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Technical analysis as a sentiment barometer and the cross-section of stock returns

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This paper explores an unexamined sentiment channel through which technical analysis can add value. We use a spectrum of technical trading strategies to build a daily market sentiment indicator that is highly correlated with other commonly used sentiment measures. This technical-analysis-based sentiment indicator positively predicts near-term returns and is inversely related to long-term returns in the cross-section. Simple trading strategies based on this sentiment indicator yield substantial abnormal returns. These results are consistent with the explanation that lack of synchronization induces rational arbitrageurs to exploit the mispricing before it is corrected.

Keywords: Investor sentiment; Technical analysis; Delayed arbitrage; Cross-sectional returns

JEL classifications: G02, G11, G12, G14

1. Introduction

There has been considerable interest in technical analysis among both finance academics and practitioners. On the one hand, traditional academic wisdom posits that publicly available information such as past prices and trading volume which serve as the basis of technical analysis are already incorporated into asset prices. On the other hand, most empirical studies, as surveyed by Park and Irwin (2007), find technical analysis generates economic benefits, although testing problems such as data snooping remain a concern. In addition, technical analysis is popular among experienced traders and sophisticated fund managers.† For example, Taylor and Allen (1992) find that at least 90% of experienced traders place some weight on technical analysis. Similarly, Schwager (2012) report that top traders and fund managers they interviewed are mostly in favor of technical analysis. Many leading hedge fund managers confirm that technical analysis forms a major part of their decision-making process (Smith *et al.* 2016). Despite all these findings, the following questions are still not fully answered: why do traders use technical analysis to design their trading strategies? And why do investors pay such traders for doing so?

This study aims at investigating an unexploited channel through which technical analysis can add value. We argue that because security prices reflect not only economically rational factors but also irrational or psychological factors,

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† For example, Sushil Wadhwani, an academic who later became a fund manager, once said that overcoming the prejudice against technical analysis was the most important lesson she had to learn when moving from the ivory tower into the laboratory of real-life experience as a trader. See 'Technical analysis pulled out of the bin', October 17, 2010, Financial Times. It is also more generally prominent in the financial media, e.g., the 200-day moving average was cited four times in the widely-read daily 'Market Forces' bulletin of the Financial Times during December 2019.

technical analysis has the potential to serve as a barometer for investor sentiment. Previous theoretical models document that, in the presence of limits to arbitrage, equilibrium prices can be a linear function of investor sentiment (e.g. Delong *et al.* 1990b). Noise, however, may stop current equilibrium prices from revealing sentiment perfectly. To illustrate how technical analysis helps extract information about investor sentiment from noisy prices, consider a three-period model in the spirit of Brown and Jennings (1989), where rational investors receive private signals in both times 1 and 2 about an unknown degree of investor sentiment, which is only revealed in time 3. Due to random supply shock, rational investors are unable to infer sentiment by observing the single period price and their own private signals in either time 1 or 2. Note that, however, the time 1 price is useful for learning about investor sentiment because it is not affected by time 2 random supply shock. Similarly, the time 2 price is useful for learning about investor sentiment because it is not affected by time 1 random supply shock. Therefore, in time 2, combining the past price (in time 1) and the current price (in time 2) yields better inferences about sentiment than does a single period price alone. Since technical analysis is essentially a tool to combine past information with current prices, it may provide a useful indication of investor sentiment. A line of studies concurs with this argument, for example, Coqueret (2020) quantifies the stock-specific news sentiment and finds that future sentiment is more likely to be predicted by historical returns. Yang *et al.* (2018) also show that when market prices move away from sideways patterns, market prices also significantly affect future investor sentiment.

Despite the absence of empirical work, the role of technical analysis as a barometer of investor sentiment has been widely recognized among practitioners and in the media. For example, in one of the most popular books on technical analysis, Pring (1991, pp. 2-3) states that:

> Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other . . .

In the same vein, an article in Barron's argues that 'technical analysis attempts to measure the collective investor psyche, calling heavily on the psychology of crowds and the cycle of greed and fear'.† Some technical analysts go even further and argue that the term 'technical analysis' is a misnomer and should be replaced as 'investor sentiment analysis'.‡ Consistent with the practitioners' view, academic researchers such as Zhou (2018) also emphasize that the link between investor sentiment and technical analysis represents a promising area for future research. Feng *et al.* (2017) find that the benefit of using technical analysis is more prominent during high-sentiment periods. Their explanation for this finding is that technical analysis can better capture the deviation of asset price from its intrinsic value when sentiment is not neutral. However, as pointed out by Zhou (2018), 'existing sentiment studies ignore technical sentiment indicators almost completely'.

This study provides the first empirical evidence of the extent to which technical analysis reflects investor sentiment. For this purpose, we build a daily market sentiment indicator (hereafter TA sentiment) based on the average of trading signals generated from applying 2127 technical trading strategies to benchmark market stock indices such as the S&P 500 index and DJIA.§ A buying/selling signal indicates that sentiment has risen/fallen; and averaging across different trading rules helps remove the idiosyncratic noise contained in trading signals from individual trading rules. We use the same universe of trading strategies as Qi and Wu (2006), which nests nearly all the trading rules studied in the top finance journals. We show that TA sentiment is significantly correlated with both market- and survey-based sentiment indicators, such as Chicago Board of Exchange (CBOE) Volatility Indicator (VIX), the CBOE Options Total Put-Call ratio, and the Bull-Bear Spread from surveys of individual investors. These correlations are not spuriously driven by the persistence in technical analysis and other sentiment indicators, as the contemporaneous correlations between innovations in TA sentiment and innovations in other sentiment indicators are also significantly positive. This finding is consistent with the practitioners' view that technical analysis reflects investor sentiment.

After showing that technical analysis reflects investor sentiment, we examine whether TA sentiment affects the cross-section of stock returns. To this end, we follow Baker and Wurgler (2006) by computing returns of sixteen long-short portfolios that take long positions in the more sentiment-prone and difficult to arbitrage stocks (e.g. small, young firms with high volatility stocks) and short positions in sentiment-resistant and easy to arbitrage stocks (e.g. large, established firms with low volatility stocks). Since market sentiment has a stronger effect on more sentiment-prone and difficult to arbitrage stocks, we also expect TA sentiment to have a stronger effect on these stocks than on easy to arbitrage counterparts.

In other words, we propose that TA sentiment positively predicts cross-sectional returns. This hypothesis is derived from the delayed arbitrage models of Abreu and Brunnermeier (2002, 2003). In these models, a single arbitrageur cannot move the market and a sufficient mass of arbitrageurs is required to correct the mispricing. If an arbitrageur attacks mispricing too early, she may find herself sailing against the wind and suffer from substantial loss. Due to this synchronization risk, a rational arbitrageur may be unwilling to correct mispricing when she is unsure whether others are aware of the mispricing or hold similar opinions. Instead, a rational arbitrageur, who detects investor sentiment through TA, may delay arbitrage and ride mispricing. Thus, we expect sentiment-prone stocks to earn higher returns, than their sentiment-resistant counterparts, both at and after the TA sentiment increase.

† See http://www.barrons.com/articles/SB116283108833814528.
‡ See http://www.centimetrics.com/explanation/.

§ Investor sentiment indicators are abundant and well accepted at the market level, whereas they are scarce at the individual stock level. To test the correlation of TA sentiment and other sentiment indicators, we restrict ourselves to market-wide TA sentiment in this paper.

Our empirical results support these predictions. Specifically, we find that a rise in TA sentiment predicts an increase in the next-day return of the long-short portfolio, but this return declines in the subsequent periods. Controlling for commonly used risk factors, such as the Fama-French five factors, a momentum factor and time-varying factor loadings, does not alter the findings. One assumption behind the delayed arbitrage is that sophisticated investors earn higher returns by riding mispricing. We test this implication by examining whether a simple 'trend-chasing' trading strategy that longs sentiment-prone stocks after a TA sentiment increase and shorts these stocks following a TA sentiment decrease earns abnormal returns.† We find that this simple strategy generates an average return of 12% per annum. This return remains significant after controlling for the traditional risk factors and transaction costs.

Our study contributes to several strands of literature. First, it adds to the literature on the value relevance of the technical analysis. Several studies suggest that past prices (or volumes) are useful for inferring private information that is not fully reflected in the current prices (e.g. Hellwig 1982, Treynor and Ferguson 1985, Brown and Jennings 1989). Technical analysis also arises naturally when traders learn about the quality of signals they receive from analyzing the sequences of price and volume (Blume *et al.* 1994, Detzel *et al.* 2021), or infer information from the order book (e.g. Kavajecz and Odders-White 2004, Chiarella and Ladley 2016). Furthermore, technical analysis improves the investment return through more efficient asset allocation, especially during episodes of high uncertainty (Zhu and Zhou 2009). We contribute to this strand of research by showing that technical analysis reflects investor sentiment and enables sophisticated investors to successfully time the market.

Second, we contribute to the work on the pricing impact of investor sentiment. A central question in this literature is how to measure investor sentiment and quantify its effects. We add to this line of research by providing a novel, easy-to-construct, real-time sentiment measure that is available on a daily frequency. The predictive ability of our sentiment index for future returns goes beyond the commonly used sentiment indicators such as VIX. Since the only data required for constructing the measure is historical prices, our approach can be useful when alternative sentiment indicators are difficult to construct due to data availability. Although we restrict the analysis to the stock market, the same methodology can be adopted in the context of other asset classes.

Finally, our study relates to the literature on the profitability of technical analysis. Most of the existing studies show that technical analysis generates significant returns in the context of both single assets or market indexes (e.g. Brock *et al.* 1992, Osler 2003, Avramov *et al.* 2018). To the best of our knowledge, we are the first to construct a market-wide sentiment indicator from technical analysis, which we then use to devise a new trading strategy using portfolios of stocks sorted by their exposure to this sentiment indicator. Our new trading strategy is motivated by the cross-sectional effect of market sentiment and generates substantial profitability in the cross-section. The closest work to ours is Han *et al.* (2013), who also report significant cross-sectional profitability for a trading strategy that applies five moving average rules to individual portfolios with different levels of information uncertainty. However, unlike Han *et al.* (2013), this study considers a much wider spectrum of trading rules and applies technical analysis to sentiment-related portfolios rather than information-uncertainty-related portfolios.

The rest of this paper is organized as follows. Section II summarizes the relevant literature. Section III describes our data and variable construction. Section IV presents the results on the return predictability of the TA sentiment indicator and the profitability of a simple trading strategy based on the TA sentiment. Section V summarizes our findings and concludes the paper.

2. Literature review

This section provides a brief review of the literature on the ability of technical analysis to predict returns and on the potential link between technical analysis and investor sentiment. It also summarizes the commonly employed investor sentiment measures and the various techniques used to examine the ability of such measures to capture investor sentiment.

2.1. *The effectiveness of technical analysis*

Theoretical literature has provided several reasons why traders may find it useful to apply technical analysis. On the rational side, it has been argued that as investors receive information at different times, it may take time for prices to revert to equilibrium and, hence, historical data can be used to assess the extent to which information has been fully incorporated into prices (Hellwig 1982, Treynor and Ferguson 1985, Brown and Jennings 1989). Even when one assumes that information is received at the same time, if investors are heterogeneously informed or process information at different speeds, past prices may help some investors to draw valuable inferences about the information processed by other agents (Brown and Jennings 1989, Grundy and McNichols 1989, Zhou and Zhu 2014). Cespa and Vives (2012) show that the presence of liquidity traders causes asset prices to deviate from their fundamental values and such deviations offer technical analysts the opportunity to devise profitable trading strategies. Detzel *et al.* (2021) build the first equilibrium model to provide a rational and endogenous justification for the use and predictability of technical analysis via investors' rational learning mechanism.

On the irrational side, Zhu and Zhou (2009) demonstrate that, because of the presence of noise traders, technical analysis can substantially improve an investor's utility in a standard asset allocation model. Most existing models generate the price drift arising from investors' behavioral biases, such as under- and overreaction, herding, and feedback trading. These behavioral biases can be exploited by trend-following

† Since it is often difficult to predict the exact time when delayed and coordinated arbitrage occurs, our trading strategy is designed to exploit the sentiment-raised momentum rather than the profit arising from the correction of mispricing that occurs when the triggered arbitrage brings stock prices to their fundamentals.

forecasters (Chan *et al.* 1996, Jegadeesh and Titman 2001, Peng and Xiong 2006). Ebert and Hilpert (2019) present a model showing that technical analysis is popular because irrational investors prefer positively skewed lottery stocks.

The popularity of technical analysis is accompanied by some debates on the effectiveness of technical analysis. On the one hand, several empirical studies show that the ability of technical trading rules to generate profit is at best limited. One of the earliest works, Cowles (1933), shows that the success rate of Hamilton's forecasts, based on Dow Theory from 1904 to 1929, does not exceed 55%. Fama and Blume (1966) show that filter rules were not profitable during the 1956–1962 period. Allen and Karjalainen (1999) find little profitability in generic algorithms in the stock market. Sullivan *et al.* (1999) construct 7846 trading rules based on five commonly used classes of rules, namely Filter Rules, Moving Averages, Support and Resistance, Channel Breakouts, and On-balance Volume Averages. They find that, from 1987 to 1996, technical trading rules are of little value after controlling for data-snooping bias. Similarly, Lee and Mathur (1996) and Qi and Wu (2006) find that the profitability of technical trading rules in foreign exchange markets weakens considerably during more recent periods, presumably because of the greatly improved market efficiency due to the cheaper computing power, lower transaction costs, and increased liquidity.

In contrast, a large number of empirical studies document that the use of technical trading rules generates considerable profits in the stock markets (see, e.g. Bessembinder and Chan 1998, Lo *et al.* 2000, Neely *et al.* 2014, Marshall *et al.* 2017, Zakamulin and Giner 2020). For example, using aggregate market returns, Neely *et al.* (2014) show that the principal components from technical trading signals have stronger predictability and higher profitability than their counterparts from macroeconomic variables. A recent strand of literature combines technical analysis with cross-sectional premium. Han *et al.* (2013) first apply moving average trading rules on overall market return to obtain buy-and-sell trading signals and test its predictability in the cross-section of the stock market. Han *et al.* (2016) construct a pricing factor from a trend-following strategy and demonstrate its explanatory power on return, particularly in environments with high information uncertainty. More recently, Lin (2018) uses partial least squares on 14 technical trading signals to construct an aligned trading signal and finds that such a signal significantly predicts cross-sectional stock returns sorted by size, value, and momentum.

The lack of consensus in the literature may be attributed, at least partly, to the different contexts in which the effectiveness of technical trading rules is investigated. For example, Neely *et al.* (1997) show that technical analysis is much less useful for individual investors in the foreign exchange market, as such investors face higher transaction costs. In the context of stock markets, Hoffmann and Shefrin (2014) also find that individual investors are disproportionately less capable of earning abnormal returns from technical trading rules. The different methodologies adopted by prior research may also be responsible for the mixed results on the effectiveness of technical analysis. In particular, the profitability of technical trading rules may be inflated by the presence of data-snooping bias, which occurs when too many rules are used to test the success of technical analysis. Including too many irrelevant rules also can reduce the test power and yield biased estimates (Hansen 2003). Qi and Wu (2006) summarize a large set of the trading rules mentioned in the top finance journals and used the five most commonly accepted technical trading rules to construct and test 2127 trading strategies. They argue that their trading rules represent a balanced and reasonable choice for testing the effectiveness of technical analysis. In this study, we use the same trading strategies listed in Qi and Wu (2006) to construct our sentiment indicator and a new sentiment-based trading strategy.

2.2. *Technical analysis and investor sentiment*

Technical trading has long been a prominent example of investor sentiment in many theoretical papers, where irrational investors are assumed to form their beliefs on mechanical trading rules rather than fundamental factors. For instance, Menkhoff (2010) argues that technical analysis users believe that prices are heavily determined by psychological influences and consequently react to this view with trend-following behavior. In a similar vein, Delong *et al.* (1990a) explain mispricing with a model where forward-looking speculators induce positive feedback trading when noise traders chase the trend, leading to bubbles and crashes. Shleifer and Summers (1990) also show that positive feedback trading leads to an autocorrelation of returns at short horizons and negative autocorrelation of returns at long horizons, both of which can be exploited by technical trading rules.

Empirical studies show that technical trading strategies, such as positive feedback trading, are largely driven by the sentiment of noise traders. For example, Kurov (2008) finds that positive feedback trading in index futures increases with optimism. Chau *et al.* (2011) also document the presence of positive feedback trading, particularly during periods of high sentiment, in the largest three US ETF contracts. Another strand of empirical studies focuses on the profitability of technical trading rules conditional on investor sentiment. Antoniou *et al.* (2013) find that the momentum effect is particularly strong during high sentiment periods. They suggest that investors may underreact more strongly to information that contradicts their sentiment due to cognitive dissonance. Because of short-selling constraints, the momentum effect may subsequently have an asymmetric influence across high and low sentiment periods. Consistent with the behavioral models, Feng *et al.* (2017) also report that the profitability of technical trading is more prevalent in high sentiment periods and is stronger for difficult-to-arbitrage securities. Similarly, Smith *et al.* (2016) demonstrate that hedge fund managers who use technical analysis have superior performance, lower risk and better market-timing ability than non-users during high sentiment periods, yet those advantages disappear and even reverse during episodes of low sentiment. Feng *et al.* (2017) and Smith *et al.* (2016) also show that technical analysis generates higher profits during periods of high sentiment, as mispricing is more prominent during these periods due to limits to arbitrage. Unlike prior studies which focus on the effectiveness of technical analysis across different sentiment states, our paper examines the ability of technical analysis to capture investor sentiment and the extent to which technical trading can exploit the variation in sentiment across sentiment-prone stocks.

2.3. *Validation of investor sentiment measures*

The extant literature has proposed several proxies for investor sentiment. Survey-based measures, such as the American Association of Individual Investors (AAII), Investors Intelligence (Advisors' Sentiment Survey), and the University of Michigan Consumer Sentiment Index, have been particularly popular among practitioners. The Bull-Bear Ratio generated by AAII is perceived as a direct proxy for sentiment and has been widely used to examine the validity of other sentiment measures. For instance, Lemmon and Portniaguina (2006) argue that consumer confidence measures represent good proxies for sentiment, as they are highly correlated to the Bull-Bear Ratio. Qiu and Welch (2006) also maintain that since survey-based indicators reflect the direct opinions of investors, new sentiment proxies should be validated by evaluating their correlations with the direct survey indicators. The Investors Intelligence survey represents the bullish/bearish expectation of over 120 market newsletters and could be presented as the percentage difference between, or the ratio of, bullish and bearish newsletters (e.g. Lee *et al.* 2002, Brown and Cliff 2005, Kurov 2008). The University of Michigan Consumer Sentiment Index is another workhorse sentiment measure (see Qiu and Welch 2006, p. 8).

More indirect proxies are formed using economic variables that are deemed to be highly related to investor sentiment. For instance, many studies show that stock returns are driven by human emotions, which are, in turn, influenced by factors such as weather, geography, and soccer or Olympic Games results. Da *et al.* (2015) argue that fear represents a contrarian indicator of sentiment and use the search volume of negative economic words to gauge investor sentiment. Brown and Cliff (2004) argue that net purchases by mutual funds indicate optimism, while net sales imply pessimism. The CBOE Volatility Index (VIX) is deemed an investor sentiment gauge in Whaley (2000) and has since been regarded as a premier sentiment barometer by both scholars and practitioners. Baker and Wurgler (2006) use principal component analysis to extract the common component of six measures of investor sentiment, namely 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. They demonstrate that the fluctuations of their new index are consistent with anecdotal history from 1961 to 2002.

In short, the investor sentiment indicators proposed by prior studies tend to be based on solid economic rationale. However, in addition to being theoretically sound, the performance of a sentiment index should be judged by (i) its ability to reflect the history of bubbles and crashes; (ii) its correlation with sentiment-related macroeconomic variables and other widely acknowledged sentiment indices; and more importantly, (iii) its ability to explain or predict the equity premium. Underpinned by the theoretical reasoning presented in the previous subsection, we investigate to what extent our newly proposed index satisfies these criteria.

While extant literature shows that investor sentiment predicts return reversals, our study provides evidence that sentiment predicts short-term momentum. Our work stems from the premise that mispricing could persist in the intermediate term (Abreu and Brunnermeier 2003). We acknowledge that daily data is noisier and mitigate this concern by controlling for the effect of bid-ask spreads in our predictive regression. Using daily frequency also provides us with an opportunity to capture the short-term effect of sentiment, which may not be present at the monthly frequency. Our study is consistent with many other studies that investigate the link between sentiment and returns at the daily frequency (e.g. Da et al. 2015, Aboody *et al.* 2018). It is also related to the stream of work on the short-term (daily) momentum and subsequent reversal (Mazouz *et al.* 2009). Our work differs from prior research by focusing on the economic significance of the short- rather than the long-term relationship between investor sentiment and cross-sectional returns.

3. Data and sample construction

3.1. *Ta sentiment indicator*

Our aim is to build a sentiment indicator from the trading signals generated by technical analysis. However, it is not clear a priori how many trading rules are required to construct this indicator. Relying on a single technical trading rule may fail to capture the overall market sentiment while considering all trading rules are unviable. As a balance, we consider 2127 trading rules, including Filter Rules, Moving Average, Support and Resistance, and Channel Breakout Rules.† This universe of trading strategies is the same as Qi and Wu (2006) and nests nearly all the trading rules studied in the top finance journals.

To build a market-wide sentiment indicator, we apply the 2127 technical trading rules to benchmark market indices including the S&P 500 index and DJIA. Each trading rule generates a buy/sell/neutral recommendation for the next day at the end of each day. We assign values of 1, 0, and -1 to each buy, neutral, and sell signal, respectively. Each day, we compute the equal-weighted average‡ of trading signals across all 2127 strategies to obtain a time series, which we then use as our TA sentiment index.§ For example, if, at a given day, 1800 strategies recommend a buy, 127 strategies recommend a sell, and the remaining strategies are neutral, TA sentiment on that day would be (1800-127)/2127 or 0.78. We argue that our TA sentiment is a measure of the overall market sentiment (i.e. a high value of TA sentiment indicates a high overall market sentiment). Averaging trading signals across

† The definitions of these trading strategies are the same as in Qi and Wu (2006), and are standard in the literature. Therefore, they do not merit further elaboration here. The parameters used for defining those technical trading strategies are provided in the Appendix.
‡ We also calculate a performance-weighted TA sentiment index, which is the average of the trading signals of 2127 technical trading rules weighted by their returns in the past year. Our results do not alter when using the performance-weighted TA sentiment index.
§ The TA sentiment index is available upon request.

trading rules helps remove the idiosyncratic noise associated with individual trading rules.

We restrict ourselves to market-wide TA sentiment because validating TA sentiment at the individual stock level by investigating its correlation with other sentiment indicators is more constrained by the availability of other daily sentiment indicators for individual stocks with a sufficiently long history. We also focus on testing the effect of TA sentiment on the cross-section of stock returns, as theory suggests that market-wide investor sentiment can have different (and even opposite) effects on individual stock returns (Baker and Wurgler 2007).

Our baseline TA sentiment is constructed from applying the technical trading rules on the S&P 500 index. Since S&P 500 constituents are mainly large capitalization stocks that are less prone to sentiment and are easier to arbitrage, a TA sentiment that is based on the S&P 500 does not capture as much sentiment as a measure constructed from a small-cap stock index. However, although our baseline TA sentiment index is biased against our findings, we choose to focus on the S&P 500 because of its popularity as the most closely monitored benchmark in the US stock market.

Figures 1 and 2 provide simple eyeball tests for the correlation between our TA index and investor sentiment. Since the daily TA sentiment values fluctuate considerably and are difficult to visualize over 50 years, we plot the monthly averages in figure 1. The plot of the TA sentiment index is in line with anecdotal accounts of market sentiment fluctuations. It drops sharply to negative values during the recession periods defined by the National Bureau of Economic Research (NBER) and is visibly consistent with historical bubbles and crashes. In addition, TA sentiment is mostly positive in the high sentiment years defined by Baker and Wurgler (2006).†

We also calculate a weekly average of TA sentiment to facilitate its comparison with the weekly Bull-Bear Spread from surveys of individual investors. Figure 2 plots the weekly average of TA sentiment and the weekly Bull-Bear Spread for a randomly selected subsample period (from 1990 to 1995). The observed co-movement between these two variables provides a first indication that our TA index tracks market sentiment.‡

To further validate our TA index as a sentiment measure, we estimate its pairwise correlations with other commonly used sentiment indicators, including the daily CBOE Volatility Index (VIX), CBOE Options Total Put-Call ratio, and the weekly individual Bull-Bear Spread based on surveys of individual investors.§

† The Baker and Wurgler sentiment index is positive for 1968–1970, 1972, 1979–1987, 1994, 1996–1997, and 1999–2001.

‡ Most of the other randomly selected samples exhibit similar co-movement.

§ VIX measures the market expectations of the volatility conveyed by S&P 500 stock index option prices over the next 30-day period. Put-Call ratio is a ratio of put volume to call volume and is a contrarian indicator of market sentiment. Individual Bull/Bear spread is the percentage of individual investors who are bullish minus the percentage of individual investors who are bearish about the stock market for the next six months. Individual Bull/Bear spread based on data from the American Association of Individual Investors, which polls opinions of AAII members on weekly basis, and is available from http://www.aaii.com/sentimentsurvey.

Table 1 reports the Pearson correlation coefficients and p-values from testing the null hypothesis that sentiment indicators are uncorrelated. Panel A shows the results of correlations between the level of the TA sentiment and the level of other sentiment measures. All three sentiment indicators are correlated with TA sentiment. The correlation between TA sentiment and VIX is -0.60 with a corresponding p-value smaller than 1%. A negative correlation is expected since high VIX proxies for low investor sentiment whereas high TA sentiment indicates high investor sentiment. As expected, the put-call ratio negatively varies with TA sentiment, with a statistically significant correlation coefficient of -0.28. As expected, individual Bull/Bear spread is strongly positively correlated with our TA sentiment.

Panel B reports the correlation between the change in TA sentiment and the change in other sentiment measures. All the signs of the correlations remain the same as in Panel A. While the correlations in Panel B are smaller in magnitude than their counterparts in Panel A, they remain statistically significant. This suggests that TA sentiment strongly correlates with other sentiment indicators both in levels and in changes, consistent with our prediction that the TA index tracks investor sentiment.

It might be argued that, because of positive feedback trading, technical analysis may generate rather than capture investor sentiment. If technical analysis does indeed generate sentiment, we would expect to observe a positive correlation between the current innovation in TA sentiment and innovations in other sentiment indicators over the next period. However, if technical analysis reflects sentiment, we expect a contemporaneous positive correlation between the innovation in TA sentiment and innovations in other sentiment indicators. To test these predictions, we first remove the persistency in TA sentiment and other sentiment indicators. We do so by regressing each indicator on its past 10 lags and defining the regression's residual as innovations in that sentiment indicator. The number of lags is not strictly selected by information criteria, but to ensure that the residuals are not significantly autocorrelated.

In Panel C, the first two columns report the contemporaneous correlation between innovations in the TA sentiment index and innovations in other sentiment indicators. We find significant contemporaneous correlations, consistent with the view that the TA index tracks investor sentiment. The last two columns in Panel C report the correlations between the lagged innovations in the TA index and the current innovations in other sentiment indicators. We find that the lagged innovations in the TA index are significantly correlated with innovations in the other two sentiment indicators, implying that TA sentiment both captures investor sentiment and generates future sentiment. While the latter role has been discussed in the literature, to the best of our knowledge, the role of technical analysis as a sentiment barometer has not been documented.

3.2. *Portfolios*

To investigate whether TA sentiment affects asset prices, we follow Baker and Wurgler (2006) in constructing portfolios based on ten firm characteristics that reflect the extent to

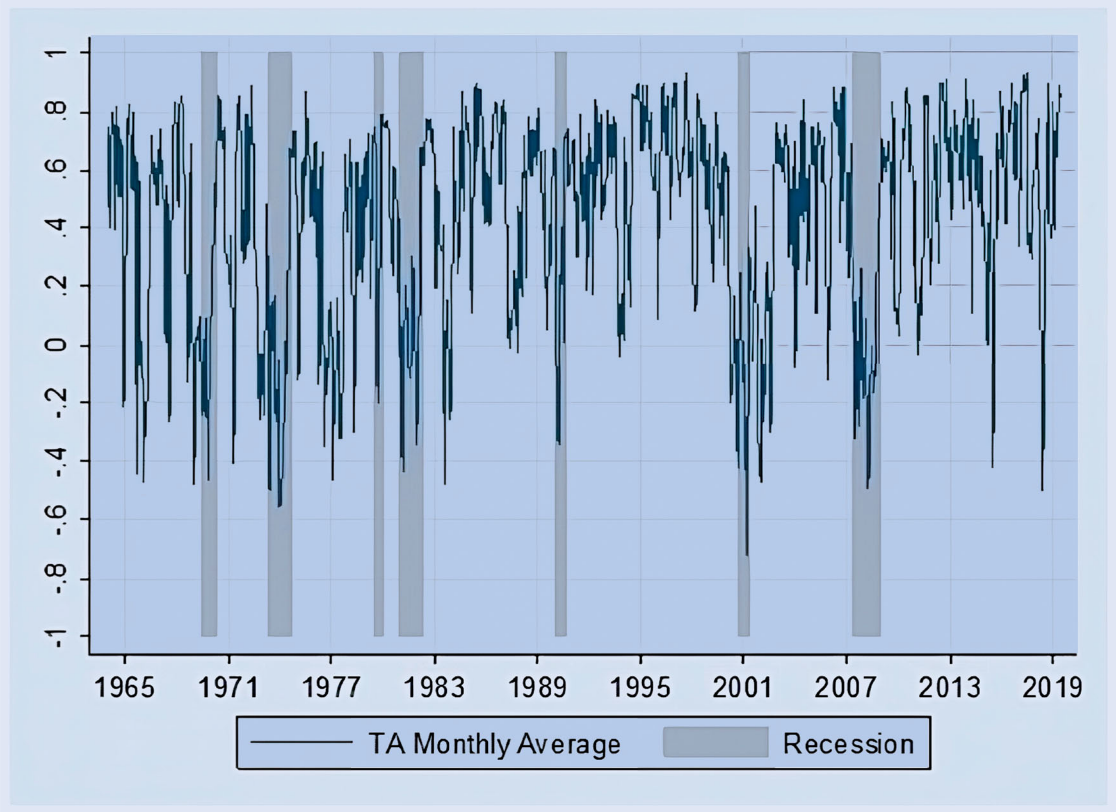

Figure 1. TA sentiment index and NBER-dated recession.
Note: This figure shows the monthly average TA sentiment from 1964 to 2019. The gray vertical bars represent NBER-dated recession periods.

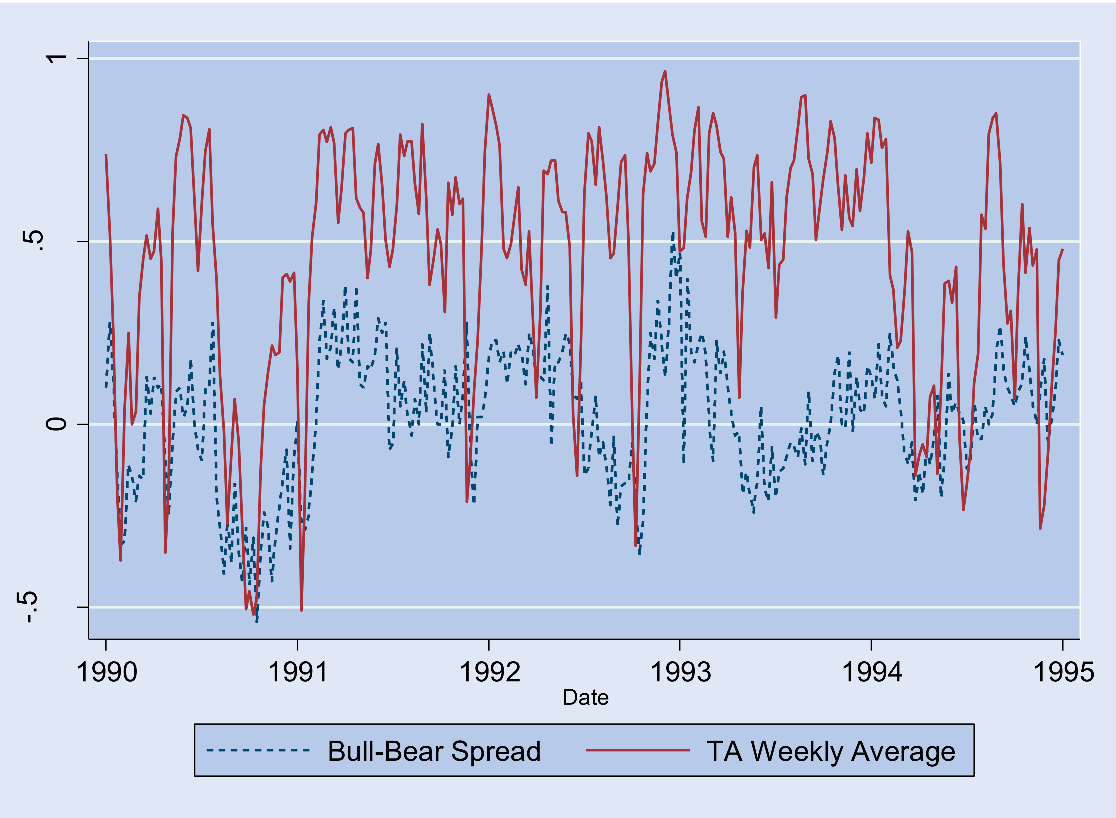

Figure 2. TA sentiment index and bull-bear spread.
Note: This figure compares weekly averaged TA sentiment index with weekly Bull-Bear Spread of individual investors from a randomly selected sub-sample period (from 1990 to 1995). The solid line is the averaged TA sentiment index. The dashed line is the Bull-Bear Spread.

Table 1. Descriptive summary statistics of sentiment indicators.

Panel A Summary of the Level of Sentiment Indicators								
	Correlations		Descriptive Statistics					
	Correlation	p-value	Obs	Mean	Std. Dev.	Min	Max	Skew
VIX	– 0.61	0.000	7,535	19.16	7.73	9.14	80.86	2.13
Put-Call ratio	– 0.25	0.000	6,044	0.85	0.20	0.30	1.82	0.23
Individual Bull-Bear Spread	0.44	0.000	8,167	7.65	17.67	– 54.00	62.86	– 0.04
TA			14,097	0.42	0.41	– 0.98	1.00	– 0.83
Panel B Summary of the Change in Sentiment Indicators								
	Correlations		Descriptive Statistics					
	Correlation	p-value	Obs	Mean	Std. Dev.	Min	Max	Skew
VIX	– 0.54	0.000	7,531	0.00	1.53	– 17.36	20.01	0.93
Put-Call Ratio	– 0.31	0.000	6,039	0.00	0.15	– 0.70	0.70	– 0.09
Individual Bull-Bear Spread	0.27	0.000	1,682	– 0.02	14.16	– 58.00	51.00	– 0.14
TA			14,096	0.00	0.11	– 0.82	0.64	– 0.69

Panel C Correlations of Filtered Sentiment Indicators				
	Correlations with Filtered TA		Correlations with One-day Lagged Filtered TA	
	Correlation	p-value	Correlation	p-value
VIX	– 0.56	0.000	– 0.01	0.257
Put-Call Ratio	– 0.37	0.000	– 0.12	0.000
Individual Bull-Bear Spread	0.21	0.000	0.35	0.000

Note: The table summarizes the Pearson correlations of TA sentiment and other sentiment indicators and the descriptive statistics for each indicator. Panel A reports the correlations and descriptive statistics of the level of the sentiment indicators; Panel B summarizes that of the change in sentiment indicators. In Panel A and B, we first report the correlation of TA sentiment and other indicators and the p-value. Panel B and Panel C report statistics of Individual Bull-Bear Spread at weekly frequency. The descriptive statistics include the number of observations (Obs), mean (Mean), standard deviation (Std. Dev), minimum value (Min), maximum value (Max) and skewness (Skew). Panel C reports the correlation between filtered TA sentiment and three filtered daily sentiment indices. We use the residuals from AR(10) regression as the filtered sentiment indicators.

which a stock is prone to investor sentiment. These characteristics include firm size (ME), firm age (Age), total risk (Sigma), earnings-book ratio (E/BE), dividend-book ratio (D/BE), fixed assets ratio (PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A) and sales growth ratio (GS).

To construct our portfolios, we collect stock market data from CRSP for all common stocks (share codes 10 and 11) between January 1964 and December 2019 in NYSE, AMEX, and NASDAQ. Firm-level accounting data is obtained from Compustat. The year-end accounting data of year t-1 is matched to daily returns from July of year t to June of year t + 1. The ten firm characteristics are used to sort stocks into deciles. For the sake of consistency, breakpoints for the deciles are defined using NYSE firms only. The portfolios are rebalanced every year to allow stocks to shift from one portfolio to another. The High (H), Medium (M), and Low (L) portfolios are defined as the top three, middle four, and bottom three deciles, respectively. Each of the sixteen portfolios is constructed by taking long positions in the sentiment-prone portfolios and shorting the sentiment-resistant portfolios. Detailed definitions of the ten firm characteristics and the long-short portfolios are provided below.

We first consider size, age, and volatility characteristics. Firm size (ME) is the price times shares outstanding in June every year. If there is more than one permanent code for a company, we sum up all the ME for the same company. Small stocks are disproportionally held by retail investors and are more difficult to value, indicating that small-cap firms are more prone to sentiment. We calculate the returns of the ME-based long-short portfolio (hereinafter referred to as ME(L-H)) as the average return differential between the Low (L) portfolio and High (H) portfolio. Firm age (Age) is the number of months between a firm's first appearance on CRSP to the nearest month. If the stock is delisted, Age is calculated by using its ending date minus its beginning date. Young firms have a short history and are typically more difficult to value and arbitrage. Therefore, we long the young portfolio and short the old portfolio and denote the age-based strategy as Age(L-H). Total risk (Sigma) is the annual standard deviation of monthly returns for the 12 months ending in June every year, and there should be no less than nine monthly returns available to estimate it. Since more volatile stocks are difficult to arbitrage, we long high-volatility stocks and short low-volatility stocks and denote this strategy as Sigma(H-L).

We then consider profitability and dividend policy characteristics. The earnings-book ratio (E/BE) is earnings scaled by book equity. Earnings (E) is income before extraordinary items (Item 18 in Compustat) plus income statement deferred taxes (Item 50) less preferred dividends (Item 19). The dividend-book ratio (D/BE) is the fiscal year-end dividends per share at the ex-date (Item 26) times shares outstanding (Item 25) scaled by book equity. Book equity (BE) is shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). Following Baker and Wurgler (2006), the E/BE long-short portfolio returns used in our regressions are the average return of non-profitable firms (E $<$ 0) minus that of profitable firms (E $>$ 0). The D/BE long-short portfolio returns used in regressions are the average return of non-dividend-paying firms (D $=$ 0) minus that of dividend-paying firms (D $>$ 0). The long-short portfolios used in regressions are denoted as E/BE(<0->0) and D/BE($=0$->0) respectively.

The fixed assets ratio (PPE/A) and research and development ratio (RD/A) are related to the asset tangibility of a firm. PPE/A is Plant, Property, and Equipment (Item 7) divided by gross total assets (Item 6). RD/A is Research and Development (Item 46) divided by gross total assets (Item 6). The coverage of R&D is poor before 1972, because the Financial Accounting Standards Board did not require research and development to be expensed until 1974. Firms with more intangible assets are more difficult to value and arbitrage, therefore the long-short portfolios take the long position in firms with less tangible assets and the short position in firms with more tangible assets. We denote these long-short portfolios as PPE/A(L-H) and RD/A(H-L) respectively.

The remaining three variables, namely book-to-market ratio (BE/ME), external finance over assets (EF/A) and sales growth ratio (GS), are defined as follows. BE/ME is the natural logarithm of the ratio of book equity to market equity. External finance (EF) is the change in gross total assets (Item 6) minus the change in retained earnings (Item 36). When the change in retained earnings is not available, we use net income (Item 172) minus common dividends (Item 21) instead. EF/A is the external finance scaled by gross total assets. Sales growth (GS) is the percentage change in net sales (Item 12). We first calculate the original sales growth ratio and then use GS to denote its decile. Baker and Wurgler (2006) argue that BE/ME, EF/A, and GS can relate to growth and distress in different ways. On the one hand, the middle deciles (M) are more stable, while the high (H) and low (L) deciles contain firms with strong growth opportunities or those with severe financial distress. High BE/ME implies that the firm is under distress, while low BE/ME indicates the presence of strong growth opportunities. High values of EF/A or GS indicate the firm is in distress, while low values imply that the firm has strong growth potential. To capture the multidimensional nature of these variables, we construct three long-short portfolios for each variable: when the three variables are considered as a generic pricing factor, the portfolios are denoted as BE/ME(H-L), EF/A(H-L), and GS(H-L); when the three variables represent firm growth opportunities, the portfolios are denoted as BE/ME(L-M), EF/A(H-M), and GS(H-M); and when the three variables represent the level of financial distress, the long-short portfolios are denoted as BE/ME(H-M), EF/A(L-M), and GS(L-M).

All decile portfolios have a sample period from January 01, 1964, to December 31, 2019, except for the RD/A portfolio, in which the R&D data is generally available after 1972. In total, we obtain 12,234 daily returns of RD/A-based long-short portfolios. For all other decile portfolios and long-short portfolios, we obtain 14,097 daily observations.

4. Tests and results

This section provides a more formal validation of our TA index as a sentiment indicator. Specifically, it examines the extent to which the TA index can predict cross-sectional stock returns and assesses the ability of the TA sentiment-based trading strategies to time the market and generate abnormal profits.

4.1. Ta sentiment and stock returns

In this section, we examine the ability of our TA sentiment to predict cross-sectional stock returns. We start with the daily predictive regressions of cross-sectional stock returns on the lagged terms in the TA sentiment.

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t, \qquad (1)$$

where R_t is the return on a given long-short portfolio at time t, ΔTA_t is the change in TA sentiment from time—t-1 to time t, and CV_t is a vector of control variables including the Fama-French five factors defined by Fama and French (2015) and the momentum factor by Carhart (1997). The Fama-French five factors are RMRF, SMB, HML, RMW, and CMA.† Any control factor used to construct the dependent variable in equation (1) will be excluded from the list of control variables. For example, SMB factor is excluded when the dependent variable is the daily return of long-short portfolio ME(L-H), and HML factor is excluded when the dependent variable is the daily return of the long-short portfolio constructed with BE/ME. We report Newey-West standard errors (Newey and West 1987) that are robust to heteroscedasticity and serial correlation.‡

The key variables of our interest are TA_{t-i}, i.e. the lagged TA sentiment indicators. Because of the synchronization problem faced by arbitragers, sophisticated investors may delay arbitrage and ride the mispricing. Thus, we expect the long-short portfolio returns to increase in the short term and reverse later. However, the exact time at which sophisticated investors can coordinate their attack on mispricing is not known with uncertainty and remains an empirical question. One way to decide the number of lags (i) of the TA sentiment indicators is to run the Likelihood Ratio test to compare the model fitness. At the significance level of 5%, eleven out of sixteen portfolios have better model fitness with only

† The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. RMRF is the market return premium over the risk-free rate, SMB is the average return on the three small portfolios minus the average return on the three big portfolios, HML is the average return on the two value portfolios minus the average return on the two growth portfolios, RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, and CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. The momentum factor (UMD) is the average return of high prior return portfolio over low prior return portfolio.
‡ We set 10 as the maximum lag to be considered in the autocorrelation structure when calculating Newey-West robust standard errors for the coefficients.

Table 2. Predictive regressions of portfolio returns.

		Panel A		Panel B			
		No Control Variables	With Control Variables	No Control Variables		With Control Variables	
		TA_{t-1}	TA_{t-1}	TA_{t-1}	TA_{t-2}	TA_{t-1}	TA_{t-2}
ME	L-H	0.18***	0.17***	0.39***	− 0.22***	0.48***	− 0.32***
		(12.51)	(11.78)	(7.96)	(− 4.49)	(10.00)	(− 6.85)
Age	L-H	0.16***	0.083***	0.44***	− 0.30***	0.19***	− 0.11***
		(12.52)	(9.82)	(10.63)	(− 6.97)	(7.26)	(− 4.27)
Sigma	H-L	0.15***	0.052***	0.78***	− 0.65***	0.24***	− 0.19***
		(8.45)	(5.30)	(14.75)	(− 12.15)	(7.32)	(− 6.22)
E/BE	< 0- > 0	0.16***	0.11***	0.38***	− 0.23***	0.20***	− 0.094**
		(11.07)	(8.27)	(8.81)	(− 5.27)	(5.10)	(− 2.44)
D/BE	= 0- > 0	0.14***	0.086***	0.47***	− 0.34***	0.19***	− 0.11***
		(10.27)	(7.93)	(11.87)	(− 8.48)	(5.85)	(− 3.55)
PPE/A	L-H	0.061***	0.031***	0.25***	− 0.20***	0.10***	− 0.074***
		(5.16)	(3.20)	(7.23)	(− 5.77)	(3.64)	(− 2.62)
RD/A	H-L	0.032***	0.014**	0.24***	− 0.21***	0.062***	− 0.050**
		(3.10)	(2.02)	(6.31)	(− 5.65)	(2.59)	(− 2.13)
BE/ME	H-L	0.029**	0.049***	− 0.17***	0.21***	0.070**	− 0.022
		(2.24)	(5.21)	(− 4.23)	(5.05)	(2.56)	(− 0.83)
EF/A	H-L	0.0051	− 0.011***	0.17***	− 0.17***	0.037**	− 0.050***
		(0.73)	(− 2.62)	(6.76)	(− 6.80)	(2.24)	(− 3.06)
GS	H-L	− 0.014*	− 0.029***	0.15***	− 0.17***	0.018	− 0.049***
		(− 1.79)	(− 5.50)	(5.98)	(− 6.71)	(1.13)	(− 3.01)
BE/ME	L-M	0.021**	0.0092	0.22***	− 0.21***	0.10***	− 0.095***
		(2.27)	(1.43)	(7.48)	(− 6.90)	(4.66)	(− 4.45)
EF/A	H-M	0.050***	0.025***	0.24***	− 0.20***	0.095***	− 0.073***
		(6.81)	(5.71)	(10.06)	(− 8.14)	(5.49)	(− 4.23)
GS	H-M	0.049***	0.014***	0.26***	− 0.22***	0.082***	− 0.071***
		(5.87)	(2.98)	(10.18)	(− 8.47)	(4.68)	(− 4.11)
BE/ME	H-M	0.050***	0.058***	0.049**	0.00094	0.17***	− 0.12***
		(7.24)	(8.96)	(2.03)	(0.04)	(8.39)	(− 5.91)
EF/A	L-M	0.045***	0.036***	0.073***	− 0.029*	0.058***	− 0.023
		(9.28)	(8.64)	(4.44)	(− 1.76)	(3.81)	(− 1.49)
GS	L-M	0.062***	0.043***	0.12***	− 0.055***	0.064***	− 0.022
		(10.09)	(7.93)	(5.80)	(− 2.75)	(3.57)	(− 1.22)

Note: Regressions of long-short portfolio returns on lagged TA sentiment and other control variables.

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the sixteen long-short portfolios constructed by sentiment-prone variables. The first column indicates the sentiment-prone proxies used to form the portfolio. The second column indicates the long and short components of the portfolio; H, M, and L are respectively the top three, middle four, and bottom three deciles. The control variables CV_t include the Fama-French five factors and the momentum factor (UMD). Any control factor will be excluded from the regression when it is the dependent variable. This table reports the coefficients for lagged TA sentiment of the regressions. Panel A reports the results of regressions with only one TA lag in independent variables, where $i = 1$. Panel B reports the results of regressions with two TA lags in independent variables, where $i = 2$. The second row indicates whether the control variables are included in the regressions. The Newey and West (1987) robust t-statistics are in parentheses. The sample period is from 1964/01/01 to 2019/12/31. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively.

two lagged TA sentiment. For robustness purposes, we also consider alternative values for i in our regressions.

Table 2 shows the regression results. Panel A reports the results of models with only one TA sentiment lag ($i = 1$) with or without control variables. Although we do not know how long the short-term momentum would persist, we expect to observe the effect just a day following a TA sentiment increase. Panel A shows that fourteen out of sixteen of the coefficients on TA_{t-1} are positive and significant at the 10% level or better. The magnitudes of the TA_{t-1} coefficients decrease in most cases after controlling for the Fama-French five factors and the momentum factor, but thirteen out of the fourteen coefficients remain positive and statistically significant. Like Baker and Wurgler (2006), we also find inconclusive results for the regressions involving EF/A(H-L) and GS(H-L) long-short portfolios.

Panel B in table 2 reports the results of models with two TA sentiment lags. The second lag would allow us to examine whether the momentum effect continues or return reversals emerge two days after a TA sentiment increase. Consistent with the results in Panel A, we find that the first-order TA lag positively predicts returns of most long-short portfolios, indicating a short-term momentum effect. The coefficients on TA_{t-2} are mostly negative, suggesting the returns on

Table 3. Robustness tests of the portfolio returns and TA sentiment.

		Model 1		Model 2	
		TA_{t-1}	TA_{t-26}^{t-2}	TA_{t-1}	TA_{t-2}
ME	L-H	0.32***	− 0.23***	0.26***	− 0.13**
		(15.03)	(− 9.21)	(4.18)	(− 2.09)
Age	L-H	0.12***	− 0.056***	0.19***	− 0.10***
		(10.31)	(− 4.08)	(5.07)	(− 2.82)
Sigma	H-L	0.092***	− 0.061***	0.44***	− 0.34***
		(6.30)	(− 3.71)	(10.13)	(− 8.50)
E/BE	< 0- > 0	0.13***	− 0.034	0.39***	− 0.23***
		(6.92)	(− 1.46)	(7.16)	(− 4.34)
D/BE	= 0- > 0	0.11***	− 0.032*	0.38***	− 0.24***
		(6.97)	(− 1.79)	(8.25)	(− 5.54)
PPE/A	L-H	0.066***	− 0.052***	− 0.019	0.035
		(4.96)	(− 3.38)	(− 0.48)	(0.87)
RD/A	H-L	0.031***	− 0.026**	0.073**	− 0.054*
		(3.09)	(− 2.16)	(2.34)	(− 1.80)
BE/ME	H-L	0.064***	− 0.023	0.094***	− 0.044
		(5.11)	(− 1.47)	(2.60)	(− 1.21)
EF/A	H-L	− 0.0094	− 0.0028	0.061***	− 0.060***
		(− 1.43)	(− 0.36)	(2.60)	(− 2.64)
GS	H-L	− 0.022***	− 0.0100	0.030	− 0.060***
		(− 3.03)	(− 1.15)	(1.33)	(− 2.63)
BE/ME	L-M	0.025***	− 0.024**	0.12***	− 0.098***
		(2.79)	(− 2.17)	(4.03)	(− 3.38)
EF/A	H-M	0.040***	− 0.022***	0.14***	− 0.10***
		(6.10)	(− 2.82)	(5.96)	(− 4.33)
GS	H-M	0.023***	− 0.013	0.15***	− 0.12***
		(3.23)	(− 1.59)	(6.64)	(− 5.19)
BE/ME	H-M	0.089***	− 0.047***	0.21***	− 0.14***
		(9.49)	(− 4.14)	(7.89)	(− 5.44)
EF/A	L-M	0.049***	− 0.019**	0.082***	− 0.041*
		(7.41)	(− 2.48)	(3.87)	(− 1.95)
GS	L-M	0.045***	− 0.0029	0.12***	− 0.058**
		(5.69)	(− 0.30)	(5.03)	(− 2.40)

Note: Regressions of long-short portfolio returns on lagged TA sentiment and control variables.

$$R_t = \alpha + \sum \beta_i TA_i + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the sixteen long-short portfolios constructed by sentiment-prone variables. The first two columns describe the long-short portfolios; H, M, and L are respectively the top three, middle four, and bottom three deciles. Model 1 regress R_t on TA_{t-1} and the smoothing average of TA sentiment between *t-2* and *t-26* TA_{t-26}^{t-2}. The control variables CV_t include the Fama-French five factors and the momentum factor (UMD). Panel B reports the results of regressions with TA_{t-1} and TA_{t-2} in independent variables, after controlling for not only pricing factors but also a set of macroeconomic variables default spread, TED spread, macroeconomic activities index (ADS), and economic policy uncertainty (EPU). The second row indicates whether the control variables are included in the regressions. The Newey and West (1987) robust t-statistics are in parentheses. Any control factor will be excluded from the regression when it is the dependent variable. The sample period is from 1964/01/01 to 2019/12/31. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively.

sentiment-prone stocks begin to drop on the second day following a sentiment increase. The absolute value of β_2 is generally smaller than that of β_1. Combining the results of Panel A with Panel B, the ability of TA sentiment to explain the future returns for BE/ME(H-L) and GS(H-L) is inconclusive. Except for these two portfolios and the GS(L-M), including control variables in the regressions does not alter the sign or significance of β_1 and β_2. When BE/ME, EF/A, and GS are used to capture the growth opportunities and financial stress, β_1 and β_2 are statistically significant in most cases as expected.

Table 3 reports several additional tests to examine the robustness of the regressions involving two lagged TA sentiment terms. Model 1 in table 3 investigates the effect of the first lag of TA sentiment and a smoothing average of TA sentiment between t-2 and t-26 on return after controlling for Fama-French five factors and momentum factor. Model 2 in table 3 examines whether the observed return patterns reflect changes in firms' fundamentals by including the following macroeconomic variables as additional controls in equation (1): default spread, TED spread, macroeconomic activities index (ADS), and economic policy uncertainty (EPU).† When testing the effect of sentiment on return, Da et al. (2015)

† These are the only microeconomic variables for which data is available on a daily frequency. Both the Default spread and TED spread are from https://fred.stlouisfed.org/. Default spread is the difference between Moody's AAA and Baa bond yields and TED spread is the spread between the three-month LIBOR based on US dollars and the three-month Treasury Bill.

employ two macroeconomics variables ADS and EPU as control variables. ADS is constructed by Aruoba *et al.* (2009) with a battery of seasonally adjusted macroeconomic variables of mixed frequencies to measure daily macroeconomic activities.† Baker *et al.* (2016) construct EPU by counting the number of US newspaper articles with terms related to economic policies.‡

Table 3 reports the two robustness tests of the predictive power of TA sentiment on cross-sectional returns. Model 1 shows that while the coefficients on the first lag of TA sentiment remain positive, the coefficients on the average of the past TA sentiment are negative. These results suggest that, on average, an increase in TA sentiment predicts momentum on the following day; if the TA sentiment has been persistently high, TA sentiment will also predict the future return reversal. The finding that TA is a contrarian predictor for future cross-sectional returns suggests that our TA sentiment index is indeed a sentiment indicator. However, the contrarian predictive power of TA_{t-26}^{t-2} is weaker than that of TA_{t-2} in Panel B of table 2. Model 2 in table 3 shows the coefficients of one-day and two-day lagged TA sentiment terms. Comparing Model 2 of table 3 with Panel B of table 2, we find that, except for the PPE/A portfolio, both the sign and significance of coefficients on TA sentiment are not altered by the inclusion of the macroeconomic variables as additional controls in equation (1). Thus, the predictive power of our TA sentiment index, particularly that of TA_{t-1}, is not subsumed by the macroeconomic factors.§

To rule out the rational explanation for the predictability of TA sentiment, we also follow Baker and Wurgler (2006) and add sentiment into a conditional CAPM model:

$$R_t = \alpha + \beta_1 TA_{t-1} + (d + \lambda_1 TA_{t-1})RMRF_t + \varepsilon_t, \quad (2)$$

where R_t is the portfolio return at time t, and $RMRF_t$ is the market return premium. Under market rationality, the TA sentiment index would vary with systematic risks (beta loadings) of the sentiment-based portfolio return premium. If the effect of TA lags on return arises from the time-varying beta-loading of market return premium, λ_1 would have the same sign as β_1 in Panel A of table 2 and remain significant; otherwise, the behavioral story would hold.

Table 4 reports the regression results of equation (2). Due to the multicollinearity issue, we test the rational explanation with only one lagged TA term in the independent variable as noted in equation (2). In table 4, most coefficients of the interaction terms of TA sentiment and market return premium (λ_1) are insignificant. The signs of significant λ_1 match those of β_1 in Panel A of table 2 in only in two out of the sixteen regressions. The results of the remaining fourteen regressions are consistent with the behavioral story. We also find that the sign and significance of coefficients on TA_{t-1} are consistent with those in Panel A of table 2, implying that the predictive ability of TA sentiment does not change after allowing for the time-variation in conditional market betas. Another systematic risk explanation assumes that the market beta loadings are fixed, while the market return premium varies with TA sentiment. If this story holds, the coefficients on the market return premium should be positive for all sixteen portfolios. We find that the signs on d vary considerably across these portfolios, inconsistent with the rational explanation.¶

Our Online Appendix reports a battery of robustness tests on the relationship between our TA sentiment and cross-sectional stock returns. The first set of regressions we run is the long-short portfolio returns regressed on contemporaneous incremental TA sentiment. We find that TA sentiment shock explains contemporaneous returns. The contemporaneous positive correlation between TA sentiment and the cross-sectional stock returns is also consistent with the view that TA sentiment is a sentiment indicator. However, this finding should be taken with caution, due to potential endogeneity concerns.

The second set of tests investigates the sensitivity of our results to the way we construct the TA sentiment. We use historical data of the Dow Jones Industrial Average Index, rather than that of the S&P 500, to construct our TA sentiment and generate similar results. Furthermore, instead of using an equal-weighted average of the technical analysis forecasts, we compute a performance-weighted average of the 2127 technical forecasts as the TA sentiment index, for which the performance of each trading rule is measured by its returns in the past year, and obtain consistent results. The performance-weighted TA sentiment captures the idea that better-performing strategies are more likely to be used. We also examine whether TA sentiment has incremental value beyond the alternative sentiment indicators, such as VIX. We find that the effect of our sentiment measure remains significant after including VIX as an additional control in our regressions.

The third set of tests investigates the robustness of our findings to alternative long-short portfolio return calculations and

† The data is downloaded from https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

‡ The daily EPU data is available from https://www.policyuncertainty.com/us_monthly.html.

§ In unreported results, we regress the one-month leading S&P 500 index returns (including dividends) on Neely et al.'s (2014) F1_TECH, our monthly aggregated TA indicator, and PCA_TA indicator, respectively. We find that both the monthly average of TA indicator and the aggregated PCA_TA indicator are poor predictors of the aggregate market return. However, based on the significance of the parameters as well as the adjusted R-squared, F1_TECH is a better predictor of the monthly aggregate monthly return than TA. This is consistent with our earlier argument that the TA indicator captures better the short-term investor sentiment and hence is more profitable in the cross-section rather than in the aggregate market. Our arguments and evidence are consistent with the argument in Baker and Wurgler (2006) that sentiment indicators are poor predictors of the aggregate market return. Further details on these results can be obtained from the authors.

¶ We extend the tests of the predictive power of TA beyond the conditional market beta model. If TA sentiment is a state variable that captures the changing conditions in macroeconomics and financial market, this can be reflected in the conditional factor loadings that are linear in the lagged TA sentiment. This would allow factor loadings to vary over time and correlate with the TA indicator. For this purpose, we estimate a conditional four-factor Carhart model. We show that while our TA sentiment indicator influences the beta loadings of Carhart four factors, it does not alter signs or the significance of the coefficients on the lagged TA indicator. Thus, the predictive power of our TA sentiment indicator could not be fully subsumed by the changing beta loadings of other pricing factors. Details are available upon request.

Table 4. Market betas conditional on TA sentiment.

		TA_{t-1}	$RMRF_t$	$TA_{t-1}RMRF_t$	α
ME	L-H	0.18***	− 0.19***	0.018	− 0.044***
		(12.54)	(− 11.89)	(0.63)	(− 4.83)
Age	L-H	0.16***	− 0.041**	− 0.026	− 0.039***
		(12.59)	(− 2.42)	(− 0.82)	(− 4.94)
Sigma	H-L	0.14***	0.36***	− 0.026	− 0.039***
		(9.95)	(26.99)	(− 0.91)	(− 4.69)
E/BE	< 0- > 0	0.16***	0.029**	− 0.0031	− 0.028***
		(11.05)	(2.47)	(− 0.13)	(− 3.21)
D/BE	= 0- > 0	0.14***	0.096***	− 0.013	− 0.030***
		(10.70)	(6.32)	(− 0.44)	(− 3.82)
PPE/A	L-H	0.057***	0.055***	0.034	− 0.024***
		(4.90)	(3.23)	(0.99)	(− 3.48)
RD/A	H-L	0.031***	0.13***	0.034*	− 0.0080
		(3.24)	(11.88)	(1.80)	(− 1.39)
BE/ME	H-L	0.034***	− 0.29***	0.059***	0.028***
		(3.22)	(− 22.39)	(2.75)	(4.29)
EF/A	H-L	0.00087	0.13***	− 0.031***	− 0.029***
		(0.15)	(20.46)	(− 2.63)	(− 8.16)
GS	H-L	− 0.020***	0.15***	− 0.029**	− 0.018***
		(− 3.07)	(18.98)	(− 2.04)	(− 4.52)
BE/ME	L-M	0.017**	0.16***	− 0.048***	− 0.019***
		(2.22)	(14.95)	(− 2.64)	(− 3.90)
EF/A	H-M	0.050***	0.11***	− 0.042***	− 0.032***
		(8.15)	(17.70)	(− 3.20)	(− 8.37)
GS	H-M	0.044***	0.14***	− 0.039**	− 0.030***
		(6.39)	(17.99)	(− 2.39)	(− 7.05)
BE/ME	H-M	0.052***	− 0.13***	0.011	0.0093**
		(8.20)	(− 25.22)	(1.16)	(2.42)
EF/A	L-M	0.049***	− 0.020***	− 0.011	− 0.0025
		(10.83)	(− 4.80)	(− 1.55)	(− 0.90)
GS	L-M	0.063***	− 0.0014	− 0.0098	− 0.013***
		(10.30)	(− 0.30)	(− 1.07)	(− 3.45)

Note: Regressions of long-short portfolio returns on market return premium, TA sentiment and market return premium interacted with TA sentiment.

$$R_t = \alpha + \beta_1 TA_{t-1} + (d + \lambda_1 TA_{t-1})RMRF_t + \varepsilon_t.$$

R_t is the daily return of the sixteen long-short portfolios constructed by sentiment-prone variables. The first columns indicate the sentiment-prone proxies used to form the portfolio. The second column indicates the long and short components of the portfolio; H, M, and L are respectively the top three, middle four, and bottom three deciles. The Newey and West (1987) robust t-statistics are in parentheses. The sample period is from 1964/01/01 to 2019/12/31. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively.

to the potential Stambaugh bias (Stambaugh 1999). Specifically, we construct the long-short portfolios by longing the most sentiment-prone decile portfolio and shorting the least sentiment-prone decile portfolio and find that our results still hold. We also calculate the value-weighted return premium to isolate the size effect on the portfolio return premium and show that the predictive power of TA sentiment does not change.† Furthermore, we address concerns of Stambaugh bias with a wild bootstrap approach, as in Huang *et al.* (2015), and find consistent results.

In addition, we address a potential multi-collinearity issue (due to the high persistency of TA similar to other sentiment indicators) by orthogonalizing TA_{t-2} to TA_{t-1} when both TA_{t-1} and TA_{t-2} are included in the regressions. We replace TA_{t-2} with recursive residuals of a rolling regression to avoid the look-ahead bias. The results show that one-day lagged TA sentiment predicts higher returns while the orthogonalized second lag of TA sentiment has a significant negative relationship with future returns, consistent with the results in table 2.

Finally, we follow the framework of Neely *et al.* (2014) and construct an aligned index based on principal component analysis. We generate a PCA_TA indicator by taking the first principal component of all of the 2127 technical trading signals. We report the predictability and profitability of PCA_TA indicator in Table A.5 and Table A.6, respectively. The results are highly consistent with those from the equal-weighted TA indicator and our conclusions remain unchanged.

4.2. A Simple TA timing strategy

One critical assumption behind the delayed arbitrage of sophisticated investors is that riding mispricing is on average profitable. While we do not know exactly which trading strategies are used by arbitrageurs, we devise a simple trading

† It has been pointed out in Baker and Wurgler (2006) that ME portfolio return premium strongly correlate with other portfolio returns. When the dependent variables are equally weighted, the size effect might play a large role.

Table 5. Profitability of A simple trading strategy.

		Panel A Original Portfolio			Panel B TA Timing Strategy (RTA)				Panel C TAP		
		Avg Ret	SRatio	Alpha	Avg Ret	SRatio	Alpha	BETC	Avg Ret	Alpha	Success
ME	1–10	16.85***	1.28	16.41***	28.32***	2.17	29.79***	32.90	11.48***	13.38***	0.78
Age	1–10	6.21***	0.60	6.99***	18.70***	1.82	20.12***	21.72	12.49***	13.14***	0.79
Sigma	10–1	11.29***	0.80	11.78***	26.13***	1.86	26.82***	30.35	14.84***	15.05***	0.78
E/BE	1–10	8.31***	1.15	7.98***	5.99***	0.83	6.40***	6.95	– 2.33*	– 1.57	0.77
D/BE	1–10	7.43***	0.86	7.86***	14.78***	1.73	15.35***	17.17	7.35***	7.49***	0.78
PPE/A	1–10	– 1.32	– 0.13	– 1.05	4.73***	0.48	5.47***	5.49	6.05***	6.52***	0.79
RD/A	10–1	5.88***	0.50	6.91***	8.89***	0.76	10.25***	10.33	3.02	3.34	0.80
BE/ME	10–1	15.18***	1.38	13.81***	3.67**	0.33	3.62**	4.26	– 11.51***	– 10.19***	0.76
EF/A	10–1	– 11.21***	– 1.38	– 10.28***	3.22***	0.39	4.00***	3.74	14.42***	14.27***	0.80
GS	10–1	– 9.71***	– 1.26	– 9.45***	– 1.92*	– 0.25	– 1.83**	– 2.23	7.79***	7.62***	0.79
BE/ME	1–5	– 1.70	– 0.21	– 0.62	4.32***	0.54	4.39***	5.02	6.02***	5.01***	0.78
EF/A	10–5	– 4.15***	– 0.53	– 3.04***	10.63***	1.35	11.25***	12.35	14.78***	14.28***	0.79
GS	10–5	– 3.80***	– 0.46	– 2.96**	8.91***	1.08	9.50***	10.35	12.72***	12.46***	0.79
BE/ME	10–5	13.48***	1.75	12.68***	7.99***	1.03	8.02***	9.28	– 5.49***	– 4.66***	0.76
EF/A	1–5	7.06***	1.24	7.24***	7.41***	1.3	7.25***	8.61	0.36	0.01	0.78
GS	1–5	5.90***	0.82	6.49***	10.83***	1.52	11.33***	12.58	4.93***	4.84**	0.78

Note: This table reports the summary statistics of original long-short portfolio returns, TA sentiment timing strategy returns, and the TAP returns. TA sentiment timing strategy is to hold the original portfolio when current TA sentiment is no less than the average TA sentiment over prior ten trading days and to short the original portfolio otherwise. TAP is the returns on the sentiment timing strategy over original portfolio returns. The first two columns show the construction of original portfolios. The 16 original portfolios are constructed in a way that longs the most sentiment-prone decile portfolio and shorts the least sentiment-prone portfolio. Avg Ret is the average return; SRatio is the Sharpe ratio; Alpha is the abnormal return of the portfolio after adjusting for Fama-French five factors and the momentum factor. BETC in Panel B is the breakeven transaction costs of TA Timing Strategy. Success in Panel C is the percentage of non-negative TAP return. All the returns are annualized and in percentages. The sample period is between 01/1964 and 12/2019. ***, ** and * indicates the t-test significance at 1%, 5% and 10% level, respectively.

strategy based on our TA sentiment. We then apply our trading strategy to the sixteen long-short portfolios, i.e. we long the most sentiment-prone decile portfolio and short the least sentiment-prone portfolio. In what follows, we refer to the sixteen long-short portfolios as the original long-short portfolios to distinguish them from the portfolios generated from the implementation of the TA timing strategy.

The basic rule of TA timing strategy is straightforward: a buy (sell) signal is generated when a TA sentiment at the end of the current trading day is higher (lower) than the moving average of TA sentiment over the previous ten days.† When we apply the trading strategy to the original sixteen long-short portfolios, we long or continue to hold the original long-short portfolio the next day when a buy signal is generated, and short the original long-short portfolio the next day when a sell signal is generated. For example, for the Age-sorted portfolio, our investment timing strategy is to long young firms and short old firms when the TA sentiment gives a buy signal, and to long old firms and short young firms when the TA sentiment generates a sell signal. Essentially, our TA timing strategy is a trend-following strategy designed to take advantage of delayed arbitrage. We do not consider a contrarian strategy to exploit return reversals, as the inability to observe coordinated events makes it difficult to time reversal. This TA timing strategy employs an out-of-sample procedure that investors adjust their portfolio holdings based on a technical trading signal generated from past prices.

Panel A in table 5 reports the average returns and risk-adjusted returns (Sharpe ratio and the Alphas adjusted for Fama-French five factors and the momentum factor) of original long-short portfolios. Most of these portfolios have significantly positive average returns and risk-adjusted returns and four of them have negative average returns and risk-adjusted returns. The highest Sharpe ratio for original long-short portfolio return is 1.75. Unlike the results in Panel A of table 5, both average returns and risk-adjusted returns of our TA timing strategies in Panel B are positive and significant in almost all portfolio returns. The only exceptions are the TA timing strategies on GS(10-1), which have significant albeit small negative average returns in Panel B. The average returns range from -1.92% to 28.32% and the Sharpe ratio ranges from -0.25 to 2.17. Most of the Sharpe ratios increase following the implementation of our TA sentiment timing strategies. Adjusting for the Fama-French five factors and the momentum factor affects average returns marginally, i.e. the abnormal alphas of TA timing strategies are slightly higher than the unadjusted average returns. The low profitability associated with the BE/ME(10-1), EF/A(10-1), and GS(10-1) is not surprising since both the long legs and short legs of these three portfolios could reflect high sentiment.

An important question is whether our TA timing strategies can survive the transaction costs. We calculate break-even trading costs (BETC) that make the average returns of our TA timing portfolio zero. BETC depends on both the profitability and the trading frequency of a strategy. Higher BETC indicates higher profitability or lower trading frequency of a strategy. The higher BETC is, the more likely a trading strategy will survive the transaction costs. The last column of Panel B shows that the BETC of four out of the sixteen TA timing portfolios is higher than the benchmark transaction cost of 25 basis points (see, Lynch and Balduzzi 2000).

† We consider moving average of alternative numbers of days (1, 5, 30, 60, 120, 250) in our robustness check.

Table 6. TA sentiment timing strategy returns and bid-ask spread.

		α	BAS	RMRF	SMB	HML	RMW	CMA	UMD
ME	1–10	41.3***	− 1.99	− 0.073**		− 0.098**	0.0062	− 0.027	− 0.075**
		(7.99)	(− 1.31)	(− 2.29)		(− 2.30)	(0.12)	(− 0.45)	(− 2.42)
Age	1–10	25.6***	0.65	− 0.019	0.066**	− 0.074*	0.018	0.024	− 0.066**
		(8.56)	(1.01)	(− 0.88)	(2.47)	(− 1.88)	(0.39)	(0.50)	(− 1.97)
Sigma	10–1	33.6***	− 2.55	− 0.021	0.079*	− 0.049	− 0.040	0.033	− 0.051
		(6.59)	(− 0.92)	(− 0.90)	(1.65)	(− 1.19)	(− 0.80)	(0.54)	(− 1.43)
E/BE	1–10	14.2***	− 1.66*	− 0.0022	0.011	− 0.039		0.010	− 0.025
		(5.31)	(− 1.67)	(− 0.24)	(0.46)	(− 1.55)		(0.36)	(− 1.34)
D/BE	1–10	23.0***	− 1.05	− 0.0100	0.053***	− 0.047*		0.031	− 0.041*
		(6.97)	(− 0.71)	(− 0.62)	(2.83)	(− 1.85)		(0.83)	(− 1.77)
PPE/A	1–10	2.97	− 3.87	0.0022	0.059*	0.026	0.012	− 0.029	− 0.019
		(1.40)	(− 1.15)	(0.16)	(1.80)	(0.68)	(0.36)	(− 0.73)	(− 1.18)
RD/A	10–1	16.6***	− 1.42	0.0088	0.096***	− 0.042	− 0.016	0.043	− 0.043
		(6.16)	(− 0.29)	(0.62)	(4.06)	(− 1.37)	(− 0.39)	(0.87)	(− 1.47)
BE/ME	10–1	− 2.21	0.74	0.00032	− 0.052*	− 0.025	0.037	− 0.031	0.014
		(− 0.77)	(0.42)	(0.03)	(− 1.77)	(− 0.90)	(0.98)	(− 0.76)	(0.72)
EF/A	10–1	9.04***	2.39	− 0.020*	0.030	− 0.00089	− 0.034	− 0.015	− 0.024
		(4.31)	(1.43)	(− 1.71)	(1.19)	(− 0.04)	(− 1.31)	(− 0.47)	(− 1.56)
GS	10–1	− 1.50	− 1.18	− 0.017*	0.0096	0.017	− 0.033	− 0.028	0.0036
		(− 0.69)	(− 0.78)	(− 1.95)	(0.41)	(0.86)	(− 1.42)	(− 0.97)	(0.32)
BE/ME	1–5	7.55***	− 6.84	0.013	0.057***	0.0091	− 0.0042	0.025	− 0.028
		(4.98)	(− 1.35)	(1.46)	(3.18)	(0.37)	(− 0.14)	(0.69)	(− 1.45)
EF/A	10–5	17.8***	− 12.5***	− 0.013	0.046**	− 0.024	− 0.025	0.024	− 0.037*
		(7.71)	(− 2.75)	(− 1.17)	(2.02)	(− 0.93)	(− 0.86)	(0.73)	(− 1.84)
GS	10–5	12.9***	− 2.21	− 0.011	0.052**	− 0.034	− 0.023	0.023	− 0.030
		(6.93)	(− 0.75)	(− 1.05)	(2.12)	(− 1.34)	(− 0.80)	(0.64)	(− 1.62)
BE/ME	10–5	6.13***	0.72	0.013	0.0059	− 0.017	0.033	− 0.0058	− 0.014
		(2.68)	(0.47)	(1.36)	(0.34)	(− 0.84)	(1.42)	(− 0.27)	(− 1.13)
EF/A	1–5	9.17***	− 1.02	0.0074	0.016	− 0.022	0.0094	0.038**	− 0.013
		(5.19)	(− 0.70)	(0.97)	(1.58)	(− 1.14)	(0.58)	(2.16)	(− 1.33)
GS	1–5	18.1***	− 4.10**	0.0061	0.043***	− 0.052**	0.010	0.050*	− 0.034*
		(6.64)	(− 2.43)	(0.70)	(3.29)	(− 2.39)	(0.40)	(1.81)	(− 1.83)

Note: This table reports the results of TA sentiment timing strategy returns (RTA) regressed on the cross-sectional bid-ask spread disparity and a set of control variables.

$$RTA_t = \alpha + \beta_1 BAS + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the sixteen long-short portfolios constructed by sentiment-prone variables. BAS is the daily bid-ask spread difference between the long leg and the short leg of each sixteen long-short portfolios. The first two columns indicate how the long-short portfolios are constructed. H, M, and L are respectively the top three, middle four, and bottom three deciles. The control variables include the Fama-French five factors and the momentum factor (UMD). The first column reports annualized abnormal returns in percentage. Any control factor will be excluded from the regression when it is the dependent variable in the regressions. The Newey and West (1987) robust t-statistics are in parentheses. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively.

The highest BETC of 32.90 bps is observed in the case of ME (1-10) portfolio. One reason why the profitability of our TA timing strategies does not survive the transaction costs of 25bs is that these strategies are highly conservative. An alternative TA timing strategy that involves buying a sentiment-prone decile following high TA and holding a sentiment-resistant decile following low TA could generate a higher profit, as the transaction costs are expected to lower in the absence of short-selling. In addition, sophisticated investors, such as hedge funds, usually have lower transaction costs. Furthermore, using a longer moving average window to generate trading signals will reduce the trading frequency and transaction costs. While we acknowledge that determining an appropriate transaction cost is not an easy issue, our results show that transaction costs reduce, but do not eliminate, the profitability of our trading strategy.†

To demonstrate the incremental value of applying our trading strategy, we also compute TAP_t, the return difference between our timing strategy and its corresponding original portfolio. Panel C in table 6 shows applying TA time strategy generates significantly positive returns over the original long-short portfolios in eleven out of the sixteen cases. The size of TAP_t is remarkable. TAP is particularly large for ME(1-10), AGE(1-10), Sigma(10-1), EF/A(10-1) and EF/A(10-5), with values exceeding 11% per annum. Adjusting TAP for risk factors yields significantly positive alphas in eleven out of the sixteen TA timing portfolios, suggesting that our TA strategies outperform their corresponding conventional long-short strategies in time the market. We also report the success rate of the TA timing strategy, defined as the percentage of trading days when TAPs are non-negative, that is, when the TA performs no worse than holding the original long-short portfolios. We find that the success rate ranges from 76% to 80%,

† We can also apply our timing strategy to individual decile portfolios as in Han et al. (2013). Returns (BETC) on the TA timing strategy are much higher (higher) for the most sentiment-prone deciles than that of the long-short portfolio constructed with the same firm characteristic.

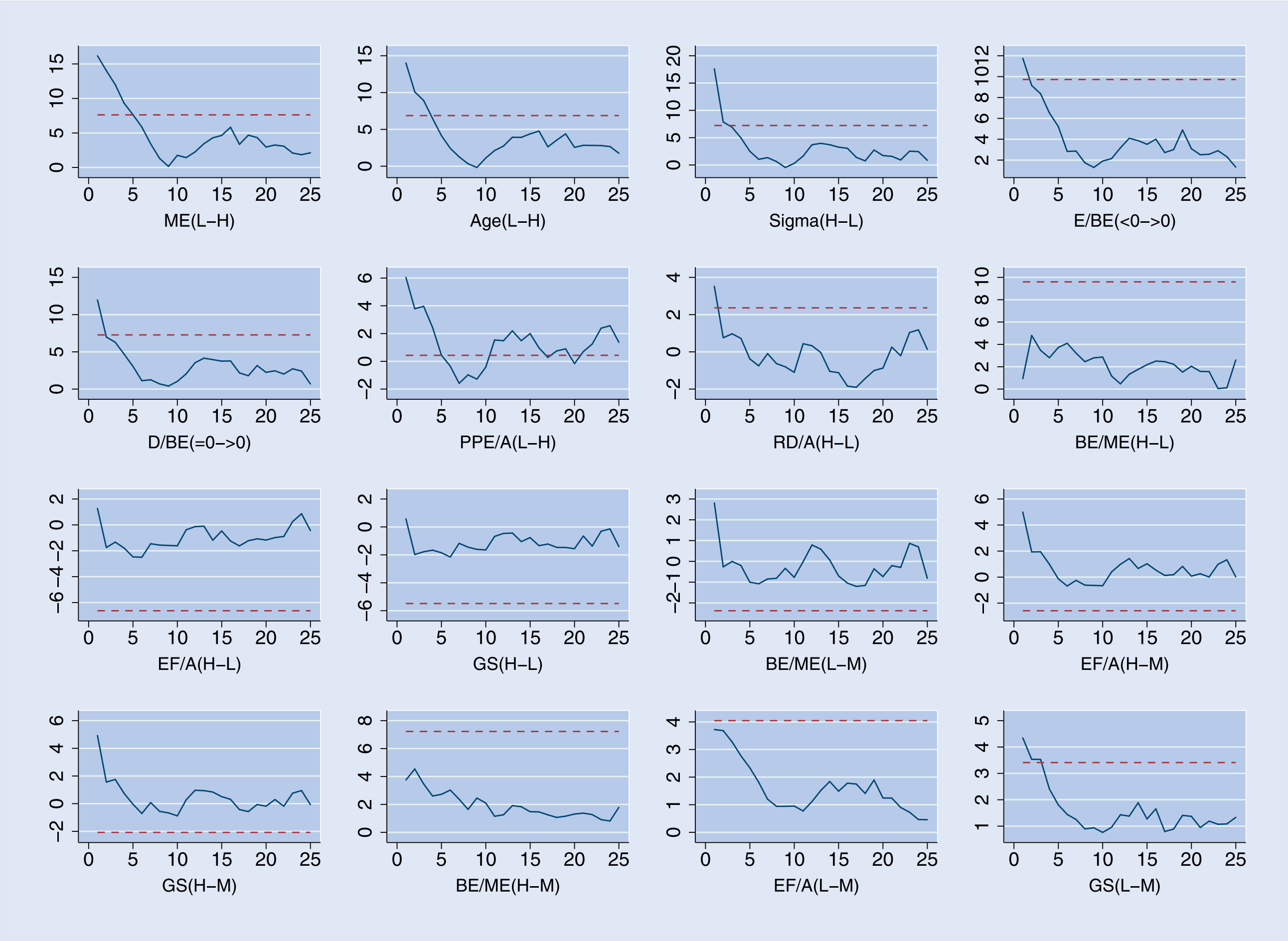

Figure 3. TA timing strategy profit over 25-days
Note: The solid line is the averaged return of holding TA timing strategy profit for continuous window period. The dashed line is the averaged return of original long-short portfolio.

indicating that the TA timing strategy is effective most of the time.

One potential rational explanation for the observed momentum pattern in the cross-sectional returns following a TA sentiment increase is liquidity. One may argue that daily TA sentiment timing strategy returns are significantly affected by bid-ask spreads and price impacts, and these effects are amplified by frictions, such as illiquidity. To address this concern, we calculate the bid-ask spread disparity for all the sixteen long-short portfolios, i.e. the average bid-ask spread of the high sentiment-prone portfolio minus that of the low sentiment-prone portfolio. Equation (3) notes the regression formula

$$RTA_t = \alpha + \beta_1 BAS + \gamma CV_t + \varepsilon_t, \qquad (3)$$

We regress TA timing strategy return (RTA) on bid-ask spread disparity after controlling for Fama-French five and momentum factors to see whether the bid-ask spread disparity could explain the return profitability and eliminate the abnormal return of our TA timing strategy. Table 5 reports the regression results of equation (3). It shows that the TA timing strategy profit is significantly related to the bid-ask spread disparity. However, comparing the abnormal alphas in table 6 with their counterparts in Panel B of table 5, the abnormal returns of the TA sentiment timing strategy remain statistically significant, and their magnitudes are unaffected by the cross-sectional variation in bid-ask spread disparity.

What happens if after applying the TA timing strategy to the original long-short portfolios based on one-day prior TA sentiment index level at date t, we continue to hold the same TA timing portfolio for the following 24 days? That is, we long the original portfolio for the next 25 days if the current TA trading signal is positive and short the original portfolio for the next 25 days if the current TA trading is negative. Figure 3 reports all the time-series daily returns of holding the TA timing strategy portfolios for 25 days. It shows that this new strategy generates substantial positive returns on day one and these returns decline afterwards and fluctuate randomly around a certain level (mostly around zero or below the average returns of the original long-short portfolios). Such a pattern echoes the reversal effect found in our predictive regression analysis in table 2.

These findings also corroborate with impulse response function graphs from Vector Autoregression models (VAR) of TA sentiment and the original long-short portfolios in our online appendix. The simple impulse response functions from VAR analysis show that, after a positive sentiment shock, the original portfolio returns experience a sharp increase on the first day and then a gradual decline in the following days. This suggests that the increase in portfolio returns following shocks in the TA sentiment tends to die out gradually.

Table 7. Market timing tests.

		Panel A. TM Regression				Panel B. HM Regression			
		α	β_m	β_{m^2}	R^2	α	β_m	γ_m	R^2
ME	1–10	− 0.70	− 0.19***	5.73***	7.69	− 29.01***	− 0.46***	0.51***	6.18
		(− 0.19)	(− 11.74)	(5.24)		(− 4.52)	(− 8.15)	(6.85)	
Age	1–10	5.90*	− 0.12***	2.96***	4.01	− 9.36*	− 0.26***	0.27***	3.42
		(1.82)	(− 7.93)	(3.11)		(− 1.93)	(− 6.19)	(4.69)	
Sigma	10–1	11.29***	− 0.18***	2.05***	2.56	− 6.11	− 0.31***	0.27***	2.73
		(3.21)	(− 9.95)	(3.12)		(− 1.05)	(− 6.93)	(4.15)	
E/BE	1–10	− 2.96*	− 0.02**	0.38	0.21	− 9.71***	− 0.07***	0.09***	0.47
		(− 1.77)	(− 2.09)	(0.94)		(− 4.06)	(− 3.49)	(3.31)	
D/BE	1–10	2.48	− 0.10***	2.22***	3.86	− 10.53***	− 0.22***	0.22***	3.55
		(1.04)	(− 9.10)	(3.40)		(− 2.73)	(− 6.77)	(4.93)	
PPE/A	1–10	5.29**	− 0.04***	0.35	0.31	3.76	− 0.06*	0.03	0.30
		(2.04)	(− 3.73)	(0.41)		(0.93)	(− 1.80)	(0.58)	
RD/A	10–1	0.97	− 0.07***	1.14***	0.81	− 3.78	− 0.11***	0.09*	0.67
		(0.35)	(− 4.94)	(2.66)		(− 0.84)	(− 3.59)	(1.92)	
BE/ME	10–1	− 11.59***	0.01	0.25	0.00	− 16.18***	− 0.02	0.06	0.05
		(− 4.66)	(0.53)	(0.39)		(− 4.35)	(− 0.78)	(1.49)	
EF/A	10–1	13.15***	− 0.05***	0.63	0.76	11.79***	− 0.07***	0.03	0.65
		(7.17)	(− 6.37)	(1.19)		(3.60)	(− 2.62)	(0.89)	
GS	10–1	7.71***	− 0.03***	0.16	0.18	10.31***	− 0.01	− 0.03	0.19
		(4.15)	(− 3.78)	(0.25)		(3.22)	(− 0.57)	(− 0.69)	
BE/ME	1–5	5.96***	− 0.05***	0.09	0.44	3.21	− 0.06***	0.04	0.48
		(3.67)	(− 4.84)	(0.50)		(1.50)	(− 3.76)	(1.62)	
EF/A	10–5	12.63***	− 0.08***	0.99***	1.89	5.89**	− 0.14***	0.11***	1.89
		(7.02)	(− 9.15)	(3.05)		(2.10)	(− 6.30)	(3.59)	
GS	10–5	10.64***	− 0.08***	1.03***	1.72	4.29	− 0.14***	0.11***	1.68
		(5.66)	(− 9.61)	(2.71)		(1.38)	(− 5.90)	(3.10)	
BE/ME	10–5	− 5.63***	− 0.04***	0.34	0.47	− 12.97***	− 0.09***	0.10***	0.78
		(− 3.13)	(− 3.76)	(0.64)		(− 4.90)	(− 3.75)	(3.18)	
EF/A	1–5	− 0.51	− 0.03***	0.36	0.55	− 5.90***	− 0.07***	0.07***	0.80
		(− 0.40)	(− 4.85)	(1.35)		(− 3.21)	(− 5.29)	(3.95)	
GS	1–5	2.93*	− 0.05***	0.88***	1.20	− 6.02***	− 0.12***	0.13***	1.50
		(1.77)	(− 5.59)	(2.86)		(− 2.87)	(− 7.39)	(6.38)	

Note: This table reports the results of market timing regressions of the TAP of the sixteen long-short portfolios. Panel A shows the results of Treynor and Mazuy (1966) quadratic regressions, and Panel B shows the results of Henriksson and Merton (1981) regressions. The alphas are annualized and in percentage. R^2 statistics are in percentage. ***, ** and * indicates the t-test significance at 1%, 5% and 10% level, respectively. The Newey and West robust t-statistics are in parentheses. The sample period is from 1964/01/01 to 2019/12/31.

The online appendix also shows that the profitability of our TA time strategy is robust when using a performance-weighted TA sentiment index, constructing TA sentiment with the technical trading signals that are generated from the Dow Jones Industrial Average Index, and applying the TA timing strategy on the value-weighted returns of the original portfolios. We also investigate the sensitivity of our results to the choice of the length of the moving average window used to generate our trading signal. We consider a buying signal if TA is higher than the past average of 1, 5, 10, 30, 60, 120 and 250 days. We find substantial trading profits remain stable in all cases, and the break-even transaction costs increase with the length of the moving average window.†

† We have also repeated the analysis using monthly data. We find that the aggregated monthly TA sentiment generally has a weaker relationship with the next-month return, suggesting that TA indicator predicts different patterns of returns across the short- and long-term. Consistent with prior literature on investor sentiment as a contrarian predictor of cross-sectional return, we also find that our TA sentiment indicator is negatively related to the next three-month returns. We also calculate the performance of a trading strategy based on monthly TA sentiment. We find that the benefit of using TA sentiment on monthly frequency disappears, showing that the sentiment-driven momentum fades away in less than 10 days. The details of these results are available upon request.

Since our TA sentiment is constructed by applying TA to the market index, the TA timing strategy is essentially a market timing strategy that selects stocks based on their exposure to investor sentiment. To examine the ability of our TA sentiment index to time the market, we employ Treynor and Mazuy (1966) quadratic regressions in equation (4) and Henriksson and Merton (1981) regressions in equation (5).

$$TAP_t = \alpha + \beta_m RMRF_t + \beta_{m^2} RMRF_t^{\,2} + \varepsilon_t, \tag{4}$$

$$TAP_t = \alpha + \beta_m RMRF_t + \gamma_m RMRF_t D_{rmrf} + \varepsilon_t, \tag{5}$$

where $D_{rmrf} = 1$ when the market return premium is above 0 and $D_{rmrf} = 0$ otherwise and the remaining variables are as defined above. The significantly positive β_{m^2} in equation (4) or γ_m in equation (5) indicates successful market timing ability and the regression alphas represent the abnormal returns after controlling for the market timing ability of TA sentiment.

Table 7 shows that β_{m^2} (Panel A) and γ_m (Panel B) are significantly positive for most of TAPs, suggesting that our timing strategy generally helps time the market. Most of the alphas in both market timing tests have been remarkably reduced and significantly positive alphas are observed in the regressions of portfolios sorted on EF/A and GS. However, it is important to emphasize that our trading strategy exploits the cross-sectional profitability after timing the market and it is perhaps for this reason we observe a very small R-squared in the market timing regressions above.

To further understand the potential sources of the profitability of our trading strategies, we also explore the decile portfolios for each strategy. We expect our timing strategy to generate high profits when it is applied to sentiment-prone stocks. Consistent with our conjecture, we find that the sentiment-prone decile portfolios have higher *TAP* (both average returns and risk-adjusted returns) than the sentiment-resistant decile portfolios (details are not reported to save space). We also compare our timing strategies with the momentum strategy. Both the momentum strategy and our trading strategies are trend-following strategies. The momentum strategy has an annualized return of 7.51%, which is substantially lower than the returns generated by our TA timing strategies. In the regressions of TA trading profits from decile portfolios, the coefficients on the momentum factor are all negative, implying that our timing strategies and momentum capture different aspects of the market. Our abnormal returns of sentiment-prone decile portfolios are still significantly large after controlling for the momentum factor.

5. Conclusions

This paper argues, as many practitioners do, that technical analysis has its merits through its role as a barometer of investor sentiment. We apply a spectrum of technical trading rules to a market index (such as the S&P 500) to build a novel market sentiment indicator termed TA sentiment. We show that this new TA sentiment indicator correlates strongly with other commonly used sentiment indicators. We also test the cross-sectional pricing effect of our TA sentiment. Baker and Wurgler (2006) argue that stocks differ in their exposure to market-wide sentiment and hence sentiment affects the cross-section of stock returns. Furthermore, when rational arbitrageurs have a synchronization problem (Abreu and Brunnermeier 2002, 2003) in the presence of sentiment, they delay arbitrage and ride mispricing until a coordinated arbitrage is triggered. Therefore, due to delayed arbitrage, we expect sentiment-prone stocks to generate higher short-term returns than their sentiment-resistant counterparts. We also expect these returns to reverse over the longer term when sentiment decays and a coordinated attack occurs. Consistent with these predictions, we find that an increase in this TA sentiment indicator is accompanied by high near-term returns and low subsequent returns in the cross-section. Finally, we test whether it is profitable to delay arbitrage by devising a trading strategy that captures the momentum effect of TA sentiment. We demonstrate that riding the TA sentiment can result in substantial profits and TA sentiment has significant market timing power. Unlike prior literature, which tests the profitability of technical analysis with single stocks or the overall market, we show that applying technical analysis to a market index, while trading in the cross-section, generates substantial profits.

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