., during the price correction process) instead of during high sentiment periods (i.e., the period that the mispricing is still severe). However, my findings so far contradict this conventional wisdom. Thus, I further explore the mutual funds' trading behaviors.

We adopt Stambaugh et al. (2015) mispricing score to measure the stocks' mispricing level. They define the mispricing score of a specific stock as the arithmetic average of its ranking percentile of 11 anomalies. Thus, a high mispricing score suggests that the stock is grossly overpriced. The mutual fund net buys are calculated from the change of holdings. Then, each quarter, I generate the correlation coefficient between portfolios' net buys and stock mispricing scores for each decile fund portfolio sorted by sentiment beta. If mutual funds are indeed engaged in trading against mispricing, the net buys of overpriced stock should be negative, and the net buys of underpriced stocks should be positive. Thus, we should expect a negative correlation coefficient between fund net buys and stock mispricing score.

Table 9 reports the results. Column (1) clearly shows that during the whole sample period, all decile fund portfolios overall trade against mispricing. The correlation coefficients between their net buys and stock mispricing scores are negative, and the difference between the two extreme deciles is insignificant. Similarly, all the correlation coefficients are negative in column (3) (i.e., the results from low sentiment level subperiod). This result implies that all decile fund portfolios trade against mispricing during low sentiment periods, and there is no significant difference between different deciles. However, during high sentiment periods, for portfolio 10, the funds with the highest sentiment beta, the correlation coefficients are positive (not significant). And the difference between the two extreme deciles is substantial. This finding suggests that the funds in portfolio 10, at least, do not trade against mispricing. When the sentiment level is high, the sentiment-driven mispricing soares, those mutual funds with high sentiment beta do not actively participate in arbitraging against mispricing. They seem passively move with the surging sentiment level and ride the sentiment bubbles. These behaviors are consistent with the "rational speculation" theory.

7. Skills and the Sentiment Beta Mutual Fund Performance Relation

Mutual funds with high sentiment beta outperform others. The most reasonable explanation should be managerial skills. I could get some initial support for this conjecture from Table 5, which shows that mutual funds with higher sentiment beta exhibit better stock picking and market timing skills. In this section, I will further investigate the skill-based explanation.

In the literature, several mutual fund characteristics related to managerial skills have been identified. Amihud and Goyenko (2013) propose an intuitive and convenient measure of mutual fund skills. According to them, fund managers with low skills may be less confident in their ability to earn alpha from idiosyncratic strategies, and they would closely track the conventional strategies, such as momentum strategy. Therefore, the factor model could better explain their performance. And consequently, they would have higher regression R-square. On the contrary, high skills fund managers would have lower regression R-square.

Specifically, each month, I estimate the R-square for each fund by running a 36-month rolling window regression of fund excess return on four factors. Then I compute the logistic transformation of R-square, defined as $TR^2 = \log[\sqrt{R^2} / (1 - \sqrt{R^2})]$. The distribution of logistic transformation of R-square is more well behaved than R-square itself. Then I regress both R-square and transformation of R-square on fund sentiment beta and other controls.

Table 10 reports the results of Fama and MacBeth (1973) regression with and without style dummies. All the coefficients before fund sentiment beta are negative and significant at a 1% significance level. The results present a robust negative relation between fund sentiment beta and R-square. One unit increase in sentiment beta could lead to a reduction of 0.069 (*t*-statistics=-3.96) in R-square. The magnitude of reduction is quite significant.

In sum, the correlation between fund sentiment beta and R-square is significantly negative. This finding suggests that the outperformance of high sentiment beta funds comes from managerial skills, from active management, and from deliberate choosing unconventional strategies.

8. Conclusions

This paper studies the relation between sentiment beta (the mutual funds' exposure to sentiment fluctuations) and fund performance. In traditional wisdom, investor sentiment relates to the irrational behavior of naïve investors. It drives asset prices high, leads to severe mispricing, and increases the arbitrage risk. Mutual funds are expected to trade against sentiment-driven mispricing as sophisticated institutional investors. However, some skilled mutual fund managers employ a totally different trading strategy. They time the sentiment fluctuations, ride the sentiment bubbles, and take advantage of the sentiment-drive mispricing. Different mutual fund managers employ different sentiment trading strategies, consequently leading to different sentiment beta. My empirical findings show that the sentiment beta is strongly, positively relates to fund performance. The return spread between the two extreme decile is 0.34% per month.

Further, I investigate the role of sentiment level in the sentiment beta-fund performance relation. My results show that the outperformance of high sentiment beta funds is mainly generated during high sentiment periods, instead of following high sentiment periods (when the sentiment-driven mispricing is getting corrected). This finding contradicts the previous belief that institutional investors bet against mispricing and profit from price correction. Moreover, the evidence from changes in holding suggests that some high sentiment beta funds seem to ride the sentiment bubble when the sentiment level is high. Finally, "Characteristic Selectivity" and "Characteristic Timing" measures show that the outperformance of high sentiment beta funds mainly comes from market timing skills, consistent with riding bubble conjecture. Also, R-square skills measure suggests that high sentiment beta funds managers deliberately choose unconventional strategies and exhibit higher managerial skills.

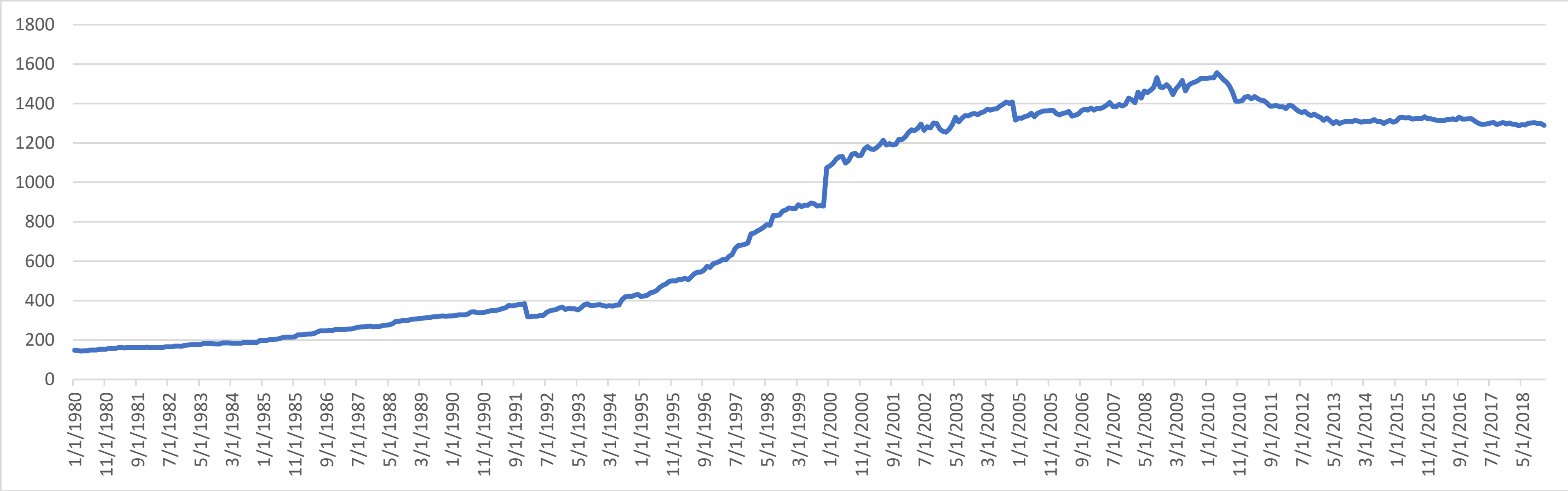
In sum, although the surge of investor sentiment may drive up mispricing and deter the arbitrage profit of institutional investors. My findings show that some mutual funds may engage in an undocumented sentiment trading strategy, ride the sentiment bubble, exploit the sentiment-introduce mispricing, and profit from sentiment fluctuation.

APPENDIX A VARIABLE DEFINITIONS

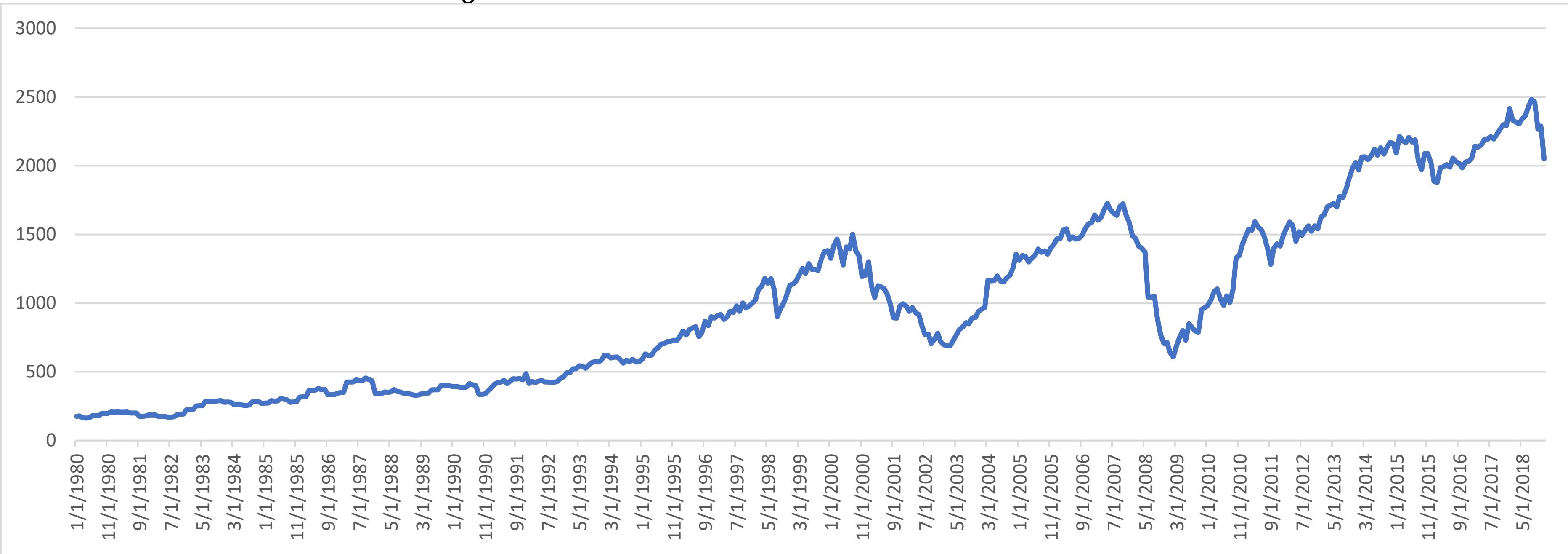
Variables Following the Methodology in Massa And Yadav (2015)	
TNA	The sum of total-net-asset of different classes of the same fund
log(TNA)	The natural logarithm of TNA at the end of the previous month.
FAMILY_SIZE	The sum of TNA of different funds belonging to the same asset management company.
log(FAMILY_SIZE)	The natural logarithm of FAMILY_SIZE at the end of the previous month.
TURN_OVER	The average aggregated sales and purchases of securities divided by the average TNA in the previous year.
AGE	The number of years since the fund was first offered.
EXPENSE_RATIO	The ratio of total investment that shareholders paid for the fund's operating expenses in the previous year.
TOTAL_LOAD	The sum of front load and rear load charged by the fund at the end of the previous year, indicated as the percentage of the money invested. Front load is the fee charged by the fund when an investor joins the fund. Rear load is the fee charged by the fund when an investor withdraws from the fund.
LAG_FLOW	Net flow of new investments in the fund in last 12 months, as a percentage of TNAs at the beginning of that period. Mathematically, $LAG\_FLOW_t = TNA_{t-1} - \left(1 + R_{t-13,t-1}\right) \times TNA_{t-13}/TNA_{t-13}$.
SIGMA_FLOW	Standard deviation of net monthly flows in last 12 months.
NET_RETURN	The CRSP reported monthly net return excluding fund expense.
GROSS_RETURN	The sum of monthly net return plus the expense ratio.
CAPM_ALPHA	The alpha from the CAPM, calculated by running 36 months rolling window regression of fund monthly excess return on market factor.
3_FACTOR_ALPHA	The alpha from Fama French Three Factor Model, calculated by running 36 months rolling window regression of fund monthly excess return on Fama-French 3 factors.
4_FACTOR_ALPHA	The alpha from Fama French and Carhart Fmy Factor Model, calculated by running 36 months rolling window regression of fund monthly excess return on Fama-French-Carhart 4 factors.

Figure 1 The Number of Mutual Funds and the Volume of Asset under Management

Panel A: The Number of Mutual Funds



Panel B: The Volume of Asset under Management



Panel A and Panel B plot the time series of the number of mutual funds and the total volum of asset under management in our sample from January 1980 to December 2018, respectively.

TABLE 1 Descriptive Statistics

Panel A: Summary statistics

Variable	Mean	Median	Std. Dev.	1st Perc.	99th Perc.
Fund_Sent_Beta	0.00	0.00	0.04	-0.11	0.10
TNA($million)	1382.89	252.70	5770.02	17.30	19259.90
Log(TNA)	5.66	5.53	1.63	2.85	9.86
Log(FAMILY_TNA)	7.86	8.04	2.29	3.02	12.88
TURNOVER(% per year)	82.72	63.00	81.66	3.00	366.00
AGE(years)	11.39	8.01	10.98	1.62	57.08
EXPENSE_RATIO(% per year)	1.22	1.16	0.49	0.12	2.53
TOTAL_LOAD(% per year)	2.83	2.50	2.90	0.00	8.50
NET_RETURN(% per month)	0.70	1.08	5.98	-15.06	12.75
GROSS_RETURN(% per month)	0.79	1.17	5.98	-14.95	12.86
CAPM_ALPHA(% per month)	0.09	0.03	1.53	-2.10	2.85
3_FACTOR_ALPHA(% per month)	0.07	0.03	0.62	-0.97	1.54
4_FACTOR_ALPHA(% per month)	0.05	0.02	0.59	-0.95	1.41

Panel B: Correlation matrix

	NET RETURN	CAPM ALPHA	3FACTOR ALPHA	4FACTOR ALPHA	Fund_Sent Beta	Log(TNA)	Log (FAMILY_TNA)	TURNOVER	AGE	EXPENSE RATIO	TOTAL LOAD
NET_RETURN											
CAPM_ALPHA	0.519										
3_FACTOR_ALPHA	0.658	0.868									
4_FACTOR_ALPHA	0.210	0.759	0.818								
Fund_Sent Beta	0.005	0.064	0.002	0.006							
Log(TNA)	-0.004	0.038	0.039	0.045	0.004						
Log(FAMILY_TNA)	-0.004	0.029	0.028	0.034	0.003	0.677					

TURNOVER	-0.016	0.002	0.003	-0.020	-0.010	-0.143	-0.075			
AGE	0.015	-0.039	-0.021	-0.025	-0.004	0.177	0.009	-0.076		
EXPENSE_RATIO	-0.017	0.001	-0.009	-0.008	0.010	-0.230	-0.199	0.114	-0.095	
TOTAL_LOAD	-0.009	0.063	0.016	0.022	0.050	0.022	0.069	-0.007	0.096	0.013

Panel A presents the summary statistics of the regression variables. I present the mean, median, standard deviation (SD), 1st percentile, and the 99th percentile of the variables. Panel B presents the Pearson correlation for each pair of variables. TNA is The sum of total-net-asset of different classes of the same fund. FAMILY_TNA is the sum of TNA of different funds belonging to the same asset management company. TURNOVER is the average aggregated sales and purchases of securities divided by the average TNA in the previous year. AGE is the number of years since the fund was first offered. EXPENSE_RATIO is the ratio of the total investment that shareholders paid for the fund's operating expenses in the previous year. TOTAL_LOAD is the sum of front load and rear load charged by the fund at the end of the previous year, indicated as the percentage of the money invested. Front load is the fee charged by the fund when an investor joins the fund. Rear load is the fee charged by the fund when an investor withdraws from the fund. NET_RETURN is the CRSP reported monthly net return excluding fund expense. GROSS_RETURN is the sum of monthly net return plus the expense ratio. CAPM_ALPHA is the alpha from the CAPM, calculated by running 36 months rolling window regression of fund monthly excess return on market factor. 3_FACTOR_ALPHA is the alpha from Fama French Three Factor Model, calculated by running a regression on Fama-French 3 factors. 4_FACTOR_ALPHA is the alpha from Fama French and Carhart Fmy Factor Model, calculated by running a regression on Fama-French-Carhart 4 factors.

Variable definitions are summarized in Appendix A.

TABLE 2 Sentiment Beta and Mutual Fund Performance: Portfolio Sorting

Panel A Net Return

Decile	Net return	Net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	0.85%	0.50%	0.10%	0.15%	0.15%
2	0.92%	0.57%	0.21%	0.24%	0.21%
3	0.92%	0.57%	0.24%	0.25%	0.24%
4	0.92%	0.58%	0.26%	0.26%	0.24%
5	0.91%	0.56%	0.25%	0.24%	0.23%
6	0.94%	0.60%	0.29%	0.28%	0.28%
7	1.00%	0.65%	0.35%	0.34%	0.34%
8	1.01%	0.66%	0.37%	0.34%	0.33%
9	1.03%	0.69%	0.39%	0.35%	0.33%
10	1.18%	0.84%	0.52%	0.50%	0.43%
diff 10-1	0.33%	0.33%	0.42%	0.35%	0.28%
t statistics	*1.82*	*1.82*	*2.30*	*1.91*	*1.52*

Panel B Gross Return

Decile	Gross return	Gross excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	0.95%	0.60%	0.20%	0.26%	0.26%
2	1.01%	0.66%	0.31%	0.33%	0.31%
3	1.00%	0.66%	0.33%	0.33%	0.32%
4	1.01%	0.67%	0.34%	0.34%	0.33%
5	0.99%	0.65%	0.33%	0.33%	0.32%
6	1.03%	0.69%	0.38%	0.37%	0.36%
7	1.08%	0.74%	0.44%	0.42%	0.42%
8	1.10%	0.75%	0.45%	0.42%	0.41%
9	1.12%	0.78%	0.48%	0.44%	0.42%
10	1.29%	0.94%	0.62%	0.60%	0.54%
diff 10-1	0.34%	0.34%	0.43%	0.35%	0.28%
t statistics	*1.84*	*1.84*	*2.32*	*1.93*	*1.54*

This table reports monthly performance of 10 equal-Weighted mutual fund portfolios sorted by sentiment beta. First, in each month, for each stock, I estimate the sentiment beta by regressing stock excess return on the sentiment changes while controlling for standard risk factors. Second, using the last report day mutual fund holding data, I construct the mutual fund sentiment beta as value-weighted portfolio beta. Panel A presents the results from net return. Panel B presents the results from gross return.

TABLE 3 Sentiment Beta and Mutual Fund Performance: Different Holding Horizon

Panel A: 3 Months

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	2.40%	1.30%	-0.97%	-0.69%	-0.87%
2	2.65%	1.58%	-0.60%	-0.44%	-0.66%
3	2.84%	1.78%	-0.32%	-0.20%	-0.33%
4	2.72%	1.65%	-0.34%	-0.26%	-0.40%
5	2.96%	1.89%	-0.18%	-0.15%	-0.23%
6	2.83%	1.78%	-0.22%	-0.22%	-0.26%
7	3.17%	2.12%	0.00%	-0.02%	-0.03%
8	3.34%	2.28%	0.13%	0.10%	0.04%
9	3.53%	2.46%	0.16%	0.10%	0.04%
10	4.24%	3.15%	1.15%	1.34%	1.02%
diff 10-1	1.90%	1.90%	2.18%	2.08%	1.95%
t statistics	*1.94*	*1.94*	*2.17*	*2.01*	*1.76*

Panel B: 6 Months

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	5.26%	3.04%	-1.71%	-1.05%	-1.33%
2	6.37%	4.23%	-0.10%	0.50%	-0.17%
3	6.04%	3.91%	-0.42%	-0.20%	-0.56%
4	5.58%	3.42%	-0.63%	-0.51%	-0.79%
5	5.88%	3.74%	-0.39%	-0.41%	-0.58%
6	5.81%	3.69%	-0.55%	-0.69%	-0.83%
7	6.29%	4.16%	-0.02%	-0.21%	-0.25%
8	6.77%	4.63%	0.21%	-0.08%	-0.26%
9	6.97%	4.83%	0.23%	-0.12%	-0.34%
10	6.84%	4.64%	0.21%	-0.08%	-0.44%
diff 10-1	1.76%	1.76%	2.03%	1.05%	0.99%
t statistics	*2.67*	*2.67*	*2.92*	*1.61*	*1.39*

Panel C: 9 Months

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	8.08%	4.74%	-2.21%	-1.08%	-1.65%
2	8.77%	5.54%	-1.15%	-0.53%	-1.21%
3	9.08%	5.87%	-0.62%	-0.29%	-1.05%
4	9.35%	6.10%	0.12%	0.65%	-0.06%
5	8.97%	5.74%	-0.56%	-0.66%	-1.00%
6	8.95%	5.76%	-0.56%	-0.86%	-1.01%
7	9.13%	5.92%	-0.23%	-0.57%	-0.58%
8	9.90%	6.66%	0.41%	-0.13%	-0.29%
9	10.14%	6.90%	0.35%	-0.27%	-0.60%
10	10.16%	6.83%	0.56%	-0.10%	-0.65%
diff 10-1	2.27%	2.27%	2.84%	1.03%	1.06%
t statistics	*2.66*	*2.66*	*3.12*	*1.25*	*1.15*

Panel D: 12 Months

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	11.12%	6.64%	-2.04%	-0.72%	-1.83%
2	12.02%	7.68%	-1.03%	-0.41%	-1.39%
3	12.83%	8.53%	0.21%	1.03%	-0.24%
4	11.49%	7.09%	-0.78%	-0.76%	-1.59%
5	11.78%	7.42%	-0.66%	-0.82%	-1.29%

6	11.78%	7.50%	-0.84%	-1.30%	-1.50%
7	12.17%	7.86%	-0.33%	-0.78%	-0.87%
8	12.94%	8.60%	0.21%	-0.53%	-0.84%
9	13.02%	8.66%	0.15%	-0.71%	-1.18%
10	12.85%	8.40%	0.01%	-0.98%	-1.72%
diff 10-1	1.90%	1.90%	2.17%	-0.18%	0.20%
t statistics	*1.87*	*1.87*	*1.94*	*-0.17*	*0.16*

This table reports the performance of 10 equal-Weighted mutual fund portfolios sorted by sentiment beta over different time horizons. Panel A presents the performance over 3 months following portfolio construction. Panel B presents the performance over 6 months following portfolio construction. Panel C presents the performance over 9 months following portfolio construction. Panel A presents the performance over 12 months following portfolio construction.

TABLE 4 Sentiment Beta and Mutual Fund Performance: Multivariate Analysis
Panel A: Fama-MacBeth Regression

	(1) Net Return	(2) Net Return	(3) CAPM Alpha	(4) CAPM Alpha	(5) 3 Factor Alpha	(6) 3 Factor Alpha	(7) 4 Factor Alpha	(8) 4 Factor Alpha
fund_beta	0.982	0.466	2.016***	1.321***	0.136	0.102	0.335***	0.314***
	(0.86)	(0.48)	(7.46)	(7.95)	(1.04)	(0.86)	(2.91)	(2.79)
log_tna	-0.053***	-0.044***	0.028***	0.028***	0.024***	0.023***	0.020***	0.019***
	(-5.62)	(-4.54)	(15.60)	(16.40)	(16.63)	(16.71)	(15.84)	(15.03)
log_family_tna	0.034***	0.028***	-0.001	-0.001	0.003***	0.003***	0.002**	0.002***
	(5.24)	(4.51)	(-0.69)	(-0.82)	(3.72)	(3.78)	(2.18)	(2.93)
turn_over	0.016	0.007	-0.016***	-0.019***	-0.002	-0.009***	-0.031***	-0.036***
	(0.69)	(0.35)	(-4.91)	(-6.08)	(-0.44)	(-2.81)	(-11.00)	(-13.04)
age	-0.001	-0.000	-0.001***	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***
	(-1.16)	(-0.31)	(-6.17)	(-7.29)	(-15.75)	(-12.59)	(-14.18)	(-11.90)
exp_ratio	-11.516***	-11.932***	-1.034	-1.338**	-0.190	-0.671	-0.287	-0.599
	(-3.08)	(-3.41)	(-1.62)	(-2.23)	(-0.43)	(-1.52)	(-0.66)	(-1.37)
total_load	-0.029	-0.119	0.183***	0.099*	0.052	0.027	0.204***	0.205***
	(-0.11)	(-0.42)	(3.50)	(1.75)	(1.04)	(0.56)	(4.27)	(4.14)
lag_flow	-0.015	-0.019	0.159***	0.164***	0.127***	0.132***	0.123***	0.126***
	(-0.50)	(-0.60)	(16.71)	(16.02)	(19.20)	(20.14)	(18.15)	(18.93)
sigma_flow	-0.013	-0.016	0.025*	0.024*	0.048***	0.043***	0.037***	0.032**
	(-0.23)	(-0.29)	(1.83)	(1.71)	(4.35)	(3.74)	(3.12)	(2.56)
cons	1.170***	1.182***	-0.076***	0.052*	-0.072***	0.046***	-0.035***	0.084***
	(6.36)	(5.73)	(-5.47)	(1.82)	(-7.72)	(2.63)	(-4.24)	(4.99)
Style dunmmies	No	Yes	No	Yes	No	Yes	No	Yes
adj. R-sq	0.131	0.221	0.191	0.246	0.151	0.172	0.130	0.147

Panel B: Panel Regression

	(1) Net Return	(2) Net Return	(3) CAPM Alpha	(4) CAPM Alpha	(5) 3 Factor Alpha	(6) 3 Factor Alpha	(7) 4 Factor Alpha	(8) 4 Factor Alpha
fund_beta	0.884**	0.895**	1.075***	1.076***	0.418***	0.418***	0.350***	0.350***
	(2.28)	(2.31)	(30.85)	(30.87)	(14.88)	(14.87)	(12.87)	(12.86)
log_tna	-0.335***	-0.338***	0.036***	0.036***	0.033***	0.033***	0.019***	0.019***
	(-11.63)	(-11.71)	(13.58)	(13.79)	(15.42)	(15.60)	(9.31)	(9.44)
log_family_tna	-0.239***	-0.251***	-0.049***	-0.048***	-0.057***	-0.057***	-0.047***	-0.046***
	(-7.74)	(-8.10)	(-17.11)	(-16.81)	(-24.85)	(-24.45)	(-20.86)	(-20.50)
turn_over	-0.101***	-0.100***	0.005**	0.005**	0.018***	0.018***	0.003*	0.003*
	(-3.90)	(-3.88)	(2.27)	(2.26)	(9.33)	(9.32)	(1.84)	(1.84)
age	0.014***	0.016***	-0.006***	-0.006***	-0.003***	-0.004***	-0.003***	-0.003***
	(5.05)	(5.68)	(-23.33)	(-23.72)	(-16.93)	(-17.30)	(-16.03)	(-16.28)
exp_ratio	-8.639***	-8.832***	2.962***	2.974***	1.678***	1.691***	1.754***	1.764***
	(-5.20)	(-5.31)	(20.05)	(20.13)	(14.09)	(14.19)	(15.21)	(15.28)
total_load	-2.677***	-2.407**	0.778***	0.774***	0.338***	0.346***	0.470***	0.475***
	(-2.77)	(-2.47)	(8.78)	(8.69)	(4.74)	(4.82)	(6.80)	(6.83)
lag_flow	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(-0.16)	(-0.13)	(8.81)	(8.79)	(9.16)	(9.14)	(9.01)	(8.99)
sigma_flow	0.000	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.12)	(0.15)	(5.14)	(5.12)	(5.86)	(5.84)	(5.74)	(5.72)
cons	4.481***	8.546***	0.260***	0.703***	0.323***	0.357*	0.301***	0.372*
	(28.42)	(2.84)	(17.23)	(2.63)	(26.56)	(1.66)	(25.54)	(1.78)
Style dunmmies	No	Yes	No	Yes	No	Yes	No	Yes
Time fixed effcts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-sq	-0.005	-0.005	0.010	0.011	0.004	0.004	0.002	0.002

This table reports the results from multivariate analysis. Panel A presents the results from Fama-MacBeth regressions, and Panel B presents the results from panel regressions. In both Panel A and B, the dependent variable of the regression model in Columns 1 and 2 is monthly net fund return, in Columns 3 and 4 is funds' CAPM alpha, in Columns 5 and 6 is funds' 3-factor alpha, in Columns 7 and 8 is funds' 4-factor alpha. Variable definitions are summarized in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5 Sentiment Beta and Mutual Fund Performance: DGTW Decomposition

	CS	CT
1	0.01%	1.55%
	(0.08)	(3.98)
2	0.07%	1.70%
	(0.61)	(4.15)
3	0.08%	1.73%
	(0.85)	(4.17)
4	0.10%	1.79%
	(1.05)	(4.31)
5	0.15%	1.80%
	(1.73)	(4.22)
6	0.14%	1.87%
	(1.66)	(4.38)
7	0.16%	1.98%
	(1.78)	(4.61)
8	0.16%	2.01%
	(1.69)	(4.73)
9	0.24%	2.02%
	(2.15)	(4.76)
10	0.29%	2.01%
	(2.18)	(4.72)
Decile10-Decile1	0.28%	0.46%
t-statistic	(1.42)	(3.42)

This table reports the quarterly CS and CT measure of 10 equal-Weighted mutual fund portfolios sorted by sentiment beta. First, in each month, for each stock, I estimate the sentiment beta by regressing stock excess return on the sentiment changes while controlling for standard risk factors. Second, using the last report day mutual fund holding data, I construct the mutual fund sentiment beta as value-weighted portfolio beta. Third, after each quarterly report date, I construct the 10 equal-Weighted mutual fund portfolios and compute the CS and CT measure of the following quarter.

TABLE 6 The Role of Sentiment Level: Portfolio Sorting

Panel A: High Sentiment Periods

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	0.35%	-0.16%	0.05%	0.28%	0.32%
2	0.54%	0.02%	0.26%	0.37%	0.37%
3	0.65%	0.13%	0.38%	0.45%	0.46%
4	0.69%	0.17%	0.42%	0.44%	0.44%
5	0.69%	0.18%	0.43%	0.42%	0.42%
6	0.77%	0.26%	0.52%	0.49%	0.49%
7	0.82%	0.31%	0.58%	0.52%	0.52%
8	0.94%	0.42%	0.70%	0.60%	0.59%
9	1.01%	0.49%	0.76%	0.64%	0.61%
10	1.01%	0.49%	0.76%	0.63%	0.58%
diff 10-1	0.65%	0.65%	0.71%	0.35%	0.25%
t statistics	*2.54*	*2.54*	*2.30*	*1.94*	*1.72*

Panel B: Low Sentiment Periods

decile	net return	net excess return	CAPM alpha	3 factor alpha	4 factor alpha
1	1.20%	0.98%	0.15%	0.13%	0.09%
2	1.19%	0.96%	0.18%	0.18%	0.14%
3	1.11%	0.89%	0.13%	0.13%	0.11%
4	1.10%	0.87%	0.13%	0.13%	0.11%
5	1.06%	0.84%	0.10%	0.10%	0.09%
6	1.07%	0.84%	0.12%	0.12%	0.12%
7	1.12%	0.90%	0.17%	0.17%	0.18%
8	1.06%	0.84%	0.10%	0.11%	0.11%
9	1.05%	0.83%	0.07%	0.08%	0.08%
10	1.31%	1.08%	0.32%	0.33%	0.29%
diff 10-1	0.11%	0.11%	0.16%	0.20%	0.21%
t statistics	*0.42*	*0.42*	*0.62*	*0.76*	*0.78*

This table reports monthly performance of 10 equal-Weighted mutual fund portfolios in different sub-periods. Panel A presents the results during high sentiment periods. Penel B presents the results from low sentiment period.

TABLE 7 The Role of Sentiment Level: Multivariate Analysis

	(1) Net Return	(2) Net Return	(3) CAPM Alpha	(4) CAPM Alpha	(5) 3 Factor Alpha	(6) 3 Factor Alpha	(7) 4 Factor Alpha	(8) 4 Factor Alpha
Dummy	-0.783***	-0.780***	0.050***	0.049***	0.101***	0.101***	0.082***	0.082***
	(-20.18)	(-20.08)	(14.12)	(13.97)	(35.85)	(35.64)	(30.09)	(29.93)
fund_beta	0.902*	0.913*	0.692***	0.693***	0.311***	0.312***	0.221***	0.221***
	(1.84)	(1.86)	(15.77)	(15.79)	(8.84)	(8.86)	(6.47)	(6.48)
fund_beta*Dummy	0.064	0.060	0.996***	0.996***	0.257***	0.256***	0.321***	0.320***
	(0.08)	(0.08)	(14.21)	(14.21)	(4.57)	(4.55)	(5.87)	(5.85)
logtna	-0.314***	-0.315***	0.035***	0.036***	0.030***	0.030***	0.017***	0.017***
	(-10.89)	(-10.93)	(13.31)	(13.49)	(14.25)	(14.36)	(8.33)	(8.40)
log_family_tna	-0.280***	-0.290***	-0.047***	-0.047***	-0.052***	-0.052***	-0.043***	-0.042***
	(-9.07)	(-9.34)	(-16.37)	(-16.14)	(-22.73)	(-22.46)	(-19.07)	(-18.82)
turn_ratio	-0.095***	-0.094***	0.005**	0.005**	0.017***	0.017***	0.003	0.003
	(-3.68)	(-3.66)	(2.14)	(2.13)	(9.06)	(9.06)	(1.57)	(1.57)
age	0.002	0.004	-0.005***	-0.005***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.74)	(1.30)	(-20.00)	(-20.34)	(-9.07)	(-9.34)	(-9.39)	(-9.56)
exp_ratio	-9.774***	-9.913***	2.999***	3.007***	1.808***	1.815***	1.857***	1.862***
	(-5.89)	(-5.97)	(20.33)	(20.38)	(15.27)	(15.32)	(16.16)	(16.19)
front_load	-2.790***	-2.494**	0.780***	0.775***	0.365***	0.369***	0.491***	0.493***
	(-2.89)	(-2.56)	(8.83)	(8.71)	(5.14)	(5.17)	(7.12)	(7.11)
flow	-0.000	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(-0.03)	(-0.00)	(8.72)	(8.71)	(8.97)	(8.96)	(8.85)	(8.84)
sigma_flow	0.001	0.001	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.25)	(0.27)	(5.08)	(5.06)	(5.68)	(5.66)	(5.59)	(5.58)
Style dunmmies	No	Yes	No	Yes	No	Yes	No	Yes
adj. R-sq	-0.001	-0.001	0.014	0.014	0.016	0.016	0.010	0.011

This table reports the results from Fama-MacBeth Regression. The dependent variable of the regression model in Columns 1 and 2 is monthly net fund return, in Columns 3 and 4 is funds' CAPM alpha, in Columns 5 and 6 is funds' 3-factor alpha, in Columns 7 and 8 is funds' 4-factor alpha. Dummy variable equals to 1 when the sentiment is high, and 0 otherwise. Variable definitions are summarized in Appendix A. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 8 The Role of Sentiment Level: DGTW Decomposition

	High Sentiment Periods		Low Sentiment Periods	
	CS	CT	CS	CT
1	-0.32%	0.57%	0.36%	2.56%
	(-1.33)	(1.11)	(1.75)	(4.48)
2	-0.08%	0.75%	0.23%	2.68%
	(-0.55)	(1.37)	(1.27)	(4.51)
3	0.00%	0.79%	0.17%	2.70%
	(-0.01)	(1.44)	(1.13)	(4.44)
4	0.06%	0.88%	0. 14%	2.73%
	(0.45)	(1.55)	(1.02)	(4.57)
5	0.13%	0.91%	0.16%	2.72%
	(1.15)	(1.59)	(1.28)	(4.36)
6	0.14%	0.91%	0.13%	2.85%
	(1.30)	(1.62)	(1.04)	(4.55)
7	0.16%	1.10%	0.16%	2.87%
	(1.22)	(1.92)	(1.31)	(4.59)
8	0.19%	1.1 7%	0.14%	2.87%
	(1.37)	(2.05)	(1.01)	(4.65)
9	0.28%	1.25%	0.20%	2.82%
	(1.80)	(2.21)	(1.23)	(4.50)
10	0.25%	1.25%	0.33%	2.79%
	(1.37)	(2.20)	(1.70)	(4.44)
Decile10-Decile1	0.57%	0.68%	-0.03%	0.23%
t-statistic	(1.94)	(3.62)	(-0.11)	(1.22)

This table reports the quarterly CS and CT measure of 10 equal-Weighted mutual fund portfolios sorted by sentiment beta. Columns 1 and 2 are the results during high sentiment periods. Columns 3 and 4 are the results during low sentiment periods. First, in each month, for each stock, I estimate the sentiment beta by regressing stock excess return on the sentiment changes while controlling for standard risk factors. Second, using the last report day mutual fund holding data, I construct the mutual fund sentiment beta as value-weighted portfolio beta. Third, after each quarterly report date, I construct the 10 equal-weighted mutual fund portfolios and compute the CS and CT measure of the following quarter.

TABLE 9 Evidence from The Change of Mutual Fund Holding Position

	Corr	High Sentiment Periods	Low Sentiment Periods
1	-2.30%	-2.19%	-2.39%
	(-3.51)	(-2.22)	(-2.73)
2	-1.40%	-0.40%	-2.30%
	(-2.32)	(-0.52)	(-2.55)
3	-0.83%	-0.56%	-1.09%
	(-1.54)	(-0.76)	(-1.37)
4	-1.02%	0.11%	-2.05%
	(-1.92)	(0.16)	(-2.65)
5	-0.21%	0.61%	-0.96%
	(-0.37)	(0.86)	(-1.07)
6	-0.96%	-0.53%	-1.34%
	(-1.89)	(-0.75)	(-1.85)
7	-0.50%	0.22%	-1.1 6%
	(-1.02)	(0.31)	(-l.68)
8	-1.03%	-0.56%	-1.45%
	(-1.76)	(-0.61)	(-1.99)
9	-1.04%	-1.26%	-0.84%
	(-1.79)	(-1.33)	(-1.19)
10	-1.34%	0.02%	-2.57%
	(-1.92)	(0.02)	(-2.86)
Decile10-Decile1	0.96%	2.21 %	-0.18%
t-statistic	(1.06)	(1.68)	(-0.15)

Table 9 reports the correlation coefficient between mutual fund portfolio net buys and stock mispricing score. The mutual fund net buys are calculated from the change of holdings. Stambaugh et al. (2015) mispricing score is the arithmetic average of its ranking percentile of the 11 anomalies. Column 1 presents the results from the whole sample. Column 2 reports the results during high sentiment periods. Column 3 presents the results from low sentiment periods.

TABLE 10 Skills and the Sentiment Beta Mutual Fund Performance Relation

	(1)	(2)	(3)	(4)
	R-Sqr	R-Sqr	Trans R-Sqr	Trans R-Sqr
fund_beta	-0.069***	-0.044**	-0.624***	-0.402***
	(-3.96)	(-2.35)	(-4.36)	(-2.97)
logtna	0.003***	0.003***	0.042***	0.042***
	(8.77)	(9.31)	(11.31)	(10.63)
log_family_tna	0.004***	0.004***	0.036***	0.037***
	(25.29)	(20.58)	(22.15)	(19.54)
turn_ratio	-0.009***	-0.008***	-0.082***	-0.072***
	(-16.23)	(-15.63)	(-17.76)	(-16.05)
age	-0.000***	-0.000***	-0.001***	-0.001***
	(-6.10)	(-5.45)	(-3.76)	(-6.68)
exp_ratio	-2.599***	-2.435***	-19.843***	-18.041***
	(-24.79)	(-24.02)	(-29.56)	(-28.59)
front_load	0.036***	0.042***	0.493***	0.657***
	(4.08)	(4.36)	(5.57)	(6.49)
flow	-0.001	-0.001	-0.012	-0.019*
	(-1.18)	(-1.52)	(-1.26)	(-1.88)
sigma_flow	-0.014***	-0.014***	-0.149***	-0.146***
	(-6.59)	(-6.40)	(-6.18)	(-5.81)
cons	0.901***	0.882***	3.062***	2.877***
	(325.98)	(173.98)	(107.95)	(65.45)
Style dunmmies	No	Yes	No	Yes
adj. R-sq	0.174	0.197	0.353	0.381

Table 10 reports the results of regression of R-square on mutual fund sentiment beta and other known determinants of fund performance. The dependent variable is R-square and the transformation of R-square. Each month, I estimate the R-square for each fund by running a 36-month rolling window regression of fund excess return on 4 factors. Variable definitions are summarized in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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