Sentiment and the Performance of Technical Indicators

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ABSTRACT

This paper studies the effectiveness of technical trading approaches in market environments of varying sentiment. Due to short-sale constraints, overpricing with high sentiment (i.e. relatively optimistic sentiment) is more prevalent compared to underpricing with low sentiment (i.e. relatively pessimistic sentiment) and this effect is stronger on difficult-to-arbitrage securities. The authors find consistent evidence over the period of 1993-2010 that the examined set of technical indicators perform better during periods of high sentiment than during periods of low sentiment. Moreover, this sentiment effect is relatively more pronounced for small stocks. These findings hold after a number of robustness checks are applied and highlight the importance of incorporating the sentiment effect when using technical indicators.

Key words: Technical indicators, sentiment, mispricing, short-sale constraints, and difficult-to-arbitrage securities.

A prevalent view in finance is that in an efficient market, asset prices are determined by expected future cash flows discounted using an appropriate risk-adjusted interest rate. Conceptually, in an efficient market, the benefits of technical analysis, which largely focuses on analyzing price action, would be limited. Recent academic research has produced evidence that sentiment can pull market prices away from intrinsic values that should prevail in an efficient market. For example, numerous studies have shown that investor sentiment affects asset prices and this tendency is not fully countered by rational investors due to limits to arbitrage (see, for example, Baker and Wurgler [2006] [2007] and Shleifer and Summers [1990]). These insights have implications for when technical approaches to making transaction decisions will be relatively more effective.

If market prices are aligned to intrinsic values when sentiment is neutral (i.e. not overly optimistic or overly pessimistic), the marginal benefits of a further analysis of price action (i.e. technical analysis) may be relatively small. Alternatively, within the mispricing environment, for example, high sentiment induced overpricing, where prices are decoupled from intrinsic value, technical analysis focusing on price patterns and trading volume might be relatively more beneficial. In a similar vein, Han, Yang and Zhou [2013], suggest that in market environments when fundamental information such as earnings and economic outlook are less precise there may be a heavier reliance on technical approaches and they contend that under such conditions technical analysis may be a more effective mode of analysis for investors and traders.

To empirically verify the contention that technical analysis approaches are relatively more effective under conditions where non-fundamental factors drive prices away from intrinsic values, we would need to identify the market environments with different degrees of mispricing. Following the argument used in Stambaugh, Yu, and Yuan [2012] and Shen and Yu [2013], high investor sentiment drives asset overpricing, and the impediments to short selling play a significant role in limiting the ability of rational traders to exploit overpricing. In contrast, the asset prices should be close to their fundamental value during the low sentiment periods, since underpricing can be countervailed by arbitrageurs taking long positions. As a result, the market tends to be more efficient during the low sentiment periods compared to the high sentiment periods and we would expect technical analysis to be more effective when applied during the high sentiment periods.

We find supportive evidence that a set of popular technical indicators perform relatively more effectively when sentiment is high, and this finding holds with different performance measures and after a number of robustness checks are applied. In addition, we document that the sentiment effect is more pronounced when applying the technical indicators to small stocks in comparison to large stocks. This finding is consistent with the contention of Baker and Wurgler [2006] [2007] that difficult-to-arbitrage securities are more impacted by sentiment and deviate from intrinsic values to a greater extent than easily arbitraged securities.

Our study is related to Antoniou, Doukas and Subrahmanyam [2013] who show that the well-known momentum effect is stronger during periods of high sentiment and substantially weaker when sentiment is low. They suggest that market participants may underreact more strongly to new information when it contradicts their sentiment because of cognitive dissonance; and that subsequent momentum affects may be stronger in high sentiment periods because arbitraging loser stocks is more difficult due to short-selling constraints. Instead of focusing on one technical strategy, we explore a set of 22 popularly employed technical indicators, and document a general relation between the profitability of these technical indicators and the market efficiency measured by investor sentiment.

Our study is also related to a concurrent study of Smith, Wang, Wang, and Zychowicz [2015] who document that hedge funds using technical analysis outperform those nonusers only during high sentiment periods. While their study focuses on the self-reported technical analysis users versus nonusers, there is no information about which technical rules are employed by hedge fund managers and whether technical analysis is still beneficial in hands of less sophisticated investors. In contrast, we focus on a set of specific technical indicators with their default setups, and demonstrate that the effectiveness of technical analysis during the high sentiment periods even when using the naïve (or default) way of applying these technical rules. Our paper can fairly be thought of as an initial step in providing some empirical insights related to this important and practical issue for finance professionals, traders, and general investors.

RELATED LITERATURE AND TESTABLE HYPOTHESES

Serious challenges to the assertion that markets are efficient and that asset prices always reflect their intrinsic values have accumulated in the academic literature. Volatility tests conducted by Shiller [1981] showed that stock market volatility is far greater than that could be justified by the fundamentals in an efficient market. Other criticisms of the efficient market hypothesis include, but are not restricted to short-run momentum, long-run reversal, seasonality, and cross-sectional return predictability based on firm characteristics. (See Malkiel [2003] for a survey of the efficient market hypothesis and its critics.)

As an alternative to the efficient market approach, Shleifer and Summers [1990] propose a noise trader approach. The noise trader approach rests on two assumptions: first, some investors are not fully rational and their demand for risk assets is affected by their beliefs or sentiment that are not fully justified by the fundamentals; second, arbitrage by fully rational investors is risky and therefore limited. These two assumptions together imply that the effect of investor sentiment is not fully countered by arbitragers and this allows for prices to deviate from intrinsic values. Baker and Wurgler [2006] [2007] provide evidence that investor sentiment affects the cross-sectional variation of stock returns, and securities whose valuation are highly subjective and difficult to arbitrage, are impacted more by sentiment and deviate from intrinsic values to a greater extent.

In our paper we examine the performance of a set of technical indicators in varying sentiment environments. This is particularly interesting in light of the literature that asserts and shows the existence of asset mispricing. If asset prices reflect fundamentally established intrinsic values in a neutral sentiment environment, technical approaches to trading and investing decisions may have negligible benefits. However, the relative efficacy of the technical approaches could be affected by sentiment environments that cause prices to be decoupled from intrinsic values. If it is indeed the case that these technical approaches represent a useful mode of analysis that continues to analyze prices even as they deviate from intrinsic values, we would expect the technical indicators to perform better in sentiment environments where such mispricing is most acute.

The existing research suggests that the sentiment driven mispricing may not be symmetrical in high and low sentiment environments due to short-sale constraints. The significance of short-sale constraints traces back to Miller [1977], who argues that the impediments to short-selling play a significant role in limiting arbitrage by rational investors. Evidence on short-sale impediments can be ascribed to institutional constraints, arbitrage risk, trading costs, and behavioral biases of traders. (For a detailed discussion of the implicit short-sale constraints, see, Stambaugh, Yu, and Yuan [2012].) During high-sentiment periods, not-fully-rational investors are overly optimistic about many securities, and these optimistic views tend to drive security overpricing. Due to short-sale constraints, rational investors are confronted with impediments, which according to the extant literature, can hinder attempts to eliminate the overpricing by short selling. In contrast, during periods of low sentiment, the passive views of the not-fully-rational investors may not be reflected as security underpricing, since rational investors can fully counter these passive views by holding long positions of securities. Hence, existing research contends that the overpricing caused by high sentiment is more prevalent than underpricing caused by low sentiment. This sentiment effect on asset prices has been documented and used to explain many asset price behaviors and anomalies, including for example, the mean-variance relation (Yu and Yuan [2011]), the idiosyncratic volatility puzzle (Stambaugh, Yu, and Yuan [2015]), the momentum phenomenon (Antoniou, Doukas, and Subrahmanyam [2013], and the forward premium puzzle (Yu [2013]).

Based on this argument, we expect that the examined technical indicators may perform relatively better in periods of high sentiment (i.e. relatively greater mispricing) in comparison to their performance during periods of low sentiment (i.e. relatively lower mispricing). Our objective is not to prove the existence of short-sale constraints or the existence of mispricing, which has already been extensively discussed and documented in the literature; rather we use the insights from existing research as the backdrop for motivating our research and formulating hypothesis about the performance of technical indicators in high and low sentiment environments.

Moreover, drawing upon the work of Baker and Wurgler [2006] [2007], small firm size is identified as one attribute that makes arbitrage more difficult. Their work shows that the prices of small stocks are affected more by sentiment. Therefore, we expect that the sentiment effect on the performance of technical indicators may be relatively stronger when applied to market decisions involving small stocks in comparison to large stocks.

The importance of market sentiment in making investment decisions has long been recognized by practicing technical analysts. However, the review of the literature to this point reveals little empirical evidence on the profitability of technical indicators in market environments with varying sentiment. For the most part, the literature has focused on studying the profitability of technical analysis. For example, Bessembinder and Chan [1998] and Brock, Lakonishok and Lebaron [1992] use the same set of 26 technical rules and report that these simple rules have significant forecasting power in the stock market. More recently, Zhu and Zhou [2009] show that applying a moving-average trading rule in conjunction with common portfolio allocation rules is utility enhancing. Overall, there appears to be an accumulating body of empirical evidence that technical techniques have predictive value, although the evidence appears mixed as to whether these approaches can generate abnormal returns (see also Lo, Mamaysky and Wang [2000]). Park and Irwin [2007] provide an extensive survey of ninety-five recent studies that assess whether technical trading strategies can generate economic profits. But none of these papers related to empirically testing technical trading strategies actually examine whether the profitability of technical indicators is different in market environments where there is variation in sentiment.

Our paper is not primarily concerned with whether the examined technical indicators generate economic profits, but rather the main research question is whether the relative performance of the technical indicators are superior in some sentiment environments over others. [1] In addition to being of academic interest as it relates to the literature dealing with the mispricing consequences of high and low sentiment, the findings we present also have practical implications for users of a set of popular technical indicators. Our study highlights the importance of the sentiment environment when technical indicators are applied, especially when used on relatively more difficult-to-arbitrage securities such as small stocks.

DATA AND METHODOLOGY

Measure of Investor Sentiment

We use the yearly market-based sentiment measure from Baker and Wurgler [2006] [2007]. They form a composite sentiment index based on the first principal component of six proxies for investor sentiment. These proxies are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. To capture the degree of mispricing, we use the orthogonal sentiment measures, which are based on sentiment proxies orthogonalized to macroeconomic conditions. Our sample uses the Baker-Wurgler yearly sentiment measures (average of the beginning-of-year and end-of-year sentiment) from 1993 to 2010.[2] Following Stambaugh, Yu, and Yuan [2012], we divide the entire sample into two subsamples. The first subsample is comprised of periods of high sentiment where the yearly sentiment is higher than the sample median. The second subsample reflects periods of low sentiment with the yearly sentiment lower than the sample median.[3] The summary statistics for the sentiment measure are listed in Exhibit 1. The mean (median) of the high sentiment period is 0.383 (0.171), and that of the low sentiment period is -0.144 (-0.088). The standard deviations of the high and low sentiment periods are 0.475 and 0.178, respectively.

EXHIBIT 1
Summary of Investor Sentiment

	Entire Sample	Low Sentiment	High Sentiment
Mean	0.119	-0.144	0.383
Median	0.019	-0.088	0.171
Std. Dev.	0.442	0.178	0.475
Min	-0.573	-0.573	0.042
Max	1.318	-0.004	1.318

This exhibit reports the yearly market-based sentiment measure from Baker and Wurgler (2006) for the 18-year period of 1993 to 2010. We divide the entire sample into two periods: 9-year high sentiment period, including the years with the yearly average sentiment higher than the sample median, and 9-year low sentiment period with the yearly average sentiment lower than the sample median.

Selection of Technical Indicators

The construction of technical indicators from the configuration of market data such as price and volume is practically limitless. Therefore we attempted to identify a source provider of technical indicators that is widespread and which readily presents some of the best known and most widely used technical indicators by market participants. Utilizing Bloomberg and its “BTST” backtesting feature provides us with 22 technical indicators as well as the capability to measure the performance of these indicators when applied to different time periods. Furthermore, we did not pursue testing indicators outside this Bloomberg list of 22 to avoid the ex post selection of trading rules. The default parameters for each strategy were maintained and used to avoid the problem of data snooping. For example, the Relative Strength Index (RSI) has default parameters of 30 and 70, where the rule generates a buy signal when the RSI is below 30 (i.e. in oversold territory) and then crosses above 30. To minimize the subjectivity that using these indicators is prone to, we left the Bloomberg default parameters and rules as they were found. (Although we fully recognize that skilled practitioners understand and make adjustments to the default settings under varying market conditions; see for example Brown [2012].)

Our goal is not to backtest and evaluate a particular technical strategy. Rather, our focus is on using these widely available and known indicators to assess whether there is a systematic difference in performance during periods of high and low sentiment. The pitfalls of overfitting when backtesting trading strategies are well documented in the literature (see, for example, Bailey, Borwein, Lopez de Prado, and Zhu [2014] [2015] and Harvey, Liu, and Zhu [2015]), and our use of the default parameters and indicators selected by Bloomberg alleviate the overfitting problem to a large extent, especially for the investigation being pursued in this paper.

The complete Bloomberg list of 22 technical indicators and the detailed strategies and default parameters for all 22 indicators are listed in the Appendix. We also calculate the overall summary of the average number of trades generated in each year, the average number of long signals, the average number of short signals and the average duration of each position. In the unreported results, we find that there is no significant difference in these overall attributes for high and low sentiment periods.[4]

Performance of Technical Indicators

We study the performance of our set of technical indicators on size groupings reflected on six U.S. stock market indexes. They are the S&P 500 Index, the S&P MidCap 400 Index, the S&P SmallCap 600 Index, the Dow Jones U.S.

LargeCap Index, the Dow Jones U.S. MidCap Index, and the Dow Jones U.S. SmallCap Index during the sample period.

We use four measures of performance in evaluating each technical indicator. First, we consider the Raw Return which directly measures the percentage change of total profit (i.e. the percentage increase or decrease in the value of an account above the initial capital amount). Specifically, we apply each technical indicator to daily close prices for each index over one year periods where, as previously noted, each year is either classified as a high or low sentiment year.

Second, we measure the Excess Return as the Raw Return minus the market returns, which is using the Raw Returns of each trading indicator minus the returns from the CRSP value-weighted market index. The Excess Return performance controls for the market effect during different sentiment periods.

Return/MaxDD is the third performance measure we use. MaxDD is the maximum drawdown, which is a popular risk metric used by professional money managers. Within a period (daily price analysis over one year intervals in our study) of all the actual drawdowns, the MaxDD is a measure of the largest intrapeak equity percentage loss in a given year. It is a measure of the maximum capital loss incurred when using a technical indicator and is popularly used in evaluating trading systems. Naturally, holding constant Raw Returns, a system or indicator with a smaller MaxDD would have a higher Return/MaxDD ratio representing better performance adjusted for maximum capital drawdown (see Kirkpatrick and Dahlquist [2011]).

Finally, the Sharpe ratio, a measure of excess return per unit of risk is used. Although commonly employed in evaluating portfolio performance, the Sharpe ratio has some significant limitations in evaluating the performance of indicators and systems. The measure of risk as portfolio variability represented in the Sharpe ratio, is not the equivalent to the risk of capital loss, since it does not account for drawdown and skewed deviation of returns. Despite the limitations of the Sharpe ratio, we include it in our study for completeness.

In the following section, we analyze the performance utilizing these four measures for all the indicators over different sample periods and on different groups of indices.

TESTS AND RESULTS

Performance Difference in High and Low Sentiment Periods

We examine the performance of the technical indicators during periods of high sentiment in comparison to low sentiment. We first obtain the performance of each indicator when applied on each index over each year (i.e., daily trading is assumed over one-year period). Then we report in the Panel A of Exhibit 2 the average performance of the technical indicators during the high and low sentiment periods, respectively. We focus on the effect of sentiment and consider the six indices as a group. The *p*-values reported in this panel are based on the non-parametric Wilcoxon rank-sum tests with the null hypothesis that the reported mean value is not different from zero. Panel A shows that the set of technical indicators exhibit superior performance in higher sentiment periods in comparison to lower sentiment periods, and the differences are statistically significant using all of the four performance measures.[5] For example, the average Raw Return of the technical indicators when applied to each of the indices is 5.213% larger during high sentiment periods compared to the low sentiment periods. The differences are statistically significant at the 0.1% level and economically large. Similarly, when we adjust the Raw Return by deducting the CRSP market index, we find that the Excess Return for the technical indicators are larger during high sentiment periods by 8.293% and the differences are again statistically significant at the 0.1% level. Profitability measured by Return/Max DD and the Sharpe Ratio exhibit similar patterns, and the differences are statistically significant at the 0.1% and 1% level, respectively.

EXHIBIT 2
Performance of Technical Indicators During High and Low Sentiment Periods

Panel A Performance of technical indicators in different sentiment periods

	Entire Sample	Low Sentiment	High Sentiment	Difference (High-Low)	Wilcoxon *p*-value
Number of Obs.	2376	1188	1188		
Raw Return (%)	0.464	-2.142	3.071	5.213	0.000
Excess Return (%)	-9.836	-13.983	-5.689	8.293	0.000
Return/Max DD	0.575	0.351	0.799	0.448	0.000
Sharpe Ratio	-0.076	-0.181	0.028	0.209	0.005

Panel B Regression of the performance of technical indicators on High Sentiment dummies

	Profitability measure			
	Raw Return (%)	Excess Return (%)	Return/Max DD	Sharpe Ratio
Sentiment Level	4.906***	21.47***	0.459***	0.195*
	(3.35)	(5.29)	(2.72)	(1.75)
Constant	-1.882	-14.16**	0.0128	-0.142
	(-0.55)	(-2.48)	(0.04)	(-0.66)
Index FE	Yes	Yes	Yes	Yes
Indicator FE	Yes	Yes	Yes	Yes
Number of obs.	2376	2376	2323	2376
Adjusted R^2	0.047	0.149	0.081	0.057

The performance of each technical indicator is measured in four ways: Raw return, which directly measures the percentage of total profit of each indicator during a year; Excess return, using the raw return minus the market return; Return/Max DD, using raw return divided by the maximum drawdown of each indicator during that year; Sharpe ratio, a measure of excess return per unit of risk for each indicator. Panel A reports the performance of technical indicators in different sentiment periods, and the *p*-value is calculated from the non-parametric Wilcoxon rank-sum test. Panel B reports the regression of the performance on the sentiment level, and *t*-statistics (in parentheses) are calculated with two-way clustered standard errors on the year level and the index-indicator level. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively (two tailed).

Next, we employ panel regression analysis to address the potential cross-sectional correlation among the returns of the technical indicators on each index, as well as the potential time-serial correlation of index returns. Specifically, we regress separately the four profitability measures, Raw Return, Excess Return, Return/Max DD and Sharpe Ratio, on the level of sentiment each year, and we include the index fixed effects as well as indicator fixed effects. The *t*-statistics are calculated with two-way clustered standard errors on the year level and the index-indicator level (see Petersen [2009]). The regression results of the performance of technical indicators on the six indices are reported in the Panel B of Exhibit 2. We show that the coefficients of the sentiment level are all significantly positive, with the significance level of 1% using the measures of Raw Return, Excess Return and Return/MaxDD, and the significance level of 10% when the Sharpe Ratio is the dependent variable. For example, the coefficient of sentiment level in the regression using Raw Return as the dependent variable is 4.906, with a *t*-statistic of 3.35. The positive coefficients of the sentiment level again verify the relative efficacy of technical indicators in high sentiment periods.

Overall, these results are consistent with the extant academic literature asserting that due to short-sale impediments, the overpricing in high sentiment periods is more prevalent than the underpricing in low sentiment periods, and hence technical analysis is more effective when market is less efficient.

Sentiment Effect on Large and Small Cap Stocks

We next examine the sentiment effect on the performance of technical indicators applied to different size categories and assess whether the sentiment effects on small stocks is greater in comparison to that on large stocks. Panel A of Exhibit 3 reports the sentiment effect (high-low) in the last column for the three size categories, respectively. The *p*-value reported in this panel is obtained using the non-parametric Wilcoxon rank-sum tests with the null hypothesis that the reported mean value is not different from zero. Once again, we find that the technical indicators generally perform better in the high sentiment periods than in low sentiment periods when applied to indices of different size categories.

EXHIBIT 3
Sentiment Effect on the Performance of Technical Indicators When Applied to Indices of Different Size Categories

Panel A: Performance of technical indicators on size categories

Index	Entire Sample	Low Sentiment	High Sentiment	Difference (High-Low)	Wilcoxon *p*-value
Number of obs.	792	396	396		
Raw return (%)					
LargeCap	-2.033	-3.555	-0.513	3.042	0.140
MidCap	1.481	-1.208	4.171	5.379	0.014
SmallCap	1.945	-1.663	5.554	7.217	0.000
Excess return (%)					
LargeCap	-12.334	-9.273	-15.395	6.123	0.002
MidCap	-8.819	-13.049	-4.589	8.460	0.001
SmallCap	-8.355	-13.504	-3.206	10.297	0.000
Return/Max DD					
LargeCap	0.315	0.268	0.361	0.092	0.647
MidCap	0.697	0.491	0.902	0.411	0.151
SmallCap	0.713	0.292	1.134	0.842	0.003
Sharpe ratio					
LargeCap	-0.260	-0.308	-0.212	0.097	0.106
MidCap	-0.015	-0.109	0.078	0.186	0.009
SmallCap	0.047	-0.125	0.219	0.344	0.000

Panel B Regression of the performance of technical indicators on High Sentiment × Small

	Profitability measure			
	Raw Return (%)	Excess Return (%)	Return/Max DD	Sharpe Ratio
High Sentiment	4.211*	7.291	0.258	0.142

	(1.74)	(0.86)	(1.34)	(1.00)
High Sent × Small	3.006*	3.006***	0.588***	0.202**
	(1.76)	(2.81)	(2.63)	(2.02)
Constant	-4.905	-16.74**	-0.0612	-0.290
	(-1.23)	(-2.19)	(-0.16)	(-1.19)
Index FE	Yes	Yes	Yes	Yes
Indicator FE	Yes	Yes	Yes	Yes
Number of obs.	2376	2376	2323	2376
Adjusted R^2	0.055	0.048	0.088	0.062

The performance of each technical indicator is measured in four ways: Raw return, which directly measures the percentage of total profit of each indicator during a year; Excess return, using the raw return minus the market return; Return/Max DD, using raw return divided by the maximum drawdown of each indicator during that year; Sharpe ratio, a measure of excess return per unit of risk for each indicator. Panel A reports the performance of technical indicators when applied to different size categories, and the *p*-values are calculated from the non-parametric Wilcoxon rank-sum tests. Panel B reports the regression of the performance on the High Sentiment dummies, and the interaction term of High Sentiment and Small, and *t*-statistics (in parentheses) are calculated with two-way clustered standard errors on the year level and the index-indicator level. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively (two tailed).

Panel A of Exhibit 3 further shows that the sentiment effect (high-low) is perfectly and inversely monotonic, obtained by applying all four performance measures to the three size categories. The large stock average is least susceptible to a sentiment effect on the performance of the technical analysis indicators, with the smallest differences measured by all four performance measures and statistically insignificant (*p*-value > 10%) in the Raw Return, Return/Max DD, and Sharpe Ratio measures, and only statistically significant with Excess Return. In comparison, the profitability differences during the high and low sentiment periods on the small stocks show the largest magnitudes and are statistically significant at 1% significant level (or better) using all of the four performance measures.

Panel B of Exhibit 3 reports the panel regression of the profitability of technical indicators on High Sentiment and the interaction of High Sentiment and Small stock dummies. Again, we include the index fixed effects and the indicator fixed effects, and the *t*-statistics are calculated with two-way clustered standard errors on the year level and the index-indicator level. Our main variable of interest is the interaction of High Sentiment and Small dummy variables. We show that signs on the coefficients of the interaction terms are all positive, and statistically significant at 1% level when Excess Return and Return/MaxDD measures are used as dependent variables, at 5% level when using Sharpe ratio, and at 10% level when using Raw Return. In addition to the statistical significance, the economic effects are also large. Using Raw Return as an example, the sentiment effect on small stocks are around 71% (=3.006/4.211) larger than that on the rest of the stocks.

Overall, these results show that the high sentiment effect on the effectiveness of the set of technical indicators are more evident on small stocks, which are more difficult to arbitrage and prone to more mispricing.

Alternative Sentiment Index

We also investigate the robustness of our results by using an alternative sentiment index: the Index of Consumer Confidence published by the Conference Board (CBIND). Many studies regarding investor sentiment have used this index, for example, Ludvigson [2004], Lemmon and Portniaguina [2006], Antoniou, Doukas, and Subrahmanyam [2013], and McLean and Zhao [2014]. The Baker and Wurgler [2006] sentiment index is measured based on stock market indicators, while the CBIND is a survey-based measure, which asks respondents to evaluate current business conditions and job availability. Following Antoniou, Doukas, and Subrahmanyam [2013], we use the residuals from a regression of the CBIND on the six macro variables used by Baker and Wurgler [2006], to remove the business cycle component from the index.

Specifically, we run the regression of the yearly level of CBIND during 1993-2010 on the following six variables: the growth in industrial production, real growth in durable, non-durable, and services consumption, growth in employment and a National Bureau of Economic Research (NBER) recession indicator. We calculate the yearly orthogonal sentiment levels using the average of the yearly residuals, and group them into high and low sentiment periods corresponding to the sample median.[6]

EXHIBIT 4
Alternative Sentiment Measures

Panel A: Regression of performance on the CBIND sentiment measure

	Profitability measure			
	Raw Return (%)	Excess Return (%)	Return/Max DD	Sharpe Ratio
High Sentiment	0.900	12.54	-0.0507	0.175
	(0.43)	(1.50)	(-0.24)	(0.98)
High Sent × Small	2.486*	2.486***	0.599***	0.170*
	(1.83)	(9.39)	(3.00)	(1.78)
Constant	-3.742	-22.45***	-0.124	-0.368
	(-1.00)	(-2.78)	(-0.37)	(-1.26)
Index FE	Yes	Yes	Yes	Yes
Indicator FE	Yes	Yes	Yes	Yes
Number of obs.	2376	2376	2323	2376
Adjusted R^2	0.038	0.076	0.077	0.061

Panel B: Regression of performance on the Michigan sentiment measure

	Profitability measure			
	Raw Return (%)	Excess Return (%)	Return/Max DD	Sharpe Ratio
High Sentiment	5.598**	-3.432	0.344*	0.158
	(2.00)	(-0.39)	(1.85)	(1.01)
High Sent × Small	3.601*	3.601***	0.621***	0.256**
	(1.89)	(2.88)	(2.67)	(2.04)
Constant	-7.429*	-11.71*	-0.367	-0.395*
	(-1.71)	(-1.77)	(-1.01)	(-1.89)

Index FE	Yes	Yes	Yes	Yes
Indicator FE	Yes	Yes	Yes	Yes
Number of obs.	2376	2376	2323	2376
Adjusted R^2	0.064	0.024	0.092	0.064

The performance of each technical indicator is measured four ways: Raw return, which directly measures the percentage of total profit of each indicator during a year; Excess return, using the raw return minus the market return; Return/Max DD, using raw return divided by the maximum drawdown of each indicator during that year; Sharpe ratio, a measure of excess return per unit of risk for each indicator. Panel A and B report the regression results of performance measures on the alternative CBIND and Michigan sentiment measures and their interactions with Small dummies, respectively. The *t*-statistics (in parentheses) are calculated with two-way clustered standard errors on the year level and the index-indicator level. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively (two tailed).

With this alternative sentiment index, we employ the same tests as those used in Exhibit 3 to examine the performance of the technical indicators during the high and low sentiment periods on different size categories.[7] The results are reported in the Panel A of Exhibit 4 and are virtually unchanged from those obtained using the Baker and Wurgler sentiment measure. With all of the four performance measures, the high sentiment effect on the profitability of the technical indicators is more pronounced on small indices.

We also investigate the robustness of our results by using another alternative sentiment index: The University of Michigan Consumer Sentiment Index. The survey-based "Consumer Sentiment Index" measure is conducted by the University of Michigan Survey Research Center, and it has also been used in Ludvigson [2004] and Lemmon and Portniaguina [2006]. We construct the Michigan sentiment measure in a similar way used in the CBIND sentiment measure.[8] The regression results on the interaction of high sentiment and small dummy variables are reported in the Panel B of Exhibit 4. We find again similar and statistically significant results as those using the Baker and Wurgler sentiment measure. Overall, our hypotheses are reconfirmed with both the CBIND and Michigan Consumer Sentiment Index as alternative sentiment measures.

Sentiment and Individual Indicators: Some Practical Considerations

In an attempt to avoid injecting excessive subjectivity into the test design, up to this point we relied upon performance output that was averaged among the Bloomberg list of 22 indicators. In this subsection, we focus on individual indicators by examining their performance in varying sentiment environments. Our purpose is to highlight some practical implications of using technical indicators in light of the empirical results presented in this paper that support the notion that the performance of technical indicators is a function of the sentiment environment.

Exhibit 5 reports the sentiment effect on the performance of each technical indicator with our primary Baker and Wurgler sentiment measure. The sentiment effects are calculated as the coefficients of regressing the performance of each indicator on the sentiment level controlling for index fixed effects, and *t*-statistics are calculated with two-way clustered standard errors on the year level and the index level. The first salient feature is that all the 22 indicators perform better (in terms of the Excess Return performance measures) in high sentiment periods as opposed to low sentiment periods, while at least 11 perform better in the high sentiment periods in terms of the Raw Return, Return/Max DD, and Sharpe Ratio performance measures. The directional tendency for most of the individual indicators are in the same direction as the average of 22 indicators where, as reported earlier, the performance was better in the high sentiment periods. However, the statistical significance of the directional tendencies is less evident when applied to the individual indicators one-by-one.[9]

EXHIBIT 5
Sentiment Effect on the Performance of Each Technical Indicator

	Indicator	Raw return (%)	Excess Return (%)	Return/Max DD	Sharpe Ratio
(1)	Boll	13.04	29.61***	0.380	0.447
(2)	CMCI	-4.909	11.66	-0.123	-0.336
(3)	DMI	-4.007	12.56	-0.0387	-0.182
(4)	MACD	-0.172	16.39**	0.163	0.163
(5)	RSI	26.70***	43.27***	2.395**	1.361***
(6)	TAS	8.028	24.59***	0.539	0.336
(7)	Wm	3.858	20.42	0.526	0.147
(8)	PTPS	-5.790*	10.78**	-0.174	-0.198
(9)	SMAvg	-4.314	12.25	-0.451	-0.247
(10)	EMAvg	-8.068	8.498	-0.669	-0.426
(11)	WMAvg	-0.219	16.35*	-0.254	-0.0241
(12)	VMAvg	3.916	20.48	0.781	0.173
(13)	TMAvg	-3.314	13.25	-0.341	-0.141
(14)	ADOsc	40.65***	57.21***	4.204***	1.750***
(15)	GOC	-1.988	14.58	0.420	0.0866
(16)	KBand	2.270	18.84	0.243	-0.0795
(17)	MAE	7.285	23.85	0.471	0.114
(18)	MAO	-2.825	13.74**	-0.112	0.0125
(19)	FG	-7.288	9.278	-0.373	-0.337
(20)	REX	18.65***	35.21***	1.136***	0.746***
(21)	ROC	23.94***	40.51***	1.373***	0.964***
(22)	TE	2.493	19.06	0.148	-0.0445

The performance of each technical indicator is measured in four ways: Raw return, which directly measures the percentage of total profit of each indicator during a year; Excess return, using the raw return minus the market return; Return/Max DD, using raw return divided by the maximum drawdown of each indicator during that year; Sharpe ratio, a measure of excess return per unit of risk for each indicator. The sentiment effects are calculated as the coefficients of regressing the performance of each indicator on the sentiment level controlling for index fixed effects, and *t*-statistics are calculated with two-way clustered standard errors on the year level and the index level. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively (two tailed).

From Exhibit 5, a notable descriptive observation is that the performance of traditional and widely used oscillators such as the RSI, ADOsc, REX, and ROC indicators are relatively larger in high sentiment environments when using all of the four performance measures. These indicators being discussed are widely known, used and reflect most closely what people view as oscillators (see for example Pring [2002], Murphy [1999], and Kirkpatrick and Dahlquist [2011]). Interestingly, when we consider the traditional Moving Average indicators and their closest variations (i.e. indicators 9 through 13) the performance differences for high and low sentiment periods for these moving average indicators are generally not significant.

RSI, ADOsc, REX, and ROC are oscillators that by design identify overbought and oversold pricing conditions. In periods of high sentiment, technical indicators with such an attribute may be relatively effective when sentiment-driven overpricing occurs. The identified overbought conditions are reflective of the aforementioned overpricing conditions thereby enhancing the efficacy of such oscillators in high sentiment environments. In contrast, the conventional moving averages are largely trend indicators. Such indicators may indeed perform better when fundamental information move prices in a neutral sentiment environment and generate transaction signals. In such fundamentally driven market episodes, oscillators often generate overbought readings which are not reflective of genuine overpricing which may be the case in high sentiment periods.

Furthermore, the type of analysis documented throughout this paper has practical implications for the selection of technical indicators that may not be factored in when traditional back-testing is conducted. Most back-testing systems examine technical indicators (or develop trading/investment systems) by examining their performance over different market conditions and the selection of optimal parameters within the technical indicators themselves. The results presented in this paper clearly show that in many cases there is a significant impact of sentiment on the performance of technical indicators. Since we use a sentiment measure that is orthogonalized to general market conditions, our analysis therefore captures the non-fundamental sentiment impact on the performance of the technical indicators. Significantly stronger performance in high relative to low sentiment environments, would suggest that certain technical indicators being used as part of an investment or trading approach, should be rotated out of as the sentiment in the market deteriorates. Furthermore, if there is no significant differential performance between high and low sentiment periods (or in the rare cases where performance is better in low sentiment periods), such an indicator would be the type of indicator that a market participant would want to rotate into as market sentiment deteriorates. Our paper provides support for such a rotational approach that could potentially enhance performance of investors and traders who have integrated technical indicators into their market decision making approaches.

CONCLUSIONS

This paper examines the impact of sentiment on the performance of a set of technical indicators. Specifically, we analyze the effectiveness of various well-known technical indicators and examine whether their performance is dependent upon the sentiment environment. Due to short-sale impediments, overpricing with high sentiment (i.e. relatively optimistic sentiment) is more pervasive in comparison to underpricing when sentiment is low (i.e. relatively pessimistic sentiment) and this observation is more significant on difficult-to-arbitrage securities. Consistent evidence is found that the examined set of technical indicators perform better during periods of high sentiment, and this sentiment effect is relatively stronger (both statistically and economically significant) for small stocks in comparison to large stocks. Overall, our paper contributes to the literature by providing initial documentation of the superior performance of a popular set of technical indicators when sentiment induced mispricing is more pronounced.

There are practical implications of the results documented in this paper related to the impact of sentiment driven by short-sale impediments on the performance of technical indicators. This sentiment driven mispricing should be an explicit consideration as technical indicators, as well as investment and trading systems, are developed and back-tested. The evidence related to this significant sentiment effect supports the case for a rotational framework for selecting and implementing the use of technical indicators within investing and trading systems. The initial findings of the sentiment effect on the performance of technical indicators documented in this paper suggest that such implications provide potentially fruitful directions for further practitioner and academic investigation.

APPENDIX

Description of the Bloomberg list of the 22 technical indicators

Indicator 1: Bollinger Bands, developed by John Bollinger, are defined using the standard deviation from a simple moving average, an excellent measure of price volatility. The study plots lines above and below the moving average at a specified number of standard deviations. This study is used to identify periods of high and low volatility, as well as periods when prices are at extreme and possibly unstable levels. These variable width bands become narrower during less volatile periods and wider during more volatile periods.

Indicator 2: The Commodity Channel Index (CMCI), developed by Donald Lambert, measures the variation of a security's price from its statistical mean. The CMCI can be used to identify possible divergences that may indicate a forthcoming trend for a selected security. A CMCI indicator falling below a value of 30 indicates an oversold condition. A buy signal is triggered when the indicator crosses 30 from below. Similarly, a CCI value greater than 70 indicates an overbought condition. A sell signal is triggered when the indicator crosses 70 from above.

Indicator 3: The Directional Movement Index (DMI), developed by J. Welles Wilder, allows you to see the directional movement of a security using today's high and low prices relative to the previous day's high and low prices. Use DMI to determine whether a security is in a valid trend, or if it is range bound. In addition, the ADX value is a measure of the strength of the trend regardless of the trend direction; the higher the value of ADX, the stronger the trend. An ADX value greater than 25 generally suggests that the market is trending, and a value less than 20 indicates no trending.

Indicator 4: Gerald Appel developed Moving Average Convergence/Divergence as an indicator of the change in a security's underlying price trend. The theory suggests that when a price is trending, it is expected, from time to time, that speculative forces "test" the trend. MACD shows characteristics of both a trending indicator and an oscillator. While the primary function is to identify turning points in a trend, the level at which the signals occur determines the strength of the reading.

Indicator 5: The Relative Strength Index (RSI), developed by J. Welles Wilder, measures the velocity of a security's price movement to identify overbought and oversold conditions. Use RSI to recognize potential turning points to help make entry/exit decisions. RSI values are calculated from either closing prices or yields RSI indicator falling below a value of 30 indicates an oversold condition. A buy signal is usually triggered when the indicator crosses 30 from below. Similarly, an RSI value greater than 70 indicates an overbought condition. A sell signal is usually triggered when the indicator crosses 70 from above.

Indicator 6: Stochastics measure the velocity of a security's price movement to identify overbought and oversold conditions. The indicator measures current price relative to highs and lows over a time period. In a trend, the highs and lows should be near the period high and low. TAS can be used to recognize potential turning points to help make entry/exit decisions.

Indicator 7: WLPR allows you to plot the Williams %R value for a selected security. It is useful in recognizing potential turning points to help make entry/exit decisions and display event tracks. Use WLPR to determine overbought/oversold levels: the Williams %R oscillator identifies whether a security is trading at a relative high or low in relation to the highs and lows of a look back period based on selected periodicity. The default period for the indicator is 14 periods for all chart types; intraday, daily, weekly, monthly.

Indicator 8: PTPS graphs stop-and-reversal (SAR) trading points for a selected security. The SAR points are a function of price movement and time. They follow price using an acceleration factor (AF) that increases with the velocity of price movement. A break of the SAR points suggests closing the current position and entering a position in the opposite direction.

Indicator 9: Simple, or arithmetic, moving average is calculated by adding the closing price of the security for a number of time periods (window lengths) then dividing this total by the number of time periods. For example, a simple moving average of a 20 day window is calculated as:
SMAVG(20) = [price(1) + price(2) + ... + price(20)] / 20.0

Indicator 10: An exponential moving average is calculated by applying a percentage of today's closing price to yesterday's moving average value.
(1) The very first point is calculated by a simple moving average.
(2) Then, the exponential value is determined as:
EXP = [2/(window length + 1)]
(3) Next, calculate the difference between today's close price and the previous moving average point.
(4) Take the difference of step 3 * EXP + previous moving average point.

Indicator 11: A weighted moving average is designed to put more weight on recent data and less weight on past data. The weight of each price is based on the sequence of the price in the specific period.

Indicator 12: Variable moving averages are exponential moving averages that automatically adjust the smoothing percentage based on the volatility of the data series. Different volatility ratios are used for variable moving averages.

Indicator 13: Triangular moving averages place the majority of weight on the middle portion of the price series. They are double-smoothed simple moving averages calculated as:
(1) X = (window length + 1) / 2
(2) If X is not an integer, X is rounded up to the nearest integer.

(3) A simple moving average is calculated using X as the window length.
(4) A simple moving average is then calculated again on the previous moving average using the same X as the window length.

Indicator 14: The Accumulation/Distribution Oscillator (ADO) is a study that measures the buying or selling pressures on an instrument, based solely on the relationships of the open, high, low and close values.

Indicator 15: The General Overview Chart (GOC) displays the Ichimoku Kinko Hyo equilibrium analysis that was developed by Goichi Hosoda, and is commonly referred to as an Ichimoku chart. These charts combine three technical indicators to define a price trend. Close and mid prices are manipulated to generate a pattern of signals that are plotted 26 days in the past, 26 days in the future, and along with the current price data. Practitioners of the Ichimoku technique use these charts to identify short-term momentum, long-term trends, and price objectives.

Indicator 16: Keltner Bands, illustrated by Charles Keltner in 1960, are bands drawn above and below a center line to illustrate bullish and bearish breakouts. The center line is a simple moving average of the 'Typical Price' ((H+L+C)/3). The bands are then drawn above and below the center line based on a simple moving average of the trading ranges (H-L). The defaults for both the center and band Moving Average periods are 10 bars. The Bloomberg Keltner Bands also allow the user to adjust the percent of that range MA that the bands will be positioned away from the center. The values for the Upper Band and the Lower Band, are defaulted to 100, i.e. 100% of the MA of the ranges over the previous bars.

Indicator 17: Use MAE to graph historical prices and percentage-based support and resistance levels for a selected security and display event tracks. These support and resistance levels form a moving average "envelope," which you can use to gauge a security's trading activity.

Indicator 18: The Moving Average Oscillator displays the difference or ratio of two moving averages that you define, a signal line, which is a moving average of that difference/ratio, and the difference between the oscillator and signal. You can determine the type and length of the moving average, as well as the data to which the moving average applies.

Indicator 19: Fear/Greed is an oscillator based on the Average True Range (daily high/low range, adjusted for gaps) to measure the ratio of buying strength to selling strength. This tells us whether the Bulls or the Bears are in control at a particular point in time. It is an excellent oscillator for divergence analysis and for identifying trend persistence, and works in real time on charts in any time frame, either intrabar or end-of-bar.

Indicator 20: The Rex Oscillator study measures market behavior based on the relationship of the close value to the open, high and low values of the same bar.

The theory is that a big difference between the high and close on a bar indicates weakness. Conversely, wide disparity between the low and close indicates strength. The difference between open and close also indicates market performance.

Indicator 21: ROC allows you to chart the rates of price change for a selected security for up to four different time periods within the specified date range. Use ROC to chart the highest and lowest rates of price change for a selected security for up to four time periods within a specified date range. ROC determines the momentum behind price movements; it measures it either as percent change or price difference. For the most part, price and ROC should move together. When the price and ROC diverge, look for the ROC to be a clearer indication of the underlying momentum of the trend.

Indicator 22: Trading Envelopes (TE) are defined using the standard deviation from a simple moving average, an excellent measure of price volatility. The study plots lines above and below the moving average at a specified number of standard deviations. This study is used to identify periods of high and low volatility, as well as periods when prices are at extreme and possibly unstable levels. These variable width bands become narrower during less volatile periods and wider during more volatile periods.

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ENDNOTES

[1] Technical indicators are maintained at their default parameter and rule settings to objectively focus on their relative performance during different sentiment periods from the perspective of a general investor.

[2] When we measure the sentiment level of each year using the beginning-of-year sentiment, our main results of analysis do not change.

[3] As another robust check, we also classify the high and low sentiment periods on a rolling basis using the median sentiment level during the preceding 15 years as the point of demarcation between low and high sentiment, the results are virtually unchanged.

[4] There is no significant difference in the number of transactions in the high and low sentiment periods. Therefore, the transaction costs will not alter the relative performance of the set of technical indicators in high sentiment periods compared to their performance in low sentiment periods.

[5] If we perform Student's t-test under the assumption that the samples are normally distributed, we obtain very similar *p*-values as those using the non-parametric Wilcoxon rank-sum tests.

[6] The sentiment categorizations based on the CBIND and the Baker and Wurgler sentiment measures almost perfectly overlap with the exception of one year.

[7] Using the alternative sentiment measure, we also obtain similar results as those reported in Exhibit 2.

[8] We run the regression of the yearly level of Michigan measure during 1993-2010 on the following six variables: the growth in industrial production, real growth in durable, non-durable, and services consumption, growth in employment and a National Bureau of Economic Research (NBER) recession indicator. We calculate the yearly orthogonal sentiment levels using the average of the yearly residuals, and group them into high and low sentiment periods corresponding to the sample median.

[9] The small number of observations for each indicator prohibits an effective statistical analysis. Our intent is to point out and discuss some practical issues that are observable from the descriptive consideration of the data. We do not discuss each individual indicator in details.