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Sentiment and the Effectiveness of Technical Analysis: Evidence from the Hedge Fund Industry

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Abstract

This article presents a unique test of the effectiveness of technical analysis in different sentiment environments by focusing on its usage by perhaps the most sophisticated and astute investors, namely, hedge fund managers. We document that during high-sentiment periods, hedge funds using technical analysis exhibit higher performance, lower risk, and superior market-timing ability than nonusers. The advantages of using technical analysis disappear or even reverse in low-sentiment periods. Our findings are consistent with the view that technical analysis is relatively more useful in high-sentiment periods with larger mispricing, which cannot be fully exploited by arbitrage activities because of short-sale impediments.

I. Introduction

Technical analysis, which involves using past prices and other past data to make investment decisions, has been widely adopted in practice. For example, Schwager (1995) and Lo and Hasanhodzic (2009) find that many of the top traders and fund managers whom they interviewed use and support technical analysis. Covel (2005) advocates the exclusive use of technical analysis by citing examples of large and successful hedge funds. Despite its popularity among practitioners, the value of technical analysis has been the subject of a long-standing academic debate. Conventional efficient market theories often assume a random walk model for stock prices (Fama (1965)), which completely rules out the profitability of

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technical analysis.[1] More recent theories such as noise trader models (De Long, Shleifer, Summers, and Waldmann (1990)), however, suggest that technical trading strategies may be profitable under uncertainty because of the presence of irrational noise traders (Zhu and Zhou (2009)). The empirical evidence is also mixed and inconclusive as to whether technical approaches can generate superior performance (see Park and Irwin (2007) for an extensive survey of the profitability of technical trading strategies).

In this article, we contribute to the debate on the value of technical analysis from a new perspective by examining how investor sentiment affects the effectiveness of technical analysis as a general investment tool in the hands of sophisticated hedge fund managers. A growing body of literature contends that sentiment could drive asset mispricing (Baker and Wurgler (2006), Shleifer and Summers (1990)) and that sentiment-induced mispricing may be asymmetrical between high- and low-sentiment environments because of short-sale constraints (Stambaugh, Yu, and Yuan (2012), Shen and Yu (2014)). Specifically, during high-sentiment periods, the optimistic views of not-fully-rational investors tend to drive security overpricing, and rational investors cannot eliminate this overpricing because of impediments to short selling.[2] In contrast, during low-sentiment periods, the passive views of not-fully-rational investors may not be reflected as security underpricing, as rational investors can fully counter these passive views by holding long positions of securities. As a result, high-sentiment-driven overpricing is more prevalent than low-sentiment-driven underpricing and the market tends to be less efficient in high-sentiment periods. Because market efficiency has important implications for the usefulness of technical analysis, it is interesting to investigate whether, and (if so) how, investor sentiment is related to the efficacy of technical analysis.

We present a unique test of the effectiveness of technical analysis in different sentiment periods by focusing on its usage by perhaps the most sophisticated and astute class of investors, namely, hedge fund managers. In particular, instead of testing specific technical rules in isolation (e.g., Antoniou, Doukas, and Subrahmanyam (2013)), we use a sample of hedge funds that are self-reported users or nonusers of technical analysis and compare the relative benefits of technical analysis users versus nonusers in different sentiment periods.

This approach is important from at least two perspectives. First, it is an indirect but realistic way to test for the usefulness of technical analysis while circumventing the empirical challenge of examining specific rules in isolation. The possible number and combinations of indicators comprising a trading or investment system are virtually unlimited and often proprietary to hedge funds, making it challenging to conduct convincing empirical tests of the effectiveness of technical analysis. Second, we focus on the use of technical analysis by perhaps the most elite, highly skilled, motivated, and rational group of investors. If there is a

[1]Bessembinder and Chan (1998), nevertheless, argue that the evidence supporting technical forecast power need not be inconsistent with market efficiency due to the measurement errors associated with trading costs.

[2]The significance of short-sale constraints traces back to Miller (1977), who argues that impediments to short-selling such as arbitrage risk, trading costs, behavioral biases of traders, and institutional constraints play a significant role in limiting arbitrage by rational investors.

nonnaïve class of technical analysis users that can effectively navigate the complexities involved in profitably applying technical approaches, it would be hedge funds.

Using data from the Lipper TASS hedge fund database from 1994 to 2010, we first document that among our sample hedge funds, technical analysis users on average significantly outperform nonusers in high-sentiment periods; however, in low-sentiment periods, the use of technical analysis is found to be less valuable and even counterproductive. In addition, technical analysis usage is associated with lower fund risk, and this benefit is more prominent in high-sentiment periods, indicating that technical analysis is an effective risk management tool. Finally, we show that only during high-sentiment periods, technical analysis users exhibit better market-timing ability than nonusers. Overall, we document the relative advantages of using technical analysis by hedge funds during high-sentiment periods when market mispricing is most acute. Our results are robust to controlling for fund characteristics and various fixed effects, employing a subperiod analysis, and using prefee returns, different volatility periods, the sentiment level, and equity-focused hedge funds.

We further examine whether hedge fund managers can exploit sentiment-induced mispricing using other available strategies, such as fundamental analysis. We find that hedge funds that report using fundamental analysis tend to underperform fundamental analysis nonusers in high-sentiment periods; however, there exists some evidence that fundamental analysis users outperform nonusers in low-sentiment periods. Hence, although technical analysis proves to be relatively more useful to exploit the more prominent overpricing that occurs during high-sentiment periods, fundamental analysis tends to be more effective in low-sentiment periods with less pronounced underpricing.

Theoretically, why is technical analysis relatively more useful to exploit high-sentiment-induced market inefficiency? We provide several explanations. First, we consider the information diffusion model, which recognizes differences in the time for investors to receive information. Under this friction, technical analysis is useful for assessing whether information has been fully incorporated into prices, and past prices and trading volume can provide useful information for investors to make better price inferences (see, e.g., Treynor and Ferguson (1985), Brown and Jennings (1989), Grundy and McNichols (1989), and Blume, Easley, and O'Hara (1994)). Thus, technical analysis users can profit from the gradual information diffusion process in high-sentiment periods when information is incorporated into prices at a slower rate due to short-sale constraints.

Second, stock markets tend to show trending patterns due to the underreaction and overreaction of investors with incomplete information (Hong and Stein (1999)). Insofar as markets exhibit stronger trends in high-sentiment periods, technical analysis techniques such as moving average and momentum strategies are informative because they are primarily designed to detect price trends (see, e.g., Han, Yang, and Zhou (2013), Antoniou et al. (2013)). In contrast, other signals such as earnings and economic outlook are likely to be imprecise during high-sentiment periods when there exist many noise traders, the market is highly volatile, and prices deviate from fundamental values (Han et al. (2013)).

Therefore, technical signals tend to be more profitable than fundamental signals in high-sentiment periods.

Finally, the model in Zhu and Zhou (2009) shows that technical analysis can add value to asset allocation under uncertainty about predictability or uncertainty about the true model governing stock prices. These uncertainties are more likely in the presence of many noise traders with irrational sentiment who can cause prices to deviate from their fundamentals due to limits to arbitrage (De Long et al. (1990)).

Empirically, evidence suggests that technical analysis is relatively more effective during high-sentiment periods. For instance, Neely, Rapach, Tu, and Zhou (2014) show that technical indicators are more useful in detecting market declines near business-cycle peaks (i.e., following high sentiment) but not as effective as macroeconomic variables in picking up market rises near business-cycle troughs (i.e., following low sentiment). On a related note, Shen and Yu (2014) document that pervasive macro-related factors are priced in the cross section of stock returns following low but not high sentiment. This evidence supports our findings that fundamental variables, including macroeconomic indicators, tend to be more useful during low-sentiment periods.

Our article makes several contributions. Despite considerable academic evidence that specific technical strategies often underperform buy-and-hold investing,[3] technical analysis is employed by one in five hedge funds industrywide. We provide supporting evidence for the rationale of these sophisticated managers that with great flexibility in their investment approaches, managers use the approach only if they consider it to have high value added. Our article also brings a new perspective to the enduring academic debate on the value of technical analysis. More important, we document that the efficacy of technical analysis is related to the prevailing sentiment in the market. Therefore, our study is part of the growing literature on the asymmetric sentiment effect, which has been used to explain many asset price behaviors and anomalies.[4] Furthermore, we offer insights into how traders and portfolio managers can enhance their performance by integrating technical and fundamental analysis into their decision-making process under different sentiment regimes. To the best of our knowledge, our article is the first to combine the strands of literature concerning hedge fund investment, technical analysis, and market sentiment. Our evidence supports the idea that technical analysis in the form it is practiced by hedge fund managers has significant benefits, but investor sentiment, which can be estimated a priori, appears to be an important catalyst.

The remainder of the article is organized as follows: Section II presents data on hedge funds and investor sentiment. Section III discusses measures of hedge

[3]There is also evidence on the forecasting potential of technical analysis techniques (see, e.g., Bessembinder and Chan (1995), Brock, Lakonishok, and LeBaron (1992), Neely, Weller, and Dittmar (1997), Lo, Mamaysky, and Wang (2000), Kavajecz and Odders-White (2004), and Menkhoff and Taylor (2007)).

[4]See, for example, the mean-variance relation (Yu and Yuan (2011)), the idiosyncratic volatility puzzle (Stambaugh, Yu, and Yuan (2015)), the momentum phenomenon (Antoniou et al. (2013)), and the forward premium puzzle (Yu (2013)).

fund performance, risk, and market-timing ability. Section IV provides empirical results, and Section V concludes.

II. Data

A. Hedge Funds

Our hedge fund data come from the Lipper TASS database, one of the most comprehensive hedge fund databases used in the literature (see, e.g., Fung and Hsieh (1997), Liang (2000), Brown, Goetzmann, and Park (2001), Getmansky, Lo, and Makarov (2004), Agarwal, Daniel, and Naik (2009), and Chen (2011)). To mitigate survivorship bias, we include both live and graveyard funds with net monthly returns denominated in U.S. dollars.[5] Our sample period extends from Jan. 1994, when TASS started to track graveyard funds, to Dec. 2010, when the sentiment data end. To alleviate backfill and incubation biases, we delete return observations of a fund before the date it was added to the database (Aggarwal and Jorion (2010)). We also require a fund to have at least 24 monthly returns during the whole sample period and at least 12 monthly returns during each sentiment period to be included in the analysis. Finally, we keep funds with the following primary investment strategies: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed-income arbitrage, fund of funds, global macro, long/short equity, managed futures, and multistrategy. Our final sample contains 5,135 hedge funds, of which 3,290 are live and 1,845 are graveyard funds.

TASS provides information on whether a hedge fund uses technical analysis.[6] Panel A of Table 1 shows that overall, 19.1% of hedge funds use technical analysis. Among live funds, 21.6% use technical analysis, in contrast to only 14.6% among graveyard funds, indicating that technical analysis users might be less likely to fail.

Panel B of Table 1 reports summary statistics of various hedge fund characteristics. As of Dec. 2010, the average fund age is 7.6 years. The average (median) fund size is \$155.5 (\$42.7) million, and the median minimum investment required by hedge funds is \$0.5 million. Lockup restrictions are imposed on investors by 26.4% of the funds in our sample, with an average length of 0.28 years (3.4 months). The average redemption notice period is 40 days (1.3 months). On average, hedge funds charge an annual management fee of 1.45% of total assets and an incentive fee of 15.7% of fund profits. Finally, roughly two-thirds of the sample funds have a high watermark or use derivatives, 58% employ leverage, and 89% use effective auditing.[7]

[5] Aggarwal and Jorion (2010) show that it is sufficient to eliminate most situations of the same fund appearing multiple times in the database by removing funds with returns reported in currencies other than U.S. dollars.

[6] Note that TASS provides a snapshot of the use of technical analysis only as of Dec. 2010 and thus might subject our analysis to a look-ahead bias. We address this issue in Section IV.G.1.

[7] Following Liang (2003), who shows that hedge fund data quality depends heavily on audit timeliness and the auditor's identity, we define effective auditing to be 1 if an auditing record exists in TASS, and 0 otherwise.

TABLE 1

Summary Statistics of Hedge Funds and Investor Sentiment

Panel A of Table 1 presents the distribution of the use of technical analysis (TA) among our sample hedge funds by reporting the number of funds, the number of TA users, and the percentage of hedge funds that use TA as of Dec. 2010. Our sample includes both live and graveyard funds with net monthly returns denominated in U.S. dollars from the Lipper TASS hedge fund database from 1994 to 2010. Panel B reports summary statistics of fund characteristics. Fund size is the time-series average of monthly assets under management for each fund. High watermark, audit, leverage, and derivatives use are dummy variables. Panel C presents summary statistics of the monthly Baker and Wurgler (2006) sentiment index from 1994 to 2010. The index is based on the first principal component of six orthogonalized sentiment proxies: the closed-end fund discount, the number and first-day returns of initial public offerings, New York Stock Exchange turnover, the equity share in total new issues, and the dividend premium. High- (low-) sentiment periods refer to months when the beginning-of-month sentiment index is above (below) the sample median value.

Sample/Subsample	Number of Funds	Number of TA Users	% of TA Users
Panel A. Distribution of the Use of TA			
All funds	5,135	981	19.1
Live funds	3,290	712	21.6
Graveyard funds	1,845	269	14.6

Panel B. Summary Statistics of Fund Characteristics

Variable	Obs.	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
Fund age (year)	5,135	7.58	4.36	1.75	4.42	6.42	9.75	33.83
Fund size ($bil)	4,555	0.16	0.41	0.00	0.01	0.04	0.13	6.87
Lockup period (years)	5,135	0.28	0.56	0.00	0.00	0.00	0.50	7.50
Notice period (years)	5,135	0.11	0.08	0.00	0.04	0.08	0.16	1.00
Management fee (%)	5,118	1.45	0.68	0.00	1.00	1.50	2.00	22.00
Incentive fee (%)	5,099	15.72	7.50	0.00	10.00	20.00	20.00	50.00
High watermark (0/1)	5,118	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Min. investment ($mil)	5,117	1.18	9.53	0.00	0.10	0.50	1.00	250.00
Audit (0/1)	5,135	0.89	0.32	0.00	1.00	1.00	1.00	1.00
Leverage (0/1)	5,135	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Derivatives use (0/1)	4,423	0.69	0.47	0.00	0.00	1.00	1.00	1.00

Panel C. Summary Statistics of Investor Sentiment

Sample Period	Obs.	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
All months, 1994–2010	204	0.15	0.56	−0.90	−0.14	0.02	0.28	2.50
High-sentiment periods	102	0.50	0.59	0.02	0.10	0.28	0.53	2.50
Low-sentiment periods	102	−0.21	0.21	−0.90	−0.30	−0.14	−0.05	0.02

To examine the relation between the use of technical analysis and fund characteristics, we estimate a logistic regression with the controls of style fixed effects. The untabulated results show that age is positively related to technical analysis use, suggesting that seasoned managers have higher reputation costs and thus have more incentives to use technical analysis to manage risk (Brown et al. (2001)) or, alternatively, that technical analysis users are less likely to fail. We also find that incentive fee, derivatives use, and leverage have positive and significant effects on technical analysis use. Finally, we find that redemption-notice period, high watermark, and minimum investment are negatively and significantly related to the use of technical analysis.

B. Investor Sentiment

To measure marketwide investor sentiment, we use the beginning-of-the-month Baker and Wurgler (2006) monthly sentiment index, which is based on the first principal component of six orthogonalized sentiment proxies: the closed-end fund discount, the number and the first-day returns of initial public offerings, New York Stock Exchange turnover, the equity share in total new issues, and the dividend premium.[8]

Panel C of Table 1 shows summary statistics of the Baker and Wurgler (2006) sentiment index over 1994–2010. Following Stambaugh et al. (2012), we divide the sample period into two subperiods, the first (second) of which covers periods of high (low) sentiment where the beginning-of-the-month sentiment level is above (below) the sample median of 0.02.[9] The mean (median) levels of sentiment in high- and low-sentiment periods are 0.50 (0.28) and −0.21 (−0.14), respectively.

III. Methodology

In this section, we discuss measures of hedge fund performance, risk, and market-timing ability used in this article. Our measures are based on monthly net-of-fee returns and are estimated over the full sample period as well as periods of high and low investor sentiment.

A. Performance Measures

We first measure hedge fund performance using each fund's average monthly return during specified sample periods. We also estimate alpha using multifactor models as follows:

$$r_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \varepsilon_{it}, \tag{1}$$

where r_{it} is the return of fund i in excess of the 1-month Treasury-bill (T-bill) rate in month t, α_i is the risk-adjusted performance measure of fund i, β_{ik} is the factor loading of fund i on factor k, F_{kt} is the risk factor k in month t, and ε_{it} is the error term.

We consider two sets of risk factors: i) Carhart (1997) 4 factors, including the market risk premium, a small-minus-big size factor, a high-minus-low book-to-market factor, and a momentum factor, and ii) Fung and Hsieh (2004) 7 factors, including the market risk premium, Wilshire small-minus-large-cap return, change in constant maturity yield of 10-year Treasury, change in the spread of Moody's Baa minus 10-year Treasury, bond primitive trend-following strategies (PTFS), currency PTFS, and commodities PTFS.

B. Risk Measures

We estimate the following eight risk measures during each sample period: total risk, market risk, idiosyncratic risk, downside risk, skewness, kurtosis, coskewness, and cokurtosis.

TOTAL_RISK is the standard deviation of monthly returns for each hedge fund and consists of both systematic risk and idiosyncratic risk. MARKET_RISK

[8] We thank Jeffrey Wurgler for making the sentiment data available at his Web site (http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_v23_POST.xlsx).

[9] The use of the full sample median to categorize high- and low-sentiment periods might subject our results to a potential look-ahead bias. To address this concern, we classify high- and low-sentiment periods on a rolling basis using the median sentiment level over the previous 10 years, and find qualitatively similar results.

and IDIOSYNCRATIC_RISK are the fund's exposure (beta) to the equity market and the standard deviation of the residuals, respectively, from the Fung and Hsieh (2004) 7-factor model.[10]

DOWNSIDE_RISK is measured following Chen's (2011) method:

$$\text{(2)} \qquad \text{DOWNSIDE\_RISK} = \beta^- - \beta = \frac{\text{cov}(r_i, r_m | r_m < 0)}{\text{var}(r_m | r_m < 0)} - \frac{\text{cov}(r_i, r_m)}{\text{var}(r_m)},$$

where r_i is the monthly return of fund i in excess of the 1-month T-bill rate and r_m is the market return in excess of the 1-month T-bill rate. Intuitively, DOWNSIDE_RISK is the fund's beta in ex post downside market conditions minus unconditional beta. The more positive the value of this measure, the higher the downside risk is to the investor.

SKEWNESS and KURTOSIS are the third and fourth moments of the distribution of returns for each hedge fund. COSKEWNESS and COKURTOSIS are the third and fourth comovements of the distribution of fund returns as follows:

$$\text{(3)} \qquad \text{COSKEWNESS} = \frac{\text{E}\left[\left(R_i - \bar{R}_i\right)\left(R_m - \bar{R}_m\right)^2\right]}{\text{E}\left[\left(R_m - \bar{R}_m\right)^3\right]},$$

$$\text{(4)} \qquad \text{COKURTOSIS} = \frac{\text{E}\left[\left(R_i - \bar{R}_i\right)\left(R_m - \bar{R}_m\right)^3\right]}{\text{E}\left[\left(R_m - \bar{R}_m\right)^4\right]},$$

where R_i denotes the fund return and R_m is the return on the equity market index. All else equal, a risk-averse investor would prefer less negative skewness and coskewness, and lower kurtosis and cokurtosis.

C. Market-Timing Measures

Following Treynor and Mazuy (1966), we measure the market-timing ability of hedge funds as follows:

$$\text{(5)} \qquad r_{it} = \alpha_i + \beta_{im} r_{mt} + \gamma_{im} r_{mt}^2 + \varepsilon_{it},$$

where r_{it} is the return of fund i in excess of the 1-month T-bill rate in month t, r_{mt} is the market return in excess of the 1-month T-bill rate in month t, and γ_{im} measures fund i's market-timing ability.[11]

In equation (5), γ_{im} captures the convexity of the fund return to the market return. Intuitively, fund managers are said to possess significant positive market-timing ability if they can forecast market returns and hold a greater proportion of the market portfolio (i.e., increase market beta) when the market return is high and a smaller proportion (i.e., reduce market beta) when the market return is low.

[10] Using the Carhart (1997) 4-factor model yields similar results.

[11] We also use Henriksson and Merton's (1981) market-timing measure and find similar results. In addition, we examine liquidity-timing and volatility-timing abilities of hedge funds as in Busse (1999), Chen and Liang (2007), Cao, Simin, and Wang (2013), and Cao, Chen, Liang, and Lo (2013), but find no significant differences in these two timing abilities between technical analysis users and nonusers in different sample periods.

Furthermore, following Chen and Liang (2007), we extend equation (5) to a multifactor market-timing model as follows:

$$r_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \gamma_{im} r_{mt}^2 + \varepsilon_{it}, \tag{6}$$

where F_{kt} represents the Carhart (1997) 4 factors or the Fung and Hsieh (2004) 7 factors defined previously.

IV. Empirical Analysis

We examine how investor sentiment affects the efficacy of technical analysis in the hands of hedge fund managers by comparing the performance, risk taking, and market-timing ability of technical analysis users versus nonusers in different sentiment periods. We also analyze the sentiment betas of technical analysis users versus nonusers. Furthermore, we compare the relative importance of technical analysis versus fundamental analysis, and investigate whether investors are aware of the relative usefulness of technical analysis under different regimes of sentiment and adjust fund flows accordingly. Finally, we provide a variety of robustness tests.

A. Use of Technical Analysis and Hedge Fund Performance

1. Univariate Analysis

Table 2 reports the performance of technical analysis users versus nonusers among our sample hedge funds in different sample periods. We focus mainly on high-sentiment periods when more sentiment-induced mispricing exists and thus technical analysis is likely to be more useful. Indeed, we find that during high-sentiment periods, technical analysis users on average significantly outperform nonusers by 0.445%, 0.113%, and 0.107% per month (or 5.3%, 1.4%, and 1.3% per annum) in terms of the average return, Carhart (1997) 4-factor alpha, and Fung and Hsieh (2004) 7-factor alpha, respectively. We observe similar but slightly weaker results during the whole sample period.

In contrast, during low-sentiment periods, technical analysis users in general underperform nonusers, and the difference is significant when fund performance

TABLE 2

Use of Technical Analysis and Hedge Fund Performance by Investor Sentiment Periods

Table 2 compares the performance (in percentage) of technical analysis users and nonusers among our sample hedge funds in high- and low-sentiment periods as well as the full sample period of 1994–2010. Performance is measured by the average monthly return (Ave. Ret.), Carhart (1997) 4-factor alpha (Alpha4), and Fung and Hsieh (2004) 7-factor alpha (Alpha7), respectively. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median value. t-diff is the t-statistic from the test of whether the difference in means is 0, and p-diff is the associated p-value.

	Entire Period: 1994–2010				High-Sentiment Periods				Low-Sentiment Periods			
Sample	Obs.	Ave. Ret.	Alpha4	Alpha7	Obs.	Ave. Ret.	Alpha4	Alpha7	Obs.	Ave. Ret.	Alpha4	Alpha7
Users	981	0.529	0.169	0.230	816	0.386	−0.010	0.212	836	0.781	0.236	0.390
Nonusers	4,154	0.447	0.124	0.164	3,199	−0.060	−0.123	0.105	3,677	0.980	0.428	0.447
Difference		0.082	0.046	0.066		0.445	0.113	0.107		−0.198	−0.192	−0.057
t-diff.		2.702	1.535	2.056		8.311	2.704	2.387		−4.534	−4.794	−1.293
p-diff.		0.007	0.125	0.040		0.000	0.007	0.017		0.000	0.000	0.196

is measured by average return or Carhart (1997) 4-factor alpha. Overall, a clear pattern is that the outperformance of technical analysis users exists only in high-sentiment periods and disappears or even reverses in low-sentiment periods.

Table 2 also shows that, irrespective of the use of technical analysis, hedge funds tend to perform better in low- than in high-sentiment periods. Although not the focus of this article, it would be interesting to understand why there is such a pattern in hedge fund performance and reconcile this result with the asset pricing anomaly literature (e.g., Stambaugh et al. (2012)). Stambaugh et al. (2012) show that a broad set of asset pricing anomalies is stronger following high levels of investor sentiment and that these anomalies are mainly driven by short positions. If hedge funds can fully exploit these anomalies, we would expect them to outperform in high-sentiment periods. However, as argued in Stambaugh et al. (2012), hedge funds may face short-sale impediments such as arbitrage risk (see also Stambaugh et al. (2015)), behavioral biases, and high shorting costs and, as a result, take insufficient short positions on average to fully exploit these anomalies.[12] In general, hedge funds are not market neutral and hold net long positions. In fact, Brunnermeier and Nagel (2004) show that hedge funds heavily invested in overpriced stocks during the technology bubble, a period characterized by high investor sentiment. Therefore, it is not surprising that hedge funds on average have lower performance in high-sentiment periods.[13]

2. Regression Analysis

We further examine the effectiveness of technical analysis usage by hedge funds in different sample periods using cross-sectional regressions. Specifically, we regress fund performance (measured by average return, 4-factor alpha, and 7-factor alpha) on a dummy variable indicating whether hedge funds use technical analysis, controlling for other fund characteristics, fund categories, and inception years.[14] The regression results are reported in Table 3 with the White (1980) heteroskedasticity-robust t-statistics.

Focusing on the effect of technical analysis usage, we find that during high-sentiment periods, technical analysis users significantly outperform nonusers by 0.116%, 0.074%, and 0.089% per month (or 1.4%, 0.9%, and 1.1% per annum) in terms of average return, 4-factor alpha, and 7-factor alpha, respectively. In contrast, the use of technical analysis has a significant negative or insignificant effect on fund performance during low-sentiment periods. Considering the entire sample

[12] The untabulated results show that hedge funds taking more short positions show no significant underperformance in high-sentiment periods. In particular, consistent with Stambaugh et al. (2012), we find that market-neutral funds even perform relatively better in high- than in low-sentiment periods, though the difference is marginally significant.

[13] To address the concern that our results could be driven by model misspecification due to a sentiment-related factor, we add the Baker and Wurgler (2006) sentiment-change index to the Carhart (1997) 4-factor and Fung and Hsieh (2004) 7-factor models, respectively, in estimating alpha. We find that the documented hedge fund underperformance in high-sentiment periods could be partially explained, but not completely explained away, by the noise trader risk considered in Chen, Han, and Pan (2014). Moreover, we show that technical analysis users still outperform nonusers in high-sentiment periods even after controlling for the sentiment-change index, indicating that our main results also remain robust to the inclusion of the sentiment factor.

[14] We exclude fund age and size in cross-sectional regressions to avoid a look-ahead bias. As a robustness check, we include these two variables and document qualitatively similar results.

TABLE 3

Regressions of Hedge Fund Performance on the Use of Technical Analysis by Investor Sentiment Periods

Table 3 reports regression results of hedge fund performance (in percentage) on the use of technical analysis after controlling for various fund characteristics and category and inception year dummies. Performance is measured by the average monthly return (Ave. Ret.), Carhart (1997) 4-factor alpha (Alpha4), and Fung and Hsieh (2004) 7-factor alpha (Alpha7), respectively. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median. The White (1980) heteroskedasticity-robust t-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Entire Period: 1994–2010			High-Sentiment Periods			Low-Sentiment Periods		
Independent Variable	Ave. Ret.	Alpha4	Alpha7	Ave. Ret.	Alpha4	Alpha7	Ave. Ret.	Alpha4	Alpha7
Technical analysis use	0.015	0.042	0.042	0.116**	0.074*	0.089*	−0.060	−0.100**	−0.015
	(0.47)	(1.29)	(1.17)	(2.22)	(1.66)	(1.74)	(−1.36)	(−2.06)	(−0.27)
Lockup period	0.066***	0.029	0.032	−0.089*	−0.025	0.009	0.140***	0.055*	0.089**
	(2.76)	(1.39)	(1.25)	(−1.94)	(−0.64)	(0.22)	(3.66)	(1.91)	(2.40)
Notice period	0.464**	0.612***	0.320	0.738**	0.878***	0.684*	−0.074	0.171	−0.138
	(2.09)	(2.91)	(1.35)	(2.16)	(3.00)	(1.94)	(−0.23)	(0.59)	(−0.39)
Management fee	0.004	−0.007	−0.029	−0.001	0.019	−0.028	0.032	0.032	0.031
	(0.12)	(−0.21)	(−1.03)	(−0.02)	(0.60)	(−0.77)	(0.94)	(0.97)	(0.92)
Incentive fee	0.011***	0.008***	0.009***	0.018***	0.006*	0.008*	0.001	0.005	0.005
	(4.14)	(3.04)	(3.00)	(3.94)	(1.67)	(1.91)	(0.15)	(1.35)	(1.35)
High watermark	0.037	0.041	0.078**	−0.097*	0.040	0.118**	−0.000	−0.036	0.022
	(1.17)	(1.26)	(2.20)	(−1.83)	(0.92)	(2.49)	(−0.00)	(−0.82)	(0.47)
Min. investment	0.009	0.022**	0.011	0.035**	0.057***	0.043***	−0.021	0.011	−0.016
	(1.04)	(2.49)	(1.11)	(2.44)	(4.94)	(3.16)	(−1.63)	(1.16)	(−1.12)
Audit	0.219***	0.354***	0.269***	0.044	0.258***	0.298***	0.281***	0.284***	0.253***
	(4.30)	(6.90)	(5.44)	(0.55)	(3.21)	(3.42)	(3.96)	(3.14)	(2.92)
Leverage	0.003	−0.001	−0.010	0.026	0.024	−0.023	−0.034	−0.071**	−0.070*
	(0.11)	(−0.05)	(−0.35)	(0.56)	(0.68)	(−0.56)	(−0.89)	(−2.07)	(−1.78)
Derivatives use	0.078***	0.059**	0.097***	0.164***	0.089**	0.085*	−0.054	−0.052	0.012
	(2.83)	(2.22)	(3.46)	(3.28)	(2.21)	(1.86)	(−1.34)	(−1.41)	(0.29)
Constant	0.084	−0.150	−0.168	−0.162	−0.502***	−0.482***	−0.459*	0.802*	0.127
	(0.60)	(−0.74)	(−0.89)	(−0.91)	(−3.52)	(−3.22)	(−1.69)	(1.78)	(0.63)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inception year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,403	4,403	4,403	3,594	3,594	3,594	3,839	3,839	3,839
Adj. R^2	0.089	0.088	0.070	0.144	0.051	0.042	0.121	0.066	0.049

period, we find no significant relation between the use of technical analysis and fund performance regardless of the performance measures used.

The effects of other fund characteristics are also worth noting. First, the lockup (redemption notice) period has a significant positive effect on fund performance only during low- (high-) sentiment periods, suggesting that the share illiquidity premium documented in Aragon (2007) is mainly driven by the lockup (redemption notice) period in low- (high-) sentiment periods. In addition, consistent with Ackermann, McEnally, and Ravenscraft (1999) and Agarwal, Boyson, and Naik (2009), we document that incentive fees are positively related to all three performance measures over the full sample period; however, this positive relation is significant only in high-sentiment periods. Moreover, we find that effective auditing improves fund performance irrespective of the sample period considered, indicating that due diligence is a source of fund alpha (Brown, Fraser, and Liang (2008)). Finally, derivatives usage improves fund performance during the whole sample period, but this result is mainly driven by high-sentiment periods.[15]

Overall, cross-sectional regressions provide robust evidence on the efficacy of using technical analysis by hedge funds. The most notable result is that even in a multivariate context, the use of technical analysis significantly associated with higher hedge fund performance only during high-sentiment periods; the outperformance of technical analysis users is not evident or even reverses in low-sentiment periods.

B. Use of Technical Analysis and Risk Taking of Hedge Funds

We have documented that technical analysis users significantly outperform nonusers during high-sentiment periods. To the extent that hedge funds using technical analysis systematically assume substantial risks during high-sentiment periods, our results may result from misclassifying as excess return some risks that are not fully reflected in the 4- and 7-factor models. Therefore, we examine the effect of technical analysis usage on the risk-taking behavior of hedge funds during different sentiment periods. Specifically, we investigate whether technical analysis users exhibit lower risk than nonusers especially in high-sentiment periods.

In Table 4, we compare risk taking of technical analysis users versus nonusers in different sample periods. Panel A shows that over the full sample period, the use of technical analysis is associated with significantly higher total and idiosyncratic risk. However, technical analysis users exhibit lower market risk, downside risk, kurtosis, and cokurtosis, and less negative skewness, all of which are desirable traits. Considering risk taking of hedge funds during high- and low-sentiment periods separately in Panels B and C yields directionally similar results, although the differences in those desirable risk traits between users and nonusers tend to be more significant when investor sentiment is high. The overall results appear in favor of technical analysis users in terms of effectively managing risk especially in high-sentiment periods.

[15] Similar to what we find for low-sentiment periods, Chen (2011) documents that derivatives usage does not enhance hedge fund performance. As a robustness check, we use exactly the same sample period as in Chen and document an insignificant relation between derivatives usage and fund performance, suggesting that our full-sample result is different from Chen mainly because of the use of an extended sample period.

TABLE 4

Use of Technical Analysis and Risk Taking of Hedge Funds by Investor Sentiment Periods

Table 4 compares the average risk levels of technical analysis users and nonusers among our sample hedge funds in high- and low-sentiment periods as well as the full sample period of 1994–2010. Risk is estimated by eight measures: TOTAL_RISK is the standard deviation (in percentage) of monthly fund returns; MARKET_RISK is the estimated coefficient of the market excess return in the Fung and Hsieh (2004) 7-factor model; IDIOSYNCRATIC_RISK is the standard deviation (in percentage) of the residuals from Fung and Hsieh's 7-factor model; DOWNSIDE_RISK is the fund's beta in ex post downside market conditions minus unconditional beta; SKEWNESS and KURTOSIS are the third and fourth moments of the distribution of fund returns; COSKEWNESS and COKURTOSIS are the third and fourth comovements of the distribution of fund returns. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median value. t-diff is the t-statistic from the test of whether the difference in means is 0, and p-diff is the associated p-value.

Sample	Obs.	TOTAL_RISK	MARKET_RISK	IDIOSYNCRATIC_RISK	DOWNSIDE_RISK	SKEWNESS	KURTOSIS	COSKEWNESS	COKURTOSIS
Panel A. Fund Risk Taking during Entire Sample Period, 1994–2010									
Users	981	4.357	0.215	3.718	−0.105	−0.182	5.677	0.187	0.157
Nonusers	4,154	3.840	0.251	3.111	0.045	−0.578	6.273	0.388	0.364
Difference		0.517	−0.035	0.608	−0.151	0.397	−0.596	−0.200	−0.207
t-diff.		4.506	−2.524	6.420	−9.748	8.884	−2.544	−3.257	−11.194
p-diff.		0.000	0.012	0.000	0.000	0.000	0.011	0.000	0.000
Panel B. Fund Risk Taking during High-Sentiment Periods									
Users	816	4.760	0.186	3.293	−0.122	−0.212	4.627	−0.023	0.130
Nonusers	3,199	4.171	0.318	2.591	0.018	−0.598	5.051	0.370	0.405
Difference		0.589	−0.133	0.702	−0.140	0.386	−0.424	−0.393	−0.274
t-diff.		4.220	−6.958	7.356	−6.903	8.663	−2.516	−5.643	−11.490
p-diff.		0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000
Panel C. Fund Risk Taking during Low-Sentiment Periods									
Users	836	3.728	0.221	2.821	−0.119	0.068	4.260	0.253	0.170
Nonusers	3,677	3.067	0.255	2.146	0.028	−0.069	4.463	0.328	0.247
Difference		0.661	−0.033	0.675	−0.147	0.136	−0.203	−0.075	−0.077
t-diff.		6.387	−2.127	8.757	−4.002	3.578	−1.461	−1.295	−4.870
p-diff.		0.000	0.034	0.000	0.000	0.000	0.144	0.195	0.000

In untabulated tests, we estimate cross-sectional regressions of hedge fund risk taking on the use of technical analysis with the same controls as those in Table 3. In general, we find that using technical analysis reduces risk taking of hedge funds in high-sentiment periods, but the evidence is mixed in low-sentiment periods. Most notably, the use of technical analysis is significantly associated with lower downside risk and cokurtosis, and less negative skewness regardless of the market sentiment regime considered. This implies that technical analysis users bear lower downside and higher moment risk than nonusers, although the evidence is slightly weaker in low-sentiment periods. However, technical analysis reduces market risk in high-sentiment periods while increasing total and idiosyncratic risk in low-sentiment periods.[16]

In general, our results suggest that the use of technical analysis is associated with lower fund risk, and the benefits are most prominent in high-sentiment periods. This finding has important implications for investors, traders, and fund managers, given that technical analysis appears to be a valuable tool of reducing downside and higher moment risk for hedge funds.

C. Use of Technical Analysis and Market-Timing Ability of Hedge Funds

Market timing has been identified as one of the important sources of hedge fund alpha (Lo (2008)). In Table 5, we estimate the market-timing ability of hedge funds from equation (5) and examine whether this ability differs significantly between technical analysis users and nonusers in different sentiment periods.[17] The results show that technical analysis users on average have significantly better market-timing skill than nonusers during high-sentiment periods. A similar pattern exists over the full sample period. However, during low-sentiment periods, technical analysis users exhibit significantly worse market-timing ability than nonusers.

To control for the possible effects of other fund characteristics, we regress market-timing estimates on the technical analysis dummy again with the same controls as those in Table 3. The untabulated results show that the coefficients for the technical analysis dummy are positive and significant during the whole sample and high-sentiment periods, but not significant during low-sentiment periods.[18]

Overall, we find strong and consistent evidence that technical analysis is an effective tool of market timing especially in high-sentiment periods when there exists more mispricing. This result may explain the documented outperformance of technical analysis users as compared to nonusers following high sentiment. Moreover, our finding is consistent with Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011), who find that during the technology

[16]The effects of other hedge fund characteristics on risk taking are in general consistent with Chen (2011). For instance, lockup (redemption notice) period has a significant positive (negative) impact on total, market, and idiosyncratic risk. Management and incentive fees are associated with higher total and idiosyncratic risk and lower market and downside risk. Moreover, high watermark, high-quality auditing, and the use of derivatives lower fund risk taking, whereas the use of leverage increases fund risk taking.

[17]We also estimate multifactor market-timing models as in equation (6) and find qualitatively similar results.

[18]Regarding other fund characteristics, we find that hedge funds using derivatives have better market-timing ability than nonusers during the whole sample period and high-sentiment periods.

TABLE 5

Use of Technical Analysis and Market-Timing Ability of Hedge Funds by Investor Sentiment Periods

Table 5 compares the market-timing ability (×100) of technical analysis users and nonusers among our sample hedge funds in high- and low-sentiment periods as well as the full sample period of 1994–2010. Market timing is estimated from equation (5) and captures the convexity of fund returns to market returns. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median value. *t*-diff is the *t*-statistic from the test of whether the difference in means is zero, and *p*-diff is the associated *p*-value.

	Entire Period: 1994–2010		High-Sentiment Periods		Low-Sentiment Periods	
Sample	Obs.	Market Timing	Obs.	Market Timing	Obs.	Market Timing
Users	981	0.445	816	1.338	836	−1.398
Nonusers	4,154	−0.522	3,199	−0.002	3,677	−0.658
Difference		0.967		1.341		−0.741
t-diff.		7.335		5.547		−3.168
p-diff.		0.000		0.000		0.002

bubble, hedge funds trade in the same direction as the tech-stock-fueled market upturn. Thus, rather than engaging in arbitrage that would tend to align prices with intrinsic values in a high-sentiment-induced market episode of overpricing, hedge funds actively time the market, riding the trend and then reducing their exposure before the bubble bursts.

D. Sentiment Betas of Technical Analysis Users versus Nonusers

To further understand our main finding that only during high-sentiment periods do technical analysis users significantly outperform nonusers, we analyze the sentiment betas of technical analysis users versus nonusers. Specifically, we add the Baker and Wurgler (2006) sentiment-change index to the 1-factor capital asset pricing model, Carhart (1997) 4-factor model, and Fung and Hsieh (2004) 7-factor model, respectively, and estimate sentiment betas of hedge funds as the sensitivities of monthly fund returns to the sentiment-change index.[19] The results (untabulated) are similar across the three models. For example, with the Fung–Hsieh 7-factor model, we find that the average sentiment beta of technical analysis users (nonusers) is 0.029 (0.102), and their difference is significant at the 5% level.

The fact that technical analysis users show a lower sensitivity to investor sentiment changes than nonusers provides an explanation for our main finding. In particular, following high (low) sentiment, the portfolios of technical analysis nonusers are more overvalued (undervalued) than those of technical analysis users, thus resulting in higher (lower) performance for technical analysis users than for nonusers.

We provide a plausible explanation for why technical analysis users and nonusers have different sensitivities to sentiment changes based on Neely et al. (2014). Neely et al. show that technical indicators can better detect the typical decline in the equity risk premium near business-cycle peaks (i.e., mostly following high-sentiment periods), but they are not as effective as macroeconomic variables in picking up the typical market rise near cyclical troughs (i.e., mostly

[19]The sentiment-change index is the first principal component of changes in the six orthogonalized proxies for investor sentiment. It is available from Jeffrey Wurgler's Web site (http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_v23_POST.xlsx).

following low-sentiment periods). (Note that these results are consistent with our earlier finding that technical analysis users exhibit superior market-timing ability in high-sentiment periods.) Neely et al. further relate the usefulness of technical indicators for predicting the equity risk premium to their ability to anticipate changes in investor sentiment. Therefore, if technical analysis users can better predict sentiment changes and detect market downturn following high sentiment and thus reduce their investment in overpriced stocks, we expect them to exhibit a lower sensitivity to sentiment changes than nonusers.

E. Technical Analysis versus Fundamental Analysis

We further examine whether hedge fund managers can exploit sentiment-induced mispricing using other available strategies, such as fundamental analysis, by comparing the relative importance of technical versus fundamental analysis in different sentiment periods. Specifically, we employ the self-reported information from TASS on whether hedge funds use fundamental analysis. Approximately 46% of our sample funds are fundamental analysis users, and the correlation between fundamental and technical analysis usage is only 0.2.

In Table 6, we perform a multivariate analysis similar to that in Table 3 by incorporating a dummy indicating the use of fundamental analysis.[20] We document that during high-sentiment periods, whereas the coefficients on the use of technical analysis are significant and positive, the coefficients on the use of fundamental analysis are significant and negative regardless of the performance measures used. This result indicates that fundamental analysis actually hurts fund performance during periods of high-sentiment-induced overpricing when technical analysis appears consistently to improve fund performance. However, during low-sentiment periods when the market is relatively more efficient, fundamental analysis shows some evidence of enhancing fund performance as measured by raw return and 4-factor alpha, whereas technical analysis is less useful or even counterproductive.

Our results have important practical implications for investors, traders, and hedge fund managers. On the one hand, technical analysis apparently improves fund performance and thus offers investors a good hedge during high-sentiment periods, which are typically associated with underperformance, indicating its importance for investor wealth and hedge fund viability. On the other hand, fundamental analysis can provide benefits to investors during low-sentiment periods. Hence, we present evidence in support of rotating investment strategies, namely, employing technical and fundamental analysis in high- and low-sentiment periods, respectively.

F. Use of Technical Analysis and Investor Flows

Given the observed pattern that technical analysis is relatively more (less) useful in high- (low-) sentiment periods, a natural question is whether investors

[20]We also use a refined sample of hedge funds exclusively using either technical or fundamental analysis, and regress fund performance on a dummy variable, which is defined as 1 (0) if hedge funds use technical (fundamental) analysis, with the same controls used in Table 6. The untabulated results show that technical analysis users significantly outperform fundamental analysis users in high-sentiment periods, and this pattern disappears or even reverses in low-sentiment periods.

TABLE 6

Regressions of Hedge Fund Performance on the Use of Technical and Fundamental Analysis by Investor Sentiment Periods

Table 6 reports regression results of hedge fund performance (in percentage) on the use of technical and fundamental analysis after controlling for various fund characteristics and category and inception year dummies. Performance is measured by the average monthly return (Ave. Ret.), Carhart (1997) 4-factor alpha (Alpha4), and Fung and Hsieh (2004) 7-factor alpha (Alpha7), respectively. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median value. The White (1980) heteroskedasticity-robust *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Entire Period: 1994–2010			High-Sentiment Periods			Low-Sentiment Periods		
Independent Variable	Ave. Ret.	Alpha4	Alpha7	Ave. Ret.	Alpha4	Alpha7	Ave. Ret.	Alpha4	Alpha7
Technical analysis use	0.005	0.051	0.053	0.158***	0.108**	0.123**	−0.105**	−0.122**	−0.017
	(0.14)	(1.46)	(1.38)	(2.88)	(2.27)	(2.25)	(−2.25)	(−2.39)	(−0.29)
Fundamental analysis use	0.036	−0.031	−0.038	−0.149***	−0.119***	−0.118***	0.153***	0.078**	0.009
	(1.32)	(−1.09)	(−1.27)	(−3.04)	(−2.89)	(−2.65)	(3.88)	(1.97)	(0.22)
Lockup period	0.066***	0.030	0.033	−0.086*	−0.022	0.011	0.137***	0.053*	0.089**
	(2.72)	(1.42)	(1.27)	(−1.86)	(−0.57)	(0.29)	(3.55)	(1.85)	(2.39)
Notice period	0.458**	0.617***	0.326	0.767**	0.901***	0.707**	−0.103	0.156	−0.140
	(2.06)	(2.93)	(1.37)	(2.24)	(3.07)	(2.01)	(−0.31)	(0.53)	(−0.40)
Management fee	0.005	−0.008	−0.030	−0.004	0.016	−0.031	0.036	0.034	0.031
	(0.15)	(−0.24)	(−1.06)	(−0.10)	(0.52)	(−0.84)	(1.05)	(1.02)	(0.92)
Incentive fee	0.011***	0.008***	0.009***	0.018***	0.006	0.008*	0.001	0.005	0.005
	(4.16)	(3.02)	(2.97)	(3.87)	(1.60)	(1.85)	(0.26)	(1.41)	(1.35)
High watermark	0.034	0.043	0.081**	−0.085	0.050	0.128***	−0.016	−0.044	0.021
	(1.06)	(1.34)	(2.28)	(−1.60)	(1.13)	(2.65)	(−0.36)	(−0.99)	(0.44)
Min. investment	0.010	0.022**	0.011	0.034**	0.056***	0.042***	−0.020	0.012	−0.016
	(1.06)	(2.47)	(1.09)	(2.36)	(4.81)	(3.07)	(−1.59)	(1.20)	(−1.12)
Audit	0.220***	0.353***	0.267***	0.043	0.258***	0.297***	0.285***	0.286***	0.254***
	(4.34)	(6.90)	(5.43)	(0.54)	(3.21)	(3.42)	(4.05)	(3.17)	(2.93)
Leverage	0.001	0.001	−0.008	0.035	0.031	−0.016	−0.044	−0.076**	−0.070*
	(0.02)	(0.02)	(−0.27)	(0.76)	(0.89)	(−0.39)	(−1.16)	(−2.22)	(−1.79)
Derivatives use	0.075***	0.061**	0.100***	0.172***	0.095**	0.092**	−0.065	−0.057	0.011
	(2.74)	(2.29)	(3.56)	(3.45)	(2.37)	(1.98)	(−1.61)	(−1.54)	(0.27)
Constant	0.059	−0.128	−0.141	0.146	−0.593***	−1.516***	−0.567**	0.747*	0.120
	(0.42)	(−0.63)	(−0.75)	(0.71)	(−3.34)	(−8.59)	(−2.04)	(1.67)	(0.60)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inception year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,403	4,403	4,403	3,594	3,594	3,594	3,839	3,839	3,839
Adj. R^2	0.089	0.088	0.071	0.146	0.054	0.044	0.124	0.068	0.049

are aware of this pattern and adjust fund flows to technical analysis users and nonusers accordingly. To address this question, we estimate the following regression at an annual frequency for each sample period:[21]

$$(7) \qquad \text{FLOW}_{it} = \alpha + \beta_1 \text{PERF}_{i,t-1} + \beta_2 \text{PERF}^2_{i,t-1} + \beta_3 \text{TA}_i + \beta_4 \text{PERF}_{i,t-1}\text{TA}_i + \text{CONTROLS} + \varepsilon_{it},$$

where FLOW_{it} is the net fund flows of hedge fund i during period t, $\text{PERF}_{i,t-1}$ is the fund return in excess of the median fund return within the same investment category during period $t-1$, and TA_i is a dummy variable indicating whether fund i uses technical analysis.

The untabulated results show that irrespective of the sample period considered, fund flows are unrelated to the technical analysis dummy and the interaction between this dummy and prior performance. These results suggest that hedge fund investors do not view the use of technical analysis particularly beneficial or perilous to their wealth and fail to adjust their flows based on whether hedge funds use technical analysis in different sentiment periods.

G. Robustness Checks

1. Subperiod Analysis

The TASS hedge fund database provides only the latest "snapshot" information on the use of technical analysis and other fund characteristics. The lack of historical time-series data raises a concern that the reported technical analysis usage might vary over time and thus our analysis might be subject to a look-ahead bias. To address this concern, we obtain the Jan. 2003 version of the TASS database, which provides technical analysis data as of year-end 2002. We find that among the 2,459 live hedge funds in the 2003 database that remain alive through Dec. 2010, only 12 funds change from technical analysis users to nonusers and 21 funds change from nonusers to users. The remaining 98.7% of funds have the same technical analysis indicator between these two dates.[22]

As an additional robustness test, we repeat our baseline analysis using a more recent subperiod of 2003–2010. This is particularly important because it mitigates the concern that the technical analysis indicator might vary significantly over the full sample period. The results from Panel A of Table 7 are similar to those from the full sample period in Table 2. We again show that the performance differences between technical analysis users and nonusers are positive and significant during high-sentiment periods but become neutral or even negative and significant in low-sentiment periods. Untabulated results also show that technical analysis users exhibit lower risk and better market-timing ability than nonusers in high-sentiment periods.

[21] We use annual frequency because of the share restrictions in the hedge fund industry. We also estimate regressions at a monthly frequency and find similar results.

[22] Our observation about technical analysis is consistent with Ackermann et al. (1999), Liang (2000), Aragon (2007), and Chen (2011), who document that fund characteristics such as incentive fees, lockup provisions, and derivatives usage rarely change.

TABLE 7

Robustness Checks: Use of Technical Analysis and Hedge Fund Performance

Table 7 provides robustness tests on the differences in performance (in percentage) of technical analysis users and nonusers among our sample hedge funds in different sample periods. Performance is measured by the average monthly return (Ave. Ret.), Carhart (1997) 4-factor alpha (Alpha4), and Fung and Hsieh (2004) 7-factor alpha (Alpha7), respectively. In Panel A, the results are obtained from a recent sample period of 2003–2010 using net-of-fee fund returns. In Panel B, the results are obtained from the full sample period of 1994–2010 using prefee fund returns. High- (low-) sentiment periods refer to months when the beginning-of-month Baker and Wurgler (2006) sentiment index is above (below) the sample median value. In Panel C, we classify the full sample period of 1994–2010 into high- and low-market-volatility periods based on the Chicago Board Options Exchange Market Volatility Index (VIX). t-diff is the t-statistic from the test of whether the difference in means is 0, and p-diff is the associated p-value.

	Entire Recent Sample: 2003–2010				High-Sentiment Periods				Low-Sentiment Periods			
Sample	Obs.	Ave. Ret.	Alpha4	Alpha7	Obs.	Ave. Ret.	Alpha4	Alpha7	Obs.	Ave. Ret.	Alpha4	Alpha7
Panel A. Recent Sample Period of 2003–2010												
Users	752	0.580	0.205	0.312	532	0.300	−0.067	0.332	724	0.808	0.232	0.453
Nonusers	3,635	0.469	0.146	0.175	2,497	−0.228	−0.163	0.089	3,446	1.020	0.435	0.469
Difference		0.111	0.060	0.137		0.528	0.095	0.243		−0.212	−0.203	−0.017
t-diff.		3.335	1.932	3.849		8.083	2.192	4.763		−4.556	−5.246	−0.360
p-diff.		0.001	0.053	0.000		0.000	0.029	0.000		0.000	0.000	0.719
Panel B. Prefee Hedge Fund Returns												
Users	981	0.690	0.329	0.390	816	0.549	0.152	0.374	836	0.941	0.393	0.549
Nonusers	4,137	0.588	0.263	0.304	3,185	0.075	0.014	0.242	3,661	1.112	0.568	0.586
Difference		0.102	0.066	0.086		0.474	0.138	0.132		−0.172	−0.175	−0.037
t-diff.		3.305	2.169	2.647		8.767	3.279	2.907		−4.090	−4.295	−0.832
p-diff.		0.001	0.030	0.008		0.000	0.001	0.004		0.000	0.000	0.406
Panel C. Market Volatility Periods												
Users	981	0.529	0.169	0.230	833	0.443	0.199	0.292	754	0.720	0.148	0.321
Nonusers	4,154	0.447	0.124	0.164	3,540	0.328	0.033	0.132	2,770	0.722	0.215	0.406
Difference		0.082	0.046	0.066		0.115	0.166	0.160		−0.002	−0.067	−0.084
t-diff.		2.702	1.535	2.056		2.623	3.847	3.641		−0.066	−1.928	−2.004
p-diff.		0.007	0.125	0.040		0.009	0.000	0.000		0.947	0.054	0.045

2. Prefee Returns

To ensure that our results are not simply driven by the different fees charged by technical analysis users and nonusers, we repeat our main analysis using prefee return estimates.[23] The results in Panel B of Table 7 are qualitatively similar to those reported in Table 2. During high-sentiment periods, technical analysis users have significantly higher prefee performance than nonusers. During low-sentiment periods, however, technical analysis users have lower or at best similar prefee performance compared to nonusers.

3. High- versus Low-Volatility Periods

The Chicago Board Options Exchange Market Volatility Index (VIX), which measures the implied volatility of S&P 500 index options, is also known as the "investor fear gauge" by practitioners. Baker and Wurgler (2006) and Stambaugh et al. (2015) show that stock volatility can proxy for the difficulty of both valuation and arbitrage. Therefore, we use VIX as an alternative sentiment measure (Da, Engelberg, and Gao (2013)) and examine how VIX is related to the effectiveness of technical analysis used by hedge funds.

[23]To approximate prefee fund returns, we follow Teo (2009) and Chen (2011) by assuming that fund returns accrue to a first-year investor, using the T-bill rate as the hurdle rate, applying a high watermark when adjusting for incentive fees, and adding back management fees.

Specifically, we classify the whole sample period into high- and low-VIX periods based on the sample median value of VIX, and compare the performance of technical analysis users and nonusers in different volatility periods. The results from Panel C of Table 7 are consistent with those based on the Baker and Wurgler (2006) sentiment index. Namely, during high-VIX periods when mispricing is more pronounced, hedge funds using technical analysis significantly outperform nonusers; however, this pattern is not significant or even reverses during low-VIX periods.

4. Sentiment Level

Instead of dividing the full sample into high- and low-sentiment periods, we examine whether technical analysis is more effective when the sentiment level is higher. Specifically, we perform panel regressions of monthly hedge fund returns (in excess of the 1-month T-bill rate) on the beginning-of-month sentiment level, the technical analysis dummy, and the interaction of these two terms, controlling for style fixed effects (column 1 of Table 8). We further control for other fund characteristics in column 2 of Table 8. The results show that the coefficients on

TABLE 8

Use of Technical Analysis, Sentiment Level, and Hedge Fund Performance

Table 8 reports panel regression results of monthly hedge fund returns (in excess of the 1-month Treasury-bill rate) on the beginning-of-month sentiment level, the use of technical analysis, and the interaction of these two terms, controlling for various fund characteristics and category dummies. Columns 1 and 2 are estimated using our entire sample of hedge funds. Columns 3 and 4 are estimated using a sample of equity-focused hedge funds. The White (1980) heteroskedasticity-robust *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Independent Variable	1	2	3	4
Sentiment level	−0.980***	−0.986***	−1.029***	−1.045***
	(−41.36)	(−41.63)	(−41.37)	(−42.04)
Technical analysis use	0.019	0.002	−0.023	0.006
	(0.75)	(0.09)	(−0.86)	(0.22)
Sentiment level × Technical analysis use	0.263***	0.264***	0.173***	0.168***
	(5.16)	(5.19)	(3.11)	(3.03)
Lockup period		0.059***		0.045**
		(2.83)		(2.16)
Notice period		0.462***		0.414***
		(3.29)		(2.80)
Management fee		−0.009		−0.021
		(−0.46)		(−0.91)
Incentive fee		0.010***		0.009***
		(5.31)		(4.53)
High watermark		−0.143***		−0.188***
		(−6.05)		(−7.40)
Min. investment		−0.000		−0.000
		(−0.98)		(−1.39)
Audit		0.214***		0.139***
		(5.22)		(3.17)
Leverage		0.043**		0.055***
		(2.06)		(2.58)
Derivatives use		0.074***		0.070***
		(3.34)		(3.05)
Constant		−0.304*		−0.146
		(−1.71)		(−0.81)
Category dummies	Yes	Yes	Yes	Yes
No. of obs.	270,530	269,501	229,680	228,907
Adj. R^2	0.009	0.010	0.011	0.012

the interaction term are positive and significant, indicating that the use of technical analysis is associated with higher performance when investor sentiment is higher. Moreover, consistent with what we document in Table 2, fund performance is negatively and significantly associated with the sentiment level. Overall, our results are robust to the use of the sentiment level.

5. Equity-Focused Hedge Funds

Because the sentiment index is developed based on investor sentiment in the stock market, as a robustness check, we examine only equity-focused hedge funds by excluding managed futures, fixed-income arbitrage, and global macro funds. Our results remain qualitatively similar. We also perform panel regressions based on the sentiment level in columns 3 and 4 of Table 8. Again the results are similar to those obtained from the full fund sample in columns 1 and 2. We show that the use of technical analysis is associated with superior hedge fund performance when investor sentiment is higher.

V. Conclusions

This article presents a unique approach to test whether technical analysis is a more useful investment tool in high-sentiment periods when short-sale constraints might inhibit the elimination of sentiment-induced overpricing, compared to low-sentiment periods when sentiment-induced underpricing can be fully exploited by optimistic market participants (Stambaugh et al. (2012)). In particular, rather than testing individual technical rules, we consider the use of technical analysis in different sentiment periods by perhaps the most sophisticated and astute class of investors, namely, hedge fund managers, irrespective of how they use it.

Using data from the Lipper TASS hedge fund database over 1994–2010, we find that during periods of high investor sentiment when overpricing is more pronounced, the use of technical analysis is associated with higher performance, lower risk, and superior market-timing ability of hedge funds. In contrast, the benefits of using technical analysis for hedge funds generally disappear and even reverse in low-sentiment periods when fundamental analysis enhances fund performance. Our results are robust to controlling for fund characteristics and various fixed effects, employing a subperiod analysis, and using prefee returns, different volatility periods, the sentiment level, and equity-focused hedge funds.

Our article contributes to the long-standing debate on the efficacy of technical analysis and thus has important implications for traders, portfolio managers, and investors. In particular, our findings can help traders and portfolio managers identify sources of alpha and decide when to implement technical analysis. For investors who have not recognized the varying benefits of technical analysis in diverse sentiment periods, our findings highlight the importance of tailoring analytical approaches to market regimes and rotating between technical and fundamental analysis in different sentiment periods.

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