Volatility Timing, Sentiment, and the Short-term Profitability of VIX-based Cross-sectional Trading Strategies[1]

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Abstract

This paper explores the profitability of simple short-term cross-sectional trading strategies based on the implied volatility index (VIX), often referred to as an "investor fear gauge" in the stock market. These strategies involve holding sentiment-prone stocks when VIX is low and sentiment-insensitive stocks when VIX is high and generate significantly higher excess returns than the benchmark long-short portfolios that do not condition on VIX. We show that the profitability of our trading strategies is not subsumed by the well-known risk factors or transaction cost adjustments. Our findings are consistent with the theory of delayed arbitrage and the synchronization problem of Abreu and Brunnermeier (2002).

Keywords: Implied Volatility; Trading Strategies; Cross-sectional Return; Investor Sentiment; Delayed Arbitrage

JEL Classification: G02, G11, G12

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1. Introduction

The Chicago Board Options Exchange's implied volatility index (VIX) is a measure of market expectation of stock return volatility implied from the supply and demand of S&P index options over the next 30 calendar days. Financial practitioners commonly use VIX-based trading strategies for hedging, speculative, and market timing purposes (see, e.g., Nagel, 2012). VIX is also commonly perceived as an "investor fear gauge" (e.g., Kaplanski and Levy, 2010; Whaley, 2000, 2009; Da, Engelberg and Gao, 2015), with low VIX indicating high overall market sentiment, and vice versa. Consistent with this view, VIX was substantially high in the NBER recessions and considerably low during the anecdotal bubble periods in the US market.

Several studies view VIX as a measure of expected volatility in a mean-variance framework, where investors are assumed to have a constant risk aversion (e.g., Merton, 1980; Fleming, Kirby and Ostdiek, 2003; Clements and Silvernnoinen, 2013). They argue that because of the positive mean-variance relationship, any increase in VIX should be associated with higher future returns. Others regard VIX as an "investor fear gauge", which can predict future returns. For example, Bekaert and Hoerova (2014) document that VIX is negatively correlated with contemporaneous returns and positively correlated with long-term future returns (e.g., 30-day/ 60-day/ monthly return). Similarly, Giot (2005) shows that high/low VIX period positively predicts future 60-day returns on S&P 100. Banerjee, Doran and Peterson (2007) also find that VIX is positively related to the next 30-day future returns in the cross-section of the stock market. This strand of studies almost exclusively uses low frequency return data to test VIX's ability to predict the long-run reversals arising from the correction of mispricing.

We depart from this literature by investigating the profitability of VIX-based strategies arising from the short-run (next-day) momentum in the cross-section of stock returns. Specifically, we test whether VIX can be used as a sentiment indicator to design trading strategies that can exploit the short-term return momentum. Our study is motivated by Abreu and Brunnermeier's (2002) theory of delayed arbitrage. In this theory, rational arbitrageurs are assumed to correct mispricing only when a significant mass of arbitrageurs come together to trade against noise trader sentiment. However, since arbitrageurs may not know when their peers recognize mispricing, they may choose to ride the sentiment until a synchronized attack takes place. The delayed arbitrage leads to short-term momentum in stock returns following sentiment increase. Our empirical tests show that the significantly negative relationship between lagged VIX and return is stronger during high sentiment periods and among sentiment-prone stocks. Therefore, carefully designed trading strategies that use VIX as a sentiment proxy has the potential to exploit the short-term return momentum caused by the delayed arbitrage.

The choice of VIX as the sentiment indicator in our trading strategies is justified on two grounds. First, VIX is obtained primarily from the trading activity of sophisticated investors on S&P options. Its ability to reflect the sophisticated investors' estimation of the overall market sentiment makes VIX an ideal candidate to test the delayed arbitrate theory. Second, VIX is one of the most widely accepted daily sentiment indicators, allowing us to test the profitability of the sentiment-based trading strategies over short time intervals.

In this study, we design trading strategies that involve holding sentiment-prone stocks when VIX is low and holding sentiment-insensitive stocks when VIX is substantially high; where substantially high (low) VIX is defined as VIX increases of 10% or more (less than 10%) relative to its moving average over the prior 25days.[3] Following Baker and Wurgler (2006), we use firm characteristics, such as size, firm age, return volatility, earning-to-book ratio, dividend-to-book ratio, fixed asset ratio, research and development ratio, book-to-market ratio, external finance over asset, and sales growth ratio, to determine the extent to which a stock is exposed to shifts in investor sentiment. Baker and Wurgler (2006) argue that firms are more prone to sentiment when they are small, young, volatile, non-profitable, non-dividend-paying, distressed, and have great growth opportunity. In this study, we conjecture that when investor sentiment is high (VIX is low), the contemporaneous returns of sentiment-prone stocks are also likely to be high due to limits to arbitrage. If the theory of delayed arbitrage holds, the prices of the already overpriced sentiment-prone stocks will increase further in the short term. Thus, longing sentiment-prone stocks when sentiment is high reflects our attempt to exploit the short-term cross-sectional momentum profits associated with these stocks.

We find that our VIX-based trading strategies generate large excess returns over the unconditional long-short portfolio trading strategy, which longs sentiment-prone portfolios and shorts sentiment-insensitive portfolios irrespective of VIX. Specifically, we find that the annualized return of our VIX trading strategy ranges from 20.97% to 40.04%, while that of the corresponding benchmark long-short portfolios ranges from -1.85% to 21.21%. We also show that the annualized excess returns of the VIX-based trading strategies over their corresponding benchmark portfolios range from 10.70% to 22.85%. The most profitable trading strategy involves switching investments between the smallest and the largest stocks deciles, while the least profitable trading strategy is the one that switches investments between the bottom and the middle book-to-market portfolios. Further analysis indicates that the Sharpe ratios increase significantly after applying VIX-based trading strategies. Switching investments between stocks with different market capitalization has the highest Sharpe ratio of 2.57, while switching investments between the bottom and the middle book-to-market portfolios has the lowest Sharpe ratio of 1.10. Furthermore, we regress the excess returns of our trading strategies and those of the benchmark portfolios on the well-known risk factors. We find that the risk-adjusted excess returns (alphas) are slightly smaller than their unadjusted excess returns counterparts, but remain positive and statistically significant, implying that the common risk factors cannot fully explain the abnormal profitability of our trading strategies. Additional analysis reveals that our trading strategy remains profitable after

[3] We also used 0%, 5%, 15% and 20% as the threshold and the profitability of our trading strategies remain strong and significant.

considering the effects of macroeconomic factors, such as term spread, default spread, TED spread and the liquidity factor. Finally, the break-even transaction costs associated with our strategies are generally higher than 50 basis points and our bootstrap tests suggest that a transaction cost of 25 basis points does not eliminate the profitability of our trading strategies.[4]

This study contributes to the literature by providing a behavioral explanation to the profitability of the volatility timing strategies in the cross-section of stock returns. Prior studies use VIX as a proxy for expected volatility, market volatility, liquidity measure, or macroeconomic expectation. Most of these studies explain the long-term positive VIX-return relation, but hardly discuss the potentially negative association between VIX and the next-day return. Unlike prior literature, we regard VIX as a market-wide sentiment indicator and design trading strategies to exploit its cross-sectional effect on stock returns in the spirit of Baker and Wurgler (2006). This cross-sectional effect combined with the delayed arbitrage theory of Abreu and Brunnermeier (2002) provides the rationale behind the success of our VIX timing strategies.

The closest study to ours is that of Copeland and Copeland (1999), who also design trading strategies that switch investments between stock portfolios based on changes in VIX. Our paper is distinct from Copeland and Copeland (1999) in two important ways. First, our explanation of the profitability of the VIX-timing strategy is based on VIX as a sentiment barometer, guided by the theoretical work on the effect of sentiment on stock returns and delayed arbitrage (Abreu and Brunnermier, 2002; Delong, Shleifer, Summers and Waldmann, 1990). In contrast, Copeland and Copeland (1999) view VIX as a proxy for future discount rate, i.e., higher VIX means higher future discount rates and falling prices, an argument that is not consistent with the widely documented return reversal effect of VIX. Thus, our use of investor sentiment channel helps to reconcile the conflicting momentum and reversal effects associated with VIX-based trading strategies. Second, our study applies VIX-based strategies on a wider spectrum of cross-sectional stock returns and shows that the VIX-based trading strategies are profitable while that of Copeland and Copeland (1999) considers only size and value portfolios. Our evidence that VIX-based strategies can generate significant cross-sectional abnormal returns also has a practical implication for the financial industry.

The rest of our paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 reports the profitability of our VIX-based trading strategy. Section 5 concludes.

[4] Existing studies usually set transaction costs at lower than 50 basis points. For example, Lynch and Balduzzi (2000) set the transaction cost at 25 basis points to calculate the profit. Frazzini, Isreal and Moskowitz (2012) measure the real-world trading costs for asset pricing anomalies such as size and value trading strategies, the trading costs they calculated are no higher than 25 basis points.

2. Related Literature

Two streams of finance literature examine the predictive power of investor sentiment on stock returns and document contradictory results at different frequencies. The first stream of research predicts a negative association between investor sentiment and future returns, as bullish (bearish) investor sentiment causes current prices to rise above (fall below) their intrinsic values and the correction of mispricing will result in lower (higher) future returns when sentiment wanes and fundamentals are revealed (Neal and Wheatley, 1998; Lemmon and Portniaguina, 2006; Lee, Shleifer and Thaler, 1991; Baker and Wurgler, 2006, 2007). To test this prediction, researchers commonly use monthly-frequency investor sentiment measures, such as mutual fund flow, consumer confidence index, closed-end fund discount, Baker Wurgler index, to predict stock returns.

The second stream of studies suggests that a rise in current sentiment is accompanied with high contemporaneous returns and positive short-term future returns. Such a momentum effect observed in the high frequency data (see, e.g., Han and Li, 2017; Chou, Hsieh, and Shen, 2016), does not conflict with the well-documented long-term reversal effect of investor sentiment. Instead, the short-term momentum effect drives the price further away from the fundamental, leading to prolonged mispricing and amplified long-term reversal effect (Yu, 2011).

One impediment for sophisticated investors to correct mispricing is the synchronization problem. Abreu and Brunnermeier (2002) postulate that in the absence of coordination, arbitrageurs may choose to beat the gun and ride the curve, leading to an amplified mispricing in the short run. Consistent with this argument, ample evidence indicates that sophisticated arbitrageurs actively ride the bubble, causing prices to deviate too far from their fundamentals (Brunnermeier and Nagel, 2004; Griffin, Harris and Shu, 2011; Xiong and Yu, 2011; Berger and Turtle, 2015; DeVault, Sias and Starks, 2019). Our study proposes an alternative approach to test the theory of delayed arbitrage, which suggests that investor sentiment generates a short-term momentum. Specifically, using VIX as a proxy for sentiment, we examine whether sentiment-prone stocks exhibit stronger short-term momentum effect, as these stocks are more attractive to speculators and more difficult to arbitrage during the bubble period. Existing literature also frequently considers VIX as a measure for expected future volatility or liquidity in the VIX-return relationship analysis. For example, Banerjee et al. (2007) propose a theory in which the positive association VIX and stock return is attributed to the possibility that VIX proxies for market volatility. Consistent with this view, Jackwerth and Rubinstein (1996), Coval and Shumway (2001), and Bakshi and Kapadia (2003) show market volatility has a negative price and high levels of volatility will translate into high price risk premiums when investors are averse to volatility risk. Thus, high VIX indicates high market volatility, which, in turn, leads to low current prices and high future returns. VIX has also been regarded as a proxy for liquidity. For example, Nagel (2012) shows that VIX strongly predicts the returns from liquidity evaporation, with high VIX implying low funding liquidity and therefore higher future returns. Nevertheless, the use of VIX as volatility or liquidity proxies cannot explain the short-run negative VIX-return relation, i.e., the return momentum.

This paper expands the literature on VIX from a behavioral finance perspective. Mispricing arises from arbitrageurs' limits to arbitrage combined with investors' biased belief. VIX not only indicates the limit to arbitrage level, but also dubs investor sentiment. Most prior studies that consider VIX as a proxy for sentiment show that VIX can positively predict monthly, quarterly, or longer-term future returns (e.g., Fleming et al., 2003; Clements and Silvernnoinen, 2013; Rubbaniy, Asmerom and Rizvi, 2014). This paper emphasizes the value of VIX as a daily sentiment that predicts short-term return momentum. If limits to arbitrage are assumed to be constant, VIX is expected to be negatively related to contemporaneous mispricing and amplified momentum return when arbitrage is delayed. Lubnau and Todorova (2015) find significant positive 20-, 40-, and 60-day stock returns following low VIX and interpret their results as evidence of market inefficiency. Guo and Qiu (2014) also find stronger evidence of negative relation between VIX and future returns for more difficult to short stocks. Tu, Hsieh and Wu (2016) explain the predictive power of VIX on mispricing through the limit to arbitrage channel. They argue that high VIX reflects increases in expected volatility and therefore stronger limits to arbitrage, which amplifies mispricing. Unlike Tu et al. (2016), we examine the over/under pricing caused by VIX. The use of VIX as a sentiment measure at the daily frequency not only explains the long-term return reversals documented in the prior literature, but also enables us to examine the potential short-term return momentum that is missing in the studies of lower frequency data. We contribute to the literature by providing evidence and explanation of a negative relationship between the current VIX level and the next day stock returns in the cross-section.

Existing literature shows that while sentiment-driven market return reversal is weak, the cross-section of return reversal is largely driven by investor sentiment. Baker and Wurgler (2007) argue that sentiment prone stocks attract more speculative demand and are more difficult to arbitrage. Certain stocks, such as young and small stocks, are more prone to sentiment than others. Hence, sentiment plays a more prominent role in predicting the return disparity between sentiment-prone stocks and sentiment-insensitive stocks than predicting the aggregate market return. Similarly, Stambaugh, Yu, and Yuan (2012) maintain that stocks with more arbitrage constraints are more sensitive to investor sentiment. When considering that momentum arises from delayed arbitrage, Ljungqvist and Qian (2016) report that sophisticated investors deliberately target stocks with severe short-sell constraints, limiting the scope of coordinated short-selling actions. Campbell, Hilscher and Szilagyi (2011) also find that distressed stocks underperform more severely when VIX increases. Therefore, this paper focuses on the profitability of riding the VIX-driven momentum in the cross-sectional stock returns.

Our study relates to the literature on the stock return predictability of option-based measures, such as implied volatility spread and implied skewness. Prior studies measure implied volatility spread as either the difference between implied volatility and realised volatility (IRVS) or the difference between implied volatilities of the call and put options (CPVS). They show that CPVS predicts market-level stock returns (e.g., Atilgan, Bali and Demirtas, 2015; Han and Li, 2020), whereas the absolute value of CPVS does not (Rösch, Subrahmanyam and Van Dijk, 2017). They also document a positive association between IRVS/CPVS and cross-sectional stock returns (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010). Bali and Hovakimian (2009) argue that the IRVS reflects volatility risk, while CPVS reflects jump risk. However, Han and Li (2020) attribute the positive relationship between CPVS and future returns to the common demand from bullish informed traders in the stock market, who exerts an upward (a downward) pressure on the prices of stocks with higher (lower) implied volatility call (put) options. While we also use the information extracted from option prices to predict stock returns, our implied volatility measure is estimated at the aggregate market level. Unlike others, we also verify the extent to which our aggregate VIX reflects market sentiment and predicts cross-sectional stock returns.

Our paper is also related to the literature on volatility timing strategies of VIX. These studies are mostly based on the mean-variance theory (e.g., DeMiguel et al., 2013; Ferson and Mo, 2016), often calculating the optimal portfolio weight using the Intertemporal Capital Asset Pricing Model (ICAPM) and the volatility from the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family models (Fleming, Kirby and Ostdiek, 2001; Johannes, Polson and Stroud, 2002; Fleming et al., 2003; Clements and Silvernnoinen, 2013). Departing from these paradigms, we use VIX as a sentiment indicator and test the profitability of the VIX-induced momentum strategies in the cross-section of stock returns. Our paper is, therefore, more related to a strand of research on the profitability of trading strategies arising from the return momentum induced by the news-based sentiment (Uhl, 2017; Huynh and Smith, 2017; Sun, Najand and Shen, 2016). The closest work to ours is Copeland and Copeland (1999), who propose a profitable trading strategy from switching investments across stocks based on VIX. However, while their trading strategy is based on the premise that VIX represents a future discount rate that influences price in the discount cash flow model, an argument that is not supported by the widely documented reversal effect of VIX on stock return, we view VIX as a sentiment indicator and use the theory of delayed arbitrage (Abreu and Brunnermeier, 2002) to reconcile conflicting momentum and reversal effects associated with VIX in the cross-section of stock returns. Furthermore, unlike Copland and Copland (1999), who base their VIX-timing strategies on size and value portfolios, our VIX-timing strategies consider a wider spectrum of cross-sectional stocks with different exposures to investor sentiment.

Finally, the present study is linked to the growing research on the low volatility anomaly. Both classical and behavioral finance theories predict a positive association between volatility and returns, albeit for different reasons. Classical finance theorists posit that, due to risk aversion, investors require high expected returns as a compensation for holding highly volatile stocks (e.g., Merton, 1980), while some behaviourists attribute the positive return-volatility relationship to loss aversion (Barberis and Huang, 2001; Li and Yang, 2013). Contrary to this prediction, numerous studies document that stocks with recent high past volatility have low subsequent returns (e.g., Ang, Hodrick, Xing and Zhang, 2006, 2009). A number of explanations have been proposed for this anomaly. These include investor sentiment and short sale constrain (Yu and Yuan, 2011), reference dependent preference (Wang, Yan and Yu, 2017), limits to arbitrage such as institutional investors' benchmarking (Baker, Bradley and Wurgler, 2011), lottery preference (Mitton and Vorkink, 2007), coskewness risk (Schneider, Wagner and Zechner, 2020), other behavioral biases, such as representativeness and overconfidence (Baker et al., 2011). While the present paper also investigates the link between volatility and subsequent returns, it extends existing work by (i) investigating the return predictive power of the market expectation of the aggregate market return volatility implied from the supply and demand of S&P index options; (ii) testing the ability of VIX, as an indicator of overall market sentiment, to predict the next day cross-sectional stock returns; and (iii) designing a VIX-based cross-sectional trading strategy and test the extent to which such a strategy can generate significant profits.

3. Research Design and Data Sources

We construct decile portfolios based on firm characteristics that are related to exposure to irrational investors' speculative demand and arbitrage constraints. Baker and Wurgler (2006) argue that sentiment-prone firms tend to be small, young, volatile, non-dividend-paying, non-profitable, informationally opaque, financially distressed, and have strong growth opportunity. Therefore, to gauge the extent to which portfolios of stocks are more prone to investor sentiment, we build decile portfolios based on firm size (ME), age (Age), return volatility (Sigma), earning ratio (E/BE), dividend ratio (D/BE), tangible and intangible asset ratio (PPE/A and RD/A), book-to-market ratio (BE/ME), external finance ratio (EF/A), and sales growth (GS).[5]

Stocks that are prone to speculative demand are also difficult to arbitrage (Baker and Wurgler, 2006). Take Age as an example. The lack of an earnings history combined with the presence of apparently unlimited growth opportunities for young firms makes young firms difficult to value. Unsophisticated investors may therefore generate a wide spectrum of valuations for these firms depending on their sentiment. Disagreement among unsophisticated investors increases the volatility of returns, which, in turn, deters rational investors from exploiting mispricing.

Following Baker and Wurgler (2006), we construct 16 long-short portfolios. Each of these long-short portfolios longs the most sentiment-prone decile portfolio and shorts the most sentiment-insensitive decile portfolio. We consider the bottom (top) deciles of ME, Age, E/BE, D/BE, and PPE/A as the most

[5] Details on these proxies are provided in the Appendix Table A.1.

sentiment-prone (sentiment-insensitive) and the top (bottom) deciles of Sigma and RD/A as the most sentiment-prone (sentiment-insensitive). The other three firm characteristics included in our analysis, namely BE/ME, EF/A, and GS, have a multi-dimensional nature, as they reflect both growth and distress. Take BE/ME as an example. High book-to-market ratio indicates distress, while a low value of the same ratio implies high growth potential. Stocks with either of these extreme BE/ME ratios are more difficult for investors to price accurately. Stocks with financial distress are highly appealing to speculative demand, so firms with high BE/ME, low EF/A, and low GS are considered as sentiment-prone. Firms with strong growth potential are also hard for investors to value. Thus, firms with low BE/ME, high EF/A, and high GS are more prone to investor sentiment and the middle deciles are the most sentiment-insensitive. For these reasons, we define the long-short portfolios for these three characteristics as the top decile minus the middle decile or the bottom decile minus the middle decile.

Firm-level accounting data is retrieved from Compustat and monthly stock returns are downloaded from CRSP. Our sample includes all common stocks (share codes 10 and 11) between January1988 and December 2018 in NYSE, AMEX, and NASDAQ (stock exchange codes 1, 2, and 3). The breakpoints for deciles are defined only using NYSE firms. We match the year-end accounting data of year t-1 to monthly returns from July t to June t+1. We obtain VIX data over the period from 1990/01/01 to 2018/12/31from WRDS. We also obtain the historical data on the implied volatility conveyed from S&P100 index, NASDAQ index, and DJIA index; those implied volatility indexes are noted as VXO, VXN, VXD, respectively. Several risk factors are downloaded from Kenneth French website,[6] including the momentum factor (MOM), defined as the average return of the high prior return portfolio over the low prior return portfolio, and the Fama-French five factors, i.e., the excess return on the market (RMRF), the average return on the three small portfolios minus the average return on the three big portfolios (SMB), the average return on the two value portfolios minus the average return on the two growth portfolios (HML), the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (RMW), and the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (CMA).

4. Empirical Results

While our main aim is to examine the profitability of VIX-based cross-sectional trading strategies, we start with testing the in-sample predictive power of VIX for the next-day cross-sectional returns using two-way sorts and predictive regressions. However, since a strong in-sample predictive power of a factor on return does not necessarily result in a strong profitability of trading on this factor, we also test

[6] The data are available on http://mba. Tuck. Dartmouth. Edu/pages/faculty/ken. French/data_library. Html.

the performance of the simple VIX-based trading strategies using both raw and risk-adjusted returns and compare with those of the benchmark portfolios.

4.1. Two-Way Sorts

We divide our sample into high and low VIX periods based on the trading signal implied by the historical and current levels of VIX. To obtain an initial insight into the ability of VIX to predict returns, we conduct two–way sorts of returns. First, we sort stock returns into deciles based on a firm characteristic that is associated with the extent to which the stock is prone to market-wide investor sentiment. Then, we further sort the returns in each decile into two groups. The first group consists of the returns following high or normal sentiment days, while the second one includes the returns following low sentiment days. A day t is classified as a low sentiment day, if VIX at time $t-1$ is at least 10% higher than the average VIX between $t-26$ and $t-2$, and a high or a normal sentiment day otherwise. Figure 1 shows the two-way sorts of returns for the period from Jan 1990 to Dec 2018. The solid bars are the annualized equal-weighted average returns following low VIX (high sentiment) days; and the clear bars are average returns following high VIX (low sentiment) days.

[Insert Figure 1]

Generally, the results in Figure 1 suggest that low VIX predicts higher next-day returns for sentiment-prone stock deciles and high VIX predicts higher next-day returns for sentiment-insensitive stocks. This indicates that when sentiment is high, stocks in the sentiment-prone deciles, such as those of young firms, are likely to have larger persistent overpricing due to delayed arbitrage. Similarly, when sentiment is low, young firms tend to be more undervalued by irrational investors, as it takes time for arbitrageurs to take synchronized actions in order to eliminate the underpricing.

Figure 1 also shows that the return difference between the solid bar and the clear baris lower for high ME, high Age, low Sigma, high earnings E/BE, and high dividend-paying D/BE decile portfolios, in line with the conjecture that these portfolios are less sensitive to sentiment. However, we do not find any conclusive pattern in the return difference between the high sentiment period and the low sentiment period in the cross-section of the tangible asset PPE/A and research and development RD/A deciles, implying that the sensitivity of stock returns to investor sentiment is not well reflected in PPE/A and RD/A. This evidence is consistent with the findings of Baker and Wurgler (2006) and Chung, Hung and Yeh (2012).

Furthermore, Figure 1 shows that sentiment-insensitive stocks outperform sentiment-prone stocks after high VIX. For example, we find that the returns of ME decile increase almost monotonically following high VIX. We also observe a general pattern of negative average return following the high VIX period across all the sentiment-prone deciles, except for PPE/A and RD/A, indicating that high VIX predicts future returns for sentiment-prone stocks. In other words, sentiment-prone stocks tend to have negative returns following periods of low sentiment.

Finally, a closer look at the graphs of the returns pertaining BE/ME, EF/A, and GS reveals that the clear bars have an inverted U-shape pattern and that the lowest differences between the solid bars and the clear bars are observed in the cases of middle BE/ME, middle EF/A, and middle GS deciles. This finding indicates that firms in the middle deciles are less sensitive to sentiment changes than those in the bottom and top deciles of BE/ME, EF/A, and GS, consistent with the multi-dimensional nature of these three characteristics.

4.2. Predictive Regressions

To test whether VIX predicts the next-day stock returns in the cross-section, we regress the portfolio returns on the one-day lagged VIX and other contemporaneous risk factors. The regression is specified as follows:

$$R_{X,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \varepsilon_t, \quad (1)$$

where$R_{X,t}$ is the portfolio X returns at time t, and the portfolio X can be one of the following: 1) a long-short portfolio that longs sentiment-pronestocks and shorts sentiment-insensitive decile portfolio (P-I); 2) a sentiment-prone decile portfolio (P); 3) a sentiment-insensitive decile portfolio (I). $VIX_{t-1}$is the standardized VIX level at time t-1, and $\mathrm{CV_t}$ is a vector of control variables, including the Fama-French (2015) five factors and the Carhart (1997) momentum factor (MOM). A control factor is excluded from the regression when it is constructed from the same firm characteristic as the dependent variable. For example, SMB factor is excluded when dependent variable is the daily return of long-short portfolio ME(1-10), and HML factor is excluded when dependent variable is the daily return of the long-short portfolio constructed from BE/ME.

Table 1 reports the coefficients on the lagged VIX in the regressions with different data samples and portfolio returns as dependent variable and the Newey-West standard errors (Newey and West, 1987) that are robust to heteroscedasticity and serial correlation.[7] Panel A reports the regression results for the entire sample period, while Panels B and C present the results for the high sentiment period (i.e., standardized lagged VIX is lower than -0.5) and low sentiment period (i.e., standardized lagged VIX is larger than 0.5), respectively. We divide the samples into high and low sentiment periods to test whether the ability of VIX to predict returns depends on investor sentiment. As previous studies show that the

[7] We set a maximum lag of 15 when calculating Newey-West robust standard errors for the coefficients.

predictability of VIX is strong when VIX is at extreme (either substantially high or substantially low), we set the threshold as 0.5.[8]

[Insert Table 1]

The coefficients on the one-day lagged VIX in the Column (1) of Panel A in Table 1 are negative and statistically significant (at the 10% or better) in 5 out of 16 long-short portfolios. This finding is consistent with the the delayed arbitrage theory, which predicts high returns following a rise in sentiment, i.e., a negative relationship between the return differential between sentiment-prone and sentiment-insensitive stocks and the one-day lagged VIX. Columns (2) and (3) of Panel A present the results of regressing the returns on the sentiment-prone decile and the sentiment-insensitive decile on the lagged VIX, respectively. The results suggest that the lagged VIX has a stronger predictive power on the sentiment-prone stocks than the sentiment-insensitive stocks, consistent with our expectation. In Column (3), apart from the top ME decile portfolio regression, none of the 16 regressions exhibits a significant relationship between the lagged VIX and future returns. For the top ME decile return regression, the coefficient of VIX is even significantly positive. One plausible explanation for this positive coefficient is the "flight-to-quality" (see also Baker and Wurgler, 2007), i.e., investors seek safer portfolios in low sentiment periods.

Panel B of Table 1 reports the regression results for the high sentiment sub-sample. We find that both the magnitude and the significance of the coefficients on the lagged VIX increase during the high sentiment periods. VIX is a significantly negative predictor of the one-day ahead return for 5 out of the 16 long-short portfolios. Similarly, we find that when sentiment is high, the ability of VIX to predict the returns of the sentiment-prone deciles also increases, with 8 out of the 16 regression coefficients of lagged VIX are significantly negative in Column (2). Column (3) of Panel B shows that when sentiment is high, even the returns of two sentiment-insensitive deciles exhibit significantly negative association with the lagged VIX.

Panel C of Table 1 shows that when sentiment is low, VIX has no predictability of the next-day return for both the sentiment-prone deciles and the sentiment-insensitive deciles, while the lagged VIX still predicts the returns of only 5 out of the 16 long-short portfolios. The reduced predictability of VIX in low sentiment period is consistent with Stambaugh, Yu and Yuan (2012), who argue that investor

[8] We choose 0.5 as the threshold to define extreme high/low VIX sub-samples because it results in a large sample size in both sub-samples. This choice is likely to make our results more conservative. We also consider 1 as threshold and we find stronger regression results. As a consequence, our trading strategy holds sentiment-insensitive stocks following a substantial rise in VIX.

sentiment is more likely to have a greater influence on stock prices during periods of high sentiment, as short sale constraints are generally more binding during these periods.[9]

4.3. VIX-Based Trading Strategies

The rule of our trading strategies is to hold sentiment-insensitive stocks when VIX increases by at least 10% more than the average of its prior 25-day historical level and to hold sentiment-prone stocks otherwise.[10] These VIX-based timing strategies aim at capturing the momentum effect of sentiment on the cross-section of stock returns. We use the relative returns of the sentiment-prone decile over the sentiment-insensitive decile (P-I) as the benchmark portfolio returns. The excess return of our trading strategies over benchmark portfolio is denoted as RVIX.

Table 2 summarizes the buy-and-hold long-short portfolio returns (i.e., the return of the benchmark portfolio), the returns of VIX-based trading strategy, the excess returns of our trading strategy over benchmark long-short portfolio (RVIX), and the success rate of our trading strategy, defined as the percentage of trading days in which RVIX is zero or higher. That is, when our VIX timing strategy performs at least as good as the benchmark portfolio. Panels A and B in Table 2 report the average returns, the standard deviation, the skewness, and the Sharpe ratio of the 16 portfolio returns. The results suggest that our VIX-based trading strategies generate higher average returns and Sharpe ratios than the benchmark portfolios. The annualized returns of benchmark portfolios in Panel A range from -1.85% (PPE/A portfolio) to 25.89% (BEME High-and-Middle portfolio), while the annualized returns of VIX-based trading strategies in Panel B range from 20.97% (PPE/A portfolio) to 40.04% (ME portfolio). The returns of VIX based trading strategies in Panel B are all higher than those in Panel A, demonstrating a strong profitability of timing the cross-sectional stock market on VIX. Although the standard deviations in Panel B are slightly higher than those in Panel A, the Sharpe ratios of the VIX-based strategies are higher than those of the benchmark portfolios. In Panel B, the annualized returns of switching investments between the top and the bottom ME-sorted deciles and the BE/ME-sorted deciles are 40.04% and 38.75%, respectively. The significant profitability associated with switching investments between size and value portfolios is consistent with the findings of Copeland and Copeland (1999). Apart from the ME-sorted portfolio, the skewness statistics of the long-short portfolio returns

[9] Although our evidence of a negative VIX-return relation is inconsistent with the liquidity evaporation explanation, we include the difference in the bid-ask spread of the sentiment-prone decile and the sentiment-insensitive decile as an additional control variable in the regression. We find that while the bid-ask spread difference plays a significant role in the return disparity, the coefficients of one-day lagged VIX on return remains significantly negative after controlling for liquidity.

[10] Note that our trading strategy does not require short selling. In addition, we argue that one could also apply our VIX-based trading strategy on the ETF funds that traces the return of small-cap stocks and large-cap stocks, so that the transaction cost would be much lower. To be specific, the trading strategy would be to hold the small-cap ETF when VIX is low and to shift the asset allocation to large-cap ETF when VIX is substantially high.

in Panel A are higher than those of the VIX-based trading strategies in Panel B, suggesting that our trading strategies incur lower crash risk than the benchmark strategy.

Panel C in Table 2 shows that the average returns of the VIX-based strategies are significantly higher than those of benchmark portfolios. Even the least profitable portfolio generates a nontrivial excess return of 10.70% (BEME Low-and-Middle portfolio) after adopting the VIX-based trading strategy. The success rate of our VIX trading strategies ranges from 0.54 to 0.59, indicating that VIX-based trading strategies generate higher returns than their benchmark portfolios for over 50% of the trading days.

[Insert Table 2]

The summary statistics suggest that our VIX-based trading strategies outperform their benchmarks. However, it is not clear whether the excess returns of our VIX strategies (RVIX) represent compensation for risk. Thus, we adjust RVIX for risk using four different models. Table 3 reports the risk-adjusted RVIX (i.e., the alphas) and the adjusted R-squared associated with six different asset pricing models. Panel A presents the results from the CAPM model, Panel B reports the results of FF3 model, Panel C adjusts the returns with the FF five factors (SMB, HML, RMRF, CMA, RMW) plus the momentum factor (MOM), and Panel D accounts for the commonly-employed eight pricing factors from Kenneth French Data Library (namely RMRF, SMB, HML, CMA, RMW, MOM, ST_Rev, and LT_Rev). In Panel D, ST_Rev is monthly short-term reversal factor and LT_Rev is the monthly long-term reversal factor. Panel E reports the results from the four mispricing factors model of Stambaugh and Yuan (2016) (RMRF, MSMB, MGMT, PERF).[11] In Stambaugh and Yuan's (2016) mispricing model, MGMT is a composite factor constructed by combining the rankings of six anomaly variables that represent quantities that firms' management can affect directly, PERF is a composite factor based on five anomaly variables that relate to performance, but are less directly controlled by management, and MSMB is the return differential between the small-cap and large-cap leg sorted on the two composite mispricing measures used to construct MGMT and PERF. Panel F uses the Hou, Xue and Zhang (2015) q-factors from WRDS.[12]

[11] The Stambaugh and Yuan "Mispricing Factors" are available on Robert F. Stambaugh's personal website http://finance. Wharton. Upenn. Edu/~stambaug/.

[12] The pricing factors in the q-factor model are the market factor, a size factor, an investment factor, and a profitability (return on equity, ROE) factor.

[Insert Table 3]

The alphas in Table 3 are generally smaller than the excess returns RVIX in Table 2, suggesting that the superior performance of our VIX trading strategies is at least partly driven by risk. The significant coefficients of risk factors and high R-squared also indicate that returns of VIX-based trading strategy are associated with risk factors. However, all alphas in Table 3 are positive and highly significant (at the 1% level or better), implying that adjusting for risk mitigates but does not fully eliminate the profitability of our VIX strategies. The magnitude of abnormal alphas does not vary considerably across different asset pricing models but is slightly smaller when using the q-factor models.

Can the profitability of our VIX-based trading strategy be attributed to market timing? Following Han, Yang and Zhou (2013), we use two approaches to test whether the superior performance of our VIX strategies stems from their ability to detect periods of low market return premium. The first approach is the quadratic regression of Treynor and Mazuy (1966)

$$TAP_t = \alpha + \beta_m RMRF_t + \beta_{m^2} RMRF_t{}^2 + \varepsilon_t \quad (2)$$

A significantly positive coefficient β_{m^2} would indicate successful market timing ability and higher profitability during extreme market return periods. The second approach is the regression of Henriksson and Merton (1981)

$$TAP_t = \alpha + \beta_m RMRF_t + \gamma_m RMRF_t D_{rmrf} + \varepsilon_t, \quad (3)$$

where D_{rmrf} is a dummy variable with a value of unity when the market return premium is positive, and zero otherwise. A significantly positive coefficient γ_m would indicate that the profitability of our trading strategies is due to their ability to predict booming periods. The intercept in both Equations (2) and (3) represents the abnormal returns of our trading strategies after controlling for the market timing ability of VIX.

[Insert Table 4]

Table 4 reports the market timing regression results. Panel A reports the results of the quadratic regression (Equation (2)). The coefficients of squared market return premium, β_{m^2}, are not statistically significant, except for the case of ME sorted portfolio. The regression intercepts are mostly significantly positive, except for the ME sorted portfolio. Based on the methodology of TM regression, the market timing explanation works only well for the ME sorted portfolio but fails to explain the profitability of remaining portfolios.

Panel B reports the results of Equation (3). The coefficients γ_m are also mostly insignificant, while the intercepts are positive and significant. For some regressions such as the PPE/A and RD/A sorted portfolio regressions, the intercepts are even larger than the dependent variable, inconsistent with the market timing explanation. Significantly positive γ_m and significantly negative alphas are only observed in the case of the ME-sorted portfolios, indicating that the market timing explanation applies exclusively to these portfolios. Taken together, we conclude that market timing cannot fully explain the profitability of our VIX-based timing strategies.

4.4. Transaction Costs and Bootstrap Tests

In this section we address two potential concerns with the tests of profitability of our trading strategies. The first is the validity of using t-tests for the significance of profitability when its distribution may differ from the assumed distribution (e.g., leptokurtosis, autocorrelation). To address it, we conduct nonparametric moving block bootstrap simulations, which relies on simulated empirical distribution instead of assumed distribution generating function for statistical inference. It has been employed by other studies to assess trading strategy profitability (e.g., Menkhoff, Sarno, Schmeling and Schrimpf, 2012; Kuang, Schröder and Wang, 2014). The second concern is the impact of transaction costs. We alleviate it by i) calculating return after netting the transaction costs; and ii) computing the breakeven transaction costs.

We now describe our simulation procedures. Moving block bootstrap resamples blocks of observations from the original data with a fixed block length b. Due to the strong persistence in returns, we run test for all the sixteen long-short portfolios to get the number of lags in the autoregressive process AR(p) regressions. We find that most of the 16 long-short portfolio returns follow AR(4) process, and hence we choose b = 4 as our block size. We also consider other block sizes such as 1, 2 and 10 for robustness checks.[13] We randomly draw data in blocks from the original dataset with replacement to generate 1000 new series of data of VIX and portfolio returns. Each series has 8000 observations. We then apply the same trading rule based on simulated VIX to obtain trading signals for simulated portfolio returns. This allows us to compute the correspondent performance measures of the VIX timing strategy, including the strategy's return and Sharpe ratio, and the return of RVIX, for all the sixteen portfolio combinations. In the final step, we compare these performance measures from our original data to the empirical distribution of their counterparts from the simulations. The null hypothesis is that our trading strategy does not produce higher profit than the randomly generated shuffled series.

[13] Moving block bootstrap with a block size of 1 is similar to the bootstrap approach adopted by Levich and Thomas (1993).

[Insert Table 5]

To account for the effect of transaction costs, we first assume a one-way transaction cost of 25 basis points. Such a transaction cost has been imposed by some studies as a conservative cost (see, Lynch and Balduzzi, 2000). Others choose to calculate the realized transaction cost (Frazzini et al. 2012). For instance, Frazzini et al. (2012) find that the trading cost is 11.21 basis points for large-cap stocks and 21.27 basis points for small-cap stocks.

Table 5 reports the returns net of transaction costs and the bootstrap tests with1-day, 4-day and 10-day block length. We report the number of simulations that have superior performance over our original trading strategy in the column named N. Since the number of bootstrap simulations is 1000, N/1000 will indicate the p-value for the null hypothesis. N1, N4 and N10 denote the number of outperforming simulations when block size b equals to 1, 4 and 10, respectively. Panel A and B show that both the net-of-cost returns and the Sharpe ratio of our VIX timing strategies are all positive and statistically significant at the 1% level when b =1. When b =4, all VIX strategies are significantly at the 1% level, with only one exception (applied to PPE/A) that is significant at the 10% level. When b = 10, both performance measures are still significantly positive at the 10% level or below in eight out of the sixteen cases. In Panel C, RVIX return column compares our VIX timing strategies with their correspondent benchmark long-short portfolios. All the sixteen trading strategies outperform the benchmark long-short portfolios when b =1 or 4, except for PPE/A, whose profit is positive, but insignificant. When b =10, RVIX generates significantly positive returns (at the 10% level) in eight out of the sixteen cases.

These results provide additional support for the profitability of our trading strategy. The profitability of our strategies should be more pronounced when considering short-selling costs. This is because the benchmark long-short portfolios require short-selling while our trading strategies do not. As the short selling tends to be more expensive than shifting asset allocation, our strategies should outperform the benchmark even more after accounting for the short-selling costs. Table 5 also shows that the larger the block size we use, the more insignificant strategies we have. This is likely due to the fact that the shuffled series with large block size maintain more information about the investor sentiment, hence applying the VIX trading strategy to simulated series will generate higher returns.

[Insert Table 6]

As a further test of the effect of transaction costs, we examine how large transaction costs can be to just eliminate the profitability of our trading strategy. This amounts to calculating the break-even trading costs (BETC) that makes the average actual returns of our VIX-based trading strategy equal to zero (Han et al, 2013). The higher the BETC of a trading strategy, the more likely that this trading strategy is profitable after transaction costs. Table 6 reveals that all estimated BETCs are larger than 30 basis points. This demonstrates that the transaction costs must be unrealistically high to eliminate the profitability of our VIX-based trading strategy. In particular, the lowest BETC for the size portfolio is 62.46 basis points, which is significantly higher for the realized transaction cost of 21.27 basis points in Frazzini et al. (2012) and the assumed 25 basis points in Lynch and Balduzzi (2000).

We also find that the BETCs increase almost monotonically with the length of the horizon used to construct the VIX strategies in Table 6. This is because BETCs depend on both the profitability and the trading frequency. In other words, for any given profitability, lower trading frequency should be associated with higher BETCs. The high BETCs associated with the VIX-based strategies suggest that these strategies do not only generate high return, but also have low transaction frequency. For example, the number of transactions required for the 25-day window of the size portfolio trading strategy is 751 (out of a total 7134 trading days), which translates into an average holding period of more than 9 trading days.

4.5. Robustness Checks

We run a battery of additional tests to examine the robustness of our VIX-based cross-sectional trading strategies.

First, to understand whether macroeconomic factors and other risk factors explain the superior performance of our VIX-based trading strategy, we also adjust the excess returns for the daily difference between the yield on interbank loans and 3-month treasuries (TED spread) and the difference between the yield on 10-year and 3-month treasuries (term spread, or TS). We find economically large and statistically significant alphas when these factors are included in the regressions. We also calculate the bid-ask spread for all the 16 long-short portfolios, i.e., the average bid-ask spread of sentiment-prone portfolio minus that of low sentiment-prone portfolio, and include it as a control variable into the respective regression. We find that the effect of TA sentiment on returns is unaffected after controlling for cross-sectional variations in the bid-ask spread.

Second, we test the robustness of returns of each VIX-based trading strategy by changing the benchmark portfolio from its correspondent long-short portfolio to the market return premium. We find that our trading strategy outperforms the market. When examining the persistence of the performance of our VIX-based trading strategy, we find (untabulated) evidence that the annual average return of our trading strategy is consistently higher than the S&P 500 index return. We also investigate whether the profitability of our trading strategies is sensitive to the choice of alternative implied volatility indexes.

We show that strategies that are based on trading signals from other implied volatilityindexes, such as the CBOE S&P 100 Volatility Index (VXO), the CBOE NASDAQ Volatility Index (VXN), and the CBOE DJIA Volatility Index (VXD), generate significant profits.

Third, we examine whether the profitability of our VIX-based trading strategies could survive the transaction costs with alternative definitions of a "substantially high" VIX. Recall that in Section 4.3, VIX is defined as substantially high when current VIX is 10% higher than its prior 25-day average, where the 25-day window represents the number of trading days in a month. We also consider alternative horizons of prior 1-day, 5-day, 10-day, 60-day, 120-day, and 250-day average. Panel A of Table 6 shows that the profitability of our VIX-based trading strategies is not sensitive to the choice of VIX definition horizon. The return differential between any two different horizons is less than 5%, with the returns being higher for the 10-day and 25-day horizons and lower for either shorter or longer horizons. We also use 0%, 5%, 15%, and 20% as alternative thresholds for our definition of a substantially high VIX. The (untabulated) results show that excess returns are positive and significant across all these thresholds.

Fourth, we design two additional VIX based trading strategies. The first strategy involves holding sentiment-prone stocks and shorting sentiment-insensitive stocks when VIX is low and shorting sentiment-prone stocks and longing sentiment-insensitive stocks when VIX is substantially high. We show that this strategy generates significantly positive excess returns and high Sharpe ratios, albeit the magnitudes of the excess returns are smaller than those reported in the baseline results. The second trading strategy is applied on the decile portfolios. This strategy involves holding the sentiment-prone decile when VIX is low and shorting the sentiment-prone decile when VIX is substantially high. We show that this strategy also generates higher returns and higher Sharpe ratios than the benchmark strategy of buy-and-hold sentiment-prone decile portfolios. Thus, both trading strategies indicate that VIX index has a value in timing the market. However, the baseline trading strategy, which shifts investments conditional on VIX, is more practical, as these alternative strategies require short selling, which can be costly and limited for some investors (e.g., mutual funds).

Finally, VIX is an index conveyed from S&P 500 stock index options, where S&P 500 index members are mostly the largest stocks in the US stock market. This makes VIX a rather conservative measure of the overall market sentiment. Furthermore, since the returns on size-based portfolio are highly correlated with the returns of other characteristics-based portfolios, one may question whether profitability of VIX timing strategies on the size portfolios is driven by the conventional size effect. To mitigate the size effect, we also examine the profitability of VIX-based timing strategy on value-weighted cross-sectional returns. We find that the VIX-based trading strategy on value-weighted returns generates significantly positive, but smaller (raw and risk-adjusted) returns than those obtained from using equal-weighted returns.

5. Conclusion

This paper explores the cross-sectional profitability of VIX-based trading strategies. Our trading strategies involve holding sentiment-prone stocks when VIX is low and sentiment-insensitive stocks when VIX is high. These strategies are motivated by the short-run negative VIX-return relation arising from the delayed arbitrage theory (Abreu and Brunnermeier, 2002). In this paper, we view VIX as a daily measure of investor sentiment and argue that the lack of coordinated actions among arbitrageurs causes mispricing to persist, leading to a short-run negative VIX-return relation. Thus, we argue that from the behavioral perspective, the short-run negative VIX-return relation represents a return momentum caused by the delayed arbitrage, while the long-run positive VIX-return relation is a correction for mispricing.

Unlike most existing studies, which focus on the in-sample positive VIX-return relation, we argue that delayed arbitrage increases the returns of sentiment-prone stocks following a decline in VIX (high sentiment), whereas flight-to-quality leads to better performance for sentiment-insensitive stocks following an increase in VIX (low sentiment). Consistent with our argument, we find that VIX strongly and negatively associates with the next day stock return in the in-sample predictive regressions. To exploit the return momentum caused by the delayed arbitrage, we hold sentiment-prone stocks when VIX is low and sentiment-insensitive stocks when VIX is high. Using bootstrap simulations, we show that these VIX-based trading strategies generate significant excess returns and higher Sharpe ratios. These excess returns cannot be fully explained by the well-known pricing factors, such as Fama-French five factors, momentum factors, liquidity, and other macroeconomic variables, and survive transaction costs. In addition to their strong profitability, our trading strategies do not require short selling. The strong and consistent profitability of applying VIX-based trading strategy on different cross-sectional sentiment-based portfolios also supports the investor sentiment explanation on VIX-return relation.

To sum up, we contribute to the existing literature by combining the delayed arbitrage theory and flight-to-quality to explain the pattern between sentiment-based cross-sectional stock returns and VIX. Using VIX as sentiment indicator, we find strong empirical evidence that the short-run return momentum is caused by investor sentiment. We also show that simple strategies that involve holding sentiment-prone stocks when VIX is low and sentiment-insensitive stocks when VIX is high generate significant abnormal returns.

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Table 1: Regressions of Portfolio Returns on Lagged VIX

This table reports the coefficients of lagged VIX in regressions of sentiment-based long-short portfolio returns on one-day lagged VIX and control variables in the whole sample and sub-samples.

$$R_{X,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the portfolio X, where X could be a sentiment-prone decile (P), a sentiment-insensitive decile (I) or the long-short portfolio of sentiment-prone decile over sentiment-insensitive decile (P-I). The control variables include the FF 5 factors and the momentum factor (Mom). Any control factor will be excluded from the regression when it is the cross-sectional return premium being forecasted. The first two columns indicate the decile rank of sentiment-prone and sentiment-insensitive portfolios. The first row indicates the selection criteria for choosing the data samples. The second row indicates the choice of X. The Newey and West (1987) robust t-statistics are in brackets. ***, ** and * indicates the statistical significance at the 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2018/12/31.

			Panel A. All Samples			Panel B VIX<-0.5			Panel C VIX>0.5		
	P	I	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$
			(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ME	1	10	-0.04**	-0.03**	0.01**	-0.08	-0.07	0.01	-0.05	-0.04	0.01
			(-2.51)	(-2.17)	(2.48)	(-1.35)	(-1.24)	(1.05)	(-1.60)	(-1.45)	(1.14)
Age	1	10	-0.00	-0.01	-0.01	-0.06	-0.06*	0.00	0.01	-0.01	-0.02
			(-0.56)	(-1.20)	(-1.19)	(-1.36)	(-1.75)	(0.00)	(0.45)	(-0.42)	(-1.31)
Sigma	10	1	-0.01	-0.01	-0.00	-0.15**	-0.10*	0.05**	-0.00	-0.02	-0.01
			(-0.67)	(-0.88)	(-0.62)	(-2.30)	(-1.84)	(2.01)	(-0.07)	(-0.59)	(-1.14)
E/BE	1	10	-0.01	-0.01	-0.00	-0.06	-0.08**	-0.02	-0.02	-0.03	-0.00
			(-1.50)	(-1.41)	(-0.47)	(-1.59)	(-2.12)	(-0.75)	(-1.28)	(-1.13)	(-0.35)
D/BE	1	10	-0.02**	-0.01	0.01	-0.06*	-0.07**	-0.01	-0.03*	-0.02	0.01
			(-2.54)	(-1.45)	(0.95)	(-1.76)	(-2.33)	(-0.28)	(-1.75)	(-1.26)	(0.36)
PPE/A	1	10	-0.00	-0.01	-0.01	0.01	-0.02	-0.02	0.02	0.00	-0.01
			(-0.14)	(-1.20)	(-0.63)	(0.08)	(-0.39)	(-0.36)	(0.77)	(0.23)	(-0.57)
RD/A	10	1	0.01*	0.01	-0.01	-0.11**	-0.11**	-0.00	-0.01	-0.01	-0.00
			(1.93)	(0.73)	(-1.05)	(-1.99)	(-2.00)	(-0.13)	(-0.40)	(-0.46)	(-0.31)
BE/ME	10	1	-0.03**	-0.03*	0.00	0.01	-0.06	-0.08**	-0.06**	-0.05	0.02
			(-2.45)	(-1.68)	(0.68)	(0.32)	(-1.34)	(-2.25)	(-2.26)	(-1.38)	(1.09)
EF/A	1	10	-0.01	-0.01	-0.00	0.03	-0.04	-0.07*	-0.04***	-0.03	0.01
			(-1.22)	(-1.36)	(-0.37)	(0.93)	(-1.10)	(-1.78)	(-3.09)	(-1.56)	(0.58)
GS	1	10	-0.01	-0.01	-0.00	0.00	-0.07	-0.07**	-0.02*	-0.02	-0.00
			(-1.14)	(-0.96)	(-0.46)	(0.07)	(-1.24)	(-2.12)	(-1.82)	(-0.98)	(-0.09)
BE/ME	1	5	0.00	0.00	-0.00	-0.07**	-0.08**	-0.01	0.02	0.02	-0.01
			(0.86)	(0.68)	(-0.10)	(-2.16)	(-2.25)	(-0.52)	(1.61)	(1.09)	(-0.43)
EF/A	10	5	-0.00	-0.00	0.00	-0.06	-0.07*	-0.02	0.02	0.01	-0.01
			(-0.52)	(-0.37)	(0.14)	(-1.58)	(-1.78)	(-1.00)	(1.15)	(0.58)	(-0.85)
GS	10	5	-0.00	-0.00	-0.00	-0.08**	-0.07**	0.02	0.01	-0.00	-0.02
			(-0.43)	(-0.46)	(-0.27)	(-2.31)	(-2.12)	(0.90)	(0.54)	(-0.09)	(-1.17)
BE/ME	10	5	-0.03*	-0.03*	-0.00	-0.06	-0.06	-0.01	-0.04	-0.05	-0.01
			(-1.90)	(-1.68)	(-0.10)	(-1.31)	(-1.34)	(-0.52)	(-1.49)	(-1.38)	(-0.43)
EF/A	1	5	-0.01*	-0.01	0.00	-0.03	-0.04	-0.02	-0.03*	-0.03	-0.01
			(-1.88)	(-1.36)	(0.14)	(-0.87)	(-1.10)	(-1.00)	(-1.71)	(-1.56)	(-0.85)
GS	1	5	-0.01	-0.01	-0.00	-0.08	-0.07	0.02	-0.01	-0.02	-0.02
			(-1.08)	(-0.96)	(-0.27)	(-1.42)	(-1.24)	(0.90)	(-0.75)	(-0.98)	(-1.17)

Table 2: Summary Statistics of the Profitability of VIX-based Trading Strategy

The table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VIX timing strategy, and the RVIX returns, where RVIX is the excess returns of VIX strategy return over the benchmark long-short portfolio return. The first number in second column represents the rank of a sentiment-prone decile and the second number represents the rank of a sentiment-insensitive decile. The first three columns indicate the construction of benchmark portfolio and the VIX Timing strategy. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-insensitive decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VIX and hold the sentiment-insensitive decile after high VIX. VIX-based trading strategy is to buy and hold the sentiment-insensitive decile following a high VIX trading day and to buy and hold the sentiment-prone decile otherwise. A high VIX trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVIX return. All the average returns are annualized and are in percentages. ***, ** and * indicates the statistical significance at the 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2018/12/31.

			Panel A. Benchmark Portfolio Return				Panel B. VIX Strategy Return				Panel C. RVIX			
	P	I	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
ME	1	10	21.21***	13.70	-0.51	1.55	40.04***	15.55	0.14	2.57	18.82***	23.12	0.95	0.54
Age	1	10	10.48***	11.19	-0.19	0.94	26.78***	16.85	-0.29	1.59	16.28***	17.44	0.25	0.55
Sigma	10	1	17.13***	15.44	-0.18	1.11	35.89***	18.06	-0.32	1.99	18.80***	10.43	-0.11	0.58
E/BE	1	10	12.32***	7.75	-0.02	1.59	31.34***	17.61	-0.36	1.78	19.02***	18.36	-0.18	0.56
D/BE	1	10	10.34***	8.69	-0.25	1.19	28.78***	16.72	-0.33	1.72	18.45***	16.14	-0.05	0.56
PPE/A	1	10	-1.85	10.34	-0.09	-0.18	20.97***	15.99	-0.22	1.31	22.85***	19.85	-0.1	0.57
RD/A	10	1	9.69***	12.65	-0.07	0.77	30.27***	20.17	-0.34	1.50	20.59***	15.67	-0.35	0.59
BE/ME	10	1	15.47***	11.93	-0.22	1.30	38.24***	17.42	-0.14	2.20	22.80***	23.77	0.17	0.58
EF/A	1	10	10.91***	8.55	-0.22	1.28	27.81***	17.66	-0.4	1.58	16.90***	22.28	-0.15	0.57
GS	1	10	11.52***	7.77	-0.11	1.48	30.01***	18.28	-0.36	1.64	18.51***	21.89	-0.14	0.57
BE/ME	1	5	10.42***	13.21	-0.03	0.79	21.10***	19.24	-0.32	1.10	10.70***	9.05	-0.3	0.57
EF/A	10	5	8.27***	13.49	-0.25	0.61	21.99***	18.63	-0.34	1.18	13.75***	8.04	-0.28	0.58
GS	10	5	7.47***	13.73	-0.23	0.54	21.56***	18.57	-0.33	1.16	14.11***	7.83	-0.15	0.59
BE/ME	10	5	25.89***	9.12	0.20	2.84	38.75***	16.01	-0.23	2.42	12.91***	10.58	0.14	0.57
EF/A	1	5	19.17***	9.22	-0.51	2.08	30.99***	15.91	-0.41	1.95	11.83***	8.30	-0.04	0.57
GS	1	5	18.98***	10.91	-0.39	1.74	33.26***	16.5	-0.38	2.02	14.31***	8.37	0.10	0.59

Table 3: Abnormal Alphas of RVIX

RVIX is the excess returns of the VIX-based trading strategy over the buy-and-hold long-short portfolio return. In Panel A, we regress RVIX on the daily market excess return. Panel B reports the results of RVIX regressed on FF3 factors and the momentum factor. Panel C reports the results of RVIX regressed on FF5 factors and the momentum factor. In Panel D RVIX is adjusted for 8 factors from Kenneth French website (namely RMRF, SMB, HML, CMA, RMW, ST_Rev, MOM, LT_Rev). Panel E shows the results of RVIX regressed on Stambaugh and Yuan (2016) four mispricing factors. Panel F employs the Hou, Xue and Zhang (2015) four-factor q-model. Any risk factor will be excluded from the regression when it is the portfolio being estimated. The alphas are annualized and are in percentages. The Newey and West robust t-statistics are in parentheses. ***, ** and * indicates the statistical significance at the 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2018/12/31.

			Panel A CAPM		Panel B FF3		Panel C FF5+Mom		Panel D 8 Factors		Panel E M4		Panel F Q-Factors	
			α	R^2	α	R^2	α	R^2	α	R^2	α	R^2	α	R^2
ME	1	10	9.66***	85.34	9.67***	85.34	9.80***	86.96	7.85***	88.03	10.85***	85.55	9.03***	85.13
			(5.74)		(5.74)		(5.85)		(4.50)		(5.69)		(5.13)	
Age	1	10	10.05***	69.36	9.31***	73.24	5.29***	80.90	6.25***	81.03	7.08***	74.46	6.55***	76.96
			(5.17)		(5.46)		(3.51)		(3.73)		(3.45)		(3.80)	
Sigma	10	1	16.82***	19.76	16.23***	24.96	14.05***	30.40	17.49***	33.59	14.05***	29.66	14.34***	26.35
			(8.82)		(8.88)		(7.75)		(8.64)		(7.08)		(7.80)	
E/BE	1	10	11.95***	80.79	11.26***	85.98	12.26***	86.51	11.30***	87.02	11.24***	85.09	11.21***	85.53
			(6.87)		(8.27)		(9.25)		(7.35)		(7.62)		(8.02)	
D/BE	1	10	12.65***	70.22	11.61***	76.26	11.63***	77.71	12.67***	78.25	9.45***	75.75	10.54***	75.58
			(7.28)		(7.54)		(7.48)		(7.14)		(5.52)		(6.63)	
PPE/A	1	10	16.75***	51.35	15.31***	61.50	13.72***	63.27	11.47***	63.97	18.32***	58.60	16.19***	62.35
			(5.63)		(6.09)		(5.27)		(3.80)		(6.43)		(6.33)	
RD/A	10	1	15.41***	59.25	13.69***	79.02	13.01***	81.29	13.46***	81.38	15.15***	75.25	13.80***	73.53
			(7.34)		(9.30)		(9.14)		(8.51)		(8.80)		(8.25)	
BE/ME	10	1	14.13***	72.32	13.31***	81.29	18.29***	85.08	14.01***	86.71	17.53***	83.75	18.68***	84.33
			(5.09)		(6.12)		(9.13)		(7.29)		(7.51)		(9.13)	
EF/A	1	10	9.06***	67.34	8.54***	80.95	13.46***	84.46	9.06***	85.66	13.97***	83.13	14.24***	84.58
			(2.81)		(3.65)		(6.55)		(4.41)		(5.86)		(6.89)	
GS	1	10	10.47***	73.23	9.87***	85.27	13.78***	87.81	10.08***	88.75	14.82***	87.09	14.60***	87.82
			(3.75)		(5.04)		(8.22)		(5.80)		(7.73)		(8.46)	
BE/ME	1	5	7.92***	51.09	7.58***	61.37	6.40***	67.68	7.45***	68.33	6.61***	63.62	6.61***	65.39
			(6.97)		(7.86)		(6.73)		(7.27)		(5.93)		(6.74)	
EF/A	10	5	11.32***	49.51	10.62***	62.71	9.61***	65.09	11.04***	66.02	9.53***	62.24	9.75***	62.08
			(10.15)		(11.24)		(10.26)		(10.65)		(8.78)		(10.12)	
GS	10	5	11.88***	44.14	11.17***	57.23	10.27***	59.74	11.82***	60.94	10.16***	57.55	10.42***	55.60
			(10.55)		(11.19)		(10.72)		(10.97)		(9.48)		(10.48)	
BE/ME	10	5	9.14***	69.16	8.77***	77.97	8.22***	79.04	7.34***	79.30	8.10***	76.89	8.52***	77.61
			(8.16)		(9.03)		(8.97)		(7.39)		(7.77)		(8.78)	
EF/A	1	5	8.84***	70.56	8.29***	81.75	8.05***	82.34	7.92***	82.36	8.16***	80.71	8.28***	80.52
			(9.76)		(12.61)		(12.73)		(11.55)		(11.10)		(11.67)	
GS	1	5	11.51***	60.67	10.89***	70.11	10.20***	72.35	10.54***	72.41	10.41***	70.27	10.42***	67.76
			(11.21)		(12.26)		(12.02)		(10.93)		(10.97)		(11.28)	

Table 4: Market Timing Tests

Table 4 reports results of market timing regressions of RVIX, the excess returns of VIX-based trading strategy over benchmark portfolio return. Panel A shows the results of Treynor and Mazuy (1966) quadratic regressions (Equations (2)), and Panel B shows the results of Henriksson and Merton (1981) regressions (Equations (3)). The alphas are annualized and are in percentages. *** and ** indicates statistical significance at the 1% and 5% level, respectively. The Newey and West robust t-statistics are in parenthesis. The sample period is from 1990/01/01 to 2018/12/31.

			Panel A. TM Regression				Panel B. HM Regression			
	P	I	α	β_m	β_{m^2}	R^2	α	β_m	γ_m	R^2
ME	1	10	1.45	1.21***	2.64***	85.84	-10.81***	1.32***	-0.22***	85.71
			(0.63)	(38.34)	(3.66)		(-2.76)	(28.91)	(-4.74)	
Age	1	10	8.90***	0.82***	0.37	69.37	9.75**	0.82***	0.00	69.35
			(3.64)	(27.28)	(0.54)		(2.54)	(19.23)	(-0.07)	
Sigma	10	1	16.53***	0.26***	0.09	19.76	17.76***	0.26***	0.01	19.76
			(8.14)	(11.21)	(0.16)		(5.22)	(9.21)	(0.24)	
E/BE	1	10	12.59***	0.94***	-0.21	80.79	15.22***	0.92***	0.03	80.8
			(6.98)	(48.39)	(-0.64)		(6.00)	(38.98)	(1.34)	
D/BE	1	10	12.72***	0.77***	-0.02	70.22	11.99***	0.77***	-0.01	70.22
			(7.42)	(29.21)	(-0.05)		(4.02)	(24.46)	(-0.19)	
PPE/A	1	10	20.37***	0.81***	-1.16	51.48	29.61***	0.74***	0.14***	51.54
			(4.89)	(18.86)	(-1.25)		(6.40)	(13.99)	(3.01)	
RD/A	10	1	19.00***	0.68***	-1.15**	59.46	26.03***	0.63***	0.11***	59.46
			(8.55)	(21.19)	(-2.24)		(7.08)	(16.07)	(2.72)	
BE/ME	10	1	14.54***	1.15***	-0.13	72.31	17.37***	1.13***	0.03	72.32
			(4.64)	(43.72)	(-0.18)		(3.73)	(28.25)	(0.68)	
EF/A	1	10	11.81***	1.04***	-0.88	67.39	22.12***	0.97***	0.14***	67.5
			(2.96)	(50.77)	(-0.95)		(4.44)	(26.51)	(2.71)	
GS	1	10	11.88***	1.06***	-0.45	73.24	19.14***	1.02***	0.09**	73.3
			(3.62)	(64.30)	(-0.67)		(4.65)	(34.01)	(2.30)	
BE/ME	1	5	9.77***	0.37***	-0.59	51.25	13.33***	0.34***	0.06**	51.25
			(7.09)	(21.04)	(-1.62)		(5.59)	(13.62)	(2.16)	
EF/A	10	5	12.52***	0.32***	-0.38	49.59	14.26***	0.31***	0.03	49.57
			(8.73)	(22.16)	(-0.94)		(6.12)	(13.99)	(1.15)	
GS	10	5	13.56***	0.29***	-0.54	44.32	15.78***	0.27***	0.04	44.25
			(9.52)	(19.89)	(-1.33)		(6.74)	(12.59)	(1.52)	
BE/ME	10	5	8.29***	0.50***	0.27	69.19	6.46***	0.51***	-0.03	69.19
			(7.44)	(39.50)	(1.33)		(3.99)	(32.12)	(-1.59)	
EF/A	1	5	8.70***	0.40***	0.05	70.56	9.18***	0.39***	0.00	70.56
			(8.64)	(46.80)	(0.20)		(6.01)	(32.59)	(0.22)	
GS	1	5	11.15***	0.37***	0.12	60.67	10.86***	0.37***	-0.01	60.66
			(9.99)	(28.42)	(0.40)		(6.20)	(22.76)	(-0.34)	

Table 5: Block Bootstrap Tests with Transaction Costs

The table reports moving block bootstrap tests on the average returns (Avg Ret) and the Sharpe ratio (SRatio) for VIX timing strategy and the RVIX returns, where RVIX is the excess returns of VIX strategy return over the benchmark long-short portfolio return. The returns are net of transaction costs set at 25 basis points per one-way transaction. All the average returns are annualized and are in percentages. The first three columns indicate the construction of benchmark portfolio and the VIX Timing strategy. N1, N4, and N10 refer to, when using a 1-day, 4-day, and 10-day block length respectively, the number of cases with the simulated performance measure larger than the correspondent measure from the original data. The number of bootstrap simulations is 1000.

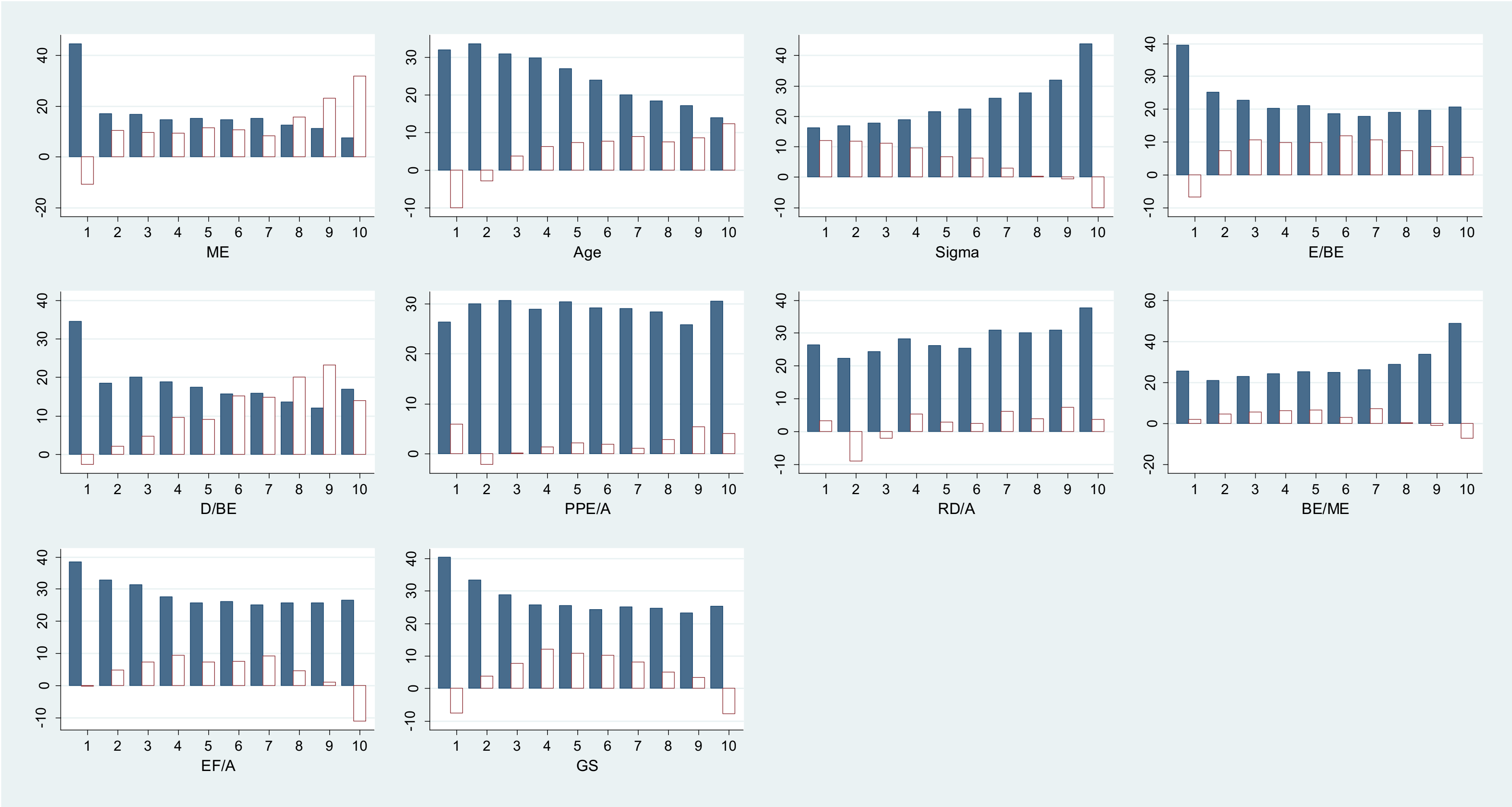
			Panel A. VIX Strategy Return				Panel B. VIX Strategy Sharpe Ratio				Panel C. RVIX Return			
	P	I	Avg Ret	N1	N4	N10	SRatio	N1	N4	N10	Avg Ret	N1	N4	N10
ME	1	10	26.79	0	0	0	1.7	0	0	0	5.57	0	0	0
Age	1	10	13.53	0	0	26	0.79	0	0	40	3.03	0	0	24
Sigma	10	1	22.64	0	0	0	1.24	0	0	47	5.55	0	0	0
E/BE	1	10	18.09	0	0	21	1.01	0	0	29	5.78	0	0	16
D/BE	1	10	15.53	0	0	35	0.91	0	0	60	5.2	0	0	25
PPE/A	1	10	7.72	0	69	959	0.47	0	65	945	9.6	0	128	899
RD/A	10	1	17.03	0	0	103	0.83	0	0	234	7.34	0	0	68
BE/ME	10	1	24.99	0	0	19	1.41	0	0	6	9.55	0	0	40
EF/A	1	10	14.56	0	5	372	0.81	0	3	280	3.65	0	24	390
GS	1	10	16.76	0	0	141	0.9	0	0	112	5.26	0	3	161
BE/ME	1	5	7.85	0	18	684	0.40	0	28	764	-2.55	0	1	855
EF/A	10	5	8.74	0	2	495	0.46	0	3	600	0.5	0	0	538
GS	10	5	8.32	0	2	512	0.44	0	3	618	0.86	0	0	541
BE/ME	10	5	25.5	0	0	6	1.56	0	0	7	-0.34	0	0	0
EF/A	1	5	17.74	0	0	171	1.1	0	0	194	-1.42	0	0	20
GS	1	5	20.02	0	0	28	1.19	0	0	72	1.06	0	0	0

Table 6: Return and BETC on Different Trading Signal Horizons

This table reports the break-even transaction costs of VIX-based trading strategy if we choose alternative horizons to compare the VIX with its past average. For instance, we define a high VIX day if current VIX is at least 10% higher than its prior 10-day average. In this table we show the results when using 1-day, 5-day, 10-day, 25-day, 60-day, 120-day and 250-day horizons. The break-even transaction costs are in basis points. The sample period is from 1990/01/01 to 2018/12/31.

			BETC on different trading signal horizons						
			1-day	5-day	10-day	25-day	60-day	120-day	250-day
ME	1	10	62.46	67.23	68.24	78.54	97.02	115.65	124.15
Age	1	10	43.23	46.97	46.93	52.45	68.9	81.72	85.78
Sigma	10	1	58.99	61.92	61.76	68.8	90.01	108.4	116.99
E/BE	1	10	51.71	54.4	54.31	60.78	76.57	94.25	99.71
D/BE	1	10	47.51	49.39	48.91	56.28	72.03	87.51	94.29
PPE/A	1	10	37.79	37.83	37.28	40.54	50.85	67.08	77.85
RD/A	10	1	54.39	55.32	53.62	58.34	74.65	92.76	101.59
BE/ME	10	1	64.31	64.48	64.18	74.11	88.87	111.39	123.18
EF/A	1	10	50.62	47.25	47.26	54.02	65.12	82.78	94.95
GS	1	10	52.12	51.03	51.89	58.33	72.36	90.56	99.61
BE/ME	1	5	37.09	37.98	37.48	40.86	53.8	68.43	75.35
EF/A	10	5	35.15	37.58	37.94	42.2	55.3	67.86	74.8
GS	10	5	33.96	35.89	35.47	41.27	54.08	66.26	72.68
BE/ME	10	5	65.69	67.27	66.64	75.32	92.85	116.89	126.93
EF/A	1	5	53.14	52.66	53.19	59.98	74.9	93.13	104.32
GS	1	5	54.32	55.62	56.21	64.34	82.15	100.84	108.61

Figure 1 Two-way Sorts: One-Day Forward Returns Sorted by VIX Levels and Sentiment-Exposure



In each subfigure, we place the daily return observations into decile bins sorted on a characteristic. The subtitles show the sentiment-sensitivity measure used to sort deciles. Then we sort return by the VIX level on the previous day. If current VIX is at least 10% higher than its prior 25-day average, we define it a high VIX day. The solid bars are the annualized equal-weighted average returns following low VIX (high sentiment) days; and the clear bars are average returns following high VIX (low sentiment) days.

Appendix

In Table A.1 below, we provide a detailed description for the variables needed to construct the portfolios.

Table A.1: Definitions of Characteristic Variables of Sentiment-Sensitivity Level

Var	Name	Description	Calculation
ME	Market equity	Price times shares outstanding in the June prior to t. If there are more than one permanent code for a company, then sum up all the ME for the same company	abs(prc)*shrout
Age	Firm age	The number of months between the firm's first appearance on CRSP and t. The firm age is measured to the nearest month. If the stock is not delisted, we calculate time between current year t and beginning date, or else the age is ending date minus beginning date.	min(date, enddat)-begdat
Sigma	Total risk	Annual standard deviation in monthly returns from CRSP for the 12 months ending in the June prior to t, and there should be no less than 9 monthly returns available to estimate it.	Standard deviation of return
E/BE	Earnings-book ratio for profitable firms	Earnings is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), if earnings are positive; book equity (BE) is shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). The profitability dummy E>0	BE = CEQ + TXDITC; E=IB+TXDI-DVP; E/BE=E/BE if E>0; E/BE=0 if E<0
D/BE	Dividend-book ratio for dividend payers	Dividend is the fiscal year-end dividends per share at the ex-date (Item 26) times Compustat shares outstanding (Item 25) divided by book equity.	D/BE=(DVPSX_F*CSHO)/BE if D>0; otherwise, D/BE=0
PPE/A	Fixed assets ratio	Plant, property, and equipment (Item 7) is scaled by gross total assets (Item 6). The data are widely available after 1971. We do not replace missing value with zero.	PPE/A=PPEGT/AT;
RD/A	Research and development ratio	Research and development (Item 46) is also scaled by gross total assets (Item 6). The data are widely available after 1971.	RD/A=XRD/AT;
BE/ME	Book-to-market ratio	This is the log of the ratio of book equity to market equity. We match fiscal year ending calendar year t-1 ME with June t BE	log(1+BE/DEC_ME)
EF/A	External finance over assets	External finance (EF) is equal to the change in assets (Item 6) less 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.	EF1=dif(RE); EF2=dif(NI-DVC); EF/A=(dif(AT)-coalesce(EF1,EF2,0))/AT;
GS	Sales growth	Sales growth is the percentage change in net sales (Item 12). We first calculate the original sales growth ratio and then use its position in the ten-decile to note GS. GS has a range from [1, 10]	GS=dif(SALE)/lag(SALE)