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Sentiment Trading and Hedge Fund Returns

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ABSTRACT

In the presence of sentiment fluctuations, arbitrageurs may engage in different strategies leading to dispersed sentiment exposures. We find that hedge funds in the top decile ranked by sentiment beta outperform those in the bottom decile by 0.59% per month on a risk-adjusted basis, with the spread being larger among skilled funds. We also find that about 10% of hedge funds have sentiment timing skill that positively correlates with fund sentiment beta and contributes to fund performance. Our findings show that skilled hedge funds can earn high returns by predicting and exploiting sentiment changes rather than betting against mispricing.

SENTIMENT, OR THE DISTORTED BELIEFS of irrational traders, is fickle. Changes in sentiment can lead to both mispricing and a reduction in arbitrage activity. A large theoretical and empirical literature examines the impact of investor sentiment, which Keynes (1936) refers to as "animal spirits," on asset prices.[1] In this paper, we focus instead on the impact of sentiment on the performance of arbitrageurs. Specifically, we investigate the relation between

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[1] See, for example, DeLong et al. (1990a, 1990b), Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Vishny (1998), Brunnermeier and Nagel (2004), Baker and Wurgler (2006, 2007),

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hedge fund returns and heterogeneity in hedge funds' trading strategies in response to sentiment fluctuations.[2]

Hedge funds' strategies are not directly observable to researchers. However, differences in arbitrageurs' strategies in the presence of sentiment fluctuations give rise to dispersion in sentiment exposures, and thus their sentiment exposures can provide insights into how they respond to changes in sentiment. Uncertainty about sentiment fluctuations reduces arbitrageurs' willingness to bet against noise traders, leading prices to diverge from fundamental values (DeLong et al. (1990a)). Arbitrageurs who bet against mispricing should have negative sentiment exposure, since overvalued securities tend to be more sensitive to changes in sentiment than undervalued securities.[3] Consistent with this expectation, we find that a betting-against-mispricing strategy that goes long undervalued stocks and short overvalued stocks has a significantly negative sentiment beta.[4]

However, skilled arbitrageurs may not always bet against mispricing. In the dynamic model of Dumas, Kurshev, and Uppal (2009), the optimal strategy of rational traders facing sentiment fluctuations is based not only on current stock mispricing, but also on their expectations about future changes in sentiment. The resulting sentiment exposure of arbitrageurs can therefore be positive or negative. Prior studies show that it can be optimal for arbitrageurs to invest in overpriced assets. For example, when sentiment traders engage in positive feedback trading (e.g., due to extrapolative expectations), rational speculators may pursue an anticipatory strategy of "jumping on the bandwagon" and purchasing ahead of noise trader demand (DeLong et al. (1990b)), which would lead to positive sentiment exposure. Similarly, Abreu and Brunnermeier (2002) argue that due to lack of synchronization, rational traders may choose to ride a bubble, increasing long positions to capture returns as the overvaluation builds. In both papers, rational traders need to predict investor sentiment or "read the mind of the market." Brunnermeier and Nagel (2004) and Griffin et al. (2011) show that "the investor sentiment driving the technology bubble was predictable to some extent" and that institutions—and in particular hedge funds—exploited this opportunity. DeVault, Sias, and Starks (2019) further show that institutions—and in particular hedge funds—purchase high sentiment beta and high volatility stocks from individual

Dumas, Kurshev, and Uppal (2009), Stambaugh, Yu and Yuan (2012, 2015), and Kozak, Nagel, and Santosh (2018).

[2] Brunnermeier and Nagel (2004) posit that hedge funds are "probably closer to the ideal of 'rational arbitrageurs' than any other class of investors." Akbas et al. (2015) and Chen, Da, and Huang (2019) find that hedge funds function as arbitrageurs whereas other types of institutional investors, such as mutual funds, do not.

[3] Baker and Wurgler (2007) find that speculative stocks (such as smaller, younger, unprofitable, high-volatility, nondividend-paying, or growth companies and firms in financial distress) are particularly sensitive to investor sentiment.

[4] Specifically, we find that the decile portfolios of undervalued and overvalued stocks, based on the mispricing score measure of Stambaugh, Yu, and Yuan (2015), have sentiment betas of 0.89 and 1.27, respectively. The portfolio that goes long undervalued stocks and short overvalued stocks has a sentiment beta of –0.38 (t-statistic = –2.18).

investors when sentiment increases. Hedge funds that engage in these trading strategies are expected to be positively exposed to sentiment fluctuations.

In this paper, we document a positive cross-sectional relation between hedge fund sentiment beta and subsequent performance. The relation is both statistically and economically significant based on a sample of 4,073 equity-oriented hedge funds over the period 1994 to 2018. To capture sentiment fluctuations, we use the sentiment changes index of Baker and Wurgler (2006, 2007), which has been shown to successfully capture variation in investor sentiment. For each fund-month, we run a time series regression of fund excess returns over the past 36 months on sentiment changes while controlling for standard risk exposures. The regression coefficient on sentiment changes captures the fund's sentiment beta. When hedge funds are sorted into deciles by their sentiment beta, the top decile on average outperforms the bottom decile by 0.31% (t-statistic = 3.16) in the next month. The return spread becomes 0.59% (t-statistic = 3.55) per month after risk adjustment. We confirm the positive relation between sentiment beta and hedge fund performance next month in Fama-MacBeth (1973) regressions controlling for fund characteristics and styles. Our results apply to both net-of-fee and gross fund returns, as well as alternative sentiment measures.

We consider two potential economic mechanisms underlying the relation between sentiment beta and hedge fund returns. The first is that the outperformance of high sentiment beta funds reflects compensation for sentiment risk exposure. Theoretically, whether sentiment risk is priced depends on the model setup—there can be positive, negative, or no relation between a *stock*'s sentiment beta and expected return. Empirically, the evidence to date is both limited and mixed.[5] Given our focus on hedge funds, we do not conduct a detailed examination of the sentiment risk premium at the individual stock level. More importantly, the sentiment beta-return relation for hedge funds can be fundamentally different than that for stocks. Hedge funds are not traded securities but rather actively managed portfolios. In particular, they employ dynamic strategies across many markets as opposed to simply holding static portfolios of stocks. Hence, while an increase in investor sentiment tends to push the prices of speculative stocks up, it does not necessarily improve hedge funds' performance. The effect of sentiment fluctuations on hedge fund returns thus depends on the fund manager's strategy and trading decisions.

To test the sentiment risk premium explanation, we construct a tradable sentiment factor as the return spread between the top and bottom decile portfolios of stocks sorted by sentiment beta. This tradable sentiment factor has a significantly positive mean over our sample period. After controlling for the sentiment factor, the difference in the risk-adjusted returns of high sentiment beta hedge funds and low sentiment beta hedge funds is still significantly positive, with little change in the magnitude. Thus, the outperformance of high sentiment beta hedge funds is largely unexplained by the sentiment risk

[5] See Section III.A for a summary of the theoretical and empirical research on the sentiment risk premium.

premium and is distinct from the relation between sentiment beta and stock returns. High sentiment beta hedge funds perform better not simply because they overweight high sentiment beta stocks.

An alternative explanation for our result is that managerial skill drives the superior performance of high sentiment beta hedge funds. Consistent with this view, we find that the relation between sentiment beta and fund performance is stronger among hedge funds with characteristics that are associated with managerial skill. For example, the outperformance of high sentiment beta hedge funds is larger among funds that adopt a high-water mark provision, charge higher management or incentive fees. When we double sort hedge funds on sentiment beta and the hedge fund skill measure of Titman and Tiu (2011), the spread between high and low sentiment beta funds has a mean return of 0.41% (t-statistic $= 4.07$) and alpha of 0.71% (t-statistic $= 4.02$) among high-skill hedge funds, in contrast to a mean return of 0.25% (t-statistic $= 2.07$) and alpha of 0.46% (t-statistic $= 2.30$) among low-skill hedge funds.

To better understand the skill that improves fund performance in the presence of sentiment fluctuations, we examine the ability of hedge funds to predict sentiment changes and front-run irrational traders. Specifically, we test three conjectures. First, skilled fund managers are able to time investor sentiment, increasing sentiment exposure in anticipation of more bullish sentiment ahead and outperformance of high sentiment beta investments. This is akin to riding the bubble, except that it applies more generally outside bubble episodes. Second, hedge funds that can time sentiment changes tend to have higher, rather than lower, sentiment beta because there are fewer opportunities to front-run sentiment traders on the downside. Sentiment traders are more likely to buy stocks when they become more bullish than sell stocks when they turn more bearish, for example, due to a reluctance to realize losses and short-sale constraints. Thus, front-running bullish sentiment traders gives rise to high sentiment beta. Third, hedge funds with positive sentiment timing skill observe better performance.

All three of these conjectures are supported by the data. To evaluate the ability of hedge funds to exploit investor sentiment fluctuations, we develop a test of sentiment timing that builds on the classic work on market timing by Henriksson and Merton (1981). Specifically, for each hedge fund, we examine whether it increases (decreases) the loading on the tradable sentiment factor when the factor return is higher (lower). We find that about 10% of hedge funds exhibit a significantly positive sentiment timing coefficient. Bootstrap simulations under multiple approaches confirm that the evidence cannot be attributed to pure luck. Moreover, hedge funds' performance increases significantly with their sentiment timing coefficient, consistent with the idea that the sentiment timing coefficient captures managerial skill that contributes to fund performance. We also find that hedge funds that exhibit sentiment timing skill tend to have a larger sentiment beta. Sentiment timing skill therefore helps explain the outperformance of hedge funds with high sentiment beta.

Our comprehensive analysis of how sentiment-related trading affects hedge fund returns contributes to several strands of literature. First, we extend the seminal work of Brunnermeier and Nagel (2004), who focus on aggregate hedge fund trading during the tech bubble, by providing evidence on heterogeneous sentiment trading strategies across individual hedge funds over the 1994 to 2018 period, which covers more general market states. Consistent with the bubble-riding behavior documented in Brunnermeier and Nagel (2004), our evidence shows that some skilled hedge funds are able to time investor sentiment and realize larger returns. Importantly, we find that hedge funds with high sentiment betas outperform those with low sentiment betas and that such outperformance reflects managerial skill. Our results therefore suggest that some skilled arbitrageurs are able to benefit from sentiment fluctuations, which are commonly perceived as a form of limits-to-arbitrage.

Our study also contributes to the literature by uncovering a new source of hedge fund performance.[6] Existing research documents timing skill with respect to market returns, volatility, liquidity, and macroeconomic uncertainty (e.g., Chen (2007), Chen and Liang (2007), Cao et al. (2013), Bali, Brown, and Caglayan (2014)). We provide strong evidence of sentiment timing and its contribution to hedge fund performance. Our results suggest that, beyond simply performing the socially useful function of betting against mispricing induced by noise trading, skilled hedge funds can profit from predicting changes in sentiment.

Finally, our paper adds to the growing literature on the impact of investor sentiment in financial markets. With few exceptions, most studies use the level of investor sentiment as a conditioning variable in asset pricing tests (Baker and Wurgler (2006, 2007), Stambaugh, Yu, and Yuan (2012, 2015), among others). While our focus is on the relation between exposure to sentiment fluctuations and hedge fund returns, we find that the level of sentiment also plays an important role: the positive relation between sentiment beta and hedge fund returns is stronger following high sentiment periods than following low sentiment periods. This finding is at odds with conventional wisdom that hedge funds generate alpha by betting against mispricing and that their main strength lies in shorting overpriced securities. That view implies that hedge funds with negative sentiment beta should outperform when the initial sentiment level is high, which is the opposite of what we find in the data. Our result instead suggests that the bubble-riding type of sentiment trading that generates a positive sentiment beta can contribute to fund performance, especially for more skilled hedge funds.

The paper proceeds as follows. Section I describes our data on hedge funds, sentiment fluctuations, and risk factors. Section II presents the baseline results and various robustness checks on the relation between sentiment

[6] For studies on the risk and performance of hedge funds, see Fung and Hsieh (1997, 2004), Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2004), Getmansky, Lo, and Makarov (2004), Chen (2007), Chen and Liang (2007), Kosowski, Naik, and Teo (2007), Fung et al. (2008), Griffin and Xu (2009), Jagannathan, Malakhov, and Novikov (2010), Sadka (2010), Chen (2011), Teo (2011), Titman and Tiu (2011), Bali, Brown, and Caglayan (2011, 2012, 2014), Sun, Wang, and Zheng (2012), Cao et al. (2013), Chen, Cliff, and Zhao (2017), and Chen, Kelly, and Wu (2020), among others.

beta and hedge fund returns. Section III investigates alternative explanations for the results based on a sentiment risk premium and fund manager skill. Section IV concludes. Auxiliary tests and results are provided in the Internet Appendix.[7]

I. Data

A. Hedge Funds

Our hedge fund sample is from the Lipper TASS database. TASS classifies hedge funds into 11 strategy categories: convertible arbitrage, dedicated short bias, emerging markets, event driven, equity market neutral, fixed income arbitrage, funds of funds, global macro, long/short equity, managed futures, and multi strategy. Since our sentiment measure corresponds largely to U.S. stock markets, we focus on U.S. equity-oriented hedge funds and drop emerging markets, fixed income arbitrage, and managed futures. Dedicated short-bias funds are also excluded since only 42 such funds satisfy our data filters.[8]

The sample is free of survivorship bias, as TASS covers both live and defunct hedge funds since 1994 and we examine the period from 1994 onward. Following prior research, we apply several screens to the fund data. To address the concern that hedge funds may backfill returns when newly added to the database, we exclude the first 12 months of returns for each fund. We only include funds that report monthly net-of-fee returns in U.S. dollars and allow for redemption at a monthly or higher frequency.[9] We also delete duplicate funds and funds with assets under management below \$5 million.[10] Finally, we require each fund to have at least 30 return observations. After these screens, our sample contains 4,073 hedge funds over the period 1994 to 2018.

Table I reports descriptive statistics for the hedge fund sample based on fund-month observations. All variables are winsorized at the 1% and 99% levels. The average fund return is 0.59% per month. The mean (median) assets under management is \$181 million (\$56 million), and the average fund age is 81 months. The mean (median) management fee is 1.35% (1.50%), while the mean (median) incentive fee is 15.05% (20%). About two-thirds of the funds use a high-water mark provision that requires the funds to recover previous losses before charging the incentive fee. In addition, 32% of the funds require a lockup period, and the redemption notice period is 1.44 months on average.

[7] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[8] The choice of U.S. equity-oriented hedge fund categories follows Cao et al. (2013). Nonetheless, our inference is robust to including all strategy categories in the sample (see the Internet Appendix).

[9] Hedge funds allowing for redemption at a monthly or higher frequency face relatively frequent capital withdrawals, which is consistent with the crucial assumption of DeLong et al. (1990a) that arbitrageurs often have short horizons.

[10] Our results are robust to alternative data filters, such as the exclusion of funds with assets under management below \$10 million and exclusion of the first 24 months of fund returns. See the Internet Appendix for details.

Table I
Summary Statistics of Hedge Funds

This table summarizes the hedge fund sample that covers both active and defunct hedge funds. For each fund, the first 12 months of returns are excluded to mitigate backfill bias. The sample includes equity-oriented hedge funds that report monthly net-of-fee returns in U.S. dollars, allow for redemption at a monthly or higher frequency, and have assets under management of at least $5 million. Each hedge fund is required to have at least 30 return observations. The sample contains 4,073 hedge funds. The summary statistics are based on fund-month observations. All variables are winsorized at the 1% and 99% levels. The sample period is from January 1994 to December 2018.

	Mean	*SD*	10%	25%	Median	75%	90%
Fund return (%/month)	0.59	3.36	−2.81	−0.69	0.61	1.89	3.95
Fund size ($million)	181.48	365.57	10.40	21.70	55.99	160.41	436.51
Fund age (month)	80.66	57.22	21.00	37.00	67.00	110.00	158.00
Management fee (%)	1.35	0.50	1.00	1.00	1.50	1.50	2.00
Incentive fee (%)	15.05	7.41	0.00	10.00	20.00	20.00	20.00
High-water mark (dummy)	0.67	0.47	0.00	0.00	1.00	1.00	1.00
Lockup period (dummy)	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Notice period (month)	1.44	0.92	0.23	1.00	1.17	2.00	3.00

B. Sentiment Changes

We adopt the Baker-Wurgler sentiment *changes* index as the main measure of sentiment fluctuations in our tests. Baker and Wurgler (2006) capture market-wide sentiment as a composite of six proxies: closed-end fund premium, New York Stock Exchange (NYSE) share turnover, number and average first-day returns of initial public offerings, equity share in new issues, and dividend premium. The sentiment level is obtained by first using principal component analysis on these proxies and then orthogonalizing against macroeconomic variables to remove the impact of business cycles.[11] To capture time variation in investor sentiment, Baker and Wurgler (2007) construct the monthly sentiment changes index from the first principal component of changes in these sentiment proxies. The Baker-Wurgler index significantly expands the traditional measure based on the closed-end fund premium (Lee, Shleifer, and Thaler (1991)) and has spurred a growing body of research on the effects of investor sentiment on asset prices and corporate decisions. As reported in Panel A of Table II, the monthly sentiment changes index has a mean of −0.50 and a standard deviation of 1.39 over our sample period, with 25th and 75th percentiles of −1.38 and 0.47, respectively.[12]

[11] In addition, we explicitly control for the macroeconomic variables that Bali, Brown, and Caglayan (2011) find to have significant explanatory power for hedge fund returns. This ensures that our results are not driven by exposures to macroeconomic factors.

[12] By construction, the Baker-Wurgler sentiment changes index has a mean of zero after orthogonalization against macroeconomic variables. However, since the original index is constructed using data going back to 1965 and our sample starts in 1994, the mean value of the index over our sample period is not exactly zero.

Table II

Summary Statistics of Sentiment Changes

Panel A describes the measures of sentiment fluctuations, including the Baker-Wurgler (2007) sentiment changes index, changes in the University of Michigan consumer sentiment index, and the FEARS index. Panel B reports the correlation coefficients between these indexes and risk factors. The risk factors include the Fung-Hsieh (2004) seven factors (market excess returns (Mktrf), a size factor (SMB), a tradable factor mimicking the change in the constant-maturity yield of the 10-year Treasury (ΔTerm), a tradable factor mimicking the change in the yield spread between Moody's Baa bond and the 10-year Treasury bond (ΔCredit), and three trend-following factors on bonds (Ptfsbd), currencies (Ptfsfx), and commodities (Ptfscom)), as well as the momentum factor (UMD), the Pastor-Stambaugh (2003) liquidity factor (LIQ), the inflation rate (INF), and the default spread between the yields on Baa-rated and Aaa-rated corporate bonds (DEF).

Panel A: Summary Statistics

	Mean	*SD*	10%	25%	Median	75%	90%
Baker-Wurgler sentiment changes	–0.50	1.39	–2.58	–1.38	–0.30	0.47	1.06
Changes in Mich. consumer sentiment	0.05	4.48	–4.75	–2.30	–0.11	2.63	5.07
FEARS index	0.00	0.03	–0.04	–0.02	0.00	0.02	0.04

Panel B: Correlation Coefficients

	BW Sent	Mich.	FEARS	Mktrf	SMB	ΔTerm	ΔCredit	Ptfsbd	Ptfsfx	Ptfscom	UMD	LIQ	INF	DEF
BW sentiment changes	1.00													
Changes in Mich. cons. sent.	0.10	1.00												
FEARS index	–0.11	0.26	1.00											
Mktrf	0.16	0.03	0.01	1.00										
SMB	0.22	0.04	–0.07	0.25	1.00									
ΔTerm	–0.09	0.01	–0.07	0.05	0.14	1.00								
ΔCredit	0.01	–0.05	0.07	0.31	0.03	–0.03	1.00							
Ptfsbd	0.03	–0.09	–0.01	–0.25	–0.05	–0.05	–0.01	1.00						
Ptfsfx	0.01	0.01	0.04	–0.19	0.01	–0.07	–0.11	0.32	1.00					
Ptfscom	0.01	0.02	–0.01	–0.17	–0.05	–0.04	–0.06	0.19	0.35	1.00				
UMD	0.00	0.08	0.02	–0.27	0.07	–0.06	–0.15	0.03	0.13	0.18	1.00			
LIQ	0.10	0.03	0.15	0.09	0.09	0.00	0.04	–0.03	–0.11	–0.05	0.06	1.00		
INF	0.22	0.02	0.12	0.04	0.03	0.00	–0.14	–0.16	–0.13	–0.09	0.01	0.06	1.00	
DEF	–0.02	–0.04	–0.18	–0.11	0.05	0.25	0.10	0.04	0.04	–0.03	–0.20	–0.01	–0.23	1.00

For robustness, we consider two alternative measures of sentiment fluctuations: the monthly change in the University of Michigan consumer sentiment index, which is based on surveys of household confidence in the economy, and the FEARS index of Da, Engelberg, and Gao (2015), which captures sentiment changes based on Internet search volume for keywords that reveal investor concerns about the economy. The FEARS index data span the period 2004 to 2011 at a daily frequency. We convert these data to a monthly series by averaging the daily values for each month. For consistency, we orthogonalize both measures against the macroeconomic variables used in the Baker-Wurgler index. As shown in Panel B of Table II, the Baker-Wurgler sentiment changes index is positively correlated with changes in the Michigan consumer sentiment index and negatively correlated with the FEARS index, since the latter captures investors' bearish attitude about economic conditions.

C. Risk Factors

To measure risk-adjusted returns (i.e., alpha), we control for exposures to standard risk factors identified in the hedge fund literature. We start with Fung and Hsieh's (2004) seven factors: an equity market factor, a small-minus-big size factor, the change in the constant-maturity yield of the 10-year Treasury, the change in the yield spread between Moody's Baa bond and the 10-year Treasury bond, and three trend-following factors for bonds, currencies, and commodities.[13] These factors are commonly used to evaluate hedge fund performance (e.g., Kosowski, Naik, and Teo (2007), Fung et al. (2008), Jagannathan, Malakhov, and Novikov (2010), Sadka (2010), and Cao et al. (2013)). We also control for the inflation rate and default spread, as Bali, Brown, and Caglayan (2011) find that exposures to these two factors are significantly related to hedge fund returns. We further include the momentum factor, as Griffin and Xu (2009) find that hedge funds engage in momentum strategies. Finally, we control for illiquidity risk using Pastor and Stambaugh's (2003) liquidity factor. Panel B of Table II shows that, overall, the Baker-Wurgler sentiment changes index is only modestly correlated with these risk factors. The three highest correlations are with the equity market, the size factor, and inflation (at 0.16, 0.22, and 0.22, respectively).

[13] Since the two bond factors capture yield changes rather than excess returns, we follow Sadka (2010) to replace them with returns on factor-mimicking portfolios so that the regression intercept can be interpreted as a risk-adjusted return. In particular, the yield change of the 10-year Treasury is replaced with the return spread between the 10-year Treasury index and the one-month T-bill rate, while the change in the spread between Moody's Baa yield and the 10-year Treasury is replaced with the return spread between the Corporate Bond Baa index and the 10-year Treasury index. The index return data come from Barclays Capital.

II. Baseline Results

A. Portfolio Sorts

We first use portfolio sorts to examine the relation between sentiment beta and hedge fund returns. Each month starting in December 1996, we form 10 equal-weighted portfolios of hedge funds based on the fund sentiment beta (i.e., the loading on the sentiment changes index) estimated from a rolling window of the most recent 36 months (including the current month), with the first rolling window spanning the period from January 1994 to December 1996.[14] We then track the portfolio returns over the next month (starting in January 1997). These portfolios are rebalanced each month to generate a time series of returns from January 1997 to December 2018.

Specifically, each fund's sentiment beta is estimated by regressing fund excess returns on the sentiment changes index controlling for standard risk factors. In month t, for each fund with at least 30 return observations during the 36-month rolling window, we perform the following time series regression:

$$r_{i,t} = \alpha + \beta^S \Delta sentiment_t + \beta' \boldsymbol{f}_t + \varepsilon_t, \tag{1}$$

where $r_{i,t}$ is the excess return (in excess of the one-month T-bill rate) on fund i in month t, $\Delta sentiment$ is the sentiment changes index, β^S is sentiment beta, and the vector $\boldsymbol{f}$ contains the Fung-Hsieh factors, momentum, liquidity, inflation, and the default spread. Thus, for month t, the rolling window covers month $t-35$ to month t. The use of a rolling window allows for time variation in the beta estimates.

We track the returns for the decile portfolios over the next month after portfolio formation. These portfolios are rebalanced each month. Finally, we estimate alpha (i.e., the risk-adjusted return) by regressing the time series of the excess returns of each decile portfolio on the Fung-Hsieh seven factors, the momentum factor, and the liquidity factors.[15] Accordingly, the spread in alpha between the two extreme decile portfolios (i.e., portfolios 10 and 1) reveals performance dispersion attributed to sentiment beta. In the test, we calculate t-statistics using Newey-West (1987) standard errors with two lags, where the number of lags is based on autocorrelations in monthly hedge fund returns.[16]

Table III reports results for both hedge fund excess returns and alpha across the sentiment beta-sorted portfolios. The decile portfolio with the highest sentiment beta (i.e., portfolio 10) delivers an average excess return of 0.58% (t-statistic = 3.48) per month and an alpha of 0.51% (t-statistic = 2.98) per month,

[14] The average fund size is similar across decile portfolios sorted by the sentiment beta (see the Internet Appendix for details). Moreover, the regression analyses below control for fund size explicitly.

[15] The two macroeconomic variables (namely, the inflation rate and default spread) are not included in the regression when estimating the risk-adjusted return, since they are not tradable factors.

[16] The average first-order (second-order) autocorrelation in hedge fund excess returns is 0.158 (0.063), and higher order autocorrelations are generally smaller.

Table III

Sentiment Beta and Hedge Fund Performance: Portfolio Sorts

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds constructed based on sentiment beta. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing the fund excess returns on the Baker-Wurgler (2007) sentiment changes index, controlling for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Based on the funds' sentiment beta, we form 10 equal-weighted portfolios and track their returns over the next month. The portfolios are rebalanced each month. Using the monthly time series of the returns of each portfolio, we estimate alpha by regressing the portfolio excess returns on the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Both monthly excess return and alpha are reported in percentage. *t*-Statistics are based on Newey-West (1987) standard errors with two lags.

Portfolio	Sentiment Beta	Excess Return	*t*-Stat	Alpha	*t*-Stat
1 (Low)	–1.07	0.27	1.77	–0.08	–0.51
2	–0.45	0.25	1.94	0.07	0.59
3	–0.25	0.34	2.95	0.14	1.48
4	–0.14	0.30	2.85	0.14	1.34
5	–0.06	0.25	2.35	0.04	0.36
6	0.02	0.25	2.51	0.10	0.96
7	0.10	0.30	2.76	0.12	1.15
8	0.21	0.34	2.99	0.21	1.99
9	0.39	0.38	2.93	0.26	2.27
10 (High)	0.96	0.58	3.48	0.51	2.98
Spread (Port. 10 – Port. 1)	2.03	0.31	3.16	0.59	3.55

indicating significantly positive abnormal performance, while the decile portfolio with the lowest sentiment beta (i.e., portfolio 1) shows an average excess return of 0.27% (*t*-statistic = 1.77) per month and an alpha of −0.08 (*t*-statistic = −0.51) per month. The return spread between the two extreme decile portfolios is 0.31% (*t*-statistic = 3.16) per month and both economically and statistically significant. On a risk-adjusted basis, the spread in alpha between the extreme decile portfolios becomes even larger, at 0.59% (*t*-statistic = 3.55) per month. While the portfolio return does not increase strictly monotonically with sentiment beta, the top three portfolios with the highest sentiment betas are also the top three portfolios with the highest average excess returns and alphas, while the portfolio with the lowest sentiment beta also has the lowest average excess return and alpha. Thus, the results from portfolio sorts indicate that sentiment beta is significantly positively related to both hedge fund excess returns next month and alpha after adjusting for standard risk factors.

Figure 1 plots the spread in one-month-ahead risk-adjusted returns (i.e., alpha) between the two extreme decile portfolios with high and low sentiment betas. The series start in January 1997, since we use a 36-month formation period. As shown in Panel A, the spread in alpha is positive for more than two-thirds of the months over our sample period. Panel B plots the cumulative

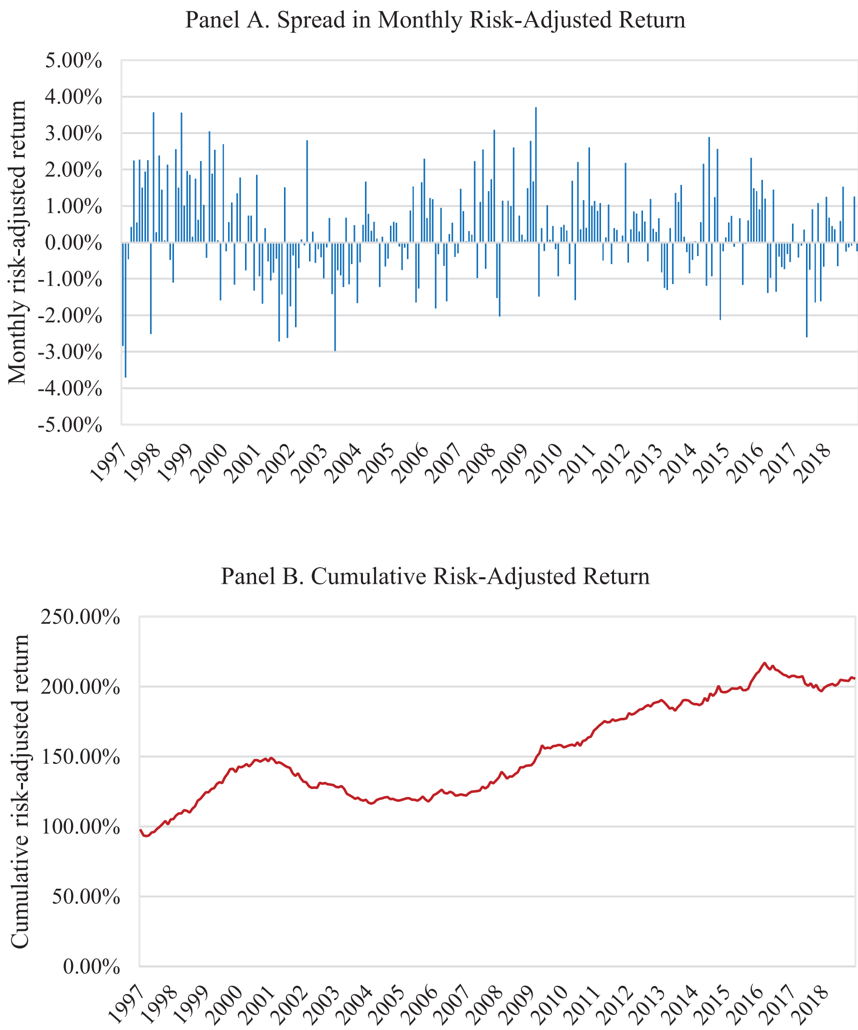

Figure 1. Spread in risk-adjusted return (i.e., alpha) between top and bottom sentiment beta hedge funds. Each month starting in December 1996, we form 10 decile portfolios based on hedge fund sentiment beta estimated over the past 36 months and track their returns over the next month. Panel A plots the time series of the spread in monthly risk-adjusted returns between the two extreme decile portfolios of top versus bottom sentiment beta hedge funds. Panel B plots the cumulative spread in risk-adjusted returns between the two extreme decile portfolios. (Color figure can be viewed at wileyonlinelibrary.com)

spread in alpha between the two extreme decile portfolios sorted by sentiment beta. Again, the plot shows a persistent difference in risk-adjusted returns between hedge funds with high and low sentiment betas.

We perform a battery of sensitivity tests. First, instead of tracking returns from the month immediately following portfolio formation, we skip one month.

Second, to address concerns about the precision of sentiment beta estimates, we use different combinations of risk factors as control variables in regression (1). Our inferences continue to hold. We also examine the effect of sentiment beta on hedge fund returns over holding periods longer than one month. The spread in monthly alpha is 0.59%, 0.51%, 0.44%, and 0.31% over the subsequent three, six, nine, and 12 months, respectively. Finally, we find that hedge fund sentiment beta displays a fair amount of persistence in the short run. For example, about 59% (45%) of the hedge funds placed in the top sentiment beta decile in a given month will continue to be in the top decile six months (one year) later. These additional findings are reported in the Internet Appendix.

B. Fama-MacBeth Regressions

To control for known determinants of hedge fund performance, we perform Fama-MacBeth (1973) cross-sectional regressions of fund excess returns or alpha on sentiment beta, along with various fund characteristics and style dummies. Specifically, we run the following cross-sectional regression of fund excess returns on sentiment beta:

$$r_{i,t+1} = \lambda_0 + \lambda_1 \hat{\beta}^S_{i,t} + \lambda' \mathbf{x}_{i,t} + e_{i,t+1}, \tag{2}$$

where $r_{i,t+1}$ is the fund excess return in month $t + 1$, and $\hat{\beta}^S_{i,t}$ is fund i's sentiment beta estimated from regression model (1) using fund returns in the 36-month rolling window from month $t - 35$ to month t. That is, the key independent variable—sentiment beta—is estimated from a backward-looking window prior to the return evaluation period for the dependent variable of the regression. The control variables $\mathbf{x}$ are predetermined fund characteristics including fund size, fund age, management fee, incentive fee, high-water mark dummy, lockup period, redemption notice period, and fund style dummies.

We also run the test in regression (2) using fund alpha instead of fund excess return as the dependent variable. For each fund in month t, we remove the sentiment changes index from the set of independent variables in regression (1) and reestimate the factor loadings using the past 36 months of data. The alpha for each fund in month $t + 1$ is then obtained as the difference between the fund excess return in month $t + 1$ and the products of its factor loadings estimated in month t and factor realizations in month $t + 1$, that is,

$$\widehat{\alpha}_{\mathrm{i,t+1}} = r_{\mathrm{i,t+1}} - \widehat{\beta}^{'}_{\mathrm{i,t}} \boldsymbol{f}_{\mathrm{t+1}}, \tag{3}$$

where the vector $\boldsymbol{f}$ denotes realized returns of factors including the Fung-Hsieh seven factors, the momentum factor, and the liquidity factor (but excluding the sentiment changes index).

Table IV reports the results from the cross-sectional regressions, with the dependent variable being either the hedge fund excess return or alpha. From the univariate regression, the regression coefficient of fund excess return on sentiment beta is 0.17 (t-statistic = 3.03). Thus, an increase in sentiment beta from −1.07 (its average level in the bottom decile in Table III) to 0.96 (its

Table IV

Cross-Sectional Regressions of Fund Performance on Sentiment Beta

This table reports results from Fama-MacBeth (1973) cross-sectional regressions of hedge fund excess return, as well as alpha, on sentiment beta, controlling for fund characteristics and style dummies. In each month and for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing the fund excess returns on the Baker-Wurgler (2007) sentiment changes index with controls for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Then, we perform cross-sectional regressions of fund excess return, or alpha, over the next month on sentiment beta with controls for fund characteristics and style dummies. The fund characteristics include fund size, fund age, management fee, incentive fee, a high-water mark dummy equal to 1 if a high-water mark provision is used, and 0 otherwise, lockup period, and redemption notice period. Both monthly excess return and alpha are reported in percentage. *t*-Statistics are based on Newey-West (1987) standard errors with two lags.

	Dependent Variable							
	Excess Return				Alpha			
	Coeff.	*t*-Stat	Coeff.	*t*-Stat	Coeff.	*t*-Stat	Coeff.	*t*-Stat
Sentiment beta	0.17	3.03	0.16	2.84	0.14	3.31	0.12	3.16
Log(fund size)			0.01	0.12			0.01	0.21
Log(fund age)			−0.03	−0.95			0.06	2.13
Management fee			0.04	1.34			0.02	1.14
Incentive fee			−0.01	−0.14			0.01	2.31
High-water mark			0.15	4.76			0.11	4.81
Lockup period			0.06	1.55			−0.06	−2.24
Notice period			0.06	3.80			0.07	5.83
Fund style dummies	No		Yes		No		Yes	
Adjusted R^2	0.01		0.07		0.01		0.05	

average level in the top decile) leads to an increase in fund monthly excess returns of 0.35% (i.e., 0.17% × 2.03) on average. Similarly, when the fund alpha is the dependent variable, the regression coefficient on sentiment beta is 0.14 (t-statistic = 3.31). These results are consistent with those from portfolio sorts and indicate that sentiment beta can positively and significantly predict hedge fund performance in the cross-section.

We obtain similar evidence from multivariate regressions. After including fund characteristics and style dummies, we continue to find that sentiment beta is significantly and positively associated with hedge fund performance next month. For example, in the regression with fund excess return as the dependent variable, the slope coefficient on sentiment beta is 0.16 (t-statistic = 2.84). In the regression with alpha as the dependent variable, adding fund characteristics as controls reduces the coefficient on sentiment beta slightly from 0.14 to 0.12 (t-statistic = 3.16). At the same time, the coefficients on fund characteristics are in line with prior studies. For example, hedge funds that have a longer track record, charge a higher incentive fee, use a high-water

Table V

Results from Changes in the Michigan Consumer Sentiment Index

This table reports results of portfolio sorts based on sentiment beta with respect to changes in the University of Michigan consumer sentiment index. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing the fund excess returns on changes in the Michigan consumer sentiment index, controlling for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Based on the funds' sentiment beta, we form 10 equal-weighted portfolios and track their returns over the next month. The portfolios are rebalanced each month. Using the monthly time series of the returns of each portfolio, we estimate alpha by regressing portfolio excess returns on the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Both monthly excess return and alpha are reported in percentage. t-Statistics are based on Newey-West (1987) standard errors with two lags.

Portfolio	Sentiment Beta	Excess Return	t-Stat	Alpha	t-Stat
1 (Low)	–0.23	0.29	1.50	–0.08	–0.49
2	–0.07	0.27	1.95	0.13	0.98
3	–0.03	0.21	1.83	0.04	0.38
4	–0.01	0.28	2.47	0.13	1.42
5	0.01	0.33	3.09	0.19	2.00
6	0.03	0.27	2.53	0.08	0.69
7	0.05	0.28	2.06	0.00	–0.02
8	0.08	0.48	3.61	0.35	2.76
9	0.12	0.40	2.66	0.09	0.72
10 (High)	0.29	0.55	2.65	0.50	1.92
Spread (Port. 10 – Port. 1)	0.52	0.26	1.88	0.58	2.17

mark provision for incentive fees, or require a longer redemption notice period tend to observe better performance. Our finding therefore suggests that these fund characteristics, traditionally used as proxies for hedge fund skill in the literature, account for only a small portion of the effect of sentiment beta on hedge fund performance.

In sum, our results from both portfolio sorts and cross-sectional regressions show a significant and positive relation between sentiment beta and hedge fund performance, even after adjusting for common risk exposures and controlling for fund characteristics.

C. Additional Robustness Tests

C.1. Alternative Sentiment Measures

In our main analysis, we employ the Baker-Wurgler sentiment changes index, which is widely used in the literature. In this subsection, we check whether our inference is sensitive to the choice of sentiment measure. As an alternative measure, we first consider the University of Michigan consumer sentiment index. The results, reported in Table V, confirm a significantly positive relation between sentiment beta and hedge fund performance. For example, on average, the top sentiment beta hedge funds outperform the bottom sentiment beta hedge funds by 0.26% (t-statistic = 1.88) per month and by 0.58% (t-statistic = 2.17) per month on a risk-adjusted basis. The spreads in excess returns and alpha are very close in magnitude to those obtained from the Baker-Wurgler sentiment measure. In addition, similar to the results based on the Baker-Wurgler measure, the top sentiment beta portfolio delivers the largest alpha (positive and significant) while the bottom sentiment beta portfolio has the lowest alpha (negative and insignificant).

As a second alternative measure of sentiment changes, we consider the FEARS index of Da, Engelberg, and Gao (2015). Since this index captures pessimistic concerns about the economy, we multiply its values by −1 such that the resulting sentiment beta has the same interpretation as those from the other two sentiment measures. Based on the FEARS index, the return spread between top and bottom sentiment beta hedge funds is 0.35% (t-statistic = 1.98) per month and the spread in alpha is 0.99% (t-statistic = 2.59) per month. We note that the FEARS index has a shorter history (spanning 2004 to 2011) than the other two sentiment measures. The results are reported in the Internet Appendix.

In sum, our evidence on the relation between sentiment beta and hedge fund returns is robust to the choice of sentiment measure. We use the Baker-Wurgler sentiment changes index as our main measure because, compared with the Michigan sentiment index, this sentiment proxy is derived from financial markets and thus is more relevant for hedge funds, and compared with the FEARS index, it has a longer history and thus can deliver more reliable inference.

C.2. Results from Gross Fund Returns

Our analysis so far relies on hedge funds' net-of-fee returns, which represent fund investors' payoffs. However, arbitrage profits could be more closely related to gross fund returns. This should not matter if all funds charge the same fees, including management and incentive fees. In reality, however, fee arrangements are heterogeneous across hedge funds. If fees charged by fund managers are systematically correlated with their sentiment betas, our inference based on net returns could be biased. To address this concern, we repeat the tests of portfolio sorts using gross fund returns. Since most hedge funds report net-of-fee returns in the data, we follow Teo (2009) and Chen (2011) to compute gross returns using a simple algorithm to add back management and incentive fees.

Table VI shows a significantly positive relation between hedge funds' gross returns and their sentiment betas. Based on gross fund returns, the top sentiment beta fund portfolio has an average excess return of 1.07% (t-statistic = 6.00) and an alpha of 1.11% (t-statistic = 5.95) per month, while the bottom sentiment beta fund portfolio has an average excess return of 0.72% (t-statistic = 4.57) and an alpha of 0.37% (t-statistic = 2.27) per month. Between the top and bottom portfolios, the spread in monthly fund returns is 0.35% (t-statistic

Table VI

Sentiment Beta and Hedge Fund Performance: Portfolio Sorts Based on Gross Fund Returns

This table reports monthly gross (i.e., before-fee) returns of 10 equal-weighted portfolios of hedge funds constructed based on sentiment beta. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing fund excess returns on the Baker-Wurgler (2007) sentiment changes index, controlling for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Based on the funds' sentiment beta, we form 10 equal-weighted portfolios and track their returns over the next month. The portfolios are rebalanced each month. Using the monthly time series of the returns of each portfolio, we estimate alpha by regressing portfolio excess returns on the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Both monthly excess return and alpha are reported in percentage. t-Statistics are based on Newey-West (1987) standard errors with two lags.

Portfolio	Sentiment Beta	Excess Return	t-Stat	Alpha	t-Stat
1 (Low)	−1.19	0.72	4.57	0.37	2.27
2	−0.50	0.64	4.68	0.52	4.05
3	−0.28	0.65	5.72	0.55	5.61
4	−0.15	0.52	4.84	0.29	2.96
5	−0.06	0.53	5.16	0.33	3.15
6	0.02	0.48	4.44	0.34	3.46
7	0.11	0.54	4.88	0.35	3.42
8	0.23	0.64	5.61	0.52	5.17
9	0.44	0.76	5.74	0.64	5.32
10 (High)	1.08	1.07	6.00	1.11	5.95
Spread (Port. 10 – Port. 1)	2.27	0.35	3.04	0.74	4.14

= 3.04) while the spread in monthly alpha is 0.74% (t-statistic = 4.14). The analysis using gross fund returns therefore leads to the same inference about the relation between sentiment beta and subsequent hedge fund performance.

III. What Explains the Sentiment Beta-Fund Performance Relation?

In this section, we investigate two potential explanations for our results. The first, a risk-based explanation, suggests that the outperformance of high sentiment beta hedge funds comes from holding high sentiment beta stocks that have higher expected returns due to a positive sentiment risk premium. The second explanation, a skill-based story, attributes the outperformance of high sentiment beta funds to managerial skill. The two explanations are not mutually exclusive.

A. Risk-Based Explanation

One potential explanation for the results is that high sentiment beta hedge funds hold stocks with large sentiment exposures and their outperformance reflects a positive sentiment risk premium. Theoretically, the extent to which sentiment risk is priced depends on the model setup: there can be a positive, negative, or no relation between stock sentiment beta and expected returns.

In the model of DeLong et al. (1990a), the price of an asset that is subject to the influence of unpredictable sentiment is lower than the fair value to compensate arbitrageurs for the risk that sentiment traders can become bearish. However, the expected price change in their model is zero (see their equation (12)). Dumas, Kurshev, and Uppal (2009) develop an equilibrium model of investor sentiment in which sentiment traders are intertemporal optimizers with overconfident beliefs. As the difference in beliefs between rational and overconfident investors, sentiment follows a driftless diffusion process with stochastic volatility proportional to investor disagreement. When there is a difference of opinion about the fundamental, rational investors realize that sentiment will fluctuate randomly in response to dividend shocks. As a result, a risk premium arises from the unpredictable fluctuations of other investors. In their model, the pricing kernel is a concave (convex) function of the sentiment level, if the coefficient of investor risk-aversion is greater (less) than one.[17] However, the instantaneous risk premium for sentiment innovations that are independent of fundamental news is zero. By construction, sentiment fluctuations in our empirical analysis, as proxied by the Baker-Wurgler sentiment changes index, are independent of fundamental news. Thus, according to Dumas, Kurshev, and Uppal (2009), our sentiment beta should not be related to expected stock returns.

Kozak, Nagel, and Santosh (2018) show that sentiment risk can be priced when there are common components of sentiment-driven asset demand because it is risky for arbitrageurs to take the other side. In their model, sentiment or belief distortion leads to systematic excess demand for risky assets, giving rise to time-varying investment opportunities and an ICAPM-like stochastic discount factor as a function of sentiment.[18] Specifically, stock prices are linear in sentiment, and the log value function of an arbitrageur is a decreasing quadratic function of sentiment. The sign of the sentiment risk premium is ambiguous, however, because more extreme sentiment (both positive and negative) leads to greater stock mispricing and investment opportunities, which translate to greater wealth and lower marginal utility for the arbitrageur. If the arbitrageur's portfolio is long-biased (e.g., induced by a high equity premium), the arbitrageur faces better investment opportunities in negative sentiment states. Thus, the marginal utility of the arbitrageur increases with sentiment and the sentiment risk premium is negative. Under alternative assumptions, however, the arbitrageur may have better investment opportunities in positive sentiment states and thus sentiment risk could be positively

[17] Han (2008) presents evidence based on stock market index option prices that the asset pricing kernel depends on various proxies for market sentiment.

[18] In a related paper, Campbell and Kyle (1993) present an equilibrium model of smart money and noise trading where the risk premium on stocks is perfectly negatively correlated with noise trader demand. Their Theorem 3.2 shows that the value function of the arbitrageur depends on noise trader demand and its square.

priced. To summarize, Kozak, Nagel, and Santosh (2018) suggest that market-wide sentiment risk could be priced but the sign is an empirical question.

Empirically, only a few papers examine the price of sentiment risk. These studies provide mixed evidence. Glushkov (2006) finds that the relation between sentiment beta and stock returns has an inverse U-shape, that is, stocks with extreme values of sentiment beta earn lower, not higher, future returns relative to those with near-zero sentiment beta. In contrast, Ho and Hung (2012) report a U-shape pattern in stock returns across portfolios sorted by sentiment beta. Shen, Yu, and Zhao (2017) show that sentiment beta is positively (negatively) priced following low (high) sentiment periods. Liang (2018) finds a positive relation between sentiment beta and expected stock returns. In short, how sentiment exposure affects expected stock returns remains an open question.

Nonetheless, if a positive sentiment risk premium exists, one may wonder whether the outperformance of high sentiment beta hedge funds is just a manifestation of the positive relation between sentiment beta and stock returns. We test this possibility in Table VII. Specifically, we run a time series regression of the hedge fund return spread between high and low sentiment beta decile portfolios on a tradable sentiment factor constructed from the stock market, which is the return spread between the top decile and the bottom decile of stocks sorted by the Baker-Wurgler sentiment beta. Over our sample period, this tradable sentiment factor has a positive mean of 0.28% (t-statistic $= 2.06$).

As shown in Table VII, after controlling for the exposures to the sentiment factor and standard risk factors, the spread in the risk-adjusted returns between the two extreme deciles of hedge funds is 0.56% (t-statistic $= 3.54$) per month. Comparing this number with the corresponding value of 0.59% (t-statistic $= 3.55$) per month in Table III (where we examine the same hedge fund portfolios but do not adjust for the sentiment factor when estimating fund alpha), the outperformance of high sentiment beta hedge funds is only 0.03% lower on average after controlling for the sentiment factor. Therefore, our result for hedge funds is largely unexplained by and distinct from the relation between sentiment beta and stock returns. The result also suggests that high sentiment beta hedge funds do not simply hold positive sentiment beta stocks. Their high sentiment exposure comes mainly from complex and dynamic trading strategies.

While the test in Table VII is not intended to deliver conclusive inference about the sentiment risk premium in general, the results lend little support to the sentiment risk premium explanation for the outperformance of high sentiment beta hedge funds.

B. Skill-Based Explanation

Next, we consider the skill-based explanation, which holds that the outperformance of high sentiment beta hedge funds is due to managerial skill. We find initial support for this possibility in Table III, which shows that after controlling for a comprehensive set of risk factors, the top three deciles

Table VII

Sentiment Beta and Hedge Fund Performance: Controlling for Sentiment Risk Premium

This table reports the beta on the tradable sentiment factor and the monthly alpha of 10 equal-weighted portfolios of hedge funds constructed based on sentiment beta. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing fund excess returns on the Baker-Wurgler (2007) sentiment changes index, controlling for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Based on the funds' sentiment beta, we form 10 equal-weighted portfolios and track their returns over the next month. The portfolios are rebalanced each month. Using the monthly time series of the returns of each portfolio, we estimate sentiment risk-adjusted alpha by regressing portfolio excess returns on the tradable sentiment factor, in addition to the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. The column "Alpha" reports the monthly sentiment risk-adjusted alpha (in percentage) for each decile portfolio of hedge funds sorted by sentiment beta. *t*-Statistics are based on Newey-West (1987) standard errors with two lags.

Portfolio	Beta on the Tradable Sentiment Factor	Alpha	*t*-Stat
1 (Low)	0.01	–0.09	–0.52
2	0.00	0.07	0.58
3	0.06	0.13	1.39
4	0.03	0.13	1.31
5	0.04	0.03	0.29
6	0.05	0.09	0.89
7	0.02	0.11	1.11
8	0.08	0.20	1.85
9	0.08	0.25	2.18
10 (High)	0.17	0.47	2.98
Spread (Port. 10 – Port. 1)	0.16	0.56	3.54

of hedge funds (especially the top decile) ranked by sentiment beta exhibit positive alphas that are economically and statistically significant, while the other hedge funds have insignificant alpha. Below we examine the skill-based explanation in detail.

B.1. Hedge Fund Skill and the Sentiment Beta-Fund Performance Relation

The literature has identified several hedge fund characteristics that are related to managerial skill. For example, skilled hedge funds tend to charge higher management and incentive fees, adopt a high-water mark, and impose longer lockup and notice periods (e.g., Ackermann, McEnally, and Ravenscraft (1999), Agarwal, Daniel, and Naik (2009)). Furthermore, Titman and Tiu (2011) propose a hedge fund skill measure based on fund returns' exposure to factor risks. According to this measure, low-skill managers, who are less confident in their ability to generate alpha from active strategies, choose greater exposure to systematic factors. This implies that low-skill managers' funds will have higher R^2 with respect to systematic factors. In contrast, high-skill managers will have lower R^2.

Consistent with the skill explanation, we find that the outperformance of high sentiment beta hedge funds is much stronger among high-skill hedge funds. Panel A of Table VIII reports results for two subsamples of hedge funds sorted by the Titman-Tiu fund skill measure. Here, the spread between high and low sentiment beta funds has a mean return of 0.41% (t-statistic = 4.07) and alpha of 0.71% (t-statistic = 4.02) among high-skill funds, in contrast to a mean return of only 0.25% (t-statistic = 2.07) and alpha of 0.46% (t-statistic = 2.30) among low-skill funds. These results indicate that the relation between sentiment beta and fund performance is especially pronounced among high-skill hedge funds.

Similarly, in Panel B of Table VIII, the sentiment beta-fund performance relation is stronger among hedge funds that are more experienced (in terms of fund size and age), charge higher management and incentive fees, use a high-water mark provision, impose a lockup period and require a longer redemption notice period. For example, the spread in alpha between high and low sentiment beta hedge funds among those charging above-median incentive fees (in percentage terms) is 0.65% (t-statistic = 3.73) per month, whereas the spread in alpha among those charging below-median incentive fees is merely 0.36% (t-statistic = 2.37) per month. Taken together, the evidence in Table VIII lends support to the skill-based explanation for the relation between sentiment beta and hedge fund returns.

B.2 Sentiment Timing

To shed light on the specific managerial skill that helps improve fund performance in the presence of sentiment fluctuations, we examine whether hedge funds can time changes in investor sentiment and position accordingly. Specifically, we test three conjectures. First, skilled fund managers can time their exposures to investor sentiment, increasing sentiment beta of their funds if sentiment change is forecast to be positive. This strategy is akin to bubble-riding, except that it applies more generally than just during bubble episodes. Our second conjecture is that hedge funds able to time sentiment fluctuations tend to have higher sentiment beta. Although skilled managers may reduce sentiment exposure when sentiment is expected to decrease, this effect should be relatively weak because there are fewer opportunities to front-run sentiment traders on the downside. Sentiment traders are more likely to buy stocks when they become more bullish than sell stocks when they turn more bearish, for example, due to a reluctance to realize losses and short-sale constraints. Third, we expect hedge funds with positive sentiment timing skill to display higher alpha.

We begin by examining sentiment timing among hedge funds. In general, timing ability refers to the ability of fund managers to adjust factor exposures

Table VIII

Hedge Fund Skill and the Sentiment Beta-Fund Performance Relation

This table reports results of portfolio sorts based on sentiment beta for subsample tests. In Panel A, we partition the hedge fund sample into high- versus low-skill funds according to the Titman-Tiu (2011) hedge fund skill measure. Specifically, in each month for each hedge fund with at least 30 return observations over the past 36 months, we estimate the R^2 by regressing fund returns on the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, ΔTerm, ΔCredit, and three trend-following factors on bonds, currencies, and commodities). A fund is classified as a high-skill fund if its R^2 is below the median level. We then report excess return and alpha for the 10 equal-weighted portfolios of hedge funds constructed based on sentiment beta for each subsample. In Panel B, we partition the hedge fund sample based on the median level of fund characteristics, including fund size, fund age, management fee, incentive fee, high-water mark dummy, lockup period, and redemption notice period. We then report the spreads in excess return and alpha between the top and bottom sentiment beta decile portfolios (i.e., portfolio 10 and portfolio 1) for the subsamples of hedge funds with values of fund characteristics above and below the median level, separately. In this panel, t-statistics are reported in parentheses. Both monthly excess return and alpha are in percentage. t-Statistics are based on Newey-West (1987) standard errors with two lags.

Panel A: Subsample Analysis Based on the Titman-Tiu Skill Measure

	High-Skill Funds				Low-Skill funds			
Portfolio	Excess Return	t-Stat	Alpha	t-Stat	Excess Return	t-Stat	Alpha	t-Stat
1 (Low)	0.20	1.38	–0.06	–0.33	0.29	1.68	–0.10	–0.53
2	0.27	2.39	0.23	1.57	0.26	1.76	–0.10	–0.90
3	0.33	3.62	0.20	1.82	0.35	2.56	0.05	0.49
4	0.23	2.67	0.17	1.69	0.27	2.07	–0.10	–0.86
5	0.24	2.83	0.16	1.57	0.25	1.92	–0.03	–0.25
6	0.24	2.98	0.16	1.55	0.28	2.19	0.03	0.24
7	0.25	3.12	0.13	1.22	0.32	2.61	0.05	0.48
8	0.32	3.54	0.30	2.51	0.37	2.61	0.15	1.64
9	0.38	3.51	0.27	2.11	0.28	1.75	0.03	0.25
10 (High)	0.62	4.08	0.64	3.36	0.55	2.82	0.36	2.18
Spread (Port. 10 – Port. 1)	0.41	4.07	0.71	4.02	0.25	2.07	0.46	2.30

Panel B: Subsample Analysis Based on Fund Characteristics

	Spread in Excess Return		Spread in Alpha	
	High	Low	High	Low
Fund size	0.35	0.29	0.73	0.53
	(3.30)	(2.47)	(4.38)	(2.76)
Fund age	0.36	0.26	0.58	0.23
	(2.23)	(2.61)	(3.60)	(0.80)
Management fee	0.49	0.23	0.71	0.29
	(3.18)	(2.04)	(3.97)	(1.15)
Incentive fee	0.33	0.23	0.65	0.36
	(2.79)	(2.57)	(3.73)	(2.37)
High-water mark	0.37	0.21	0.61	0.26
	(3.14)	(1.82)	(3.23)	(1.31)
Lockup period	0.34	0.30	0.78	0.47
	(2.47)	(2.97)	(3.27)	(2.95)
Notice period	0.28	0.29	0.63	0.50
	(2.45)	(2.12)	(3.30)	(2.48)

at opportune times as market conditions change.[19] Theoretical justification for sentiment timing can be found in DeLong et al. (1990b), who argue that arbitrageurs may jump on the bandwagon and purchase ahead of sentiment traders if the latter follow positive-feedback strategies. Brunnermeier and Nagel (2004) provide evidence that hedge funds in aggregate were able to predict investor sentiment during the tech bubble. Here, we test sentiment timing at the individual hedge fund level during more general market states over a longer period spanning 1994 to 2018.

We propose a sentiment timing model based on the classic market timing test of Henriksson and Merton (1981) in which fund managers have higher (lower) exposure to the stock market when market returns are expected to be higher (lower). Since the sentiment changes index itself does not capture investment returns, we examine the dynamics of hedge fund exposure to the tradable sentiment factor, as proxied by the return spread between the portfolio of stocks with high sentiment beta (top decile) and the portfolio of stocks with low sentiment beta (bottom decile).

We perform the analysis at the individual fund level rather than at the hedge fund index level as not all hedge funds are expected to be able to time sentiment. More importantly, we are interested in whether heterogeneity in hedge fund sentiment timing skill is related to the cross-sectional dispersion in hedge fund sentiment beta and performance. Specifically, for each hedge fund with at least 30 monthly return observations, we perform the sentiment timing regression:

$$\begin{aligned} r_{i,t} &= \alpha + \beta^S \Delta sentiment_t + \gamma\, sent - factor_t \\ &\quad \times I(sent - factor_t > \overline{sent - factor}) + \ \beta' \boldsymbol{f}_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $r_{i,t}$ is the excess return on fund i in month t, Δ*sentiment* is the sentiment changes index, *sent-factor* is the tradable sentiment factor constructed as the return spread between high and low sentiment beta stock portfolios, and $I(.)$ is a dummy variable equal to 1 when the tradable sentiment factor is greater than its time series mean, and 0 otherwise.[20] The risk factors that are included are the same as in equation (1). The coefficient γ picks up the fund manager's sentiment timing skill. A fund manager with ability to time investor sentiment would increase the fund's exposure to the tradable sentiment factor when the factor return is high, leading to a positive γ in regression (4). We therefore refer to γ as the sentiment timing coefficient.

[19] Prior hedge fund studies find evidence of timing skill with respect to market returns, volatility, liquidity, and macro uncertainty (e.g., Chen (2007), Chen and Liang (2007), Cao et al. (2013), Bali, Brown, and Caglayan (2014)).

[20] Equation (4) uses the ex post mean of the sentiment factor return as the reference point for hedge funds. This practice, which follows the market timing literature, should not cause a concern as we are interested in evaluating whether a fund's loading is large when the realized factor return is high, as opposed to proposing an implementable trading strategy based on available information in real time.

Jagannathan and Korajczyk (1986) point out that fund managers without true timing skill may sometimes appear as successful market timers under the Henriksson-Merton timing model when they adopt strategies with nonlinear payoffs, even though these strategies do not contribute to fund performance. This caution applies to our sentiment timing test for hedge funds because regression (4) follows the spirit of the Henriksson-Merton model and hedge funds tend to use derivatives and dynamic trading strategies (e.g., Chen (2011)). To verify the validity of our sentiment timing proxy, we investigate the relation between the sentiment timing coefficient and hedge fund performance (see Table X). The idea here is that, if the sentiment timing coefficient captures at least part of true timing skill, it should be positively correlated with fund performance.

Panel A of Table IX reports the cross-sectional distribution of the t-statistic for the sentiment timing coefficient γ. The panel shows the percentage of t-statistics that exceed the indicated cutoff values under the assumption of a normal distribution. In our sample, 13.82% of funds have a t-statistic greater than 1.65 (i.e., 5% significance level in the right tail under normality), whereas only 2.77% have a t-statistic less than -1.65 (5% significance level in the left tail under normality). Thus, the right tail is thicker than the left tail, which suggests that the positive sentiment timing coefficient is more pronounced than the negative sentiment timing coefficient.

The above inference is drawn under the assumption of normality, but hedge fund returns are not normally distributed (e.g., Fung and Hsieh (1997)). We therefore apply the bootstrap technique, which imposes no assumption of normality, to analyze statistical significance of the sentiment timing coefficient. We use three alternative bootstrap approaches. The baseline approach follows Kosowski et al. (2006) and assumes independently and identically distributed (IID) residuals from the sentiment timing regression. The second approach accounts for serial correlation in the residuals, as in Cao et al. (2013). When implementing these two approaches, we require each fund to have at least 30 observations. The third approach follows Fama and French (2010) and allows for cross-sectional correlation in the residuals. When implementing this approach, we follow Harvey and Liu (2020) and require each fund to have at least 60 observations. Details on these bootstrap approaches are provided in the Appendix.

Panel B of Table IX shows that the results hold across three bootstrap approaches. The reported empirical p-values correspond to the t-statistics of the sentiment timing coefficients in both tails. The empirical p-values for the right tail are below the usual threshold for statistical significance. This holds true across the alternative approaches. Meanwhile, the empirical p-values for the left tail are all close to 1. Thus, the result suggests that the top sentiment timing coefficients are unlikely due to pure luck. Our evidence of sentiment timing for hedge funds suggests that the bubble-riding type of sentiment trading first documented in Brunnermeier and Nagel (2004) during the tech bubble episode holds more generally. Our results also reveal large

Table IX

Sentiment Timing

This tables reports results of sentiment timing. Panel A presents the cross-sectional distribution of t-statistics for the sentiment timing coefficient across funds. The numbers in parentheses are the significance level under the normality assumption. Panel B presents bootstrap results. The first row reports ranked t-statistics of the sentiment timing coefficient, requiring each fund to have at least 30 observations. The second row reports empirical p-values from the baseline approach assuming IID regression residuals. The third row reports empirical p-values from the approach accounting for serial correlation in residuals, as in Cao et al. (2013). The fourth row reports ranked t-statistics of the sentiment timing coefficient, requiring each fund to have at least 60 observations. The last row reports empirical p-values from the Fama and French (2010) approach, accounting for cross-sectional correlation in residuals. The number of resampling iterations is 1,000. t-Statistics are based on Newey-West (1987) standard errors with two lags.

Panel A: The Cross-Sectional Distribution of t-Statistic of the Sentiment Timing Coefficient

	Percentage of the Hedge Funds							
Number of Funds	$T \leq -2.33$ (1%)	$T \leq -1.96$ (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%)	$T \geq 2.33$ (1%)
4,073	0.64%	1.50%	2.77%	5.60%	22.96%	13.82%	8.45%	4.27%

Panel B: Bootstrap Results of the Sentiment Timing Coefficient

Number of Funds		Bottom t-Statistic for $\hat{\gamma}$				Top t-Statistic for $\hat{\gamma}$			
		1%	2.5%	5%	10%	10%	5%	2.5%	1%
Requiring at least 30 Observations									
4,073	t-Statistic	–2.15	–1.71	–1.34	–0.88	1.86	2.25	2.58	2.88
	p-Value$^{\text{IID residuals}}$	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00
	p-Value$^{\text{Serial correlation}}$	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00
Requiring at least 60 Observations									
2,314	t-Statistic	–2.03	–1.59	–1.12	–0.71	1.97	2.32	2.64	2.87
	p-Value$^{\text{Cross-sectional corr.}}$	0.95	0.97	1.00	1.00	0.01	0.02	0.03	0.09

Table X

Sentiment Timing and Hedge Fund Performance

In this table, Panel A reports the cross-sectional correlation between sentiment timing skill and sentiment beta among hedge funds. Panel B reports results from Fama-MacBeth (1973) regressions of hedge fund excess returns, as well as alpha, on the sentiment timing coefficient. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment timing is estimated from regression (4). We then perform cross-sectional regressions of fund excess returns, or alpha, over the next month on the sentiment timing coefficient together with sentiment beta, various fund characteristics, and style dummies. The fund characteristics include fund size, fund age, management fee, incentive fee, high-water mark dummy equal to 1 if a high-water mark provision is used, and 0 otherwise, lockup period, and redemption notice period. Both monthly excess return and alpha are expressed in percentage. t-Statistics are based on Newey-West (1987) standard errors with two lags.

Panel A: Correlation between the Sentiment Timing Skill and Sentiment Beta

	Sentiment Timing	Sentiment Beta
Sentiment timing	1.00	
Sentiment beta	0.08	1.00
	(p-Value < 0.0001)	

Panel B: Sentiment Timing and Hedge Fund Performance

	Dependent Variable							
	Excess Return				Alpha			
	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
Sentiment timing	0.02	2.40	0.02	2.09	0.01	2.39	0.01	1.89
Sentiment beta	0.17	2.96	0.16	2.89	0.13	3.07	0.11	2.86
Log(fund size)			0.01	0.32			0.00	0.25
Log(fund age)			–0.01	–0.17			0.07	2.61
Management fee			0.03	1.13			0.02	0.83
Incentive fee			–0.00	–0.13			0.01	2.41
High-water mark			0.15	4.73			0.10	4.64
Lockup period			0.08	2.30			–0.05	–1.71
Notice period			0.05	3.54			0.07	5.52
Fund style dummies	No		Yes		No		Yes	
Adjusted R^2	0.02		0.08		0.02		0.06	

heterogeneity in the sentiment timing coefficient across individual hedge funds. The tests in Table X take advantage of this heterogeneity.

Next, we check whether sentiment timing is related to sentiment beta in the cross-section of hedge funds. We find that the two variables are significantly positively correlated, as shown in Panel A of Table X. This result supports our second conjecture, which holds that hedge funds with better sentiment timing skill tend to have a larger sentiment beta.

Finally, consistent with our third conjecture, we find that the sentiment timing coefficient does indeed contribute to hedge fund performance. In Panel B of Table X, we perform Fama-MacBeth regressions of one-month-ahead fund performance (excess return or alpha) on the sentiment timing coefficient.

As in Section II, the sentiment timing coefficient is estimated from running regression (4) using data from a 36-month backward-looking rolling window. Regardless of whether we use the excess return or alpha as the dependent variable, the coefficient of the sentiment timing skill is positive and statistically significant. Meanwhile, sentiment beta continues to exhibit a strong relation with hedge fund performance. We also confirm the positive relation between our measure of sentiment timing skill and hedge fund performance using the portfolio sorting approach.[21] These findings again suggest that our inference about sentiment timing skill is unlikely to be artificial.

To summarize, we find that hedge funds with positive sentiment timing skill have higher sentiment beta as well as superior performance. However, sentiment timing ability seems to account for only a small portion of the effect of sentiment beta on hedge fund performance, leaving a large portion of the effect unexplained. A more comprehensive study of hedge funds' sentiment trading strategies would lead to a better understanding of hedge fund performance in general, and in particular its relation to sentiment beta documented in this paper.

B.3. The Role of Investor Sentiment Level

Most existing research on investor sentiment focuses on the level of sentiment as a conditioning variable.[22] While we focus on hedged funds' exposure to sentiment fluctuations, we are interested in exploring the role of the aggregate sentiment level in the relation between sentiment beta and hedge fund performance.

Following the literature, we partition the full sample into high and low sentiment periods based on whether the level of investor sentiment in each month exceeds the time series median. We then examine the relation between sentiment beta and fund performance following the different periods. As shown in Table XI, the spread in excess returns between the two extreme decile portfolios of hedge funds sorted by sentiment beta is 0.34% (0.29%) per month following high (low) sentiment periods. After risk adjustment, the contrast in terms of the spread in alpha becomes starker at 0.73% (t-statistic = 3.59) versus 0.38% (t-statistic = 1.50), with the spread in alpha following high sentiment periods nearly twice as large as that following low sentiment periods.

This result is at odds with the conventional wisdom that hedge funds generate alpha by betting against mispricing and that their main strength lies in shorting overpriced securities. That view implies that hedge funds with negative sentiment beta would do well, especially following periods of high

[21] We find that the decile portfolio of hedge funds with the highest sentiment timing coefficients significantly outperforms the decile portfolio of hedge funds with the lowest sentiment timing coefficients. The spread in alpha between these two decile portfolios is 0.44% (t-statistic = 2.80) per month. See the Internet Appendix for details.

[22] See Baker and Wurgler (2006), Brown and Cliff (2005), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Yu and Yuan (2011), Stambaugh, Yu, and Yuan (2012, 2015), Shen, Yu, and Zhao (2017), DeVault, Sias, and Starks (2019), among others.

Table XI

Sentiment Level and the Sentiment Beta-Fund Performance Relation

This table reports results of portfolio sorts based on sentiment beta following periods of high and low aggregate investor sentiment. We partition the full sample into high and low sentiment periods based on whether the level of investor sentiment exceeds the time series median. We then examine the sentiment beta-fund performance relation following the two periods separately. In each month for each hedge fund with at least 30 return observations over the past 36 months, sentiment beta is estimated by regressing fund excess returns on the Baker-Wurgler (2007) sentiment changes index, controlling for the Fung-Hsieh (2004) seven factors (including market excess returns, a size factor, $\triangle$Term, $\triangle$Credit, and three trend-following factors on bonds, currencies, and commodities), the momentum factor, the Pastor-Stambaugh (2003) liquidity factor, the inflation rate, and the default spread. Based on the funds' sentiment beta, we form 10 equal-weighted portfolios and track their returns over the next month. The portfolios are rebalanced each month. Using the monthly time series of the returns of each portfolio, we estimate alpha by regressing portfolio excess returns on the Fung-Hsieh seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Both monthly excess return and alpha are reported in percentage. *t*-Statistics are based on Newey-West (1987) standard errors with two lags.

	Level of Investor Sentiment							
	High				Low			
Portfolio	Excess Return	*t*-Stat	Alpha	*t*-Stat	Excess Return	*t*-Stat	Alpha	*t*-Stat
1 (Low)	–0.11	–0.53	–0.14	–0.67	0.66	3.66	0.17	0.77
2	0.00	0.03	0.20	1.47	0.50	3.37	–0.13	–0.80
3	0.12	0.65	0.21	1.87	0.56	4.92	0.12	0.88
4	0.12	0.76	0.24	2.07	0.49	4.34	–0.01	–0.08
5	0.05	0.28	0.11	0.89	0.46	4.21	–0.03	–0.17
6	0.08	0.54	0.20	1.70	0.43	3.86	–0.06	–0.36
7	0.11	0.66	0.20	1.70	0.49	4.26	0.01	0.04
8	0.16	0.90	0.33	2.72	0.52	4.66	0.08	0.47
9	0.12	0.62	0.34	2.45	0.65	4.75	0.20	1.03
10 (High)	0.22	0.86	0.59	3.08	0.95	5.12	0.55	1.79
Spread (Port. 10 – Port. 1)	0.34	2.07	0.73	3.59	0.29	2.60	0.38	1.50

sentiment, which is opposite of what we find in the data. Our result does lend support, however, to the view that skilled managers can improve fund performance with the bubble-riding type of sentiment trading that generates a positive sentiment beta.

IV. Conclusion

In this paper, we explore how hedge fund exposure to sentiment fluctuations (i.e., sentiment beta) is related to fund performance. On the one hand, unpredictable fluctuations in investor sentiment could deter arbitrage activity. On the other hand, skilled arbitrageurs may be able to predict and take advantage of changes in investor sentiment. Different sentiment trading strategies by hedge funds can lead to cross-sectional variation in their sentiment exposures. We show robust evidence that hedge funds with large positive exposures to changes in investor sentiment significantly outperform other funds. The return spread between the top and bottom deciles of hedge funds ranked by sentiment beta is as large as 0.59% (t-statistic = 3.55) per month on a risk-adjusted basis.

We investigate two distinct but not mutually exclusive economic explanations. The first, a risk-based explanation, holds that the outperformance of high sentiment beta hedge funds comes from a sentiment risk premium on the high sentiment beta stocks they hold. The second explanation, a skill-based story, holds that managerial skill drives the outperformance. Our analyses provide more support for the skill-based explanation. The relation between sentiment beta and fund returns is much stronger among skilled hedge funds. Moreover, we find evidence of sentiment timing skill for a subset of hedge funds, with sentiment timers exhibiting both high sentiment beta and large alpha. Thus, although sentiment fluctuations can deter arbitrage activity, some skilled arbitrageurs are able to profit from such fluctuations (e.g., by predicting changes in sentiment). Extending the existing evidence of Brunnermeier and Nagel (2004), our results show that the bubble-riding type of sentiment trading that generates a positive sentiment beta can enhance fund performance beyond the socially useful function of betting against mispricing.

It would be fruitful to further advance our understanding of the interaction between sentiment traders and arbitrageurs (e.g., hedge funds' trading strategies based on mispricing and how arbitrageurs respond to sentiment fluctuations) when finer information on hedge fund positions becomes available. The pricing of market-wide sentiment risk in financial markets also deserves closer scrutiny. We leave these topics for future research.

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Appendix

Procedures of the Bootstrap Analysis

A. Baseline Bootstrap Assuming IID Residuals

The baseline bootstrap approach follows Kosowski et al. (2006), assuming IID residuals. The basic idea is to resample the data randomly to generate pseudo-funds that have no sentiment timing skill but the same factor exposures as the actual funds. Empirical p-values are then computed by comparing t-statistics of the estimated timing coefficients of the actual funds at various cutoff percentiles with the distribution of the t-statistics of the pseudo-funds at the same cutoff percentiles. We perform the bootstrap for the t-statistic, because, as a pivotal statistic, it has favorable sampling properties in bootstrapping (e.g., Horowitz (2001)). The bootstrap procedure is as follows.

Step 1: Perform the sentiment timing regression (4) for fund i and store the estimated coefficients $\{\hat{\alpha}, \hat{\beta}^S, \hat{\gamma}, \hat{\beta}\}$ as well as the time series of the residuals

$\{\hat{\varepsilon}_{i,t},\ t = 1, \ldots, T_i\}$, where T_i is the number of monthly observations for the fund.

Step 2: Resample the regression residuals with replacement to obtain a randomly resampled time series $\{\hat{\varepsilon}^b_{i,t}\}$, where b is the index of bootstrap iteration ($b = 1, 2, \ldots, B$). Next, generate monthly excess returns $\{\hat{r}^b_{i,t}\}$ for a pseudo-fund that has no sentiment timing (i.e., $\gamma = 0$) by construction. That is, set the sentiment timing coefficient to 0:

$$r^b_{i,t} = \widehat{\alpha} + \widehat{\beta}^S\, \Delta sentiment_t + \widehat{\beta}' \boldsymbol{f}_t + \widehat{\varepsilon}^b_{i,t}. \tag{A1}$$

Step 3: Run the sentiment timing regression (4) using the pseudo-fund returns from Step 2 and store the t-statistic of the estimated timing coefficient. Since the pseudo-fund has a true γ of zero, any nonzero timing coefficient comes from randomness.

Step 4: Complete Steps 1 to 3 for all funds, so that we can observe the cross-sectional statistics (e.g., the top 10^{th} percentile) of the t-statistic for the pseudo-funds.

Step 5: Repeat Steps 1 to 4 for B iterations to generate the empirical distributions for the cross-sectional statistics (e.g., the top 10^{th} percentile) of the t-statistic for the pseudo-funds. We set $B = 1{,}000$. Finally, compute the empirical p-value for a given cross-sectional statistic as the frequency of the values of the bootstrapped cross-sectional statistic for the pseudo-funds from B iterations exceeding the actual value of the cross-sectional statistic.

B. Accounting for Non-IID Residuals

We consider two extensions to the baseline bootstrap to account for non-IID residuals. Both extensions modify Step 2; the other steps remain unchanged.

The first extension accounts for serial correlation in the residuals using the sieve bootstrap (e.g., Bühlmann (1997)), as in Cao et al. (2013). This approach assumes that the residuals $\{\hat{\varepsilon}_{i,t}\}$ of fund i follow a p-order autoregressive process, that is, AR(p), with the value p (up to 6) chosen by the Akaike information criterion for each fund separately. Next, we resample error terms from the AR model and generate bootstrap residuals $\{\hat{\varepsilon}^b_{i,t}\}$ by plugging the resampled error terms into the model. With the bootstrap residuals, we perform the remaining steps as before.

The second extension accounts for cross-sectional correlation in the residuals, using the approach of Fama and French (2010). This approach resamples factors and residuals jointly across all funds. Recently, Harvey and Liu (2020) show that the Fama-French approach, when including funds with short histories, has low power to detect skilled funds. They recommend requiring at least 60 observations for each fund when using the approach.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix
Replication Code.