# 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-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 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 synchronization problem of Abreu and Brunnermeier (2002).

**Key words:** 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" (Kaplanski and Levy, 2010; Whaley, 2000, 2009; Da et al, 2015), with low VIX indicating high overall market sentiment, and vice versa. Consistent with this view, VIX was substantially high in the NBER recession and considerably 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 (e.g., Merton, 1980; Fleming et al., 2003; Clements and Silvernnoinen, 2013). They argue that because of the positive mean-variance relationship, an increase VIX should be associated with higher future return. Other studies deem VIX as an "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 (e.g., 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. Banerjee et al. (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 whether VIX predicts the long-run reversals arising from the correction of mispricing.

Unlike previous studies, which commonly focus on the in-sample ability of VIX to predict 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 stock returns following sentiment increase. Our empirical tests show significant 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 indicator, allowing us 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-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]. We use firm characteristics, namely 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 changes 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, and have high financial distress and great growth opportunity. In this study, we argue 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 always longs sentiment-prone portfolios and shorts sentiment-immune portfolios. Specifically, 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 the VIX-based trading strategies over their correspondent benchmark portfolios range from 11.66% to 25.55%. 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

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

shows that our trading strategy remains profitable after considering effects of macroeconomic factors such as term spread, default spread, TED spread and the liquidity factor. Finally, we calculate the breakeven transaction cost to see whether our trading strategy could survive the transaction costs The break-even transaction costs associated with our strategies are generally higher than 50 basis points, suggesting that transaction costs are unlikely to eliminate the profitability of our trading strategies[5].

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 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) view VIX as a proxy for future discount rate, i.e., higher VIX means higher future discount rates and falling prices. However, this argument is not consistent with the widely documented reversal effect of VIX on stock return. Our study uses the investor sentiment channel to reconcile between the momentum and reversal effects of VIX. 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. The finding that VIX-based strategies can generate significant abnormal returns may help explain the wide application of such strategies in 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.

[5] 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 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.

## 2. Related Literature

Existing empirical studies commonly show that investor sentiment and future returns are inversely related. The contrarian predictive power of investor sentiment on future return are usually tested with low frequency data, as most of the commonly used investor sentiment measures, including mutual fund flow, consumer confidence index, closed-end fund discount, Baker Wurgler index, are only available at monthly frequency (see, e.g., Neal and Wheatley, 1998; Lemmon and Portniaguina, 2006; Lee et al., 1991; Baker and Wurgler, 2006, 2007). Most prior studies investigate the extent to which these monthly sentiment indicators predict the monthly, quarterly, or longer-term future returns. These studies often argue that bullish investor sentiment pushes current price above fundamentals and the correction of mispricing results in lower future returns.

However, the delayed arbitrage model of Abreu and Brunnermeier (2002) implies that the negative relation between investor sentiment and future return may not hold in the short run. This is because in a market where arbitrageurs do not know their sequence in notifying the mispricing, sophisticated investors choose to beat the gun and ride the trend. The lack of coordination among arbitrageurs may, in turn, lead to a persistent mispricing particularly in the short run (Abreu and Brunnermeier, 2002). Ample empirical studies also indicate that sophisticated arbitrageurs actively ride the bubbles and contribute to the bubble (e.g., 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 returns. The momentum effect of investor sentiment on future returns does not conflicts with the well-documented reversal effect of investor sentiment. To quote Yu (2011, P179), who studies the reversal effect of investor sentiment, “the synchronization problem among arbitrageurs may create limits to arbitrage or even amplify the mispricing”. In another word, the arbitrageurs fail to conduct synchronized actions to exploit profit from the mispricing, and therefore they are more willing to jump on the bandwagon and benefit from the growing bubble. In this case, the reversal effect of investor sentiment could be more pronounced due to the delayed arbitrage. Our study compliments the previous literature by investigating at the momentum effect of sentiment on the short-run future returns.

While several studies have already examined the predictive power of VIX on future returns, these VIX studies usually view VIX as a proxy for expected future volatility or liquidity rather than as a sentiment measure. For example, Banerjee et al. (2007) propose a theory in which the positive association between 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 that market volatility has a negative price and high levels of volatility 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 often regarded as 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 hence higher future returns.

However, while the theories proposed by Banerjee et al. (2007) and Nagel (2012) explain the positive long-term VIX-return relation, i.e., the reversal effect, they do not work well in explaining the negative short-run VIX-return relation, i.e. the return momentum. To reconcile the reversal with the momentum effects of VIX on return, we consider VIX as a measure of investor sentiment.

In this study, we argue that VIX is not only an indicator of a limit of arbitrage but also a measure of investor sentiment. Tu et al. (2016) argue that VIX can predict absolute mispricing because of the limit to arbitrage. Specifically, they argue that high VIX implies high expected volatility and therefore stronger limits to arbitrage, which in turn amplifies mispricing. However, VIX can also be view as a sentiment measure. If limit to arbitrage is assumed to be constant, VIX is expected to be negatively related to the contemporaneous mispricing, resulting in higher return momentum r when arbitrage is delayed. Unlike the Tu et al. (2016), we use VIX-based strategies to exploit mispricing. Viewing VIX as a sentiment indicator reconciles the long-term return reversals with the short-term return momentum following increases in VIX.

Existing studies find that the long-term return reversals following sentiment increases 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. Some stocks, such as young and small stocks, are more prone to sentiment while others are tend to be sentiment immune. Hence, sentiment may play a more prominent role in predicting the return disparity between sentiment-prone stocks and sentiment immune stocks than predicting aggregate market returns. Stambaugh, Yu and Yuan (2011) argue that stocks with more constraints to arbitrage are more sensitive to investor sentiment. Ljungqvist and Qian (2016) argue that, because of the synchronization problem (Abreu and Brunnermeier, 2002), sophisticated investors may deliberately target stocks with sever short-sell constraints, limiting the scope of coordinated short-selling actions. Campbell et al. (2011) also find that distressed stocks underperform more severely following increases in VIX. This evidence suggests that the short-term return momentum caused by delayed arbitrage may also be stronger in the cross-section. Specifically, we hypothesize that sentiment-prone stocks will exhibit stronger momentum effect as they are more prone to sophisticated arbitrageurs and more difficult to arbitrage during the bubble periods.

Several studies use VIX to time the market. Some of these studies apply the mean-variance theory to design VIX-based volatility timing strategies (Fleming et al. 2001; Johannes et al. 2002; Fleming et al., 2003; Clements and Silvernnoinen, 2013). 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).[8]

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 exploiting 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 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 investor to value. Thus, firms with low BE/ME, high EF/A, and high

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

GS are more prone to investor sentiment. The middle deciles for BE/ME, EF/A, and GS portfolios are the most sentiment-immune. Hence, the long-short portfolios for these three characteristics are defined as the top decile minus the middle decile or the bottom decile minus the middle decile. 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, 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 2018/12/31 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 (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 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.[9]

## 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 these returns with the returns of the benchmark portfolios.

### 4.1. 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:

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

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). $\mathrm{VIX}_{t-1}$ is the

[9] 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.

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 (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.[10] 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 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 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.[11]

**[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 for the remaining 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-immune 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-immune decile on the lagged VIX, respectively. The results suggest that the lagged VIX has a much stronger predictive power on the sentiment-prone stocks than the sentiment-immune stocks. 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

[10] We set a maximum lag of 15 when calculating Newey-West robust standard errors for the coefficients.
[11] 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.

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 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 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 that the lagged VIX is 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 periods of high sentiment, as short sale constraints are generally more binding during these periods.[12]

## 4.2. Two-way Sorts

We divide our sample into high and low VIX periods based on 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 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 into two groups. The first group consists of the returns following high sentiment days, while the second one includes the returns following high or normal 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 $\mathrm{t}-26$ 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.

**[Insert Figure 1]**

[12] 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-immune 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.

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 for 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 the 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 characteristics.

### 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.[13] 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

[13] 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 (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 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 adjusted abnormal alphas are mostly even higher than the unadjusted original trading strategy returns. The magnitude of the abnormal alphas in Table 2 clearly demonstrates 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 shifting 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 shifting investments between size and value portfolios is consistent with the findings of Copeland and Copeland (1999). Apart from the ME-sorted portfolio, 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 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.

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 six asset pricing models. Panel A presents the results from the CAPM model, Panel B reports the results of FF3 model, Panel C

RVIX is adjusted for the FF five factors plus the momentum (SMB, HML, RMRF, CMA, RMW, MOM ), Panel D adjust RVIX 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).[14] 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.

**[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)

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

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

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

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

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 $\gamma_m$ 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, $\beta_{m^2}$, are not statistically significantly positive, except for the 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 strong profitability of timing other portfolios on VIX.

Panel B reports the results of Equation (3). The coefficients $\gamma_m$ 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 $\gamma_m$ and significantly negative alphas are only observed in the case of ME-sorted portfolios, indicating that the market timing explanation applies exclusively 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 a "substantially high" VIX. 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. 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 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 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 the BETC of a trading strategy, the more likely that this trading strategy is profitable after 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), while other studies choose to calculate the realized transaction costs (Frazzini et al. 2012). For instance, Frazzini et al. (2012) find that 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 the size portfolio is 99.18 basis points, which is significantly higher for the realistic transaction cost of 21.27 basis points documented by Frazzini et al. (2012).

We also find that the BETCs increase almost monotonically with the length of the horizon used to construct the VIX strategies in Panel B of Table 5. 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. Take the 25-day window of the size portfolio trading strategy as an example. The actual number of transactions required in this strategy is 1356 (out of a total 11329 trading days), which translates into an average holding of 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.

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 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. 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 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 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 than these two alternative trading strategies because 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 US stock market. This makes VIX a rather conservative measure of the overall market sentiment. Furthermore, because the 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 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. However, both 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 sentiment-immune 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 positive VIX-return relation, we argue that delayed arbitrage increase the returns of sentiment-prone stocks following a decline in VIX (high sentiment), whereas flight-to-quality leads to better performance for sentiment-immune 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-immune stocks when VIX is high. We find that these 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 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 to sentiment-immune 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-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 (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-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 2016/12/31.

| | | | Panel A. All Samples | | | Panel B VIX<-0.5 | | | Panel C VIX>0.5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | P | I | $R_{P-I,t}$ | $R_{P,t}$ | $R_{I,t}$ | $R_{P-I,t}$ | $R_{P,t}$ | $R_{I,t}$ | $R_{P-I,t}$ | $R_{P,t}$ | $R_{I,t}$ |
| ME | 1 | 10 | -0.05*** | -0.04** | 0.01** | -0.18*** | -0.16*** | 0.02* | -0.05 | -0.05 | 0.01 |
| | | | (-2.69) | (-2.41) | (2.32) | (-3.19) | (-3.10) | (1.73) | (-1.54) | (-1.49) | (0.81) |
| Age | 1 | 10 | -0.01 | -0.01 | -0.01 | -0.08* | -0.09** | -0.01 | 0.01 | -0.01 | -0.02 |
| | | | (-0.71) | (-1.37) | (-1.28) | (-1.77) | (-2.53) | (-0.49) | (0.35) | (-0.64) | (-1.51) |
| Sigma | 10 | 1 | -0.01 | -0.01 | -0.00 | -0.16*** | -0.13** | 0.03 | -0.00 | -0.02 | -0.02 |
| | | | (-0.90) | (-1.17) | (-0.81) | (-2.74) | (-2.43) | (1.38) | (-0.16) | (-0.79) | (-1.42) |
| E/BE | 1 | 10 | -0.02* | -0.02* | -0.00 | -0.08* | -0.14*** | -0.07** | -0.02 | -0.03 | -0.01 |
| | | | (-1.77) | (-1.82) | (-0.88) | (-1.86) | (-3.46) | (-2.57) | (-1.38) | (-1.32) | (-0.49) |
| D/BE | 1 | 10 | -0.02*** | -0.02* | 0.01 | -0.10*** | -0.10*** | 0.00 | -0.03* | -0.03 | 0.00 |
| | | | (-3.05) | (-1.90) | (0.89) | (-2.80) | (-3.06) | (0.23) | (-1.68) | (-1.43) | (0.17) |
| PPE/A | 1 | 10 | 0.00 | -0.01 | -0.01 | 0.02 | -0.03 | -0.05 | 0.02 | -0.00 | -0.02 |
| | | | (0.05) | (-1.35) | (-0.91) | (0.39) | (-1.00) | (-1.07) | (0.81) | (-0.06) | (-0.77) |
| RD/A | 10 | 1 | 0.01** | 0.00 | -0.01 | -0.09* | -0.12** | -0.04* | -0.01 | -0.01 | -0.01 |
| | | | (1.98) | (0.52) | (-1.45) | (-1.81) | (-2.36) | (-1.65) | (-0.50) | (-0.67) | (-0.54) |
| BE/ME | 10 | 1 | -0.04*** | -0.03** | 0.00 | 0.01 | -0.10** | -0.11*** | -0.07** | -0.05 | 0.01 |
| | | | (-2.74) | (-2.00) | (0.44) | (0.18) | (-2.02) | (-2.88) | (-2.46) | (-1.61) | (0.87) |
| EF/A | 1 | 10 | -0.01 | -0.02* | -0.00 | -0.01 | -0.10*** | -0.09** | -0.04*** | -0.03* | 0.01 |
| | | | (-1.60) | (-1.79) | (-0.48) | (-0.34) | (-2.69) | (-2.28) | (-3.06) | (-1.77) | (0.31) |
| GS | 1 | 10 | -0.01 | -0.01 | -0.01 | -0.02 | -0.11*** | -0.09** | -0.02 | -0.02 | -0.01 |
| | | | (-1.55) | (-1.31) | (-0.69) | (-0.63) | (-2.65) | (-2.41) | (-1.54) | (-1.03) | (-0.36) |
| BE/ME | 1 | 5 | 0.00 | 0.00 | -0.00 | -0.10*** | -0.11*** | -0.02 | 0.02 | 0.01 | -0.01 |
| | | | (0.74) | (0.44) | (-0.41) | (-2.80) | (-2.88) | (-0.86) | (1.45) | (0.87) | (-0.63) |
| EF/A | 10 | 5 | -0.00 | -0.00 | 0.00 | -0.07* | -0.09** | -0.03 | 0.01 | 0.01 | -0.01 |
| | | | (-0.57) | (-0.48) | (-0.07) | (-1.93) | (-2.28) | (-1.55) | (0.80) | (0.31) | (-0.83) |
| GS | 10 | 5 | -0.00 | -0.01 | -0.00 | -0.08** | -0.09** | -0.01 | 0.00 | -0.01 | -0.02 |
| | | | (-0.55) | (-0.69) | (-0.58) | (-2.20) | (-2.41) | (-0.55) | (0.30) | (-0.36) | (-1.41) |
| BE/ME | 10 | 5 | -0.03** | -0.03** | -0.00 | -0.09** | -0.10** | -0.02 | -0.05* | -0.05 | -0.01 |
| | | | (-2.19) | (-2.00) | (-0.41) | (-1.97) | (-2.02) | (-0.86) | (-1.68) | (-1.61) | (-0.63) |
| EF/A | 1 | 5 | -0.02** | -0.02* | 0.00 | -0.08** | -0.10*** | -0.03 | -0.03** | -0.03* | -0.01 |
| | | | (-2.38) | (-1.79) | (-0.07) | (-2.50) | (-2.69) | (-1.55) | (-1.98) | (-1.77) | (-0.83) |
| GS | 1 | 5 | -0.01 | -0.01 | -0.00 | -0.10*** | -0.11*** | -0.01 | -0.01 | -0.02 | -0.02 |
| | | | (-1.40) | (-1.31) | (-0.58) | (-2.67) | (-2.65) | (-0.55) | (-0.72) | (-1.03) | (-1.41) |

## 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 statistical significance at 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*** | 13.7 | -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 | 1.5 | 20.59*** | 15.67 | -0.35 | 0.59 |
| BE/ME | 10 | 1 | 15.47*** | 11.93 | -0.22 | 1.3 | 38.24*** | 17.42 | -0.14 | 2.2 | 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 | 1.1 | 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 | 0.2 | 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*** | 8.3 | -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 | 0.1 | 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. 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 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 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $\alpha$ | $R^2$ | $\alpha$ | $R^2$ | $\alpha$ | $R^2$ | $\alpha$ | $R^2$ | $\alpha$ | $R^2$ | $\alpha$ | $R^2$ |
| 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 show the results of Henriksson and Marton (1981) regressions Equations (3). 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 2018/12/31.

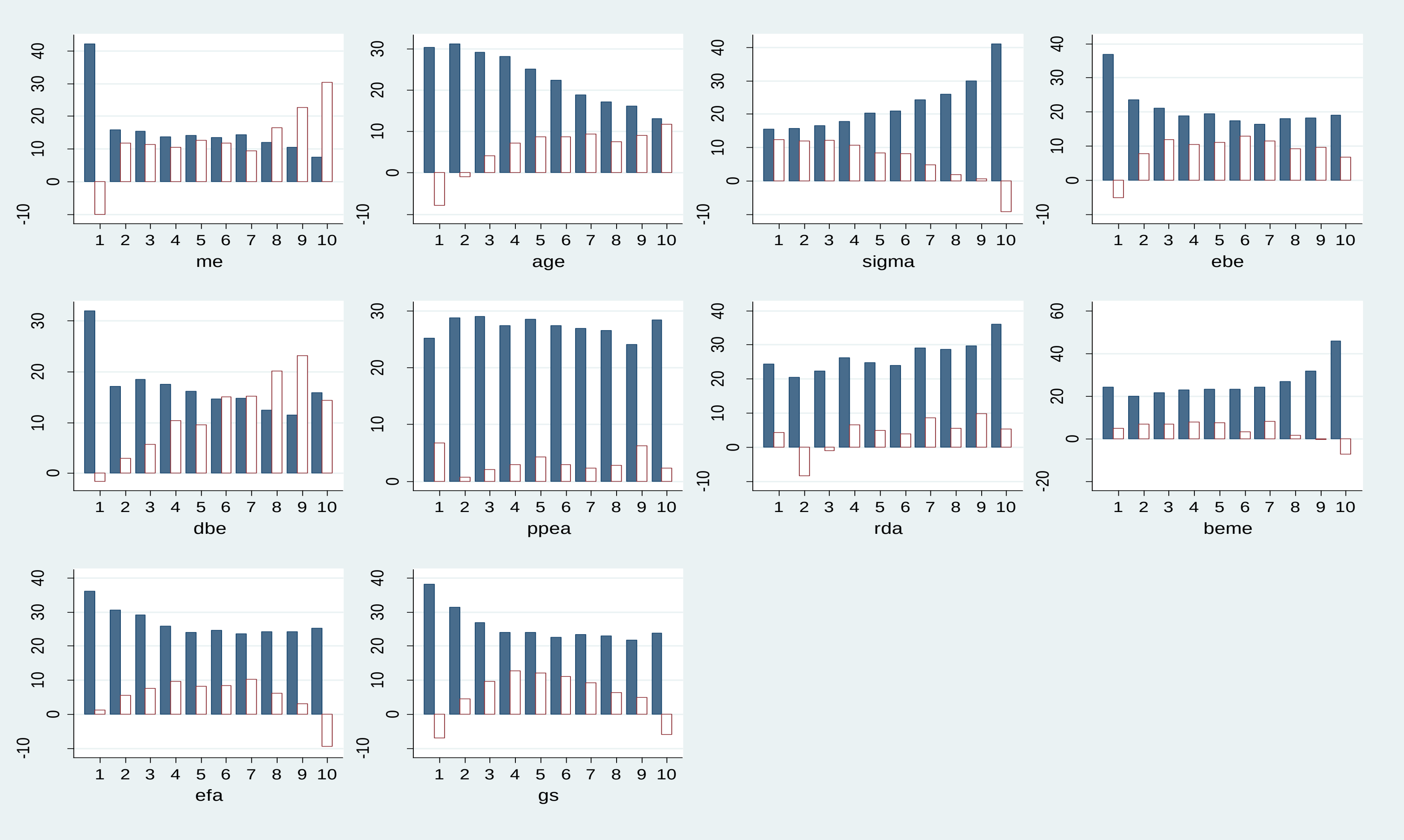
| | | | Panel A. TM Regression | | | | Panel B. HM Regression | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | P | I | $\alpha$ | $\beta_m$ | $\beta_{m^2}$ | $R^2$ | $\alpha$ | $\beta_m$ | $\gamma_m$ | $R^2$ |
| ME | 1 | 10 | 1.45 | 1.21*** | 2.64*** | 85.84 | -10.81*** | 1.32*** | -0.22*** | 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: 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 2018/12/31.

| | | | 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 | 36.00 | 39.33 | 40.11 | 40.78 | 40.10 | 37.83 | 35.70 |
| Age | 1 | 10 | 24.92 | 27.48 | 27.58 | 27.23 | 28.47 | 26.73 | 24.66 |
| Sigma | 10 | 1 | 34.01 | 36.22 | 36.30 | 35.73 | 37.20 | 35.46 | 33.64 |
| E/BE | 1 | 10 | 29.81 | 31.82 | 31.92 | 31.56 | 31.64 | 30.83 | 28.67 |
| D/BE | 1 | 10 | 27.39 | 28.89 | 28.75 | 29.22 | 29.77 | 28.62 | 27.11 |
| PPE/A | 1 | 10 | 21.78 | 22.13 | 21.91 | 21.05 | 21.02 | 21.94 | 22.39 |
| RD/A | 10 | 1 | 31.35 | 32.36 | 31.52 | 30.30 | 30.85 | 30.34 | 29.21 |
| BE/ME | 10 | 1 | 37.07 | 37.72 | 37.72 | 38.48 | 36.73 | 36.44 | 35.42 |
| EF/A | 1 | 10 | 29.18 | 27.64 | 27.78 | 28.05 | 26.91 | 27.08 | 27.30 |
| GS | 1 | 10 | 30.05 | 29.85 | 30.50 | 30.29 | 29.91 | 29.62 | 28.64 |
| BE/ME | 1 | 5 | 21.38 | 22.22 | 22.03 | 21.22 | 22.23 | 22.38 | 21.67 |
| EF/A | 10 | 5 | 20.27 | 21.98 | 22.30 | 21.91 | 22.86 | 22.20 | 21.51 |
| GS | 10 | 5 | 19.58 | 20.99 | 20.85 | 21.43 | 22.35 | 21.67 | 20.90 |
| BE/ME | 10 | 5 | 37.87 | 39.35 | 39.17 | 39.11 | 38.37 | 38.23 | 36.50 |
| EF/A | 1 | 5 | 30.63 | 30.81 | 31.27 | 31.15 | 30.96 | 30.46 | 30.00 |
| GS | 1 | 5 | 31.32 | 32.53 | 33.04 | 33.41 | 33.95 | 32.99 | 31.23 |
| | | | 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 | 99.18 | 106.76 | 108.37 | 124.72 | 154.06 | 183.66 | 197.16 |
| Age | 1 | 10 | 68.65 | 74.59 | 74.53 | 83.29 | 109.41 | 129.77 | 136.22 |
| Sigma | 10 | 1 | 93.68 | 98.33 | 98.08 | 109.26 | 142.95 | 172.14 | 185.78 |
| E/BE | 1 | 10 | 82.11 | 86.39 | 86.25 | 96.52 | 121.59 | 149.67 | 158.35 |
| D/BE | 1 | 10 | 75.45 | 78.44 | 77.67 | 89.37 | 114.38 | 138.97 | 149.74 |
| PPE/A | 1 | 10 | 60.01 | 60.08 | 59.20 | 64.38 | 80.75 | 106.53 | 123.63 |
| RD/A | 10 | 1 | 86.37 | 87.84 | 85.15 | 92.65 | 118.55 | 147.30 | 161.32 |
| BE/ME | 10 | 1 | 102.13 | 102.39 | 101.92 | 117.69 | 141.12 | 176.89 | 195.61 |
| EF/A | 1 | 10 | 80.39 | 75.03 | 75.05 | 85.78 | 103.42 | 131.46 | 150.79 |
| GS | 1 | 10 | 82.77 | 81.03 | 82.41 | 92.63 | 114.92 | 143.81 | 158.18 |
| BE/ME | 1 | 5 | 58.91 | 60.32 | 59.52 | 64.89 | 85.43 | 108.67 | 119.65 |
| EF/A | 10 | 5 | 55.83 | 59.68 | 60.25 | 67.01 | 87.82 | 107.77 | 118.78 |
| GS | 10 | 5 | 53.94 | 56.99 | 56.33 | 65.53 | 85.88 | 105.22 | 115.41 |
| BE/ME | 10 | 5 | 104.32 | 106.82 | 105.82 | 119.62 | 147.45 | 185.62 | 201.56 |
| EF/A | 1 | 5 | 84.39 | 83.63 | 84.47 | 95.25 | 118.95 | 147.89 | 165.66 |
| GS | 1 | 5 | 86.27 | 88.32 | 89.27 | 102.17 | 130.45 | 160.14 | 172.48 |

**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) |