Sentiment Risk and Hedge Fund Returns

Yong Chen
Texas A&M University
ychen@mays.tamu.edu

Bing Han
University of Toronto
bing.han@rotman.utoronto.ca

Jing Pan
University of Utah
jing.pan@utah.edu

December 20, 2014

Abstract

This paper documents a new and important cross-sectional determinant of hedge fund returns, their exposures to sentiment risk, measured as beta of fund returns to fluctuations in sentiment proxies. For a large sample of equity-oriented hedge funds, those whose sentiment beta ranks in the top decile subsequently outperform the bottom decile by 0.67% per month, after controlling for fund's exposures to existing risk factors. Sentiment risk is also priced in stocks, but it explains only a small friction of the abnormal return spread between high versus low sentiment-beta hedge funds. High sentiment-beta funds tend to increase their exposures to sentiment risk the most when doing so turns out to be profitable. This positive sentiment timing contributes to the abnormal performance of high sentiment-beta hedge funds.

Keywords: Hedge funds, sentiment risk, sentiment timing, alpha

* We are grateful to seminar and session participants at the Chinese University of Hong Kong, Nanyang Technological University, Peking University, Shanghai University of Finance and Economics, Singapore Management University, Texas A&M University, Virginia Tech, and the 2014 China International Conference in Finance for very helpful comments. We also thank Zhi Da, Ken French, David Hsieh, Lubos Pastor, and Jeffrey Wurgler for making a large amount of data available on their websites. All remaining errors are our own.

1. Introduction

Hedge funds have become an important investment vehicle in financial markets. During the past two decades, the hedge fund industry experienced dramatic growth in both number of funds and assets under management.[1] One of the main reasons for the fast growth of hedge funds is their superior performance. The academic literature has generally documented significant alpha delivered by hedge funds, and superior performance by top hedge funds cannot be explained by pure luck.[2] Understanding the sources of such superior performance is an important motivation for our paper.

In this paper, we examine whether sentiment risk can explain hedge fund returns in the cross section. We measure sentiment risk as the unexpected changes in the measures of sentiment including the widely adopted Baker and Wurgler (2006) investor sentiment index as well as the Michigan Index of Consumer Sentiment and the Da, Engleberg, and Gao (2014) index of Financial and Economic Attitudes Revealed by Search based on daily internet search volume from millions of households. Our central finding is that hedge fund exposure to sentiment risk, i.e., sentiment beta, is significantly and positively related to their expected returns, above and beyond the impact of financial and macroeconomic factors identified in previous studies.[3] This finding is robust and suggests that sentiment risk is priced in the cross-section of hedge fund returns.

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[1] According to Lipper TASS, the hedge fund industry has evolved from a few hundred funds managing less than $50 billion in the early 1990s to over 9,000 funds managing more than $2 trillion by the end of 2010. The total hedge fund capital increases to about $2.8 trillion in the third quarter of 2014 according to HFR and BarclayHedge.

[2] For example, Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Liang (1999), Kosowski, Naik, and Teo (2007), Fung, Hsieh, Naik, and Ramadorai (2008), and Titman and Tiu (2011) document abnormal performance in hedge funds. One exception is Griffin and Xu (2009) who find that in aggregate, hedge funds have similar (or slightly better) stock picking ability compared with mutual funds.

[3] The existing studies on hedge funds have suggested a wide range of financial and macroeconomic factors to capture hedge fund returns, including equity factors (market, size, liquidity factors), interest rate-related factors (term premium and credit spread), options-related and trend-following factors, and macroeconomic factors (e.g., inflation and default premium). See, e.g., Fung and Hsieh (1997, 2001, 2004), Agarwal and Naik (2004), Getmansky, Lo, and Marakov (2004), Sadka (2010), Bali, Brown, and Caglayan (2011, 2012, 2013), and Teo (2011).

A common belief is that hedge funds, as sophisticated investors, are able to exploit mispricing caused by noise traders. However, as suggested in the seminal work of DeLong, Shleifer, Summers, and Waldmann (1990), the sentiment of noise traders can fluctuate and move asset prices further away from fundamental values, which impose a systematic risk on arbitrageurs. Another motivation for our test of whether sentiment is a priced risk comes from the previous findings that sentiment risk is non-diversifiable because investor sentiment influences many securities in the same direction and at the same time (e.g., Baker and Wurgler (2006), Lemmon and Portniaguina (2006)), noise trades are correlated and have systematic price impact (e.g., Barber, Odean, and Zhu (2009)). Moreover, a large economic literature has documented that sentiment forecasts consumption expenditures and real activities.[4] Thus, sentiment may serve as a state variable under Merton (1973)'s intertemporal capital asset pricing model. Our paper examines whether hedge funds' exposures to sentiment risk explain part of their superior performance.

Our analysis covers 5,329 equity-oriented hedge funds over the period of 1994–2010. Each month, we run a time-series regression of a given hedge fund's returns over the previous 36 months on the sentiment risk factor while controlling for financial and macroeconomic factors, and use the regression coefficient as the fund's sentiment beta for that month. Then, we examine the cross-sectional relation between sentiment beta and future hedge fund returns using both portfolio sorts and Fama-MacBeth (1973) regressions. For example, when we sort funds into 10 portfolios based on their sentiment beta, the top decile on average outperforms the bottom decile by about 0.47% in the following month (t-statistic = 3.35). After controlling for the Fung and Hsieh (2004) seven factors, momentum, liquidity, inflation rate and default premium (Bali,

[4] See, e.g., Mishkin (1978), Carroll, Fuhrer, and Wilcox (1994), and Bram and Ludvigson (1998). Ludvigson (2004) surveys more recent studies documenting the predictability of consumer confidence (such as the Michigan Index of Consumer Sentiment) for aggregate consumption growth. Souleles (2004) finds that the Michigan Index is useful in forecasting the one-quarter-ahead consumption of individual households, even after controlling for lagged consumption growth, other household characteristics and several macroeconomic variables.

Brown, and Caglayan, 2011), the spread of alpha between the top and bottom decile portfolios sorted on sentiment beta becomes even larger, at 0.67% per month (t-statistic = 3.33). According to the Fama-MacBeth regressions, when sentiment beta increases from -1.29 (the average value of sentiment beta for the bottom decile funds) to 1.14 (the average value of sentiment beta for the top decile funds), the average return is expected to increase by 0.61%.

Since our study focuses on equity hedge funds, our finding may reflect a sentiment risk premium in the stock market if high sentiment beta funds hold more stocks with larger exposures to sentiment risk and less or even short positions in stocks with lower exposure to sentiment risk. Indeed, we find that during our sample period, sentiment beta is also priced in equity markets and spreads stock returns. A portfolio that is long in stocks ranked in the top decile sorted by sentiment beta and short in stocks from the bottom decile has a significantly positive average return (about 0.55% per month). Further, this portfolio's return is positively correlated with the return of the 10 minus 1 spread portfolio of hedged funds sorted by sentiment beta. However, the sentiment beta portfolio of stocks explains only less than 10% of the alpha of the portfolio of hedged funds sorted by sentiment beta. After controlling for the sentiment beta portfolio of stocks, the alpha of the portfolio of hedged funds sorted by sentiment beta is still economically and statistically significant. This is consistent with hedge funds employing dynamic and potentially nonlinear trading strategies.

We explore a new form of market timing: do hedged funds display positive timing ability with respect to fluctuation in investor sentiment? Our sentiment-timing test extends Henriksson and Merton (1981) to a new setting. Using bootstrap analysis, we find strong evidence that at least 10% of the hedge funds displays significant positive sentiment timing ability: they increase exposures to the sentiment factor when the high sentiment-beta stocks outperform low sentiment-beta stocks. Such nonlinear comovement pattern between hedge funds and the high minus low portfolio of stocks sorted by sentiment-beta explains why the latter portfolio (whose return captures the sentiment risk premium in the stock market) cannot fully explain the return spread between high and low sentiment-beta hedged funds. Further, we find that the sentiment timing ability increases monotonically as sentiment beta increases across funds. Funds ranked in the top decile by sentiment beta tend to increases their exposure the most to sentiment risk exactly when doing so turns out to be profitable. Such positive sentiment timing contributes to the abnormal performance of high sentiment-beta hedge funds.

To gain further insights, we conduct a wide array of additional analyses and robustness checks. We first examine the returns to the high-minus-low sentiment-beta portfolio for different holding periods as long as twelve months. We find that the average return spread declines with the holding period, suggesting that the outperformance of high sentiment-beta funds is concentrated in the near future. For example, the high minus low sentiment-beta portfolio of hedge funds has a monthly alpha of 0.63%, 0.54%, 0.46%, and 0.31% over the next 3-, 6-, 9-, and 12-month periods, respectively. This also suggests time variation in hedge fund's sentiment beta, which could result from the dynamic nature of hedge fund trading strategies. Indeed, we find that only about 60% (50%) of the funds ranked in the top decile by sentiment beta in a month still remains in the top decile after 6 months (12 months).

We also examine how the relation between hedge fund returns and their sentiment beta depend on various proxies of market conditions. In general, we find that high-sentiment beta hedge funds on average significantly outperform low sentiment-beta funds mainly when the market return is high, or market volatility is high, or during periods of high economic activity.

On the other hand, our results are robust across both high flow funds and low flow funds, and hold for alternative measures of sentiment risk.

Our paper makes several important contributions to the literature. First, our results contribute to a better understanding of how investor sentiment affects asset returns. We document that a non-fundamental risk—sentiment risk—is priced for hedge fund returns. Though prior studies has examined whether the *level* of investor sentiment can predict stock market returns and whether sentiment can serve as a *conditioning variable* in cross-sectional asset pricing tests,[5] we differ from them by focusing the role of *sentiment beta* (as opposed to sentiment level) in explaining asset returns. Our paper is the first to investigate the impacts of sentiment risk for hedge funds, arguably the group of traders most exposed to such risk.

Second, our paper relates to a growing literature on what drives performance in hedge funds. Fung and Hsieh (2004) propose a seven-factor model that can explain time-series variations in hedge fund returns. Sadka (2010) and Teo (2011) show that liquidity risk can help to explain the cross-section of hedge fund returns, especially for funds imposing less strict redemption restrictions. Bali, Brown, and Caglayan (2011) show that default premium beta and inflation beta significantly predict hedge funds' future returns. Bali, Brown, and Caglayan (2012) find that several measures of systematic risk have significant explanatory power for the cross section of hedge fund returns. Recently, Bali, Brown, and Caglayan (2013) show that hedged funds' exposure to macroeconomic uncertainty is positively related to future fund returns. Furthermore, Patton and Ramadorai (2013) find that hedge fund risk exposure varies over time. Cao, Chen, Liang, and Lo (2013) show that hedge fund's market risk varies with aggregated market liquidity condition. We find that some hedge funds' exposures to the sentiment risk vary with market conditions.

[5] See, e.g., Lee, Shleifer, and Thaler (1991), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Yu and Yuan (2011), and Stambaugh, Yu, and Yuan (2012).

For example, high sentiment-beta hedge funds exhibit significant positive sentiment timing, and this partly explains their high abnormal returns.

Finally, our study contributes to an ongoing debate of fund alpha versus beta, i.e., managerial skill versus systematic risk exposure. Titman and Tiu (2011) find that hedge funds with low exposure to systematic factors have high alpha. Our finding suggests that part of abnormal return of hedge funds may be compensation for noise trader risk. This lends support to Cochrane (2011) who argues that the previously documented alpha may be attributed to "exotic beta."[6]

The rest of this paper is organized as follows. Section 2 provides justification about why sentiment risk can be priced. Section 3 describes the data. Section 4 reports the main findings about the relation between sentiment beta and hedge fund returns. In Section 5, we present additional tests and robustness checks. Finally, section 6 concludes.

2. Why Can Sentiment Risk be Priced?

This section explains the mechanism through which sentiment risk can command a risk premium. The debates about whether sentiment of noise traders can affect asset prices date back at least to Keynes (1936) and Friedman (1953). Keynes argues that market prices can be viewed as the outcome of investor sentiment ("animal spirits"), while Friedman contends that sophisticated investors will trade against irrational investors and quickly eliminate mispricing. Since then, there have been both theoretical and empirical advances suggesting that sentiment risk can be priced in securities markets.

[6] Cochrane (2011, p.1087) argues that "there is no 'alpha.' There is just beta you understand and beta you do not understand."

DeLong, Shleifer, Summers, and Waldmann (1990) model investor sentiment as a general tendency to speculate, which can cause security prices to deviate from fundamental values. Arbitrageurs betting against mispricing face the risk that sentiment can become more extreme and prices move even further away from fundamental values. Hence, the fluctuation of investor sentiment generates a systematic risk for which sophisticated investors must be compensated with higher returns. An implication of their model is that investors that have greater exposures to sentiment risk should, on average, earn larger expected returns (see, e.g., Baker and Wurgler (2006)).

Shleifer and Vishny (1997) make a related argument that betting against investor sentiment is costly and risky. As a result, arbitrage costs and risks limit arbitrageurs' capacity to aggressively and quickly force asset prices back to fundamentals as Friedman (1953) suggests. In this setting, the fluctuation of noise trader sentiment is one source of arbitrage risk.

Dumas, Kurshev, and Uppal (2009) consider a general-equilibrium model in which some investors are overconfident while others are rational. In their setting, difference in beliefs is time varying because the beliefs of rational investors get revised differently from those of the overconfident investors. Overconfident agents change their expectations too often, sometimes being excessively optimistic, sometimes being excessively pessimistic. In the model, sentiment risk refers to the fluctuations in the probability beliefs of overconfident agents relative to agents with the proper beliefs. Overconfident traders introduce an additional source of risk, the "noise-trader risk", for rational arbitrageurs, thereby creating a limit to arbitrage. Sentiment risk carries a risk premium in the model because sentiment, or difference in beliefs, enters the state price density.

Anther motivation for why sentiment may be a priced risk factor comes from a literature in economics documenting that consumer sentiment can forecast future changes in consumption expenditures even after controlling for lagged consumption growth, other household characteristics and several macroeconomic variables (e.g., Mishkin (1978), Carroll, Fuhrer, and Wilcox (1994), and Bram and Ludvigson (1998), Ludvigson (2004) and Souleles (2004)). This suggests that sentiment could be a relevant state variable under Merton (1973)'s intertemporal capital asset pricing model (ICAPM). Thus, sentiment beta may command a return premium.

On the empirical ground, prior studies have shown that sentiment has a pervasive and systematic effect on asset prices. Shiller (1981) finds that stock prices are excessively volatile relative to their future realized values, suggesting that prices move for reasons other than information about fundamentals. One source of the excess volatility is fluctuations in investor sentiment. Baker and Wurgler (2006) find that sentiment affects stocks of similar characteristics in similar ways.[7] Lemmon and Portniaguina (2006) present evidence that consumer confidence negatively predicts future returns of small stocks. Barber, Odean, and Zhu (2009) document that correlated trading of retail investors driven by sentiment. As sentiment influences sufficiently many securities in the same direction and at the same time, sentiment risk is non-diversifiable and may be priced in equilibrium.

Finally, Han (2008) provides additional empirical motivation for examining the cross-sectional implication of sentiment exposure on expected returns. It is well known that index option prices can be used to estimate the Arrow-Debreu state prices or the asset pricing kernel (e.g., Breeden and Litzenberger, 1978). Han (2008) shows that investor sentiment significantly affects S&P500 index option prices and hence the pricing kernel. Given that the pricing kernel depends

[7] For example, when beginning-of-period sentiment is low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks.

on investor sentiment, fundamental asset pricing theorem implies that the expected returns of risky assets should be related to their exposure to investor sentiment risk.

3. Data and Variables

This section describes our data and the key variables for the empirical work. We use four sources of data to study the role of sentiment risk exposures in explaining hedge fund returns. First, our data on hedge fund returns and characteristics are from Lipper TASS. Second, we use the Baker and Wurgler (2006) sentiment index as proxy for aggregate investor sentiment, while we also consider two alternative sentiment proxies. Third, we control for funds' exposures to financial and macroeconomic factors. Finally, we obtain monthly stock returns from the Center for Research on Security Prices (CRSP). Our sample period spans from January 1994 to December 2010.

3.1 Hedge fund data

Individual hedge funds in TASS are classified into 11 categories according to their primary investment strategies: convertible arbitrage, dedicated short bias, event driven, emerging markets, equity market neutral, fixed income arbitrage, funds of funds, global macro, long-short equity, managed futures, and multi-strategy. Our study focuses on equity-oriented hedge funds. We exclude the strategies of fixed income arbitrage, emerging markets and managed futures. We also remove dedicated short bias funds because this category contains too few individual funds. As a result, there are seven categories of funds remaining in our sample. The definitions of these hedge fund categories are provided in the Appendix.

TASS covers both active and defunct hedge funds since 1994, and our sample includes both of them to mitigate survivorship bias. To address the concerns that fund returns may be backfilled when funds are newly added to the database, we exclude the first 12 months of returns for each fund. Following prior research, we include only funds that report monthly net-of-fee returns and allow for redemption at a monthly or higher frequency.[8] We also delete duplicate funds. Finally, we require sample funds to have assets under management (AUM) of at least $5 million.[9] Given these filters, our sample has 5,329 unique equity hedge funds. The top one percent of returns is winsorized to prevent outliers from affecting our analyses.

Table 1 reports descriptive statistics of hedge fund excess return (in excess of one-month T-bill rate) and characteristics. Panel A shows that the number of hedge fund increases rapidly from 387 in 1994 to 2888 in 2008 and then declines to 2109 in 2010 after the recent financial crisis. The average monthly excess return ranges from a low of -1.66% in 2008 to a high of 1.5% in 1999. During our sample period, hedge funds earn the highest returns in 1999, the peak of tech bubble. They experience the lowest returns in 2008 during the financial crisis. Panel B reports the summary statistics by investment style. Across the different styles of funds we study, long/short equity hedge funds have the highest monthly excess return of 0.58% during our sample period, while funds of funds have the lowest average excess return of 0.19% per month.

Table 1 Panel C reports the summary statistics of fund characteristics including management fee, incentive fee, minimum investment amount, fund size, lockup period, total redemption notice period, and whether the fund has a high water mark. These summary statistics are similar

[8] Teo (2011) classifies hedge funds allowing for monthly redemptions or better as funds granting favorable redemption terms. Aragon (2007) finds a positive relationship between the hedge funds' use of redemption restrictions and the illiquidity of the underlining assets. Thus, hedge funds in our sample hold relatively liquid assets.

[9] Our results are robust when we exclude funds with AUM under $10 million or the first 24 months of fund returns in the TASS database.

to and comparable with those in the previous studies that use the TASS data on hedge funds. There is no selection bias in our sample of hedge funds.

3.2 Sentiment measures

Our main sentiment proxy is the Baker and Wurgler (2006) monthly market-wide investor sentiment index. The index starts from July 1965, and derives from six proxies of investor sentiment: closed-end fund discount, the number and the first-day returns of IPO's, NYSE turnover, the equity share in total new issues, and the dividend premium. To remove the potential impacts of business cycles on these six sentiment proxies, Baker and Wurgler regress each of six proxies on a set of measures for the economics cycles and use the residuals from the regressions as the orthogonalized proxies for sentiment. The sentiment-change index is the first principal component of changes in six orthogonalized sentiment proxies. Throughout this paper, our empirical tests use the Baker-Wurgler sentiment-change index as the main proxy for sentiment risk.

Figure 1 plots the Baker-Wurgler sentiment-change index over our sample period. This index is highly volatile, ranging from a low value of about -3.0 to a high value of around 3.0. The standard deviation of the monthly sentiment index is 1.11. The mean and median of the sentiment index are both about zero. The distribution of the sentiment index is roughly symmetric around zero, with the 25th (75th) percentile being -0.66 (0.65).

For robustness, we use two alternative sentiment proxies. The first is the monthly University of Michigan Consumer Sentiment index, which is based on surveys of consumer confidence. The second is the Financial Economic Attitudes Revealed by Search (FEARS) index proposed by Da, Engelberg, and Gao (2014), which is based on Internet searches for keywords revealing households' concerns. The original FEARS index is measured at daily frequency but goes back to only January 2004. We convert it into monthly frequency by taking average of the daily sentiment index values within each month in order to match the frequency of hedge fund returns data. We use monthly change in the University of Michigan Consumer Sentiment index or the FEARS index to proxy for sentiment risk. We do not take change in FEARS index because the original FEARS index already captures change in sentiment.

3.3 Other risk factors

In addition to the sentiment risk, we include various factors identified in the literature to affect the risk exposures and expected returns of hedge funds (e.g. Fung and Hsieh, 2004; Bali, Brown, Caglayan, 2011; Teo, 2011).

We first consider for the seven factors proposed in Fung and Hsieh (2004): equity market factor (MKT-RF) and the size factor (SMB), the change in the constant maturity yield of the 10-year Treasury (YLDCHG), the change in the spread between Moody's Baa yield and the 10-year Treasury (BAAMTSY), and three trend-following factors for bonds (PTFSBD), for currency (PTFSFX), and for commodities (PTFSCOM). As the factors of YLDCHG and BAAMTSY are non-traded factors, one cannot interpret the regression intercept as alpha. To calculate alphas, we replace the two factors by returns of tradable factor mimicking portfolios. Specially, we use the spread between 10-year treasury constant maturity rate and risk-free rate (ΔTerm) to mimic the change in term spread, and use the spread between Barclays corporate bond Baa index and 10-year treasury constant maturity rate (ΔCredit) to proxy the change in credit spread. Many recent studies use the Fung-Hsieh seven-factor model to examine hedge fund performance (e.g., Kosowski, Naik, and Teo, 2007; Titman and Tiu, 2011).

We further control for the inflation rate and default premium (as the spread between the yields on the BAA-rated and AAA-rated corporate bonds). This is motivated by Bali, Brown, and Caglayan (2011) who find that among 15 financial and macroeconomic risk factors they tested, betas with respect to these two factors are significantly related to the cross-section of hedge fund returns. We also control for the Carhart (1997) momentum factor, and following Teo (2011), we use the Pastor and Stambaugh (2003) aggregate liquidity factor to control for liquidity risk.[8]

Panel A of Table 2 reports the summary statistics of these risk factors. Panel B presents the correlation matrix of the sentiment index and other factors. The main take-away is that sentiment does not significantly co-vary with any of the other factors. The factors that are most correlated with sentiment are equity market factor and size factor, and the correlations are 0.33 and 0.34 respectively. This suggests that investor sentiment tends to increase when the stock market performs well, especially when small cap stocks outperform large cap stocks. Based on these positive correlations, we expect that if sentiment factor is priced, it would carry a positive risk premium. The only other factor whose correlation with sentiment is larger than 0.1 in magnitude is inflation. Also, the Baker-Wurgler bears a positive correlation with the University of Michigan Consumer Sentiment index, and a negative correlation with the FEARS index. This makes sense since the FEARS index captures investors' pessimistic attitudes toward financial markets.

[8] For robustness, we control for additional factors such as the Agarwal and Naik (2004) option return factors, the Hirshleifer and Jiang (2010) misevaluation factor, and the Gao, Gao, and Song (2014) "rare disaster" factor. Our results are unchanged. See the Internet Appendix for the details of the tests.

4. Empirical Results

In this section, we first report the relation between sentiment beta and hedge fund returns based on portfolio sorts. Then, we perform Fama-MacBeth regressions to evaluate the effect of sentiment risk on hedge fund returns, while controlling for fund characteristics. Next, we examine potential relations between sentiment beta and fund characteristics. Finally, we investigate whether the stock-level return spread based on sentiment beta can explain our finding of sentiment-beta based spread in hedge fund returns, and report evidence about sentiment timing.

4.1 Sentiment-beta sorted portfolios

We start by analyzing the relationship of sentiment beta and hedge fund returns using portfolio sorts. Each month starting from January 1997, we form ten equal-weighted hedge fund portfolios based on their loadings on the sentiment-change index (i.e., sentiment beta). These hedge fund portfolios are rebalanced every month. The sentiment beta for each fund is calculated each month by regressing the fund's monthly excess return on the sentiment-change index, controlling for other factors suggested in the literature that affect hedge fund returns. For each hedge fund with at least 30 non-missing returns observations over the prior 36 months, we estimate the following model using the past 36-month rolling window.

$$\text{Excess return}_{i,t} = \alpha + \beta_0 \text{Sentiment}_t + \beta' \mathbf{f}_t + \varepsilon_t \qquad (1)$$

where i=1, 2…N funds, t=1…T months, β_0 is the sentiment risk loading of fund i. The vector f contains the Fung-Hsieh seven-factors, the momentum factor, the Pastor-Stambaugh liquidity factor, as well as the inflation rate and default spread (see Section 3.3). The 36-month rolling window provides sufficient observations to estimate the sentiment risk loading while allowing for time variation in the sentiment beta.

Therefore, portfolio formation begins in January 1997 and ends in December 2010 (168 monthly observations). We then evaluate the performance for each of the ten portfolios by regressing their monthly portfolio returns on the Fung-Hsieh seven factors, the momentum factor, and the liquidity risk factor. The regression intercept is fund alpha. The difference in alpha between high sentiment-beta funds (portfolio 10) and low sentiment-beta funds (portfolio 1) represents the dispersion in expected returns as a result of hedge funds' different exposures to the sentiment risk that is not accounted for by exposures to other factors.

Table 3 reports both the excess return and alpha for each portfolio. Throughout the paper, we base statistical inference on Newey-West standard errors unless otherwise indicated. Table 3 shows an economically and statistically significant spread in the excess returns between high sentiment-beta hedge funds (portfolio 10) and low sentiment-beta hedge funds (portfolio 1) at 0.47% per month (t-statistic = 3.35). After controlling for the other factors, the spread in alpha between portfolio 10 and portfolio 1 becomes even more remarkable, both economically and statistically, at 0.67% per month (t-statistic = 3.33). The t-statistics are high, given our sample period of only 14 years. These results suggest that hedge funds with high sentiment risk exposure earn a significant positive return premium and outperform those with low sentiment risk exposure.

As a robustness check, we also examine gross fund returns by adding fund fees, including management fee and incentive fee, back to net returns, and repeat the above analysis. Our inference is unchanged by using pre-fee returns. The details are not reported to conserve space but available upon request.

4.2 Fama-MacBeth regressions of hedge fund returns

To control for fund characteristics that may affect both fund performance and their sentiment beta, we run the Fama-MacBeth (1973) regressions of monthly hedge fund returns or alphas on funds' sentiment beta, controlling for fund characteristics and investment styles.

We first calculate monthly fund risk-adjusted return relative to the Fung-Hsieh seven factors, the momentum factor, and Pastor-Stambaugh factor for each hedge fund with at least 36 months return observations. Hence,

$$\mathrm{Alpha}_{\mathrm{i,t}} = \mathrm{Excess\ return}_{\mathrm{i,t}} - \beta'\mathbf{f}_{\mathrm{t}}, \qquad (2)$$

where i=1, 2…N funds, t=1…T months, $\mathrm{Alpha}_{i,t}$ is the risk-adjusted return of fund i for month t, and Excess $\mathrm{return}_{i,t}$ is fund return in excess of the risk-free rate. The vector f contains the realizations of the Fung-Hsieh seven-factors, the momentum factor, and the Pastor-Stambaugh liquidity factor in month t.

Next, we estimate the following cross-sectional regression for monthly hedge fund alphas (as well as excess returns as the dependent variable):

$$\mathrm{Alpha}_{\mathrm{i,t}} = \lambda_0 + \lambda_1 \mathrm{Sentiment\ Beta}_{\mathrm{i,t-1}} + \lambda' \mathbf{x}_{\mathrm{i,t-1}} + \mathrm{e}_{\mathrm{i,t}}\ , \qquad (3)$$

where $\mathrm{Sentiment\ Beta}_{\mathrm{i,t-1}}$ is β_0 of fund i for month t-1 estimated from model (1) using past 36-month rolling estimation window. Besides the sentiment beta, the independent variables are various fund characteristics including log of fund age, log of fund size, management fee, incentive fee, the high-water mark dummy, minimum investment, lockup period, and redemption notice period, and investment category dummies.

Table 4 reports the results of the Fama-MacBeth cross-sectional regressions. In both univariate (with sentiment beta as the only independent variable) and multivariate regressions, with either fund excess return or alpha as the dependent variable, the coefficient on sentiment beta is positive and significant. This reveals a robust positive relationship between sentiment risk exposure and hedge fund performance. The coefficients of control variables are generally consistent with prior studies. For example, funds with high-watermark, older funds, funds with higher management fee and higher minimum investment amount tend to have better performance. After controlling for fund characteristics, the regression coefficient of hedge fund excess return on sentiment beta is 0.25 (t-statistic=3.42). Thus, when sentiment beta increases from -1.29 (the average value of sentiment beta for the bottom decile, see Table 5) to 1.14 (the average value of sentiment beta for the top decile), the average return is expected to increase by 0.61% according to the Fama-MacBeth regression. This collaborates the results about the effect of sentiment beta on hedge fund returns in Table 3 based on portfolio sorts.

4.3 Hedge fund sentiment beta and fund characteristics

Given the significant relationship between hedge fund expected returns and sentiment risk exposure, it is useful to know what determines the fund's sentiment beta. To identify a possible link of fund characteristics to sentiment beta, we examine average fund characteristics for hedge funds within each of the ten sentiment-beta sorted portfolios. The fund characteristics include management fee, incentive fee, the high-water mark dummy, minimum investment, fund age, fund size, lockup period, and redemption notice period.

Table 5 reports the result. The sentiment beta ranges from an average of -1.29 in the low sentiment-beta portfolio (decile 1), to -0.05 and 0.05 in the middle portfolios (deciles 5 and 6 respectively), and to 1.14 in the high sentiment-beta portfolio (decile 10). However, across the fund characteristics we look at, none of them has a monotonic relationship with sentiment beta. For example, average incentive fee is 17.64% in the high sentiment-beta portfolio, while the low sentiment-beta portfolio has an average incentive fee of 17.54%. So the difference in incentive fee between the two extreme portfolios is only as small as 0.1%. Moreover, we find no monotonic pattern in terms of incentive fee (or any other fund characteristic) across the ten portfolios. In general, the average fund characteristics exhibit rather small differences between the two extreme portfolios.

The result is important for understanding the source of hedge fund performance. Some funds maintain large exposure to sentiment risk and earn a higher return on average as a result of bearing the risk. On the other hand, funds' exposure to sentiment risk is not significantly associated with fund attributes, especially unrelated to such characteristics as incentive fee and lockup period that potentially reveal managerial skill (e.g., Aragon, 2007). This lends support to Cochrane's (2011) argument that hedge fund alpha may reflect "exotic beta."

4.4 Can our results be explained by sentiment risk premium for stocks?

Since we focus on equity hedge funds, it is possible that the positive relation between hedge fund returns and their sentiment beta arises only because a similar relation holds for the stock market—it might be that hedge funds with higher sentiment beta hold stocks that are more exposed to investor sentiment risk and sentiment risk commands a positive premium in the stock market. To test whether sentiment risk can also influence the cross-section of stock returns, we obtain monthly stock returns from the Center for Research on Security Prices (CRSP) over our sample period. Following common practice, we restrict the sample to common stocks listed at NYSE, AMEX, and NASDAQ.

Table 6 examines whether sentiment beta spreads stock return and if so, whether our results for equity hedge funds is a mere reflection of such a relation for stocks. Panel A of Table 6 uses the same approach as Table 3, but replaces hedge funds with individual stocks. We estimate sentiment beta of each stock using 36-month rolling window and then form 10 portfolios of stocks sorted by their sentiment beta. We find that over the 1994-2010 sample period, sentiment beta significantly spreads stock returns. The high sentiment-beta minus low sentiment-beta portfolio of stocks has an average raw return of 0.55% per month (t-statistic = 2.7) and a Fama-French 3-factor model alpha of 0.48% per month (t-statistic = 2.4), which is lower than the alpha of the high minus low sentiment-beta portfolio of hedged funds (see Table 3).

Table 6 Panel B reports the results of a time-series regression where the dependent variable is the returns of the portfolio of the high minus low sentiment beta hedge funds, with the key regressor being the returns of the spread portfolio of stocks sorted by sentiment beta. We also control for standard risk factors for hedge funds. There is a significant and positive correlation between the returns of the two spread portfolios sorted on sentiment beta (one for stocks, and the other for hedge funds). However, after we control for the top-minus-bottom spread portfolio of stocks sorted by their sentiment beta, high sentiment beta hedge funds still earn significantly higher returns. The alpha of the portfolio of the high minus low sentiment beta hedge funds becomes 0.63% after controlling for the portfolio of high minus low sentiment beta stocks. This barely changes from the 0.67% alpha of the spread portfolio of hedge funds in Table 3. Thus, the positive relation between equity hedge fund returns and their sentiment beta cannot be simply explained by the effect of sentiment risk in the stock market.

In an unreported table (available upon request), we find that equity mutual funds whose sentiment betas rank in the top decile on average outperform those in the bottom decile by 0.30% next month, which is about half the magnitude as the case for hedge funds.[9] More importantly, once we control for returns of the high sentiment beta minus low sentiment beta portfolio of stocks, the effect of sentiment beta for mutual funds becomes insignificant, both economically and statistically. This is in sharp contrast to our results for hedge funds. One explanation for this contrast is that hedge funds engage in dynamic trading strategies with nonlinear payoff patterns. We next explore such an explanation.

4.5 Sentiment timing of hedge funds

It is well known that hedge funds use dynamic trading strategies and have time-varying systematic risk exposures (Fung and Hsieh, 1997, 2001; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004; Cao, Chen, Liang, and Lo 2013, Patton and Ramadorai, 2013). As one form of dynamic strategies, actively timing means that fund managers adjust their risk exposures based on forecasts about market conditions. For example, in the case of market timing (e.g., Henriksson and Merton, 1981), managers with positive timing ability tilt their portfolios to have a high (low) loading on the aggregate stock market when the market return turns out to be high (low). Here, we examine a new type of timing activity—sentiment timing: do hedged funds display positive timing ability with respect to fluctuation in investor sentiment?

Specifically, for each hedge fund with at least 30 monthly return observations, we perform the following sentiment timing regression:

[9] Similarly, Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2003) use equity mutual fund flows as a proxy for investor sentiment, and find that the exposure to sentiment is positively associated with fund returns.

$$r_{i,t} = \alpha + \beta\, sent\text{-}factor_t + \gamma\, sent\text{-}factor_t * I(sent\text{-}factor_t > 0) + controls + e_t, \qquad (4)$$

where $r_{i,t}$ is the excess return on fund i in month t. *sent-factor* is the return on the top-minus-bottom sentiment-beta stock portfolio (as described in Section 4.4). $I(sent\text{-}factor_t>0)$ is a dummy variable that equals one when the return on the high-minus-low sentiment-beta stock portfolio is positive, and zero otherwise. The control variables includes the other factors described in Section 3.3. The coefficient γ measures sentiment timing, and a significantly positive γ coefficient means that the fund tends to increase its exposure to the sentiment factor when high sentiment beta stocks outperform low sentiment beta stocks.

Table 7 Panel A presents the cross-sectional distribution of *t*-statistic for the sentiment-timing coefficient across hedge funds. For the ease of illustration, the table shows the percentage of times where the *t*-statistics exceed the indicated cutoff values corresponding to various significance level under the normal distributional assumption. For our sample, 27% of the funds have *t*-statistics greater than 1.28 (i.e., 10% significance level in the right tail), whereas only 8.76% have t-statistics smaller than -1.28 (i.e., 10% level in the left tail). Thus, right tails appear thicker than the left tails. Overall, the distribution suggests that there exist sentiment timing among hedge funds, and the evidence of positive timing is more pronounced than negative timing.

However, it is important to note that the above inference is drawn based on the normality assumption, and hedge fund returns often do not follow normal distributions. Moreover, when we evaluate timing across a sample of funds, a multiple hypothesis testing issue arises—by random chance some funds will appear to have "significant" *t*-statistics under the conventional levels even if their true timing coefficient is zero. Next, we employ a bootstrap analysis to assess the significance of the timing coefficients without the normality assumption. The bootstrap analysis helps determine whether or not the estimated timing coefficients occur by chance.

Our bootstrap procedure follows Kosowski, Timmermann, White, and Wermers (2006) and Fama and French (2010), both of which building on Efron (1979). The basic idea of the bootstrap analysis is that we randomly resample the data (e.g., residuals from regression equation (4)) to generate hypothetical funds that, by construction, have the same factor loadings as the actual funds but have no timing ability, and then we evaluate if the *t*-statistics of the estimated timing coefficients for the actual funds are different from the bootstrapped distribution that contains no funds with timing ability. The details of our bootstrap procedure are described in the Internet Appendix.

Panel B of Table 7 reports the empirical *p*-values corresponding to the *t*-statistics of sentiment-timing coefficients in both tails. For all extreme percentiles considered, the result shows that top (positive) sentiment-timing funds are unlikely to be due to pure chance. For the sample funds, the $t_{\hat{\gamma}}$'s for the top 1%, 2.5%, 5% and 10% most positive sentiment-timing coefficient are 3.52, 2.97, 2.52 and 2.1, respectively, with empirical *p*-values all close to zero. Meanwhile, the empirical *p*-values in the left tail at the bottom 1%, 2.5%, 5% and 10% levels are all rather large and close to one.

Panel C of Table 7 reports the relationship between sentiment beta and sentiment timing. We first place hedge funds into ten deciles by their sentiment beta, and find that sentiment timing moves monotonically with the level of sentiment beta. Then, we sort hedge funds by their sentiment timing, and find that sentiment beta moves nearly monotonically with sentiment timing. Therefore, funds ranked in the top decile by sentiment beta tend to increases their exposure the most to sentiment risk exactly when doing so turns out to be profitable. Such positive sentiment timing contributes to the abnormal performance of high sentiment-beta hedge funds.

In sum, the analysis above shows strong evidence that a portion of hedge funds exhibit a nonlinear comovement with the high minus low portfolio of stocks sorted by sentiment-beta that is consistent with a positive sentiment timing ability: they increase exposures to the sentiment factor when the high sentiment-beta stocks outperform low sentiment-beta stocks. This nonlinear comovement pattern is consistent with prior findings that hedge funds use dynamic trading strategies and have time-varying systematic risk exposures. It explains why the sentiment-beta return spread in hedge funds cannot be fully explained by the sentiment risk premium for stocks.

5. Additional Results and Robustness

In this section, we investigate in greater depth the relation between sentiment beta and hedge fund returns. We first examine long-horizon effect of sentiment risk on hedge fund returns. Then, we investigate the relation between sentiment risk exposure and hedge fund returns in three subperiods. Next, we take into account the heterogeneity among hedge funds in terms of their fund flows. We also analyze the relation between sentiment risk exposure and hedge fund returns during periods of different levels of investor sentiment. Finally, we show the robustness of our results to alternative sentiment measures.

5.1 Long-horizon effect of sentiment risk

We have thus far focused on the relation between hedge fund sentiment beta and fund average return over the next month. Here, we examine long-term effect of sentiment risk exposure. Table 8 reports the average monthly returns of portfolios of hedge funds sorted by their sentiment beta over various holding horizon (ranging from 3 months to 12 months) after portfolio formation.

We find the average monthly excess returns and alphas both decline with the length of holding period. Over the next 3 (resp. 6, and 9) months, the hedge funds belonging to the top sentiment beta decile on average outperform those from the bottom decile by 0.39% (resp. 0.30%, and 0.24%) per month. At the 12-month horizon, the difference in return shrinks to 0.17%, which is no longer statistically significant. Similar finding holds for alpha. The high minus low sentiment-beta portfolio of hedge funds has a monthly alpha of 0.63%, 0.54%, 0.46%, and 0.31% over the next 3-, 6-, 9-, and 12-month periods, respectively.

The results in Table 8 are consistent with the time variation in hedge fund's sentiment beta, which could result from the dynamic nature of hedge fund trading strategies. In untabulated tests, we find that only about 60% (resp. 50%) of the hedge funds currently ranked in the top decile by sentiment beta still remains in the top decile after 6 months (resp. 12 months).

5.2 Subperiod analysis

Table 9 repeats the portfolio sorts in Table 3 separately for three sub-periods: from 1997 to 2001, from 2002 to 2006, and from 2007 to 2010. The effect of sentiment beta on hedge fund return is significant both economically and statistically for the first and the third subperiods. For example, from 1997 to 2001, high sentiment-beta hedge funds on average outperform low sentiment-beta funds by 0.67% (t-statistic = 2.32) per month or an alpha of 0.95% (t-statistic = 3.15) per month. From 2007 to 2010, high sentiment-beta hedge funds on average outperform low sentiment-beta funds by 0.84% (t-statistic = 4.18) per month or an alpha of 0.64% (t-statistic = 2.01) per month. For the middle subperiod from 2002 to 2006, there is no significant difference in the average return or alpha between the top and the bottom decile hedge funds sorted by their sentiment beta. This is a period characterized by low market volatility and low sentiment volatility. Given this and the short time-series, the insignificance could be due to a lack of statistical power for our test.

5.3 Effect of fund flows

Now, we examine how the relation between sentiment beta and hedge fund returns may be affected by fund flow, given fund flow is likely to affect fund trading and thus both fund's exposure to sentiment risk and returns.

Following the literature, we measure net fund flow for each fund i as the percentage change in assets under management of the fund between the beginning and the end of month t, net of investment returns, assuming flows are invested at the end of the period:

$$\mathrm{Flow}_{i,t} = \frac{\mathrm{AUM}_{i,t} - \mathrm{AUM}_{i,t-1}(1 + r_{i,t})}{\mathrm{AUM}_{i,t-1}} \quad (5)$$

where $\mathrm{AUM}_{i,t}$ is asset under management of fund i in month t, and $r_{i,t}$ is after-fee return for fund i in month t. The top one percent of flows is winsorized to prevent outliers from affecting our analysis.

Each month, we first sort hedge funds into terciles (low, medium and high) based on their net flow. Within each group, hedge funds are then sorted into quintiles based on their sentiment beta. Table 10 reports the average returns of the portfolios over the next month after portfolio formation, separately among the high flow funds (Panel A) and among the low flow funds (Panel B). When fund flows are high, the high sentiment beta quintile funds on average outperform the low sentiment beta quintile funds by 0.29% (t-statistic = 2.15). By comparison, the difference becomes 0.36% (t-statistic = 3.03) among the low flow funds. Similar comparison holds for alpha. While the effect of sentiment risk is somewhat stronger among funds that just experienced lower inflows (or larger outflows), it is economically and statistically significant for the high flow funds as well.

5.4 Effect of market conditions

In Table 11, we study whether the relation between sentiment beta and hedge fund return depends on the prevailing market conditions at the time of portfolio formation. We use four proxies of market conditions: level of investor sentiment; U.S. aggregate stock market return; market volatility level; and level of economic activity. This analysis is motivated by Stambaugh, Yu, and Yuan (2012). They document that many asset pricing anomalies are profitable only when the initial level of investor sentiment is high.

Following Stambaugh, Yu, and Yuan (2012), we classify each month into either high-sentiment period or low-sentiment period based on whether the beginning of the month value of Baker-Wurgler sentiment index is higher or lower than its median value over the sample period January 1997 to December 2010. Each month, hedge funds are sorted into ten portfolios based on their sentiment beta. Table 11 Panel A reports the next month average return of the ten portfolios, separately for the months when the initial sentiment level is high and for the months when the initial sentiment level is low.

The relation between hedge fund return and sentiment beta is significantly positive for the high sentiment periods. It has the right sign, is economically significant but statistically insignificant during the low sentiment periods. Thus, our result is stronger for the high sentiment periods than for the low sentiment periods. Similarly, Table 11 Panels B, C, and D show that the significant positive relation between hedge fund return and sentiment beta mainly holds when market return is high, market volatility is high. It is significant for both high and low states of economic activities, although the result is stronger and more significant during periods of high economic activities.

5.5 Using alternative sentiment measures

As a robustness check, we use two alternative sentiment proxies: the University of Michigan Consumer Sentiment index and the FEARS index proposed by Da, Engelberg, and Gao (2014) based on Internet searches. Table 12 reports that, based on the two alternative proxies for sentiment, there is still an economically and statistically significant spread in both hedge fund's excess return and alpha between those funds with high exposures to the sentiment risk and those with low sentiment-beta. For example, corresponding to the University of Michigan Consumer Sentiment index, high sentiment-beta hedge funds on average outperform low sentiment-beta funds by 0.3% (t-statistic = 2.01) per month or an alpha of 0.44% (t-statistic = 1.88) per month. Note that the FEARS index of Da, Engelberg, and Gao (2014), as a measure of households' concerns, is negatively correlated to proxies of sentiment risk based on the Baker-Wurgler index or University of Michigan Consumer Sentiment index. Thus, the negative return for the spread portfolio based on the FEARS index is consistent with the positive relation between hedge fund returns and their exposures to sentiment risk.

6. Conclusion

In this paper, we examine whether fluctuation in investor sentiment is a priced risk factor in hedge funds. Using a large sample of equity hedge funds from January 1994 to December 2010, we find a significant and positive relation between sentiment beta and future returns of hedge funds. Funds that ranked in the top decile by sentiment beta on average outperform those in the bottom decile by 0.67% over the next month, even after controlling for financial and macroeconomic risk factors identified in previous studies on hedge fund returns. Fama-MacBeth regression results confirm this positive relation, after further controlling for fund characteristics. The positive relation between sentiment beta and hedge fund return cannot be explained by a similar effect of sentiment risk in the stock market, or by the effect of fund flows. We also find evidence of sentiment timing that cannot be attributed to pure randomness.

Our paper contributes to a better understanding of how sentiment matters for asset pricing. We are the first to show that exposure to the fluctuations in investor sentiment is positively related to hedge fund returns. Our paper also contributes to the alpha versus beta debate surrounding hedge fund performance. We find that sentiment beta is uncorrelated with fund characteristics indicating fund skill, such as incentive fee and lockup period for redemption. Thus, for those funds with high sentiment beta, what appears to be alpha with respect to the risk factors used in previous studies could partially be compensations for exposures to sentiment risk.

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Figure 1 Time series of the Baker-Wurgler sentiment factor

This figure plots monthly time series of the Baker and Wurgler sentiment-change index for the period Jan 1994 to Dec 2010. The Baker and Wurgler (2007) sentiment index derives from six proxies of investor sentiment: closed-end fund discount, the number and the first-day returns of IPO's, NYSE turnover, the equity share in total new issues, and the dividend premium. To remove the potential impacts of business cycle on these six sentiment proxies, Baker and Wurgler regress each of six proxies on a set of measures for the economics cycles and use the residuals from the regressions as the orthogonalized proxies for sentiment. Their sentiment-change index is the first principal component of changes in six orthogonalized sentiment proxies.

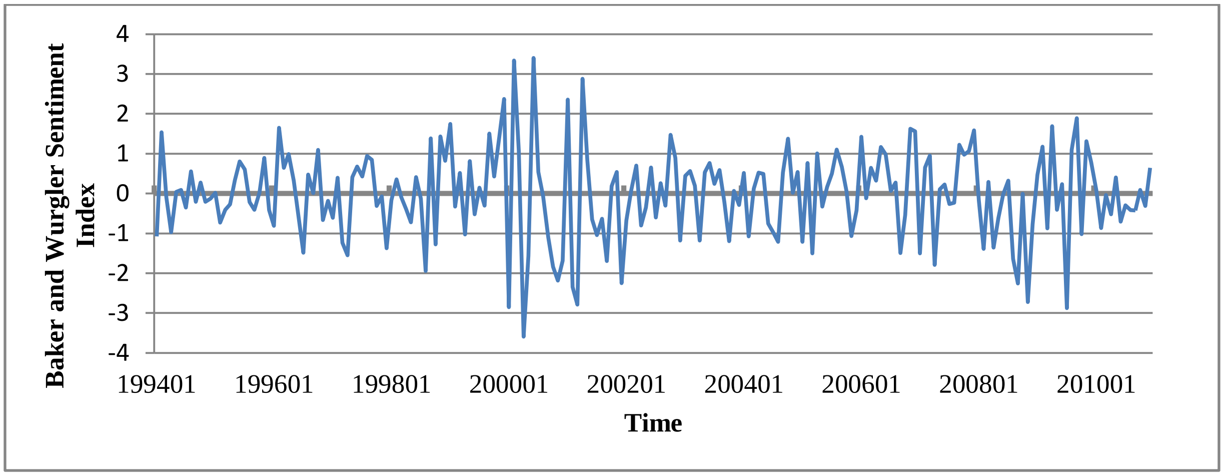
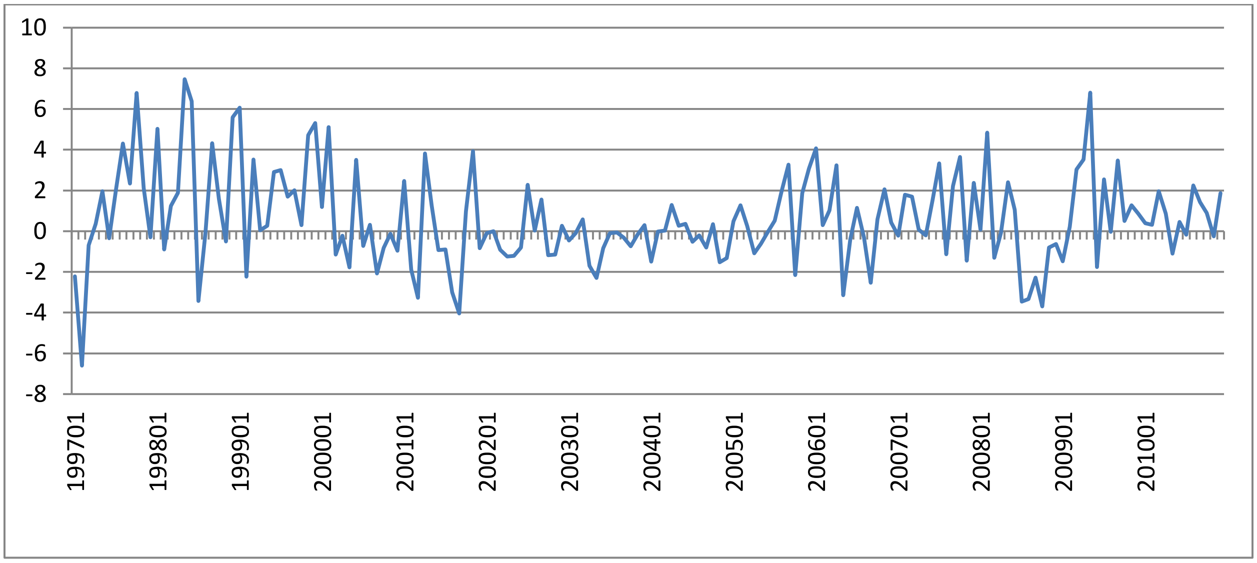


Figure 2 Time series of high-minus-low sentiment-beta portfolio of hedge funds

This figure plots the time series of returns of the high-minus-low sentiment-beta portfolio of hedge funds. In each month, hedge funds are sorted into 10 equally weighted portfolios based on their sentiment betas. The sentiment beta for each fund is estimated by regressing the fund's monthly excess returns on the sentiment index, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.. We use a rolling window of 36 previous months data to estimate the sentiment beta for each hedge fund that has at least 30 non-missing return observations in the previous 36 months. The panels plot the returns to the high-minus-low portfolio for one-, three-, and six-month holding periods.

Panel A. One-month holding period



Panel B. Three-month holding period

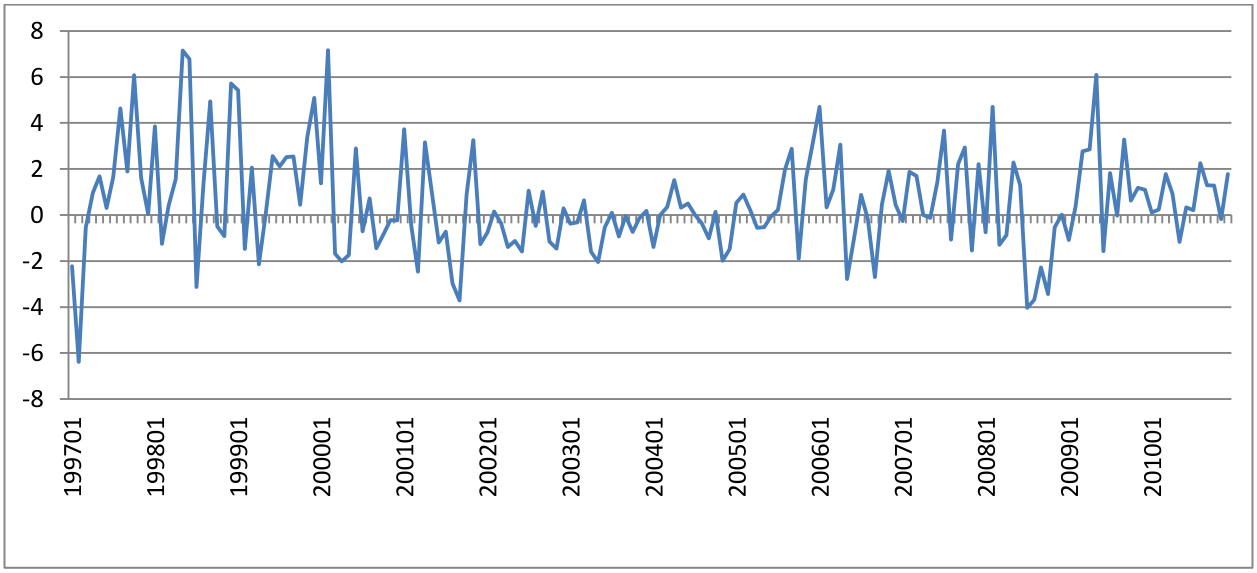


Figure 2, cont.

Panel C. Six-month holding period

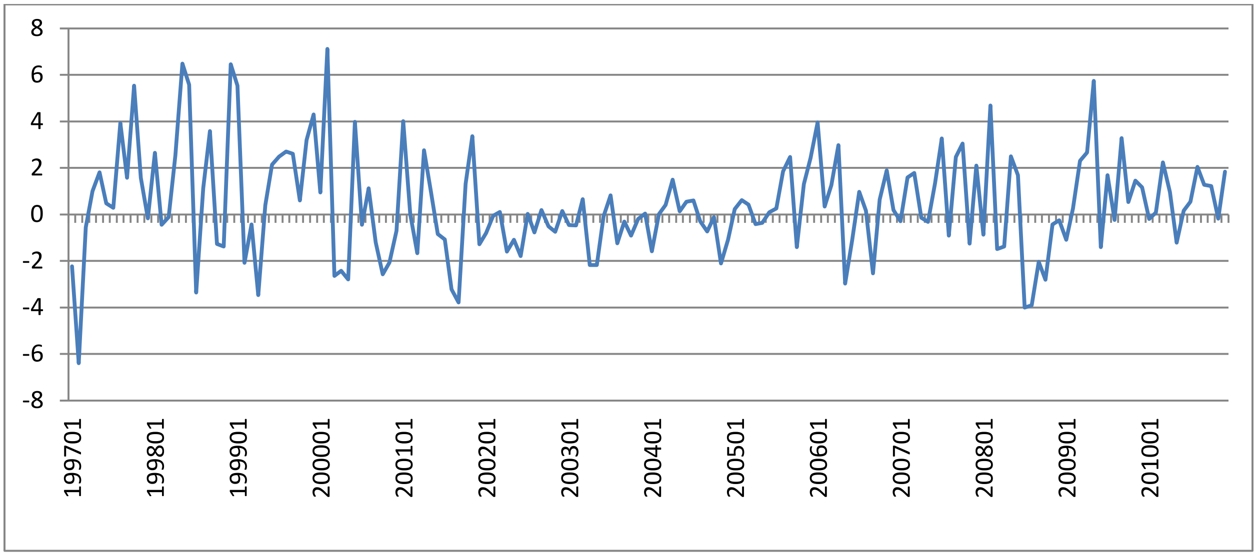


Table 1 Summary statistics of hedge funds

The hedge fund data are from Lipper TASS. The database covers both active and defunct hedge funds. For each fund, the first 12 months of return are excluded to address backfilling bias. Our sample includes only equity-oriented funds that report net-of-fee returns in US dollar on a monthly basis and have assets under management of at least $5 million. Panel A summarizes monthly fund excess returns (in excess of one-month T-bill rate) over years, and Panel B summarizes monthly fund returns across fund categories. The returns are in percent. Panel C summarizes fund characteristics. Fund characteristics include management fee, incentive fee, the high-water mark dummy (1 if a high-water mark provision is used and 0 otherwise), minimum investment, log of fund age, log of fund size, lockup period, and redemption notice period. The sample period is from January 1994 to December 2010.

	# of funds	Mean	Median	STD	25%	75%
Panel A: Average fund returns by year						
1994	387	-0.45	-0.28	3.56	-2.27	1.18
1995	517	1.03	0.77	3.73	-0.61	2.46
1996	689	0.88	0.79	3.89	-0.66	2.42
1997	827	0.95	0.73	4.31	-0.86	2.82
1998	1,023	0.26	0.38	5.17	-1.86	2.62
1999	1,195	1.50	0.82	4.73	-0.70	3.24
2000	1,423	0.16	0.29	5.31	-2.10	2.25
2001	1,582	0.08	0.25	4.14	-1.26	1.55
2002	1,752	-0.16	0.11	3.56	-1.30	1.16
2003	2,025	1.22	0.81	2.93	-0.06	2.06
2004	2,265	0.56	0.43	2.66	-0.49	1.51
2005	2,460	0.41	0.43	2.72	-0.80	1.54
2006	2,576	0.56	0.53	2.70	-0.56	1.65
2007	2,742	0.43	0.46	3.07	-0.87	1.73
2008	2,888	-1.66	-1.05	4.54	-3.75	0.91
2009	2,375	1.24	0.87	3.70	-0.34	2.52
2010	2,109	0.57	0.49	3.36	-0.83	1.95
Overall	5,329	0.37	0.42	3.76	-1.01	1.79
Panel B: Average fund returns by category						
Convertible Arbitrage	186	0.35	0.44	2.84	-0.38	1.23
Event Driven	537	0.50	0.51	2.9	-0.39	1.55
Equity Market Neutral	309	0.28	0.26	2.42	-0.77	1.32
Fund of Funds	1845	0.19	0.39	2.82	-0.84	1.39
Global Macro	303	0.53	0.32	4.13	-1.48	2.27
Long/Short Equity	1773	0.58	0.54	4.6	-1.60	2.73
Multi-strategy	376	0.46	0.51	3.47	-0.75	1.72

Table 1, continued

Panel C: Summary of fund characteristics

	Mean	Median	STD	25%	75%
Management fee (%)	1.35	1.40	0.51	1.00	1.50
Incentive fee (%)	15.29	20.00	7.34	10.00	20.00
High-water mark dummy	0.63	1.00	0.48	0.00	1.00
Minimum investment ($mil)	0.88	0.50	1.41	0.10	1.00
Log(fund age)	4.54	4.60	0.58	4.16	4.99
Log(fund size)	17.44	17.50	1.75	16.34	18.62
Lockup period (mo.)	3.82	0.00	6.25	0.00	12.00
Notice period (mo.)	1.34	1.00	0.88	1.00	2.00

Table 2 Summary Statistics of sentiment index and other factors

In the table, Panel A describes the Baker-Wurgler sentiment-change index, the University of Michigan consumer confidence index, and the FEARS index as proxies for investor sentiment. The other factors include the Fung-Hsieh seven factors namely the market index, size factor, ΔTerm as a tradable factor mimicking the change in the constant maturity yield of the ten-year Treasury, ΔCredit as a tradable factor mimicking the change in the spread between Moody's Baa yield and the ten-year Treasury, and three trend-following factors on bonds (Ptfsbd), foreign exchange (Ptfsfx) and commodity (Ptfscom), as well as the momentum factor (UMD), the Pastor-Stambaugh liquidity factor, inflation rate (INF), and the default spread (DEF) between the yields on Baa-rated and Aaa-rated corporate bonds. Panel B reports the correlations between these indexes and factors. The sample period is January 1994 to December 2010.

Panel A: Summary statistics

	Mean	STD	1%	25%	Median	75%	99%
BW sentiment index	-0.02	1.11	-2.85	-0.66	0.03	0.65	2.88
Michigan consumer confidence	-0.04	4.97	-15.91	-2.82	-0.15	2.49	10.14
FEARS index	0.00	0.03	-0.11	-0.02	0.00	0.02	0.09
Mktrf	0.51	4.71	-10.76	-2.34	1.27	3.56	8.76
SMB	0.24	3.67	-6.78	-2.07	-0.06	2.40	7.66
ΔTerm	0.14	0.11	-0.08	0.06	0.13	0.24	0.33
ΔCredit	0.24	2.70	-7.75	-1.23	0.30	1.57	6.02
Ptfsbd	-1.45	14.97	-23.74	-11.50	-4.82	3.96	43.65
Ptfsfx	0.00	19.41	-29.74	-13.13	-4.31	8.85	66.01
Ptfscom	-0.38	13.77	-22.72	-9.60	-2.95	5.94	39.62
UMD	0.48	5.65	-16.31	-1.30	0.71	3.06	13.20
Liquidity	0.01	0.04	-0.09	-0.01	0.01	0.03	0.11
INF	0.20	0.35	-1.01	0.05	0.20	0.40	0.91
DEF	0.96	0.48	0.55	0.68	0.84	1.08	3.09

Table 2, cont.

Panel B: Correlations

	Sentiment	Confdns	FEARS	Mktrf	SMB	ΔTerm	ΔCredit	Ptfsbd	Ptfsfx	Ptfscom	UMD	Liquidity	INF	DEF
BW sentiment index	1.00													
Michigan consumer confidence	0.27	1.00												
FEARS index	-0.13	0.25	1.00											
Mktrf	0.33	0.03	-0.07	1.00										
SMB	0.34	0.04	-0.01	0.23	1.00									
ΔTerm	0.00	0.01	-0.06	0.04	0.16	1.00								
ΔCredit	0.00	-0.05	0.03	0.35	0.06	-0.03	1.00							
Ptfsbd	-0.01	-0.05	-0.01	-0.20	-0.06	-0.04	-0.01	1.00						
Ptfsfx	-0.10	0.06	0.19	-0.18	-0.01	-0.06	-0.12	0.23	1.00					
Ptfscom	-0.04	0.10	0.12	-0.13	-0.03	-0.05	-0.08	0.18	0.38	1.00				
UMD	-0.03	0.08	0.02	-0.28	0.09	-0.06	-0.17	-0.01	0.12	0.21	1.00			
Liquidity	0.01	0.00	0.09	0.09	0.03	0.01	0.07	-0.01	-0.16	-0.08	0.03	1.00		
INF	0.28	0.05	0.06	0.03	0.02	-0.02	-0.15	-0.19	-0.14	-0.08	0.02	0.08	1.00	
DEF	-0.07	-0.04	-0.03	-0.12	0.06	0.30	0.11	0.05	0.07	-0.02	-0.21	0.00	-0.25	1.00

Table 3 Sentiment risk and hedge fund returns: Portfolio sorts

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds constructed based on the funds' sentiment beta. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the Baker-Wurgler sentiment-change index, with controls of the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Based on funds' sentiment beta, we form 10 equal-weighted portfolios that are rebalanced each month. For each portfolio, alpha is estimated based on the monthly time-series of the portfolio relative to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. The monthly excess return and alpha are reported in percent. The t-statistics are based on Newey-West standard errors.

Portfolio	Excess return	t-stat	Alpha	t-stat
10 (High)	0.73	3.13	0.52	2.56
9	0.47	2.72	0.27	2.02
8	0.43	2.78	0.22	1.52
7	0.34	2.55	0.14	1.19
6	0.32	2.38	0.15	1.22
5	0.29	2.09	0.07	0.49
4	0.34	2.45	0.17	1.41
3	0.37	2.33	0.13	1.00
2	0.36	2.20	0.18	1.29
1 (Low)	0.26	1.28	-0.14	-0.72
Spread (10 minus 1)	0.47	3.35	0.67	3.33

Table 4 Fama-MacBeth regressions of fund returns on sentiment beta

This table reports results from Fama-MacBeth regressions of hedge fund excess return, as well as alpha, on funds' sentiment beta with controls of characteristics and categories. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the Baker-Wurgler sentiment-change index, with controls of the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Then, we perform cross-sectional regressions of fund excess return (or alpha) on sentiment beta with controls of fund characteristics and categories. Fund characteristics include management fee, incentive fee, the high-water mark dummy (1 if a high-water mark provision is used and 0 otherwise), minimum investment, log of fund age, log of fund size, lockup period, and redemption notice period. The t-statistics are based on Newey-West standard errors.

	Dependent Variable							
	Excess Return				Alpha			
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.64	3.67	-0.24	-0.48	0.26	4.05	-0.85	-2.97
Sentiment Beta	0.27	3.38	0.25	3.42	0.17	3.29	0.16	3.53
Management fee			0.08	1.60			0.11	4.17
Incentive fee			0.00	0.25			0.01	2.64
High-water mark			0.17	4.24			0.10	3.99
Minimum investment			0.03	2.11			0.03	3.89
Log(fund age)			0.32	5.00			0.18	3.80
Log(fund size)			-0.06	-2.20			-0.01	-1.10
Lockup period			0.01	0.11			-0.05	-1.22
Notice period			0.03	1.22			0.03	1.57
Category Dummies	No		Yes		No		Yes	
Adj. R^2	0.02		0.08		0.02		0.06	

Table 5 Sentiment risk and fund characteristics

This table reports average fund characteristics for ten equal-weighted portfolios of hedge funds sorted by their sentiment beta. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the Baker-Wurgler sentiment-change index, with controls of the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, and the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Fund characteristics include management fee, incentive fee, the high-water mark dummy (1 if a high-water mark provision is used and 0 otherwise), minimum investment, log of fund age, log of fund size, lockup period, and redemption notice period.

Portfolio	Sentiment beta	Mfee	Ifee	HWM	Min. inv	Log(age)	Log(size)	Lockup	Notice
10 (High)	1.14	1.28	17.64	0.60	0.77	4.82	17.32	0.38	1.16
9	0.49	1.29	16.61	0.56	0.86	4.84	17.58	0.31	1.26
8	0.27	1.30	14.90	0.54	0.91	4.87	17.76	0.29	1.36
7	0.15	1.29	13.90	0.55	1.02	4.88	17.90	0.29	1.42
6	0.05	1.31	13.48	0.56	1.03	4.89	17.99	0.29	1.51
5	-0.05	1.32	13.57	0.55	1.01	4.90	17.95	0.27	1.46
4	-0.15	1.31	14.44	0.57	0.99	4.88	17.82	0.29	1.43
3	-0.30	1.34	15.74	0.59	0.96	4.86	17.70	0.30	1.32
2	-0.55	1.37	16.92	0.60	0.84	4.84	17.49	0.32	1.21
1 (Low)	-1.29	1.38	17.54	0.61	0.83	4.81	17.19	0.33	1.09
Spread (10 minus 1)	2.43	-0.10	0.10	-0.01	-0.05	0.01	0.13	0.04	0.07

Table 6 Sentiment Beta and Stock Returns

In the table, Panel A reports the returns of ten portfolios of stocks sorted by sentiment beta over the first month after portfolio formation. In each month for each stock with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the stock's excess returns on the Baker-Wurgler sentiment-change index, with controls of the Fama-French-Carhart four factors namely the market index, size factor, value factor, and momentum factor. Panel B reports the result of a time-series regression, with differences in returns between high and low sentiment-beta hedge funds as the dependent variable, and the returns of a spread portfolio of stocks (high-minus-low sentiment beta) and other risk factors as the independent variables. The t-statistics are based on Newey-West standard errors.

Panel A: Portfolio sorts of stocks

Portfolio	Excess return	t-stat	Alpha	t-stat
10 (Highest)	1.31	1.66	0.64	2.01
9	1.20	1.92	0.55	2.86
8	1.10	2.00	0.48	3.15
7	0.91	1.87	0.30	2.43
6	0.89	1.98	0.27	2.33
5	0.82	1.80	0.22	1.81
4	0.87	1.91	0.32	2.69
3	0.71	1.47	0.09	0.68
2	0.71	1.27	0.07	0.45
1 (Lowest)	0.77	1.04	0.15	0.57
Spread (10 minus 1)	0.55	2.70	0.48	2.40

Panel B: Regressing the return spread of high-minus-low sentiment-beta hedge funds on the return spread of high-minus-low sentiment-beta stocks and other factors.

Dependent variable = return spread of high-minus-low sentiment-beta hedge funds		
	Coeff.	t-stat
Intercept	0.63	3.27
Stock sentiment-beta spread	0.22	4.42
Mktrf	0.11	3.28
SMB	0.00	0.02
ΔTerm	-1.76	-1.76
ΔCredit	-0.14	-2.78
PTFSBD	0.01	1.57
PTFSFX	-0.01	-1.04
PTFSCOM	0.01	0.88
UMD	-0.01	-0.49
Liquidity	0.40	0.12

Table 7 Sentiment timing

This tables reports the results about sentiment timing. For each hedge fund with at least 30 return observations over the sample period January 1994 to December 2010, we perform the following regression:

$$r_{i,t} = \alpha + \beta\, sent\text{-}factor_t + \gamma\, sent\text{-}factor_t * I(sent\text{-}factor_t > 0) + controls + e_t,$$

where $r_{i,t}$ is the excess return on fund i in month t. *sent-factor* is the return on the top-minus-bottom sentiment-beta stock portfolio. $I(sent\text{-}factor_t>0)$ is a dummy variable that equals one when the return on the high-minus-low sentiment-beta stock portfolio is positive, and zero otherwise. The coefficient γ measures sentiment timing. The control variables include the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Panel A presents the distribution of t-statistic for the sentiment-timing coefficient in the cross section of hedge funds. The numbers shown in the parentheses are significance level under the normality assumption. Panel B presents the results of the bootstrap analysis of sentiment timing, in which the first row reports the sorted *t*-statistics of sentiment-timing coefficients across individual funds, and the second row is the empirical *p*-values from bootstrap simulations. The t-statistics are based on Newey-West standard errors. The number of resampling iterations is 1,000. Panel C reports the relation between sentiment beta and sentiment timing.

Panel A: Cross-sectional distribution of t-statistic of sentiment timing coefficient

	Percentage of the funds					
# of funds	$T \leq -1.96$ (2.5%)	$T \leq -1.65$ (5%)	$T \leq -1.28$ (10%)	$T \geq 1.28$ (10%)	$T \geq 1.65$ (5%)	$T \geq 1.96$ (2.5%)
3,345	3.26%	5.26%	8.76%	27.00%	18.36%	12.59%

Panel B: Bootstrap analysis of sentiment timing

# of funds		Bottom *t*-statistics for $\hat{\gamma}$				Top *t*-statistics for $\hat{\gamma}$			
		1%	2.5%	5%	10%	10%	5%	2.50%	1%
3,345	t-statistic	-2.66	-2.15	-1.69	-1.15	2.10	2.52	2.97	3.52
	p-value	0.90	0.98	1.00	1.00	0.00	0.00	0.00	0.00

Panel C: Relation between sentiment beta and sentiment timing

Sort by sentiment beta			Sort by sentiment timing		
Portfolio	Sentiment beta	Sentiment timing	Portfolio	Sentiment timing	Sentiment beta
10 (High)	1.14	0.22	10 (High)	1.49	0.27
9	0.49	0.15	9	0.72	0.20
8	0.27	0.12	8	0.47	0.16
7	0.15	0.11	7	0.31	0.05
6	0.05	0.10	6	0.20	0.01
5	-0.05	0.09	5	0.11	0.07
4	-0.15	0.07	4	0.02	0.01
3	-0.30	0.05	3	-0.10	-0.02
2	-0.55	0.00	2	-0.30	-0.06
1 (Low)	-1.29	-0.07	1 (Low)	-0.99	-0.34

Table 8 Long-horizon analysis

In each month, hedge funds are sorted into ten equally weighted portfolios based on their sentiment beta. Portfolios are then held for different holding periods, i.e. 3-, 6-, 9- and 12-month. This table also reports the excess return and alpha of the high-minus-low spread portfolio for different holding periods. Excess return is the fund net-of-fee return in excess of the risk free rate. Alpha is estimated relative to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Both excess return and alpha are expressed in percent per month. The t-statistics based on Newey-West standard errors are in the parentheses.

	Sentiment Beta Deciles										
Portfolio	10 (High)	9	8	7	6	5	4	3	2	1 (Low)	Spread (10 minus 1)
Panel A: Holding period=3 months											
Excess return (%/month)	0.69	0.49	0.42	0.34	0.32	0.31	0.37	0.38	0.35	0.29	0.39
	(2.83)	(2.49)	(2.52)	(2.33)	(2.14)	(1.99)	(2.38)	(2.26)	(1.92)	(1.37)	(2.91)
Alpha (%/month)	0.47	0.31	0.25	0.16	0.13	0.12	0.21	0.16	0.10	-0.16	0.63
	(2.31)	(2.35)	(1.92)	(1.36)	(0.97)	(0.81)	(1.62)	(1.37)	(0.75)	(-0.83)	(3.57)
Panel B: Holding period=6 months											
Excess return (%/month)	0.64	0.46	0.40	0.35	0.33	0.33	0.37	0.39	0.34	0.34	0.30
	(2.67)	(2.30)	(2.41)	(2.33)	(2.13)	(2.05)	(2.29)	(2.23)	(1.82)	(1.56)	(2.28)
Alpha (%/month)	0.41	0.27	0.22	0.19	0.13	0.14	0.20	0.20	0.08	-0.13	0.54
	(2.16)	(2.05)	(1.67)	(1.62)	(0.94)	(0.96)	(1.48)	(1.68)	(0.51)	(-0.68)	(3.51)
Panel C: Holding period=9 months											
Excess return (%/month)	0.61	0.42	0.39	0.36	0.34	0.34	0.38	0.39	0.36	0.37	0.24
	(2.53)	(2.05)	(2.29)	(2.26)	(2.16)	(2.14)	(2.27)	(2.20)	(1.99)	(1.66)	(1.81)
Alpha (%/month)	0.36	0.21	0.21	0.19	0.15	0.16	0.20	0.20	0.11	-0.10	0.46
	(2.22)	(1.61)	(1.51)	(1.57)	(1.10)	(1.13)	(1.45)	(1.77)	(0.70)	(-0.55)	(3.45)
Panel D: Holding period=12 months											
Excess return (%/month)	0.56	0.41	0.37	0.34	0.34	0.34	0.39	0.39	0.40	0.39	0.17
	(2.38)	(2.00)	(2.20)	(2.17)	(2.14)	(2.19)	(2.40)	(2.27)	(2.33)	(1.82)	(1.27)
Alpha (%/month)	0.28	0.20	0.19	0.17	0.15	0.17	0.21	0.20	0.17	-0.03	0.31
	(2.01)	(1.51)	(1.35)	(1.39)	(1.05)	(1.09)	(1.54)	(1.82)	(1.14)	(-0.2)	(2.40)

Table 9 Subperiod analysis

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds constructed based on the funds' sentiment beta for three subperiods: 1997–2001; 2002–2006; 2007–2010. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the Baker-Wurgler sentiment-change index, with controls for the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Based on funds' sentiment beta, we form 10 equal-weighted portfolios that are rebalanced each month. For each portfolio, alpha is estimated based on the monthly time-series of the portfolio relative to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. The monthly excess return and alpha are reported in percent. The t-statistics are based on Newey-West standard errors.

	1997–2001				2002–2006				2007–2010			
Portfolio	Excess ret.	t-stat	Alpha	t-stat	Excess ret.	t-stat	Alpha	t-stat	Excess ret.	t-stat	Alpha	t-stat
10 (High)	0.73	1.63	0.70	2.62	0.56	1.94	0.81	1.73	0.93	2.02	0.34	0.81
9	0.55	1.79	0.35	1.75	0.49	2.51	0.58	2.10	0.33	0.85	-0.05	-0.14
8	0.55	1.92	0.32	1.43	0.42	2.65	0.44	2.01	0.31	0.85	-0.02	-0.07
7	0.41	1.73	0.24	1.42	0.42	3.06	0.38	2.00	0.17	0.53	-0.13	-0.46
6	0.40	1.90	0.31	1.95	0.43	3.07	0.43	2.16	0.08	0.23	-0.29	-1.08
5	0.30	1.34	0.16	0.70	0.49	3.22	0.39	2.05	0.04	0.11	-0.19	-0.74
4	0.48	2.12	0.34	2.04	0.42	2.56	0.24	1.33	0.07	0.21	-0.22	-0.80
3	0.42	1.51	0.24	1.06	0.53	2.55	0.36	1.87	0.10	0.29	-0.16	-0.69
2	0.50	1.79	0.44	1.92	0.53	2.34	0.30	1.42	-0.01	-0.04	-0.34	-1.37
1 (Low)	0.06	0.18	-0.26	-0.63	0.59	1.90	0.43	1.64	0.10	0.23	-0.30	-0.96
Spread (10 minus 1)	0.67	2.32	0.95	3.15	-0.03	-0.17	0.38	0.93	0.84	4.18	0.64	2.01

Table 10 Double sorts on fund flows and sentiment beta

Every month, we sort hedge funds into terciles (low, medium and high) based on their net flows. Within each group, hedge funds are then sorted into quintiles based on their sentiment beta. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the Baker-Wurgler sentiment-change index, with controls of the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. In Panel A, we report the average excess return and alpha (in percent) for the sentiment-beta sorted portfolios of the high-flow hedge funds. Panel B is for the low-flow hedged funds. Alpha is estimated relative to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. The t-statistics based on Newey-West standard errors are in the parentheses.

	Sentiment Beta Quintile					
Portfolio	5(High)	4	3	2	1(Low)	Spread (5 minus 1)
Panel A: High flow funds						
Excess return (percent/month)	0.75	0.45	0.41	0.37	0.46	0.29
	(3.57)	(2.90)	(3.03)	(2.64)	(2.47)	(2.15)
Alpha (percent/month)	0.60	0.27	0.23	0.15	0.17	0.44
	(3.38)	(1.75)	(1.66)	(1.41)	(0.93)	(2.15)
Panel B: Low flow funds						
Excess return (percent/month)	0.55	0.32	0.28	0.30	0.19	0.36
	(2.69)	(2.18)	(2.06)	(2.01)	(1.05)	(3.03)
Alpha (percent/month)	0.35	0.09	0.11	0.17	-0.19	0.54
	(1.96)	(0.67)	(0.87)	(1.24)	(-0.98)	(3.03)

Table 11 Dependence on market conditions

In Panel A, we partition sample period based on whether the change in Baker-Wurgler sentiment level is positive. In Panel B, we partition sample period based on whether the monthly market excess return is positive. In Panel C, we partition sample period based on whether VIX index is higher than its time-series median value over the sample period January 1997 to December 2010. In Panel D, we partition sample period based on whether the Chicago Fed National Activity Index (CFNAI) is higher than its time-series median value over the sample period January 1997 to December 2010. Separately for each of the two periods, hedge funds are sorted into ten portfolios based on their sentiment beta. Sentiment beta of each fund is estimated using a regression of the fund's monthly excess return on Baker-Wurgler sentiment-change index, while controlling for the Fung-Hsieh seven factors, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Both excess return and alpha are expressed in percent per month.

		High State				Low State			
	Portfolio	Excess ret.	t-stat	Alpha	t-stat	Excess ret.	t-stat	Alpha	t-stat
Panel A: BW Sentiment level	10 (High)	1.38	4.61	0.54	1.84	0.01	0.04	0.25	0.87
	9	0.98	4.61	0.43	2.05	-0.10	-0.40	-0.04	-0.19
	8	0.83	4.88	0.34	1.83	-0.01	-0.02	0.10	0.43
	7	0.69	4.74	0.21	1.39	-0.04	-0.17	0.08	0.39
	6	0.72	4.97	0.26	1.64	-0.12	-0.59	-0.01	-0.08
	5	0.68	4.64	0.17	0.96	-0.14	-0.58	-0.04	-0.19
	4	0.75	4.80	0.19	1.31	-0.10	-0.48	0.13	0.65
	3	0.86	4.84	0.27	1.72	-0.17	-0.72	0.01	0.03
	2	0.83	4.37	0.22	1.14	-0.14	-0.57	0.15	0.70
	1 (Low)	0.78	3.56	-0.22	-0.79	-0.31	-0.99	-0.01	-0.02
	Spread	0.60	3.06	0.76	3.02	0.33	1.52	0.26	0.91
Panel B: Market return	10 (High)	2.40	10.78	0.51	1.32	-1.68	-7.19	-0.44	-1.00
	9	1.62	10.52	0.24	0.99	-1.18	-6.01	-0.25	-0.85
	8	1.39	9.51	0.20	0.87	-0.94	-4.69	-0.02	-0.06
	7	1.23	11.61	0.30	1.55	-0.92	-4.88	-0.29	-1.35
	6	1.14	10.24	0.28	1.39	-0.86	-4.55	-0.16	-0.65
	5	1.13	9.81	0.37	2.04	-0.90	-4.28	-0.23	-0.94
	4	1.24	10.68	0.19	1.00	-0.95	-5.08	-0.11	-0.47
	3	1.41	10.68	0.33	1.68	-1.12	-5.65	-0.25	-0.95
	2	1.45	10.60	0.44	1.90	-1.19	-5.89	-0.42	-1.47
	1 (Low)	1.65	9.09	0.35	1.16	-1.74	-7.63	-1.04	-2.85
	Spread	0.76	4.28	0.17	0.48	0.06	0.25	0.60	1.28

Table 11, cont.

	Portfolio	High State Excess ret.	High State t-stat	High State Alpha	High State t-stat	Low State Excess ret.	Low State t-stat	Low State Alpha	Low State t-stat
Panel C: VIX	10 (High)	0.28	0.64	0.28	0.82	1.17	3.86	0.47	1.65
	9	0.04	0.14	0.04	0.15	0.89	4.62	0.38	2.40
	8	0.09	0.32	0.21	0.75	0.77	4.99	0.36	2.68
	7	-0.02	-0.07	0.01	0.06	0.71	5.07	0.33	2.79
	6	-0.03	-0.11	0.01	0.05	0.67	4.81	0.30	2.21
	5	-0.05	-0.20	-0.04	-0.14	0.64	4.63	0.27	2.02
	4	-0.07	-0.27	0.02	0.08	0.76	5.21	0.33	2.49
	3	-0.04	-0.15	0.14	0.61	0.78	4.43	0.15	1.03
	2	-0.10	-0.32	0.14	0.53	0.82	4.48	0.16	1.02
	1 (Low)	-0.43	-1.26	-0.54	-1.47	0.95	3.63	0.19	0.83
	Spread	0.71	3.28	0.82	2.15	0.22	1.32	0.28	1.14
Panel D: CFNAI	10 (High)	1.39	4.08	0.51	1.66	0.07	0.18	0.22	0.86
	9	1.00	4.52	0.37	1.48	-0.06	-0.22	0.07	0.39
	8	0.99	5.42	0.55	2.39	-0.12	-0.49	-0.02	-0.13
	7	0.79	5.24	0.38	2.74	-0.10	-0.43	-0.07	-0.43
	6	0.72	4.41	0.23	1.50	-0.08	-0.35	-0.03	-0.19
	5	0.71	4.40	0.16	0.85	-0.12	-0.51	0.00	-0.03
	4	0.79	4.77	0.26	1.71	-0.10	-0.44	0.05	0.29
	3	0.93	4.92	0.31	1.79	-0.19	-0.72	-0.06	-0.27
	2	0.93	4.48	0.22	1.13	-0.20	-0.76	-0.01	-0.07
	1 (Low)	0.86	3.06	-0.38	-1.32	-0.35	-1.05	-0.18	-0.67
	Spread	0.53	2.57	0.89	2.94	0.41	2.16	0.40	1.61

Table 12: Alternative measures of sentiment risk

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds constructed based on the funds' sentiment beta. We use two alternative sentiment measures: the University of Michigan Consumer Confidence Index, and the FEARS index. In each month for each hedge fund with at least 30 returns observations in the past 36 months, sentiment beta is estimated by regressing the fund's excess returns on the sentiment-change index, with controls of the market index, size factor, ΔTerm, ΔCredit, three trend-following factors on bonds, foreign exchange and commodity, the momentum factor, the Pastor-Stambaugh liquidity factor, inflation rate, and default spread. Based on funds' sentiment beta, we form 10 equal-weighted portfolios that are rebalanced each month. For each portfolio, alpha is estimated based on the monthly time-series of the portfolio relative to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. The monthly excess return and alpha are reported in percent. The t-statistics are based on Newey-West standard errors.

	University of Michigan Consumer Confidence Index				The FEARS index			
Portfolio	Excess ret.	t-stat	Alpha	t-stat	Excess ret.	t-stat	Alpha	t-stat
10 (High)	0.60	2.66	0.34	1.33	0.48	1.45	-0.01	-0.02
9	0.53	3.00	0.21	1.41	0.30	1.08	-0.16	-0.76
8	0.43	2.73	0.20	1.49	0.21	0.78	-0.09	-0.44
7	0.33	2.12	0.12	0.77	0.26	1.02	-0.11	-0.56
6	0.37	2.67	0.25	1.94	0.26	1.04	-0.06	-0.29
5	0.36	2.83	0.18	1.66	0.27	1.20	-0.03	-0.20
4	0.29	2.29	0.07	0.60	0.28	1.29	0.01	0.03
3	0.33	2.22	0.24	1.98	0.37	1.65	-0.05	-0.27
2	0.38	2.21	0.19	1.37	0.48	1.97	0.13	0.80
1 (Low)	0.30	1.42	-0.10	-0.80	0.75	2.87	0.38	1.70
Spread (10 minus 1)	0.30	2.01	0.44	1.88	-0.27	-1.60	-0.38	-2.04

Appendix: Definition of TASS hedge fund categories

Hedge funds in the TASS database are divided into 11 categories designed to reflect their investment styles. Below are the definitions of the different styles.

Convertible arbitrage: This strategy is identified by hedge investing in the convertible securities of a company.

Dedicated short bias: This strategy is to maintain net short as opposed to pure short exposure. Short bias managers take short position in mostly equities and derivatives.

Event driven: This strategy is defined as equity-oriented investing designed to capture price movement generated by an anticipated corporate event.

Emerging markets: This strategy involves equity or fixed income investing in emerging markets around the world.

Equity market neutral: This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a county.

Fixed income arbitrage: The fixed income arbitrage aims to profit from price anomalies between related interest rate securities.

Global macro: Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influence by major economic trends and/or events.

Long-short equity: This directional strategy involves equity-oriented investing on both the long and short sides of the market. Managers have the ability to shift from value to growth, from small to median to large capitalization stocks, and from net long position to a net short position.

Managed futures: This strategy invests in listed financial and commodity futures markets and currency markets around the world.

Multi-strategy: This strategy invests in a combination of different strategies to reduce market risk.

Funds of funds: This strategy invests in a diversified portfolio of numerous underlying single-manager hedge funds.