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 "investor fear gauge" in the stock market. These strategies involve holding sentiment-prone stocks when VIX is low and sentiment-immune stocks when VIX is high. We show that our trading strategies generate significantly higher excess returns than the benchmark long-short portfolio strategies that does not condition on VIX. We also find that profitability of our trading strategies is not subsumed by the well-known risk factors or transaction cost adjustments. We argue that the synchronization problem of arbitrageurs (Abreu and Brunnermeier, 2002) may explain our results.

Key words: VIX; Trading Strategies; Cross-section; 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 "investor fear gauge" (Kaplanski and Levy, 2010; Whaley, 2000, 2009; Da et al, 2015), with low VIX indicating high overall market investor sentiment, and vice versa. VIX is high in the NBER recession and low during the anecdotal bubble period in US market.

Several studies view VIX as a measure of expected volatility in a mean-variance framework where investors are assumed to have constant risk aversion. Merton (1980) among many others argue for the positive mean-varainace relationship, and therefore VIX increase should be associated with higher future return. Others deem VIX as "investor fear gauge" and use VIX to predict future returns. For example, Giot (2005), Banerjee et al. (2007) and Bekaert and Hoerova (2014) document strong negative associations between contemporaneous returns and incremental VIX and between long-term future returns (eg. 30-day/ 60-day/ monthly return) and the VIX level. Similarly, Giot (2005) shows that during very high/low VIX period, VIX positively predicts future 60-day returns on S&P 100. Though most paper use VIX to predict aggregate market return, Banerjee et al. (2007) look into the cross-section stock market and find VIX to be positively related to the next 30-day future returns. This strand of studies almost exclusively uses low frequency return data to test whether VIX predicts long-run future return reversal arises from the correction of mispricing.

Unlike previous studies, which commonly focus on in-sample predictability of VIX and on the long-term (one month or longer) return reversals, this study investigates the profitability of VIX-based strategies arising from the short run (next day) momentum in the cross-section of stock returns. Specifically, we are interested in testing 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 the stock returns following sentiment increase. Our empirical tests show significant negative relationship between lagged VIX and return is stronger during high sentiment periods and it is stronger 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. One reason for using VIX to design our trading strategy is that VIX is obtained primarily from the trading of sophisticated investors on S&P options, and hence we argue VIX reflect the sophisticated investors' estimation of the overall market investor sentiment, which works better with the delayed arbitrage theory. Another reason is that VIX is one of the most widely accepted daily sentiment indicator.

In this study, we design trading strategies that involve holding sentiment-prone stocks when VIX is low and holding sentiment-immune 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 25 days[4]. The sentiment-prone stock portfolio consists of firms that are small, young, volatile, non-profitable, non-dividend-paying, and with high financial distress and great growth opportunity. Therefore, stock portfolios are constructed with 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. Our choice of these trading strategies is motivated by the fact that investor sentiment has differential impact across stocks (Baker and Wurgler, 2006). When investor sentiment is high (VIX is low), contemporaneous returns of sentiment-prone stocks are also likely to be high in the presence of limits to arbitrage. If the theory of delayed arbitrage holds, prices of these more over-priced stocks will increase further in the near term than the less over-price stocks. 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 all our trading strategies generate large excess returns over the unconditional long-short portfolio trading strategy, which always longs sentiment-prone portfolios and shorts sentiment-immune portfolios. We find that the annualized return of our VIX trading strategy ranges from 22.05% to 42.38%, while the correspondent benchmark long-short portfolios have returns ranging from -3.15% to 28.01%. We also show that the annualized excess returns of VIX trading strategy over its correspondent benchmark portfolio range from 11.66% to 25.55%. Among the 16 trading strategies, we find that the most profitable trading strategy involves shifting investments between the smallest and the largest stocks deciles, while the least profitable trading strategy is the one that shifts 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 in 14 out of 16 cases. Shifting investments based on size has the highest Sharpe ratio of 2.70, while shifting investments between the bottom and the middle book-to-market portfolios has the lowest Sharpe ratio of 1.13. 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 shows that our trading strategy remains profitable after considering effects of macroeconomic factors such as term spread, default spread,

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

TED spread and the liquidity factor. Finally, we calculate the breakeven transaction cost (the estimated cost that will make profit zero) to see whether our trading strategy could survive the transaction costs. We find that transaction costs are unlikely to eliminate the profitability of our strategies since the break-even transaction costs associated with our strategies are generally higher than 50 basis points. In literature, transaction costs are usually set lower than 50 basis points[5]. Our high break-even transaction costs indicate that our trading strategies are still profitable after taking the transaction costs into account.

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 a proxy for expected volatility, market volatility, liquidity measure or macroeconomic expectation. Studies that see VIX as expected volatility and liquidity explain the positive VIX-return relation but could hardly explain the return momentum, i.e., the short-run negative relationship between VIX and one-day forward return. Unlike them, we regard VIX as a market-wide sentiment indicator and 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. Indeed, shifting investments between sentiment-prone and sentiment-immune stocks on basis of VIX timing signals can generate significant abnormal returns. This paper also provides the first evidence that VIX level negatively predicts the next-day return of sentiment-prone stocks over sentiment-immune stocks. This in-sample near-term predictability lends further support to our behavioural explanation.

The closest study to ours is that of Copeland and Copeland (1999), who also design trading strategies that involve shifting investments across stock portfolios on the basis of changes in VIX. Our paper is distinct from Copeland and Copeland (1999) in two ways. First, as we intend to explain the profitability of the VIX-timing strategy with a sentiment story, our hypothesis derives from the theoretical work on the effect of sentiment on stock returns and delayed arbitrage (Abreu and Brunnermier, 2002; Delong et al., 1990). Copeland and Copeland (1999) see VIX as a proxy for future discount rate, higher VIX means higher future discount rate and price will therefore be falling. However, this explanation does not explain the reversal effect of VIX on return as shown in ample existing literature. Our explanation integrates the explanations for both return momentum and reversal caused by VIX through the investor sentiment channel. In addition, 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 if the portfolios are constructed with a good proxy for stocks' sentiment-

[5] For example, Lynch and Balduzzi (2000) set the transaction cost at 25 basis points to calculate the profit. Frazzini et al. (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.

sensitivity level. The finding that VIX-based strategies can generate significant returns may help explain the wide application of such strategies in the financial industry.

The rest of our paper proceeds as follows. Section II reviews the related literature. Section III describes the data. Section IV reports the profitability of our VIX-based trading strategy. Section V concludes.

2 Related Literature

In short, previous empirical studies on the relationship between investor sentiment and stock return generally show two findings: first, investor sentiment is negatively related to future stock return; second, the predictive power of investor sentiment on stock return is more pronounced in the cross-section. The contrarian predictive power of investor sentiment on future return are usually tested with low frequency data. Most of the commonly used investor sentiment measures, such as mutual fund flow, consumer confidence index, closed-end fund discount, Baker Wurgler index, are in monthly frequency (Neal and Wheatley, 1998; Lemmon and Portniaguina, 2006; Lee et al., 1991; Baker and Wurgler, 2006, 2007). Those papers looks into the predictability of those monthly sentiment level on monthly, quarterly or longer-term future return. They argue that bullish investor sentiment pushes current price high and the mispricing will be corrected in the future which means lower future return, and vice versa.

It has come to our attention that the negative relationship between investor sentiment and future return may not hold in the short run with high frequency data. Several recent papers show that investor sentiment also predicts short-term momentum (see, e.g., Han and Li, 2017; Chou et al., 2016). Abreu and Brunnermeier (2002) postulated that in a market where arbitrageurs do not know their sequence in notifying the mispricing, the lack of coordination among arbitrageurs may lead to a persistent mispricing, and sophisticated investors may choose to beat the gun and ride the mispricing which amplify the extent of mispricing further in the short run. Ample empirical studies indicate that sophisticated arbitrageurs actively ride the bubbles and contribute to the bubble (Brunnermeier and Nagel, 2004; Griffin et al., 2011; Xiong and Yu, 2011; Berger and Turtle, 2015; DeVault et al., 2017). Therefore, we argue that investor sentiment may have a momentum effect on short-run future return. The momentum effect of investor sentiment on future return does not conflicts with the well-documented reversal effect of investor sentiment. To quote Yu (2011) which studies the reversal effect of investor sentiment, “the synchronization problem among arbitrageurs may create limits to arbitrage or even amplify the mispricing”, and in this case the reversal effect of investor sentiment could be more pronounced due to the delayed arbitrage. This paper compliments to previous literature by looking at the momentum effect in the short-run.

The proposal of high frequency investor sentiment measures enables tests of the predictability of investor sentiment on stock return at daily or higher frequency. For instance, daily investor sentiment could be measured by google search volume for positive/negative words[6], detrended daily trading volume, implied volatility and so on. One important daily sentiment measure is VIX. However, most papers on the predictive power of VIX on future returns does not see VIX as a sentiment measure but deems VIX as a measure for expected future volatility or liquidity in their analysis of the positive VIX-return relation. For example, Banerjee et al. (2007) proposed 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), Bakshi and Kapadia (2003) show market volatility has a negative price and high levels of volatility will translate to high price risk premiums when investors are averse to volatility risk. Thus, high VIX indicates high market volatility and therefore low current price and high future return. VIX is also a liquidity measure. In Nagel (2012), VIX is deemed as a liquidity measure that strongly predicts the returns from liquidity evaporation. High VIX indicates low funding liquidity and therefore higher future returns. However, those theories do not work well in explaining the short-run negative VIX-return relation, i.e. the return momentum. To address the momentum and reversal effect of VIX on return, we see VIX as investor sentiment measure.

This paper contributes to studies on VIX from a behavioural finance perspective. Mispricing arises from arbitrageurs' limit of arbitrage combined with investors' biased belief. VIX not only indicates limit of arbitrage level but also dub investor sentiment. On one hand, Tu et al. (2016) explain the predictive power of VIX on absolute mispricing level through the limit to arbitrage channel. They argue that high VIX means high expected volatility and therefore stronger limits to arbitrage, and therefore mispricing will be amplified. On the other hand, high VIX means low sentiment. If limits of arbitrage assumed constant, VIX is expected to be negatively related to contemporaneous mispricing and amplified momentum return when arbitrage is delayed. Unlike the Tu et al. (2016), this paper exploits the over/under pricing caused by VIX. The advantage of using sentiment channel is that it not only explains return reversal found in ample existing literature but also enables us to look at the return momentum. We contribute to the literature by explaining the negative relationship between VIX level and one-day forward stock return in the cross-section through the sentiment channel.

Existing studies find the reversal effect of investor sentiment is controversial in the aggregate market level but strong in the cross-section. Baker and Wurgler (2007) argue that stocks that are more prone to speculative demand and more difficult to arbitrage are more prone to sentiment. Certain stocks, such as young and small stocks, are more prone to sentiment in the cross-section while some are more sentiment-immune. Hence, sentiment plays a more prominent role in predicting the return disparity between sentiment-prone stocks and sentiment immune stocks than predicting the aggregate market return. Stambaugh, Yu and Yuan (2011) argue that stocks with more constraints to arbitrage is more

[6] Some studies find google search volume positively associates with future return in high frequency, and they design profitable trading strategies to capture the momentum effect of investor sentiment.

sensitive to investor sentiment. When considering about the momentum effect arises from delayed arbitrage, Ljungqvist and Qian (2016) reason that sophisticated investors deliberately target stocks with sever short-sell constraints, limiting the scope of coordinated short-selling actions. Campbell et al. (2011) find the distressed stocks underperform more severely at times of increases in VIX. Therefore, we expect the momentum effect of sentiment caused by delayed arbitrage will also be stronger in the cross-section. We hypothesize that sentiment-prone stocks will show stronger momentum effect as they are more prone to sophisticated arbitrageurs and more difficult to arbitrage during the bubble period.

Strong predictive power of a factor on return does not necessarily results in strong profitability of trading on this factor.Previous literature on volatility timing often calculate 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 et al. 2001; Johannes et al. 2002; Fleming et al., 2003; Clements and Silvernnoinen, 2013). Volatility timing strategy with VIX are mostly based on the mean-variance relation theory. To the best of our knowledge, A strand of studies demonstrate the profitability of trading strategies that benefit from the return momentum induced by the news-based sentiment (Uhl, 2017; Huynh and Smith, 2017; Sun et al., 2016). Copeland and Copeland (1990) propose to shift asset allocation in the cross-section based on VIX. Their motivation for this trading strategy is that VIX represent future discount rate and therefore influence price in discount cash flow model; however, this explanation does not strongly illustrate why VIX has asymmetric predictability on future return in the cross-section. We see VIX as sentiment indicator and based on the asymmetric effect of investor sentiment in the cross-section stock market, we design a wider spectrum of trading strategies by building portfolios based on different sentiment sensitive level measures. To the best of our knowledge, few paper view VIX as sentiment and test trading strategies that capture the VIX-induced return momentum in the cross-section stock market, and this paper contributes to the existing literature by filling this gap.

3 Research design and data sources

We construct decile portfolios based on firm characteristics that relate 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).[7]

Baker and Wurgler (2006) argue that stocks that are prone to speculative demand are also difficult to arbitrage. 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. This lack of consensus among unsophisticated investors increases the volatility of returns, which in turn deters rational investors from trading fully against mispricing.

Similar to 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-immune decile portfolio. We consider the bottom (top) deciles of ME, Age, E/BE, D/BE, and PPE/A as the most sentiment-prone (sentiment-immune) and the top (bottom) deciles of Sigma and RD/A as the most sentiment-prone (sentiment-immune). Three of the 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 represents serious distress, while a low value of the same ratio indicates extreme 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 investor to value, so returns of firms with low BE/ME, high EF/A, and high GS are more prone to investor sentiment. The middle deciles are considered most sentiment-immune for those three characteristics. Hence, the long-short portfolio could be top-minus-middle and bottom-minus-middle decile for BE/ME, EF/A, and GS. In addition, BE/ME (EF/A, GS) itself could be seen as generic pricing factor, and therefore the top BE/ME (bottom EF/A, GS) decile is expected to be more sensitive to VIX than the bottom BE/ME (top EF/A, GS) 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 in 10 and 11) between January 1988 and December 2016 in NYSE, AMEX, and NASDAQ (with stock exchange code in 1 2 3). All the firm characteristic variables are winsorized at 99.5 and 0.5% annually. 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 2016/04/30 from WRDS. We also obtain the historical data on the implied volatility conveyed from S&P 100 index, NASDAQ index, and DJIA index. The momentum factor (UMD), defined the average return of high prior return portfolio over low prior return portfolio, and the Fama-French five factors, i.e., the

[7] Details on these characteristics variables are provided in the Appendix.

market return premium over risk-free rate (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), are downloaded from Kenneth French website[8].

4. Empirical Results

In this section, we start with in-sample predictive regressions of VIX on the next-day cross-sectional returns. We then report the returns of the simple VIX-based trading strategies, both raw and risk-adjusted, and compare them with those of the benchmark portfolios.

4.1 Predictive Regressions

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

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

where $R_{X,t}$ is the portfolio returns X at time t, and the portfolio X can be one of the following: 1) a long-short portfolio that longs sentiment-prone stocks and shorts sentiment-immune decile portfolio (P-I); 2) a sentiment-prone decile portfolio (P); 3) a sentiment immune decile portfolio (I). VIX_{t-1} is the standardized VIX level at time t-1, and CV_t is a vector of control variables, including the Fama-French (2015) five factors and the Carhart (1997) momentum factor (UMD). 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 of 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.[9] Panel A reports the regression results for the entire sample period, while Panel B and Panel 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 sample into high and low sentiment periods to test whether the ability of VIX to predict returns depends on investor sentiment. As previous studies show

[8] The data are available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth R. French for providing the data.
[9] We set a maximum lag of 15 when calculating Newey-West robust standard errors for the coefficients.

that the predictability of VIX is strong when VIX is at extreme (either substantially high or substantially low), we set the threshold as 0.5.[10]

[Insert Table 1]

The coefficients on the one-day lagged VIX in Panel A of Table 1 are negative and statistically significant (at the 10% or better) in 6 out of 16 long-short portfolios and insignificant in the rest 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 relative return of sentiment-prone stocks over sentiment-immune stocks and the one-day lagged VIX. Columns (2) and (3) of Panel A present the results of regressing the returns on sentiment-prone decile and sentiment-immune decile on lagged VIX, respectively. The results suggest that lagged VIX has a much stronger predictive power on sentiment-prone stocks than sentiment-immune stocks. In Column (3), apart from the top ME decile portfolio regression, none of the 16 regressions exhibits a significant relationship between 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 "flight-to-quality" (see also Baker and Wurgler, 2007), i.e., investors seek safer portfolios in low sentiment period.

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 period. VIX is a significantly negative predictor of the one-day forward return for 11 out of the 16 long-short portfolios. Similarly, we find that the ability of VIX to predict the returns of the sentiment-prone deciles also increases when sentiment is high. Column (3) of Panel B shows that when sentiment is high, even the returns of some of the sentiment-immune deciles exhibit significantly negative association with the lagged VIX.

Panel C of Table 1 shows that when sentiment is low, VIX has little predictability of the next-day returns, regardless of whether the returns of the sentiment-prone deciles or those of the sentiment-immune deciles are used as the dependent variables in the regression. Specifically, we find the lagged VIX to be a significant return predictor for 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 sentiment is more likely to have a greater influence on stock prices during

[10] 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-immune stocks following a substantial rise in VIX.

periods of high sentiment, as short sale constraints are generally more binding during these periods. Recall that Tu et al. (2016) explain the predictive power of VIX on return through the limit to arbitrage channel. in is that high VIX imposes stronger limits to arbitrage VIX is a measure of expected volatility, therefore we expect high VIX imposes stronger limits to arbitrage. Therefore mispricing may be amplified, if we keep sentiment constant. On the other hand, high VIX means low sentiment, if limits arbitrage assumed constant, we expect VIX is negatively related to contemporaneous mispricing. This paper focuses on the sentiment channel though, not the limits to arbitrage channel. Our study extends this strand of literature by documenting a strong negative association between VIX and the next day return. This finding is consistent with the delayed arbitrage argument, while the mean-variance theory and the liquidity evaporation theory do not work well in explaining this empirical finding.

To test the robustness of our results, we add more control variables into the regression. First, even though the liquidity evaporation explanation explains the positive relationship between VIX and return and we find the negative short-run relationship, we build a liquidity measure and add it as a control variable in the robustness test. Our liquidity control variable is the difference of the average bid-ask spread between the correspondent long and short portfolio used in each regression. We find that sentiment-prone decile portfolios have higher bid-ask spread. In the unreported regressions, the bid-ask spread difference of sentiment-prone decile over sentiment-immune decile is negatively related to the future return, which indicates that higher bid-ask spread in sentiment-prone deciles indicates lower future return momentum. Though the bid-ask spread difference plays a significant role in return disparity, the coefficients of one-day lagged VIX on return remains significantly negative. By controlling for liquidity risk factor, we could at least say that the momentum effect of VIX on return is not fully contributed by the liquidity evaporation.

4.2 Two-way Sorts

We divide our sample into high and low VIX periods on the basis of the trading signals 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 decile portfolio returns. First, we sort stock returns into ten 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 sort the returns in each decile conditional on whether the return is following a high sentiment day or a low sentiment day. In this case, 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 $\mathrm{t}-26$ and $t-2$, otherwise day t is classified as a high or normal sentiment day. Figure 1 shows the two-way sorts of returns for the period from Jan 1990 to Dec 2016.

[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-immune stocks. This indicates that when sentiment is high, sentiment-prone deciles, such as 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 white bar is lower for high ME, high Age, low Sigma, high E/BE, and high 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 PPE/A and 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 et al. (2012).

Furthermore, Figure 1 shows that sentiment-immune 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 from PPE/A and RD/A. This indicates 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 returns pertaining BE/ME, EF/A, and GS reveals that the white bars has an inverted U-shape pattern and that the lowest differences between the solid bars and the white 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 variables.

4.3 VIX-based Trading Strategies

The rule of our trading strategies is to hold sentiment-immune 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.[11] 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 sentiment-prone decile portfolio over

[11] 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.

sentiment-immune decile portfolio (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, and the success rate of our trading strategy, defined as the percentage of trading days in 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 reports 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 -3.15% (PPE/A long-short portfolio) to 23.11% (ME long-short portfolio), while the annualized returns of VIX-based trading strategies range from 22.05% to 42.38%. Although the standard deviations in Panel B is slightly higher than those standard deviation 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 shifting investments between top and bottom ME-sorted deciles and BE/ME-sorted deciles are 42.38% and 40.49%, respectively. The significant profitability associated with shifting investments between size and value portfolios is consistent with the findings of Copeland and Copeland (1999). With the exception of ME-sorted portfolios, the skewnesses of the long-short portfolio returns 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.

[Insert Table 2]

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 11.66% after adopting the VIX-based trading strategy. The success rate of our VIX trading strategies ranges from 0.54 to 0.60 for the 16 cases, indicating that more often than not the VIX-based trading strategies generate larger returns than the benchmark portfolios.

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-square associated with the four models. Panel A presents the results of the CAPM model, Panel B reports the results from the FF three factors plus the momentum (SMB, HML, RMRF, UMD), Panel C shows the results from the FF five factors plus momentum (SMB, HML, RMRF, CMA, RMW, UMD), and Panel D shows the results of the four mispricing factors model of Stambaugh and Yuan (2016) (RMRF, MSMB, MGMT, PERF).[12] 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 between the small-cap and large-cap leg sorted on the two composite mispricing measures used to construct MGMT and PERF.

[Insert Table 3]

The alphas in Table 3 are generally smaller than the excess returns 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-square 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 1% or better), implying that adjusting for risk mitigates but does not fully eliminate the profitability of our VIX strategies.

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)

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

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

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

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 alpha in each regression shows to the abnormal returns after controlling for market timing ability of our VIX-based trading strategy.

[12] We thank Yu Yuan for making the Stambaugh and Yuan daily mispricing factors available on his personal website.

[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 significantly, except for the ME sorted portfolio. The regression alphas are mostly significantly positive, except for the ME sorted portfolio. Panel B reports the results of Equation (3). The coefficients γ_m are also mostly insignificant, while the intercepts (α) 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 ME-sorted portfolios, indicating that the market timing explanation exclusively applies to these portfolios.

4.4 Robustness checks

We run a battery of additional tests to examine the robustness of our VIX-based cross-sectional trading strategies. We first examine whether the profitability of our VIX-based trading strategies is robust to alternative definitions of what a "substantially high" VIX means. Recall that in the previous tables, 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 there are 25 trading days in 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 5 shows that the profitability of our VIX-based trading strategies is not very 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 horizon. We also use 0%, 5%, 15% and 20% as alternative thresholds for our definition of substantially high VIX. The untabulated results show that the excess returns are positive and significant across all these thresholds.

[Insert Table 5]

We then test whether transaction costs can eliminate the profitability of our trading strategy in Panel B of Table 5. Following Han et al. (2013), we calculate Break-even trading cost (BETC) to check whether our VIX-based trading strategy survives the transaction costs without taking a stand on actual transaction costs. Break-even trading cost is the trading cost that makes the average actual returns of our VIX-based trading strategy become zero. The higher BETC of a trading strategy, the more likely that this trading strategy is profitable after the transaction costs. Panel B of Table 5 reveals that all estimated BETCs are larger than 50 basis points. This demonstrates that the transaction costs must be unrealistically high to eliminate the profitability of our VIX-based trading strategy. Some studies choose to set the transaction costs at a conservative rate of 25 basis points (see, Lynch and Balduzzi, 2000), other studies choose to calculate the realized transaction costs (Frazzini et al. 2012). For instance, Frazzini et al. (2012) find the trading costs is 11.21 basis points for large-cap stocks and 21.27 basis points for small-cap stocks. In our case, the lowest BETC for trading on size portfolio is 116.53 basis points calculated with 1-day VIX benchmark, and even the lowest BETC for size portfolio is significantly higher for the 21.27 bps realistic transaction costs in Frazzini et al. (2012).

We also find that the BETCs increase almost monotonically with the length of the horizon used in the definition of VIX strategies in Panel B of Table 5. When longer horizons are used as benchmarks, the average returns tend to be more stable and consecutively high or low VIX days may be obtained without trading. Take the 25-day window period as an example, the BETCs range from 73.47 to 143.25 basis points, which is much larger than 50 basis points. 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. Our trading strategies have such reasonably high BETC relies not only on the high return but also on the low transaction frequency. Take 25-day window period size portfolio trading strategy as an example, the actual number of actual transactions is 1356 out of 11329 trading days, which means in this sample period the average portfolio holding time length is more than 8 trading days.

Furthermore, 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 high 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. Interestingly, the difference between Moody's AAA and Baa bond yields (Default Spread, or DS) could explain the excess return very well. We find only 8 out of 16 trading strategies still have significant and large positive abnormal return after controlling for Default Spread.

Moreover, 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 reasonably outperforms the market. We also examine the persistence of the performance of our VIX-based trading strategy. In unreported results, we show that the annual average return of our trading strategy is consistently higher than the S&P500 index return every calendar year in our sample. We also investigate whether the profitability of our trading strategies is sensitive to choice of alternative implied volatility indexes. We show that strategies that based on trading signal from other indexes, 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.

Additionally, we design two additional VIX based trading strategies. The first strategy involves holding sentiment-prone stocks and shorting sentiment-immune stocks when VIX is low and shorting sentiment-prone stocks and longing sentiment-immune stocks when VIX is substantially high. We show that this strategy generates significant positive excess returns and high Sharpe ratios, albeit the magnitudes of the excess returns are smaller than those reported in our baseline results. The second trading strategy is applied on the decile portfolios. This strategy involves holding 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 than these two alternative trading strategies because these alternative strategies require short-selling, which can be costly and limited for some investors. For example, mutual funds are typically prohibited from short-selling.

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 US stock market. In this case, we argue that VIX is a very conservative measure of the overall market sentiment. Also, because size-based portfolio return is highly correlated with other characteristics based portfolio return, one may question the profitability of VIX on timing those portfolios are mainly due to the size effect. To To mitigate the effect of size, we also examine the profitability of VIX-based timing strategy on value-weighted cross-sectional returns. It turns out that when applying VIX-based trading strategy on value-weighted returns, the profitability is slightly smaller than applying it on equal-weighted returns. Still, the raw and risk-adjusted returns of VIX-based trading strategy remain significantly positive in most cases.

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 holding sentiment-immune stocks when VIX is high. The motivation of our trading strategies is the short-run negative VIX-return relation arises from the delayed arbitrage theory (Abreu and Brunnermeier, 2002). In this paper, VIX is deemed as a daily measure of investor sentiment, and due to the lack of coordinated actions among arbitrageurs, the mispricing caused by investor sentiment may even amplify, which leads to a short-run negative VIX-return relationship. Interpreting VIX-return relation from behavioural perspective enables us to interpret the negative short-run relation as the return momentum caused by delayed arbitrage and interpret the positive long-run relation as the correction of mispricing. Unlike most existing literature that focus on interpreting the positive VIX-return relation, we argue that delayed arbitrage leads to high returns for sentiment-prone stocks following a decline in VIX (high sentiment), and that flight-to-quality leads to the better performance of sentiment-immune stocks over sentiment-prone stocks following an increase in VIX (low sentiment).

Consistent with our explanation, we find that VIX strongly and negatively associates with one-day forward stock return in the in-sample predictive regressions. This finding is robust with or without controlling for other well-documented risk factors. We conduct various robustness tests to further demonstrate that seeing VIX as investor sentiment could better explain the return momentum and reversal. For instance, we find the effect of VIX is stronger during the high sentiment period, which is consistent with the argument that sentiment plays a less important role due to the short-sell constraints in low sentiment period.

Following on the short-run negative VIX-return pattern, we devise trading strategies to capture the return momentum attributed by investor sentiment. We not only cover the value and size rotation based on VIX, but also explore the profitability of VIX timing over a large spectrum of cross-sectional portfolios based on the extent to which a stock is exposed to market wide investor sentiment. We find that our VIX-based trading strategies generate significant excess returns and higher Sharpe ratios. The excess returns of our trading strategies cannot be fully explained by Fama-French five factors, momentum factors, liquidity, and other macroeconomic variables. 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 perspective explanation on VIX-return relation.

To sum up, we contribute to existing literature by combine the delayed arbitrage theory and flight-to-quality to explain the pattern between sentiment-based cross-sectional stock returns and VIX. We show strong empirical evidence supporting the short-run return momentum caused by VIX. From the behavioural finance point of view, we use the negative VIX-return relationship to design highly profitable and practical trading strategies which is to shift asset allocation to sentiment-prone stocks when VIX is low and to sentiment-immune stocks when VIX is high.

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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-immune decile (I) or the long-short portfolio of sentiment-prone decile over sentiment-immune decile (P-I). The control variables include the FF 5 factors and the momentum factor (UMD). 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-immune 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 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A. All Samples			Panel B VIX<-0.5			Panel C VIX>0.5		
	P	I	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$
ME	1	10	-0.045***	-0.037**	0.008**	-0.181***	-0.158***	0.023*	-0.054	-0.046	0.008
			(-2.688)	(-2.406)	(2.323)	(-3.231)	(-3.168)	(1.684)	(-1.547)	(-1.489)	(0.822)
Age	1	10	-0.007	-0.014	-0.007	-0.078*	-0.090**	-0.012	0.007	-0.014	-0.021
			(-0.708)	(-1.372)	(-1.284)	(-1.760)	(-2.535)	(-0.485)	(0.361)	(-0.641)	(-1.508)
Sigma	10	1	-0.011	-0.015	-0.004	-0.162***	-0.133**	0.029	-0.004	-0.022	-0.018
			(-0.899)	(-1.173)	(-0.805)	(-2.850)	(-2.570)	(1.306)	(-0.166)	(-0.792)	(-1.414)
E/BE	1	10	-0.016*	-0.021*	-0.005	-0.075*	-0.145***	-0.070***	-0.024	-0.031	-0.007
			(-1.769)	(-1.821)	(-0.875)	(-1.881)	(-3.604)	(-2.673)	(-1.410)	(-1.330)	(-0.492)
D/BE	1	10	-0.024***	-0.016*	0.008	-0.105***	-0.099***	0.005	-0.029*	-0.025	0.004
			(-3.045)	(-1.905)	(0.887)	(-2.875)	(-3.221)	(0.226)	(-1.678)	(-1.448)	(0.170)
PPE/A	1	10	0.001	-0.009	-0.010	0.022	-0.031	-0.053	0.018	-0.001	-0.019
			(0.050)	(-1.347)	(-0.906)	(0.380)	(-0.973)	(-1.064)	(0.805)	(-0.059)	(-0.776)
RD/A	10	1	0.014**	0.005	-0.009	-0.086*	-0.120**	-0.035*	-0.007	-0.015	-0.007
			(1.979)	(0.522)	(-1.452)	(-1.875)	(-2.483)	(-1.721)	(-0.498)	(-0.676)	(-0.533)
BE/ME	10	1	-0.037***	-0.033**	0.003	0.008	-0.098**	-0.106***	-0.068**	-0.055	0.013
			(-2.745)	(-2.001)	(0.438)	(0.186)	(-2.147)	(-2.943)	(-2.450)	(-1.620)	(0.872)
EF/A	1	10	-0.011	-0.016*	-0.005	-0.011	-0.098***	-0.086**	-0.040***	-0.034*	0.006
			(-1.601)	(-1.791)	(-0.482)	(-0.348)	(-2.858)	(-2.314)	(-3.071)	(-1.789)	(0.317)
GS	1	10	-0.009	-0.015	-0.006	-0.022	-0.109***	-0.087**	-0.016	-0.023	-0.007
			(-1.546)	(-1.307)	(-0.686)	(-0.640)	(-2.746)	(-2.494)	(-1.530)	(-1.040)	(-0.364)
BE/ME	1	5	0.005	0.003	-0.003	-0.097***	-0.106***	-0.019	0.018	0.013	-0.010
			(0.739)	(0.438)	(-0.406)	(-2.853)	(-2.943)	(-0.866)	(1.445)	(0.872)	(-0.632)
EF/A	10	5	-0.005	-0.005	0.000	-0.070**	-0.086**	-0.033*	0.012	0.006	-0.011
			(-0.574)	(-0.482)	(-0.073)	(-1.971)	(-2.314)	(-1.662)	(0.806)	(0.317)	(-0.840)
GS	10	5	-0.004	-0.006	-0.004	-0.081**	-0.087**	-0.012	0.004	-0.007	-0.021
			(-0.554)	(-0.686)	(-0.581)	(-2.280)	(-2.494)	(-0.569)	(0.304)	(-0.364)	(-1.415)
BE/ME	10	5	-0.032**	-0.033**	-0.003	-0.088**	-0.098**	-0.019	-0.050*	-0.055	-0.010
			(-2.193)	(-2.001)	(-0.406)	(-2.081)	(-2.147)	(-0.866)	(-1.688)	(-1.620)	(-0.632)
EF/A	1	5	-0.016**	-0.016*	0.000	-0.081***	-0.098***	-0.033*	-0.028**	-0.034*	-0.011
			(-2.378)	(-1.791)	(-0.073)	(-2.616)	(-2.858)	(-1.662)	(-2.003)	(-1.789)	(-0.840)
GS	1	5	-0.013	-0.015	-0.004	-0.103***	-0.109***	-0.012	-0.012	-0.023	-0.021
			(-1.399)	(-1.307)	(-0.581)	(-2.739)	(-2.746)	(-0.569)	(-0.724)	(-1.040)	(-1.415)

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-immune 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-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VIX and hold the sentiment-immune decile after high VIX. VIX-based trading strategy is to buy and hold the sentiment-immune 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 t-test significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

			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	23.11***	13.95	-0.53	1.66	42.38***	15.70	0.17	2.70	19.26***	23.58	0.97	0.54
Age	1	10	10.90***	11.21	-0.20	0.97	28.35***	16.99	-0.27	1.67	17.42***	17.75	0.27	0.55
Sigma	10	1	18.85***	15.55	-0.20	1.21	38.25***	18.20	-0.32	2.10	19.45***	10.44	-0.10	0.58
E/BE	1	10	13.37***	7.91	-0.03	1.69	33.41***	17.90	-0.37	1.87	20.05***	18.65	-0.18	0.57
D/BE	1	10	11.58***	8.84	-0.26	1.31	30.83***	16.95	-0.33	1.82	19.26***	16.39	-0.04	0.56
PPE/A	1	10	-3.15	10.12	-0.12	-0.31	22.38***	15.98	-0.20	1.40	25.55***	19.91	-0.11	0.57
RD/A	10	1	9.23***	12.58	-0.05	0.73	31.43***	20.34	-0.34	1.54	22.20***	15.74	-0.36	0.60
BE/ME	10	1	17.60***	12.04	-0.24	1.46	40.49***	17.59	-0.14	2.30	22.92***	24.08	0.18	0.58
EF/A	1	10	11.84***	8.55	-0.24	1.38	29.67***	17.79	-0.40	1.67	17.82***	22.49	-0.14	0.58
GS	1	10	12.39***	7.56	-0.17	1.64	31.82***	18.35	-0.37	1.73	19.45***	22.09	-0.13	0.57
BE/ME	1	5	10.42***	13.41	-0.02	0.78	22.05***	19.51	-0.32	1.13	11.66***	9.16	-0.29	0.58
EF/A	10	5	8.61***	13.60	-0.24	0.63	23.02***	18.82	-0.34	1.22	14.44***	8.11	-0.28	0.58
GS	10	5	8.08***	13.88	-0.22	0.58	22.73***	18.80	-0.32	1.21	14.66***	7.92	-0.14	0.59
BE/ME	10	5	28.01***	9.20	0.20	3.04	41.31***	16.15	-0.23	2.56	13.35***	10.68	0.14	0.57
EF/A	1	5	20.46***	9.24	-0.53	2.21	32.93***	16.03	-0.42	2.05	12.49***	8.40	-0.03	0.58
GS	1	5	20.47***	10.81	-0.42	1.89	35.11***	16.56	-0.39	2.12	14.66***	8.41	0.12	0.59

Table 3: CAPM and Fama-French 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. Panel D reports the results of RVIX regressed on Stambaugh and Yuan (2016) four mispricing factors. 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 significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A CAPM		Panel B FF3 and UMD		Panel C FF5 and UMD		Panel D Mispricing 4	
	P	I	α	R^2	α	R^2	α	R^2	α	R^2
ME	1	10	10.03***	85.35	10.07***	85.35	10.35***	87.04	10.89***	85.56
			(5.48)		(5.48)		(5.68)		(5.50)	
Age	1	10	11.11***	70.30	10.07***	74.07	5.88***	81.62	6.40***	74.66
			(5.34)		(5.59)		(3.68)		(3.07)	
Sigma	10	1	17.49***	19.53	16.65***	24.79	14.55***	30.44	13.86***	29.73
			(8.56)		(8.51)		(7.48)		(6.88)	
E/BE	1	10	12.94***	80.75	11.90***	85.95	12.97***	86.46	11.59***	85.13
			(6.91)		(8.19)		(9.18)		(7.35)	
D/BE	1	10	13.45***	69.98	11.92***	76.28	11.90***	77.71	10.13***	76.06
			(7.21)		(7.23)		(7.17)		(5.55)	
PPE/A	1	10	19.46***	52.24	17.41***	62.24	15.53***	64.12	17.38***	59.37
			(6.34)		(6.79)		(5.78)		(6.07)	
RD/A	10	1	17.00***	60.73	14.50***	80.47	13.95***	82.49	14.92***	75.27
he			(7.81)		(9.66)		(9.62)		(8.51)	
BE/ME	10	1	14.26***	72.15	12.99***	81.24	18.42***	85.22	17.68***	83.73
			(4.71)		(5.49)		(8.47)		(7.30)	
EF/A	1	10	9.98***	67.64	9.14***	81.01	14.11***	84.54	14.18***	83.25
			(2.84)		(3.59)		(6.32)		(5.71)	
GS	1	10	11.43***	73.47	10.47***	85.31	14.54***	87.98	14.79***	87.27
			(3.79)		(4.95)		(8.14)		(7.44)	
BE/ME	1	5	8.89***	51.18	8.39***	61.02	7.02***	67.55	6.53***	63.34
			(7.43)		(8.27)		(7.01)		(5.75)	
EF/A	10	5	12.01***	50.06	10.99***	63.02	10.02***	65.29	9.34***	62.61
			(10.19)		(11.04)		(10.19)		(8.54)	
GS	10	5	12.42***	44.63	11.39***	57.46	10.53***	59.86	9.97***	57.74
			(10.44)		(10.80)		(10.48)		(9.26)	
BE/ME	10	5	9.59***	69.11	9.04***	77.72	8.46***	78.83	8.01***	76.89
			(8.04)		(8.60)		(8.61)		(7.45)	
EF/A	1	5	9.49***	71.05	8.69***	82.02	8.47***	82.58	8.15***	80.59
			(9.95)		(12.63)		(12.85)		(10.86)	
GS	1	5	11.86***	61.85	10.96***	71.28	10.35***	73.41	10.30***	70.05
			(11.17)		(12.02)		(11.87)		(10.69)	

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, and Panel B show the results of Henriksson and Marton (1981) regressions. The alphas are annualized and are in percentages. *** and ** indicates statistical significance at 1% and 5% level, respectively. The Newey and West robust t-statistics are in parenthesis. The sample period is from 1990/01/01 to 2016/04/30.

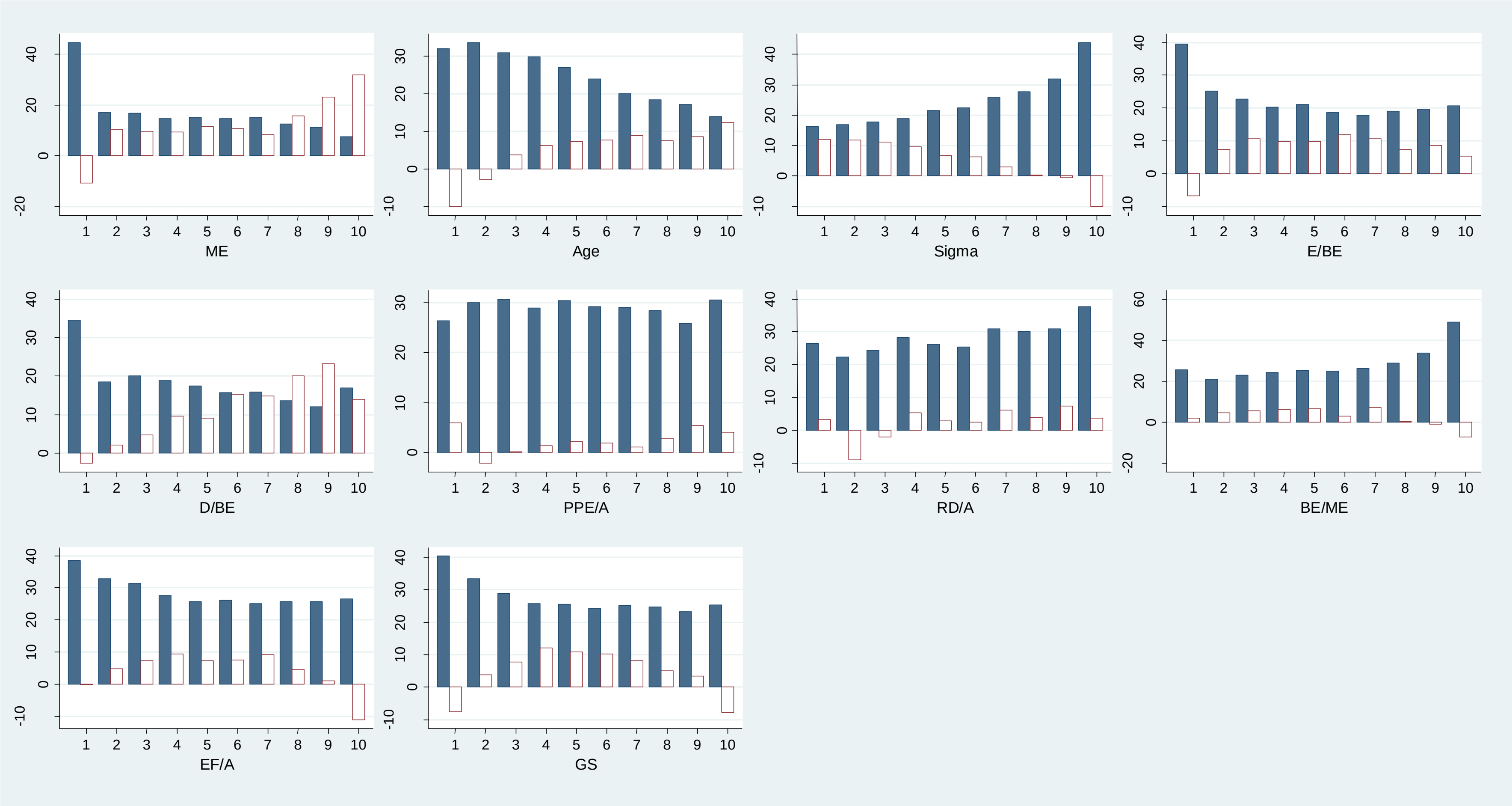
			Panel A. TM Regression				Panel B. HM Regression			
	P	I	α	β_m	β_{m^2}	R^2	α	β_m	γ_m	R^2
ME	1	10	1.60	1.22***	2.62***	85.86	-10.98***	1.11***	0.22***	85.72
			(0.66)	(34.82)	(3.63)		(-2.66)	(30.27)	(4.63)	
Age	1	10	9.92***	0.83***	0.37	70.32	10.98***	0.83***	0.00	70.3
			(3.79)	(25.20)	(0.54)		(2.68)	(24.68)	(0.03)	
Sigma	10	1	17.13***	0.26***	0.11	19.52	18.06***	0.26***	-0.01	19.52
			(7.85)	(10.10)	(0.20)		(4.97)	(7.16)	(-0.14)	
E/BE	1	10	13.66***	0.94***	-0.22	80.75	16.79***	0.95***	-0.04	80.77
			(7.04)	(43.66)	(-0.70)		(6.23)	(38.57)	(-1.50)	
D/BE	1	10	13.51***	0.76***	-0.02	69.97	12.75***	0.76***	0.01	69.98
			(7.33)	(26.24)	(-0.03)		(3.97)	(21.36)	(0.19)	
PPE/A	1	10	23.35***	0.80***	-1.21	52.38	33.55***	0.87***	-0.15***	52.46
			(5.56)	(17.10)	(-1.37)		(7.37)	(18.83)	(-3.31)	
RD/A	10	1	20.94***	0.68***	-1.22**	60.97	28.80***	0.74***	-0.12***	60.99
			(9.08)	(19.11)	(-2.39)		(7.49)	(18.36)	(-2.88)	
BE/ME	10	1	14.87***	1.14***	-0.19	72.15	18.53***	1.16***	-0.04	72.16
			(4.42)	(40.03)	(-0.26)		(3.73)	(33.49)	(-0.85)	
EF/A	1	10	12.83***	1.03***	-0.89	67.7	23.69***	1.10***	-0.14***	67.81
			(3.04)	(47.60)	(-0.97)		(4.51)	(37.08)	(-2.72)	
GS	1	10	13.02***	1.06***	-0.49	73.48	20.85***	1.10***	-0.10**	73.55
			(3.76)	(61.26)	(-0.75)		(4.84)	(51.84)	(-2.42)	
BE/ME	1	5	10.77***	0.37***	-0.59	51.34	14.54***	0.39***	-0.06**	51.35
			(7.43)	(19.06)	(-1.59)		(5.80)	(19.74)	(-2.15)	
EF/A	10	5	13.28***	0.32***	-0.40	50.15	15.28***	0.34***	-0.03	50.12
			(9.09)	(20.19)	(-1.01)		(6.32)	(18.12)	(-1.24)	
GS	10	5	14.13***	0.29***	-0.53	44.8	16.57***	0.32***	-0.04	44.75
			(9.63)	(18.20)	(-1.35)		(6.78)	(16.27)	(-1.56)	
BE/ME	10	5	8.78***	0.50***	0.25	69.13	7.22***	0.48***	0.02	69.13
			(7.53)	(35.63)	(1.25)		(4.24)	(29.78)	(1.34)	
EF/A	1	5	9.36***	0.40***	0.04	71.05	10.01***	0.40***	-0.01	71.05
			(8.77)	(42.75)	(0.17)		(6.08)	(31.70)	(-0.31)	
GS	1	5	11.51***	0.37***	0.11	61.86	11.25***	0.37***	0.01	61.85
			(10.06)	(25.69)	(0.38)		(6.16)	(20.62)	(0.31)	

Table 5: Return and BETC on Different Trading Signal Horizons

This table reports the returns and 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. Panel A reports the returns of our VIX-based trading strategy when using different horizon average to define high VIX, and the returns are in percentages. Panel B reports the correspondent break-even transaction costs and the costs are in basis points. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A. Profitability on different trading signal horizons						
			1-day	5-day	10-day	25-day	60-day	120-day	250-day
ME	1	10	38.00	41.81	42.51	43.21	42.44	40.00	37.91
Age	1	10	26.24	29.05	29.25	28.95	30.08	28.21	26.15
Sigma	10	1	36.34	38.43	38.67	38.13	39.34	37.44	35.62
E/BE	1	10	31.81	34.03	34.11	33.69	33.78	32.89	30.8
D/BE	1	10	29.38	31.04	30.91	31.34	31.76	30.46	29.00
PPE/A	1	10	22.93	23.26	23.08	22.51	22.64	23.56	23.61
RD/A	10	1	32.58	33.29	32.58	31.57	32.04	31.62	30.38
BE/ME	10	1	39.54	40.36	40.11	40.77	38.9	38.53	37.54
EF/A	1	10	30.97	29.52	29.66	29.81	28.68	28.84	29.1
GS	1	10	31.88	31.97	32.45	32.05	31.59	31.65	30.75
BE/ME	1	5	22.27	23.02	23.02	22.16	23.26	23.50	22.68
EF/A	10	5	21.32	22.99	23.37	23.00	23.96	23.30	22.55
GS	10	5	20.78	22.01	21.98	22.68	23.49	22.64	21.95
BE/ME	10	5	40.58	42.14	41.90	41.70	40.93	40.80	38.99
EF/A	1	5	32.53	32.74	33.27	33.05	32.88	32.37	31.88
GS	1	5	33.22	34.54	34.98	35.28	35.63	34.84	33.25
			Panel B. BETC on different trading signal horizons						
			1-day	5-day	10-day	25-day	60-day	120-day	250-day
ME	1	10	116.53	124.14	124.57	143.25	177.3	205.27	220.78
Age	1	10	80.47	86.25	85.72	95.97	125.67	144.78	152.31
Sigma	10	1	111.45	114.12	113.32	126.41	164.37	192.12	207.45
E/BE	1	10	97.56	101.04	99.97	111.69	141.15	168.77	179.38
D/BE	1	10	90.09	92.16	90.57	103.92	132.70	156.34	168.90
PPE/A	1	10	70.30	69.07	67.65	74.63	94.60	120.92	137.48
RD/A	10	1	99.92	98.87	95.49	104.67	133.86	162.29	176.92
BE/ME	10	1	121.26	119.84	117.56	135.18	162.53	197.72	218.62
EF/A	1	10	94.98	87.64	86.93	98.84	119.84	147.98	169.44
GS	1	10	97.77	94.94	95.11	106.26	131.98	162.43	179.06
BE/ME	1	5	68.29	68.34	67.45	73.47	97.18	120.62	132.07
EF/A	10	5	65.37	68.26	68.49	76.26	100.10	119.58	131.33
GS	10	5	63.73	65.37	64.41	75.20	98.13	116.20	127.83
BE/ME	10	5	124.43	125.13	122.78	138.26	171.00	209.37	227.04
EF/A	1	5	99.74	97.22	97.50	109.58	137.36	166.13	185.67
GS	1	5	101.86	102.56	102.53	116.98	148.85	178.82	193.64

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



We place the daily return observations into bins according to the decile rank that a characteristic takes. The subtitles show the sentiment-sensitivity measure used to sort deciles. Then we sort return by 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

Table A gives a detailed description for the variables needed to construct the portfolios.

Table A: 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 period 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 raio 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) less 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)