The Joint Effect of Arbitrage Risk and Investor Sentiment on the Cross-Section of Stock Returns

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Abstract

We examine how stock return performance is a joint function of arbitrage risk and investor sentiment. We posit that arbitrage risk and investor sentiment have a complementary effect on the cross-section of stock returns. This is because the former, proxied by idiosyncratic volatility, relates a firm's stock variation to its specific firm characteristics while the latter links to individual beliefs on a firm's future cash flows and risks. Our results indicate that the joint effect on the cross-section of stock returns changes from negative to positive as it grows. The joint effect performs better for smaller stocks but not for those with higher book-to-market ratios. The significantly negative (positive) pricing power of the joint effect is crowded into the lowest (highest) sentiment portfolio. These results highlight the importance of measuring and controlling for the effects of arbitrage risk and investor attention when analyzing the performance of the cross-section of stock returns. The impact of the interaction is not susceptible to the replacement of the sentiment index, different exclusion schemes and business cycles.

Keywords: Asset pricing; Cross-sectional returns; Arbitrage risk; Idiosyncratic volatility; Investor sentiment
JEL classifications: C53; G11; G12; G17

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1. Introduction

The relationship between idiosyncratic volatility (IVOL) and stock returns in over sixty percent of firm-specific stock return variations cannot be explained by either systematic market movements, industry movements, or public news events unique to the firm (French and Roll, 1986; Roll, 1988). An anomalous negative relation between lagged IVOL and cross-sectional expected stock returns is documented in Ang, Hodrick, Xing and Zhang (2006) (hereafter AHXZ (2006)) while a positive relationship is found much earlier by Merton (1987). There is no consensus on direction for the relation between IVOL and stock returns, which remains a puzzle. IVOL relates investor sentiment to firm-specific information (Hou, Peng, and Xiong, 2013; Glasserman and Mamaysky, 2019). In this paper, we present evidence that the cross-section of stock returns is a joint function of IVOL and investor sentiment. Our in-depth analysis of the cross-section of expected returns is motivated by a substantial literature showing that investor sentiment constitutes an essential part of asset prices (De Long et al., 1990, Lee et al., 2002; Baker and Wurgler, 2006; Wang et al., 2022).[1]

We propose the joint effect of IVOL and investor sentiment as the sentimentalized idiosyncratic volatility (hereafter sentimentalized IVOL) by combining the channels introduced by Baker and Wurgler (2006) into a single characteristic. By doing so, we are able to test the effect of sentimentalized IVOL on pricing cross-sectional stock returns. We find a strong predictability from the one-month lag of sentimentalized IVOL to the cross-sectional stock returns across IVOL, sentiment, and sentimentalized IVOL portfolios, which cannot be

[1] De Long et al. (1990) describe two sources that lead to the unwillingness of risk-averse arbitrageurs with short horizons to bet on noise traders' misperceptions. One is the fundamental risk which limits the arbitrage while the other is the unpredictable sentiment of noise traders which drives the price deviation even further. Studies by Lee et al. (2002) and Wang et al. (2022) consider sentiment as a priced systematic risk and its impact on expected returns could pass indirectly through conditional volatility. Baker and Wurgler (2006) introduce two parallel channels through which cross-sectional mispricing effects are imposed by investor sentiment on stock returns. The first is based on holding arbitrage risk constant while various investor sentiments drive distinct speculative demands impact across stocks. The second assumes that investor sentiments are homogeneous while arbitrage risks affect stocks differently.

subsumed by control variables chosen in the cross-sectional predictability literature. To proxy the first channel of heterogeneous sentiments, we adopt the sentiment index and the cleaner version of the sentiment index orthogonalized on a set of six macroeconomic indicators of Huang, Jiang, Tu and Zhou (2015) (hereafter HJTZ (2015)). To rule out irrelevant information contained in the first principal component, which is used to calculate investor sentiment index in Baker and Wurgler (2006), HJTZ (2015) implement the partial least squares (PLS) method to generate their aligned investor sentiment index. Empirically, the HJTZ (2015) aligned (orthogonalized) investor sentiment index outperforms the Baker and Wurgler (2006) (orthogonalized) sentiment index in predictive ability for both the aggregate market return and cross-sectional stock returns[2]. Similarly, the aligned (orthogonalized) investor sentiment index's cross-sectional predictability matches our cross-section of regressions better. We adopt IVOL as the proxy for arbitrage risk (see Wurgler and Zhuravskaya, 2002; Stambaugh, Yu and Yuan, 2015), which gives us the interactive (orthogonalized) sentimentalized IVOL. We examine the pricing ability of the (orthogonalized) sentimentalized IVOL to capture stock returns at both the time-series level and the cross-section level.

Our sample period starts from July 1965 to December 2020, providing us with a total of 666 months longer than HJTZ (2015). We obtain daily stock returns from all the ordinary common equities on the NYSE, AMEX and NASDAQ collected from CRSP, giving 28,523

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[2] Compared to the initial proposers, Baker and Wurgler (2006) build the sentiment index using the first principal method while HJTZ (2015) are the first one to implement the PLS method to extract the common sentimental information contained in the six (standardized) raw sentiment proxies. The six sentiment proxies are the following: the dividend premium, the first-day returns on IPOs, the IPO volume, the closed-end fund discount, the equity share in new issues and the NYSE share turnover (although the NYSE share turnover has been dropped from the six sentiment proxies, per the notes in the sentiment dataset downloaded from Professor Jeffrey Wurgler's website). The proxies stated above are used to calculate the orthogonalized sentiment index as well, but these proxies have been orthogonalized on a set of six macroeconomic indicators in advance, namely, the industrial production index, the nominal durables consumption, the nominal nondurables consumption, the nominal services consumption, NBER recession indicator, the growth of employment, and the consumer price index.

stocks before we apply exclusions. We may assume that the number of stocks excluded during a factor construction process will impact the results since excluded stocks will be those that are illiquid and noisy. We implement a consistent exclusion scheme for stocks by calculating three idiosyncratic volatilities and three sentimentalized IVOLs separately under 5-day, 10-day, and 11-day exclusions with the objective of finding a robust exclusion scheme.[3] Empirically, we begin by estimating time-series alphas for the zero-investment portfolios and sorting the whole sample every month according to the (orthogonalized) sentimentalized IVOL. Fama-MacBeth regression with a 60-month rolling window is taken to examine the pricing ability accordingly for the one-month lag of (orthogonalized) sentimentalized IVOL during the lowest and highest IVOL, sentiment, and (orthogonalized) sentimentalized IVOL periods. We report Fama-MacBeth regression coefficients on the (orthogonalized) sentimentalized IVOL within each quintile, double-sorted by the sentiment with the IVOL. As a robustness check, the sentimentalized IVOL is reconstructed by replacing its two components. We first substitute the HJTZ (2015) sentiment index aligned with Baker and Wurgler (2006) sentiment index. We then examine the potential effects of illiquid stocks on previous findings through considering the joint characteristics under different exclusion schemes of IVOL calculation. We also carry out another two pairs of double-sorting, investigating the interaction of sentimentalized IVOL with sizes and with book-to-market ratios. We analyze whether the sentimentalized IVOL could explain the pattern of cross-sectional stock returns within size and book-to-market ratio quintiles. We account for the

[3] Bali and Cakici (2008) summarize that the direction of the relation as dependent on the data frequency, weighting scheme, breakpoints in portfolio sorting and exclusions with the criteria on stock size, price and liquidity. In detail, a significantly negative relation is noticed just when using daily data, value-weighted, and using CRSP breakpoints simultaneously. However, previous studies implement inconsistent exclusion schemes for stocks throughout the same research methodology. For example, Goyal and Santa-Clara (2003) exclude stocks with less than 5 trading days in a month. Fu (2009) requires a minimum of 15 trading days. Chen and Petkova (2012) arbitrarily mix up the exclusion of stocks with less than 5 trading days in a month and the exclusion of stocks with less than 15 trading days a month in their calculation.

influence of business cycles on the performance of sentimentalized IVOL. We also address earnings announcement effects in further analysis.

We find a significant relation between the (orthogonalized) sentimentalized IVOL and the cross-sectional excess stock returns during our sample period. This relation is unimpaired by controls such as the market beta, one-month lag of stock return, near-term lagged return, the log of market capitalization and the log of book-to-market ratio. It also survives when controlling for its two components, the idiosyncratic volatility and the (orthogonalized) sentiment index and it exhibits a directionally swinging impact as these two constituents increase. Specifically, we demonstrate that the (orthogonalized) sentimentalized IVOL shows an outstanding pricing ability. This pricing ability shifts from negative to positive the (orthogonalized) sentimentalized IVOL increases and reaches a strong negative position in the lowest (orthogonalized) sentimentalized IVOL quintile. The pricing effect's opposite direction highlights both the leading role of the sentiment when IVOL is low and the leading role of IVOL when it is at its maximum. The (orthogonalized) sentimentalized IVOL effect is more prominent in small-sized stocks, but not in those with a high book-to-market ratio. Our results hold true throughout various factor constructions (including the replacement of the sentiment index and other two stock exclusion schemes) and NBER business cycles. The pricing effect of the (orthogonalized) sentimentalized IVOL at least offers a lower bound for representing the errors in earnings expectations, particularly inside the extreme characteristic deciles.

The rest of this paper is organized as follows. Section 2 reviews related literature in the areas concerning the exploration for investor sentiment index, the relation between IVOL and arbitrage risks, and the interaction of IVOL and sentiment. Section 3 describes the sample, data (including the main variable of interest - the (orthogonalized) sentimentalized IVOL and other variables used in analyses), and the methodology. Section 4 discusses empirical results.

Section 5 provides robustness tests for different constructions, for size and book-to-market ratios effects and for performance in NBER business cycles. Section 6 presents further analysis of earnings announcement effects. Section 7 concludes.

2. Related literature

2.1 Investor sentiment index

Investor sentiment, according to Baker and Wurgler (2006), is an unwarranted belief towards future cash flows and risks. Investors who are high (low) in sentiment may make optimistic (pessimistic) decisions but sentiment itself cannot be observed (Keynes, 1936; Goetzmann and Massa, 2008; Huang et al, 2015). Empirical studies capture investors' sentiment by using a single time-series proxy such as the closed-end fund discounts (Lee et al, 1991; Swaminathan, 1996; Neal and Wheatley, 1998), the average first-day returns and the number of IPOs (Ritter, 1991; Ibbotson et al., 1994), net mutual fund redemptions (Neal and Wheatley, 1998), the ratio of issues of equity to the total issues of equity and debt (Baker and Wurgler, 2000), NYSE share turnover (Baker and Stein. 2004), the dividend premium between market-to-book ratios of dividend payers and nonpayers (Baker and Wurgler, 2004). Some studies use direct survey data, such as Investors Intelligence by the American Association of Individual Investors (Brown and Cliff, 2004), consumer confidence by the University of Michigan and the Conference Board (Lemmon and Portniaguina, 2006). Others extract textual content from message boards (Antweiler and Frank, 2004), media reports (Tetlock, 2007; Garcia, 2013), user-generated opinions (Loughran and McDonald, 2011; Chen et al., 2014; Jiang et al., 2019), and Internet search volumes (Da et al., 2015).

The first strand of investor sentiment measurement in the literature concentrates on market data. Lee et al. (1991) empirically confirm the suggestion of Zweig (1973) that closed-end fund discounts could reflect the fluctuations in the sentiment of individual investors. The difference between the market price and the net asset value of closed-end funds narrows with promising performance of small stocks. Neal and Wheatley (1998) find an asymmetric relation between sentiment proxies and expected stock returns. For their proxy of closed-end fund discounts, there is a positive relationship between investor sentiment and stock returns for small firms while no relation is detected for large firms. For their proxy of net mutual fund redemptions, a weakly positive relation exists for small firms while a weakly negative relation is found for large firms. The number of IPOs issuance and the average first-day returns on IPOs are considered as the indicator of market timing and investors' optimism (Ritter, 1991; Ibbotson et al., 1994). During "windows of opportunity", where many firms go public, over-optimistic investors usually face disappointment in the long run. The ratio of equity issues to the total equity and debt issues is interpreted as another sentiment measure by Baker and Wurgler (2000). The share of equity issues negatively predicts market returns. NYSE share turnover, expressed as the logarithm of original turnover and detrended by 5-year moving average, serves as a sentiment proxy for Baker and Stein (2004). High turnover indicates the domination of irrational investors with high sentiment and forecasts lower returns. Following Fama and French (2001), Baker and Wurgler (2004) use the difference of market-to-book ratios of dividend payers and nonpayers to proxy for the relative demand which drives the difference in stock returns.

Another strand of studies directly adopts survey data for its supposed independence from other economic factors compared to market data. For instance, Brown and Cliff (2004) include two surveys' measure of investors' altitudes towards the stock market in 6 months by the American Association of Individual Investors and Investors Intelligence regarding weekly bull-bear spreads, demonstrating their relations to other indirect popular sentiment proxies and near-term stock market returns. Lemmon and Portniaguina (2006) use two American consumer confidence datasets surveyed by the Conference Board and the University of

Michigan. Focusing on small stocks, their measure forecasts stock returns but not the variations in both value and momentum. They document a weak relation between their measure and both the Baker and Wurgler (2006) composite index and the closed-end fund discount. Da et al. (2015), however, cast doubt on the survey-based measures in terms of their low frequency and reliability.

Besides these market- and survey-based measures, with the development of technology and the internet, media-based measures have been paid more attention in terms of their high volume and frequency. Antweiler and Frank (2004) textually analyze over 1.5 million postings in Internet stock message boards of Yahoo! Finance and Raging Bull and find a negative predictive ability of shocks to next day returns and a helpful role in forecasting market volatility. Tetlock (2007) quantifies the pessimism of new media content in the 'Abreast of the Market' column of the *Wall Street Journal* and notes a downward pressure brought by pessimism as a proxy for investor sentiment on market prices and the forecasting ability of abnormal pessimism to market trading volume. The effect is more prominent and persistent for small stocks. Garcia (2013) investigates news coverage in two financials columns from the *NEW YORK TIMES*, where the predictability of the ratio of positive to negative words is concentrated in recessionary periods (see also Loughran and McDonald, 2011; Chen et al., 2014, and Jiang et al., 2019 for textual tone analysis). The FEARS (Financial and Economic Attitudes Revealed by Search) index constructed by Da et al. (2015) aggregates Internet search volumes for 'recession', 'bankruptcy', and 'unemployment' from millions of U.S. households and predicts market return and the transitory market volatility. In contrast with the earlier single-sourced measures, Sun et al. (2016) build their intra-day sentiment measure on multiple sources from new wires, internet news sources and social media in Thomson Reuters and document a convincing forecasting ability of their measure lagged by a half-hour to the intra-day S&P 500 index returns.

In the leading study of market-based measures, Baker and Wurgler (2006) extract the first principal component of the six previously used time-series proxies and find that their composite index is negatively related to stock returns. The six proxies are the average closed-end fund discount, NYSE share turnover, the number of IPOs, the average first-day returns on IPOs, the equity share in total new issues of equity and debt, and the dividend premium between the market-to-book ratios of dividend payers and nonpayers respectively. It has been documented that there is a negative effect of investor sentiment on stock returns especially for small, young, volatile, unprofitable, distressed, fast growing or non-dividend-paying firms (Baker and Wurgler, 2006). This result has been extended to the non-U.S. markets Canada, France, Germany, Japan and U.K. (Baker, Wurgler and Yuan, 2012). Using the newly introduced partial least squares method, the sentiment index of HJTZ (2015) outperforms the Baker and Wurgler (2006) index statistically and economically in that the sentiment index aligned efficiently rules out noise and converges to the 'true' sentiment. It survives when compared to 14 widely used macroeconomic predictors and is a negative predictor itself to the aggregate market returns. Extant studies largely set the HJTZ (2015) index as an alternative to the Baker and Wurgler (2006) index for checking robustness rather than directly building their empirical analysis on the former (Shen et al., 2017; Jiang et al., 2019). Some other studies refer to HJTZ (2015) for its employment of partial least squares method (Light et al., 2017).

2.2 Arbitrage risk and idiosyncratic volatility

Wurgler and Zhuravskaya (2002) use IVOL as a proxy for arbitrage risk. The suggestion that high IVOL is unfavorable for arbitrageurs is reasserted. Pontiff (2006) points out that holding costs force arbitrageurs to take limited positions in mispriced securities, enabling mispricing to continue. Thus, arbitrageurs cannot hedge idiosyncratic risk and must tradeoff between expected profit from a position and the idiosyncratic risk it exposes them to. Pontiff (2006) notes the common thread in the empirical studies that idiosyncratic risk appears to be the single largest impediment to market efficiency. In Gagnon and Karolyi (2010), IVOL is statistically reliable compared to other proxies such as dividend yield and interest rates. The link between IVOL and arbitrage has been investigated in the accounting literature by taking accruals into account. For example, arbitrageurs cannot readily find close substitute stocks which are proxied by stocks with higher IVOL and are highly correlated with returns for stocks subject to accrual mispricing (Mashruwala, Rajgopal and Shevlin, 2006; see also Hirshleifer et al., 2011). Relatedly, Stambaugh et al. (2015) suggest that IVOL can closely represent arbitrage risk if arbitrageurs are able to offset their exposure to aggregate volatility. The negative IVOL-return relation for overpriced stocks reverses for underpriced stocks. The negative relation is stronger for overpriced stocks with short-sale constraints. In addition, Liu et al. (2018) show that the strong negative IVOL-return relation for overpriced stocks is only significant simultaneously with high IVOL-beta relation and high overpricing likelihood.

2.3 Idiosyncratic volatility, investor sentiment, and stock returns

The firm characteristics found in the sentiment literature tend to be coincident with those being influenced deeper by IVOL. The asymmetric influence cast by the sentiment proxy of closed-end funds is stronger for small stocks, as documented in Lee et al. (1991) and Neal and Wheatley (1998). The underperformance in the high IPO volume period which represents sentiment is also concentrated in young and growing firms (Ritter, 1991).

The negative relation between the Baker and Wurgler (2006) composite sentiment index and stock returns from subsequent period is found among small, young, volatile, unprofitable or distressed firms as well as firms that pay no dividends or grow fast. Higher IVOL augments the abnormal overvaluation for growth stocks, stocks defined as recent losers with lowest price momentum and stocks with negative earnings surprises (Brav et al., 2010). This is confirmed by Stambaugh et al. (2015) for overpriced small stocks.

Existing studies highlight the significant role of sentiment in the IVOL-return relation (Blitz and Van Vliet, 2007; Blitz, Van Vliet and Baltussen, 2019; Baker, Bradley and Wurgler, 2011). Shleifer and Vishny (1997) argue that the negative IVOL-return relation is more pronounced with higher sentiment. Overvaluation is more pronounced when sentiment is high (Peterson and Smedema, 2011; Feng, Wang and Zychowicz, 2017). Stambaugh et al. (2015) find asymmetry in the augmentation effect of investor sentiment in that it strengthens the negative IVOL-return relation for overpriced stocks but weakens the positive relation for underpriced stocks. However, it is unclear whether the joint effect of IVOL and sentiment influences expected returns differently based on portfolio choices is unclear.

So far, we have reviewed related literature concerning investor sentiment index, the role of idiosyncratic volatility to proxy arbitrage risk and the link between investor sentiment and idiosyncratic volatility. Investor sentiment and idiosyncratic volatility both play significant roles in pricing stock returns, when studied separately. Their effects overlap, depending on stock characteristics and periods. We identify the joint effect and analyzing its pricing ability to the cross section of stock returns.

3. Data and methodology

3.1 Sample

The sample period is from July 1965 to December 2020, totaling 666 months. The start point, July 1965, is chosen to be in line with HJTZ (2015). Updates are taken from the daily stock file of the Centre for Research in Security Prices (CRSP). Daily stock returns including all the ordinary common equities (share code 10 or 11) on the NYSE, AMEX, and NASDAQ (exchange code 1 or 2 or 3) are collected from CRSP. There are overall 28,523 stocks identified by the unique PERMNO during the sample period without any exclusion.

3.2 Sentimentalized IVOL

IVOL has been constructed via different approaches in prior studies. For example, IVOL can be directly estimated by using GARCH or EGARCH model for the latter relaxes the symmetry requirement of the former (Spiegel and Wang, 2005; Brockman et al., 2009; Fu, 2009; Huang et al., 2010; Peterson and Smedema, 2011; Eiling, 2013; Guo et al., 2014; Cao and Han, 2016). However, the out-of-sample performance of this model measurement has been called into doubt. That is, based on Fama-French three factor model, IVOL is measured simply by the standard deviation of the residuals in the model as in AHXZ (2006 and 2009), Bekaert et al. (2012), Stambaugh et al. (2015), Chen et al. (2020), and Yang et al. (2020). Some studies include two more risk factors from the Fama-French five factor model (Switzer and Picard, 2015; Switzer et al., 2017). However, despite the simpleness and robustness of estimating residuals, the disturbing impact of microstructure noise, especially in small firms, is raised by Bali and Cakici (2008). Roll (1988), Durnev et al. (2003), Fresard (2012) and Becchetti et al. (2015) use *R*-square measurement to define IVOL. *R*-square is calculated from the relation between returns of the specific stock and returns of its corresponding industry and market. A stronger relation indicates less idiosyncratic information conveyed by the specific stock. Malkiel and Xu (1997), followed by Xu and Malkiel (2004) and Irvine and Pontiff (2009), use the value-weighted or equal-weighted variance between excess returns of each individual stock to the industry return to which the stock belongs, arguing that the result of this measurement is close to the results from a market model but avoids the estimation of beta. Boehme et al. (2009) follow the market model from the Brown and Warner (1985) and use the root mean squared error (RMSE) to proxy for IVOL in that model. Similarly, Nam et al. (2017) use RMSE of each stock's monthly regression from three different asset pricing models: the simple CAPM, the augmented CAPM with four lags, and the Fama-French three factor model.

In this study, we adopt the prevalent measurement of computing the standard deviation of the residuals from the Fama and French (1993) three-factor model as follows:

$$XRET_{i,d} = \alpha_i + \beta_M RET_{M,d} + \beta_{HML} HML_d + \beta_{SMB} SMB_d + \epsilon_{i,d}\,, \tag{1}$$

where $XRET_{i,d}$ is the excess return for stock *i* in day *d; $RET_{M,d}$*, HML_d, SMB_d are Fama-French three factors in day *d*. After the estimation, in every month for stock *i*, the standard deviation of the residual series on stock *i* and day *d* will be computed to represent the monthly idiosyncratic volatility (*IVOL*) for the stock *i*. Specifically, *IVOL* is estimated monthly using daily data and is scaled by the square root of the number of trading days inside the correspondent month. Stocks with less than 5 trading days in a month are excluded in the main section (Different exclusions of days will be covered in the robust tests and appendices). Data for the monthly excess market return (RET_M), *HML*, *SMB* and risk-free rate are obtained from Professor French's website.[4] The risk-free rate is the monthly T-bill return compounded from a simple daily rate from Ibbotson and Associates Inc. Excess market return RET_M is calculated by subtracting risk-free rate. *HML* stands for the returns on high book-to-market ratio stocks minus low book-to-market ratio stocks while *SMB* stands for the returns on small market capitalization stocks minus big market capitalization stocks. We also compute excess stock return $XRET_{i,t}$ for each stock *i* in month *t* by extracting the risk-free rate from the original returns. For the time-series regressions, we include common time-series control variables (AHXZ, 2006; Peterson and Smedema, 2011). In addition to the aforementioned Fama-French three factors, we also acquire the momentum factor *MOM*, which is the difference between the

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

average return on the two high prior (2-12 month) return portfolios and the two low prior (2-12 month) return portfolios; the short-term reversal factor *ST_Rev*, which is the difference between the average return on the two high prior (1 month) return portfolios and the two low prior (1 month) return portfolios; the profitability factor *RMW*, which is the return on robust operating profitability stocks minus weak operating profitability stocks; and the investment factor *CMA*, which is the return on conservative stocks minus aggressive stocks from Professor French's website. We also include the liquidity factor (*PS*) of Pastor and Stambaugh (2003), which is available from Professor Stambaugh's personal website[5].

To investigate whether the impact of sentimentalized IVOL can be more pronounced in predicting time-series and cross-sectional stock returns, we consider the product between the HJTZ (2015)'s (orthogonalized) sentiment index aligned, *SENTA* (*SENTA*$^{\perp}$), and idiosyncratic volatility (*IVOL*), which is notated as *SENTA*IVOL* (*SENTA*$^{\perp}$**IVOL*). The data for both investor sentiment index aligned and the orthogonalized investor sentiment index aligned (*SENTA* and *SENTA*$^{\perp}$) during the sample period July 1965 to December 2020 are downloaded from Professor Zhou's personal website.[6] The sentiment index aligned of HJTZ (2015) efficiently incorporates the most pertinent common information contained in the six raw sentiment proxies used in the pioneering study of Baker and Wurgler (2006) through the partial least squares method. The six raw investor sentiment proxies are the closed-end fund discount rate, share turnover, IPO volume, IPO first-day returns, dividend premium and equity share in new issues. The six raw sentiment proxies are first orthogonalized on the growth of industrial production, the growth of durable consumption, the growth of nondurable consumption, the growth of service consumption, the growth of employment, and the NBER

[5] https://finance.wharton.upenn.edu/~stambaug/.
[6] The investor sentiment data are used in the study of Huang et al. (2015), which are updated and available from this website apps.olin.wustl.edu/faculty/zhou/zpublications.html.

expansionary and recessionary dummy variable, after which the orthogonalized sentiment index aligned is extracted to rule out the effects of macroeconomic factors. Even cross-sectionally, the (orthogonalized) sentiment index aligned is proven to be a strong predictor of stock returns than Baker and Wurgler's (2006) (orthogonalized) sentiment index.

3.3 Other variables

Aligning with the control variables chosen in cross-sectional predictability literature, the market beta (*BETA*), the lagged one-month return (RET_{t-1}), the near-term lagged return ($RET_{t-2,\,t-12}$), the log of market capitalization (*lnSIZE*), the log of book-to-market ratio (*lnBE/ME*) are used (Fu, 2009; Huang et al., 2010; Peterson and Smedema, 2011). *BETA* measures systematic risk and is estimated following Fama and French (1992). We estimate for each stock, monthly, on the market return with a 60-month rolling window requiring at least 24 months of previous returns. Stocks are then assigned to 10x10 portfolios sorted on size and beta. Size deciles are allocated based on NYSE-listed stocks' market capitalization. The sorting process is balanced every month. For each portfolio, we take the equal-weighted stock return and regress it on the current market return and the one-month lagged market return over the full periods. *BETA* is the sum of the two coefficients for the adjustment of time-series non-synchroneity (Dimson, 1979). Finally, we assign *BETA* to each stock according to the correspondent size-beta portfolios. For each stock in the sample, the lagged one-month return (RET_{t-1}) is included to control for return reversals (Huang et al., 2010). The near-term lagged return ($RET_{t-2,\,t-12}$), which is the gross return from month *t-12* to month *t-2* (inclusive), controls for momentum (Peterson and Smedema, 2011). The log of market capitalization (*lnSIZE*) is the log of market capitalization in month *t* for each stock. The log of the book-to-market ratio (*lnBE/ME*) is calculated following Fama and French (1992) by using the book value of equity from the previous fiscal year upon the market capitalization from the previous calendar year.

3.4 Methodology

We conduct our empirical investigation in a variety of sorted portfolio scenarios. The rationale for portfolio sorting is discussed below. There will not be any distinction between the outcomes in the five quintiles after portfolio sorting if the sentimentalized IVOL asserts no influence on stock returns, in the time-series or in the cross-section. The discrepancy between quintiles is an indication of the unique exposure to stock returns, if the sentimentalized IVOL is, in fact, an omitted characteristic. The sorting process is balanced every month.

On the threshold, we examine the effect of the sentimentalized IVOL through the alphas of time-series regressions. Every month, we sort the entire sample into quintiles with respect to the *IVOL*, *SENTA*IVOL* and *SENTA⊥*IVOL*. Market capitalization-based value-weighted returns and equal-weighted returns are computed for each quintile. Weighted stocks by value will not place large and small stocks on the same level, alleviating the influence of micro-structure issues. We create zero-investment portfolios through buying the stocks allocated in the highest portfolio and shorting the stocks allocated in the lowest portfolio (hereafter *H-L*). We then regress the returns of value-weighted and equal-weighted *H-L* portfolios on the time-series control variables and record the corresponding alphas (in percentages), as in the following Equation (2).

$$
\begin{aligned}
(H-L)_t = {} & \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t \\
& + \beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \epsilon_t \qquad (2)
\end{aligned}
$$

In another specification, we incorporate the monthly sentiment index aligned (*SENTA*) or the monthly orthogonalized sentiment index aligned (*SENTA⊥*) in the time-series regressions, with respect to portfolios sorted on the *IVOL*. We include *SENTA* ($SENTA^{\perp}$) in line with portfolios sorted on *SENTA*IVOL* ($SENTA^{\perp}$*IVOL*).

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t$$
$$+\beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t$$
$$+\beta_{SENTA}\, SENTA_t\, (\beta_{SENTA^{\perp}} SENTA_t^{\perp}) + \epsilon_t. \tag{3}$$

Fama-Macbeth two-step regressions are then used cross-sectionally, as indicated in the following Equations (4) and (5). To determine the monthly beta exposures, the excess returns of each stock *i* are regressed on the one-month lag of the proposed sentimentalized IVOL together with control variables in the first stage of the Fama-Macbeth regression. In the second stage, the risk premium for each factor in each time *t* is calculated using stage 1 betas as independent variables. The one-month lag of the investor sentiment index aligned ($SENTA_{t-1}$) (or its orthogonalized counterpart, $SENTA^{\perp}_{t-1}$), the one-month lag of IVOL ($IVOL_{t-1}$), the market beta (*BETA*), the one-month lag of stock return (RET_{t-1}), the near-term lagged return ($RET_{t-2,\, t-12}$), the log of market capitalization (*lnSIZE*) and the log of the book-to-market ratio (*lnBE/ME*) as described in Section 3.3 are all included as control variables in the regression.

$$XRET_{i,t} = \alpha_i + \beta_{SENTA*IVOL,i} SENTA*IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1}$$
$$+\beta_{SENTA,i} SENTA_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \tag{4}$$

$$XRET_{i,t} = \alpha_i + \beta_{SENTA^{\perp}*IVOL,i} SENTA^{\perp}*IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1}$$
$$+\beta_{SENTA,i^{\perp}} SENTA_{t-1}^{\perp} + \beta_{controls} Controls_t + \epsilon_{i,t}. \tag{5}$$

3.5 Descriptive statistics

Table 1 provides time-series summary statistics and autocorrelations of *SENTA*IVOL* and $SENTA^{\perp}$*IVOL* under 5-day exclusion. After excluding stocks with less than 5 trading days in a month, 24,721 stocks, which are identified by the PERMNO, are left in the sample.

Altogether, the cross-sectional sample has 3,177,422 observations. In Panel A, we first compute value-weighted *SENTA∗IVOL* and *SENTA⊥*IVOL* based on correspondent market capitalization in every month across sample period while in Panel B, we take equal-weighted *SENTA∗IVOL* and *SENTA⊥*IVOL*. The mean and standard deviation of value-weighted sentimentalized IVOLs are higher than those of equal-weighted version, implying that stocks with larger market capitalization account for the major part in the sample period, especially when those of equal-weighted sentimentalized IVOLs are negligible. Autocorrelations of all lags here show high persistence for value-weighted sentimentalized IVOLs. However, there is no such pattern for equal-weighted sentimentalized IVOLs. The persistence of sentimentalized IVOLs could be seen in the later Fama-Macbeth regressions where their impact to cross-sectional stock returns significantly lasts to the next period.

[TABLE 1]

4. Empirical results

To explore in the joint pricing effect of idiosyncratic volatility and investor sentiment, we first consider our novel characteristic, the sentimentalized IVOL at the time-series level. The sentimentalized IVOL is then cross-sectionally examined under the context of portfolios.

4.1 Time-series regressions

We begin by examining the time-series alphas (in percentages) of both value-weighted and equal-weighted zero-investment (*H-L*) portfolios which are sorted on *SENTA*IVOL* and *SENTA⊥*IVOL*. Every month, the quintiles are sorted, and either equally weighted or value-weighted by market capitalization. In Equation (2), we regress the *H-L* returns while controlling for the Fama-French (1993) three factors, *MOM*, *ST_Rev*, *RMW*, *CMA*, *PS*, as reported in regressions (1) of Table 2 under both value-weighted and equally weighted sections. We are also interested in further controlling for the sentiment effect as shown in

Equation (3). For *SENTA*IVOL*-sorted *H-L* portfolios, *SENTA* is included in the time-series regressions (2) whereas for $SENTA^{\perp}$**IVOL*-sorted *H-L* portfolios, $SENTA^{\perp}$ is included in regressions (3). The square parenthesis surrounds the Newey-West (1987) robust t-statistics with correction for autocorrelation and heteroskedasticity. All time-series alphas in Table 2 have negative significance. The equal weighting, the addition of the correspondent sentiment index, and the use of the orthogonalized sentimentalized IVOL all result in higher absolute values for alphas. For example, in contrast to its orthogonalized counterpart, $SENTA^{\perp}$**IVOL*, whose alpha is -0.0369% and significant at the 5% level, and to its equal-weighted counterpart, whose alpha is -0.0558% and is significant at the 1 % level, the value-weighted *H-L* portfolio's alpha sorted on *SENTA*IVOL* is -0.0446% and significant at the 5% level. When *SENTA* is included in the regression, as in Equation (3), the alpha for *SENTA*IVOL* is -0.0421% and is still significant at the 5% level. Equal-weighted *H-L* portfolios' greater alpha significance levels could be explained by the small size effect, which will be further examined in subsequent robustness checks. The negative alphas indicate that the time-series stock returns decrease as *SENTA*IVOL* ($SENTA^{\perp}$**IVOL*) grows. The following Fama-MacBeth regressions also evaluate this overall pattern.

[TABLE 2]

4.2 Fama-MacBeth regressions

For further inspection, we run Fama-MacBeth regressions for portfolios single-sorted on *IVOL*, *SENTA* ($SENTA^{\perp}$), and *SENTA∗IVOL* ($SENTA^{\perp}$**IVOL)*, as well as portfolios double-sorted on *SENTA* ($SENTA^{\perp}$) and *IVOL*, with a 60-month rolling window. We include one-month lag of *SENTA∗IVOL* ($SENTA^{\perp}$*IVOL), one-month lag of *SENTA* ($SENTA^{\perp}$) and the one-month lag of *IVOL* in the regression as shown in Equations (4) and (5) while controlling for the market beta (*BETA*), the lagged one-month return (RET_{t-1}), the near-term lagged return ($RET_{t-2, t-12}$), the log of market capitalization (*lnSIZE*), the log of book-to-market ratio (*lnBE/ME*), cross-sectionally.

Inside our single-sorting procedure, we first record the loadings for *SENTA*IVOL* (*SENTA⊥*IVOL*) in the lowest and highest quintiles in Panel A (Panel B) of Table 3. The collection of observations has led to our concentrate on the two extreme quintiles as the cross-sectional idiosyncratic volatilities naturally outweigh the time-series sentiment index. *SENTA*IVOL* (*SENTA⊥*IVOL*) predicts the cross-section of stock returns within extreme sentiment quintiles in reverse directions, negative with the lowest sentiment and positive with the highest sentiment. In the lowest sentimentalized IVOL quintile, the one-month lag of *SENTA*IVOL* (*SENTA⊥*IVOL*) negatively predicts the stock returns at a 1% significance level. The coefficient for the orthogonalized sentimentalized IVOL is -0.0351, which is marginally less than the coefficient of -0.0484 for the non-orthogonalized counterpart. However, in the highest sorted quintile, the pricing direction for both sentimentalized IVOLs shifts to be positive but insignificant. The difference in directions between the lowest and highest sentimentalized IVOL quintiles is in accordance with the time-series alphas reported in Table 2. Ruling out the influence brought by macro-economic factors will not affect the significance of the sentimentalized IVOL's pricing ability.

Next, we could observe from our double-sorting results that, all the sentimentalized IVOLs in the highest *IVOL* quintile predict the cross-section of stock returns in the opposite direction from those in the other four *IVOL* quintiles. The impact of the one-month lag of (orthogonalized) sentimentalized IVOL in the lowest quintile of sentiment changes from positive to negative as idiosyncratic volatility increases, and it reaches the lowest coefficient of -0.1582 (-0.1020) at 1% significance level in the highest *IVOL* quintile. Contrarily, for the highest sentiment quintile, the impact of the one-month lag of (orthogonalized) sentimentalized IVOL is significantly negative with a greater coefficient in higher *IVOL* quintile. However, we spot that there is no prominent pricing effect of the sentimentalized IVOL in the highest sentiment and highest *IVOL* double-sorted quintile. When we combine the single- and double-sorted results, the idiosyncratic volatilities elicit the pricing ability of sentimentalized IVOL more strongly. The leading position of the highest *IVOL* inside the lowest and highest sentiment quintiles is what causes the overall negativity in the lowest sentimentalized IVOL portfolio and the overall positivity, albeit insignificance, in the highest sentimentalized IVOL portfolio. Other traditional, widely employed explanatory variables for the cross-sectional stock returns cannot mitigate the influence of the sentimentalized IVOL.

In an unreported table, value-weighted and equal-weighted idiosyncratic volatilities at one-month lag are regressed on the sentiment index, respectively. The results show that the value-weighted $IVOL_{t-1}$ positively predicts both $SENTA_t$ and $SENTA^{\perp}_t$. It is in opposition to the volatility hypothesis, which expects a negative relation between sentiment index and volatility and is consistent with what is found in HJTZ (2015) for the aggregate market volatility. However, both variables $SENTA_t$ and $SENTA^{\perp}_t$ are negatively predicted by the equal-weighted $IVOL_{t-1}$. It is possible that stocks of smaller sizes contribute to the predicting ability of sentimentalized IVOL. In the next robustness tests, we will account for the size effect.

[TABLE 3]

5. Robustness checks

To corroborate the above results, we first recreate our sentimentalized IVOL by replacing the (orthogonalized) sentiment index aligned of HJTZ (2015) with the (orthogonalized) sentiment index of Baker and Wurgler (2006). Additionally, we compute the idiosyncratic volatility under the 10-day and 11-day exclusions, which takes the impact of stock exclusion into account, rather than using the prior 5-day exclusion. Furthermore, by controlling for size as well as book-to-market ratios, we also conduct additional examinations to the interaction effect of the sentimentalized IVOL on the cross-sectional stock returns. Last, we consider the NBER influence for the non-orthogonalized sentimentalized IVOLs.

5.1 Alternative measure of the investor sentiment index

The (orthogonalized) investor sentiment index during the period of July 1965 to December 2020 are obtained from Professor Jeffrey Wurgler's website[7]. Each month, the index is constructed using the first principal component of five sentiment proxies: value-weighted dividend premium, first-day returns on IPOs, IPO volume, closed-end fund discount and equity share in new issues. The orthogonalized investor sentiment index is calculated by orthogonalizing the five sentiment proxies on a set of six macroeconomic indicators first (the industrial production index, the nominal durables consumption, the nominal nondurables consumption, the nominal services consumption, NBER recession indicator, the growth of employment, and the consumer price index). In the following robustness examinations, the investor's sentiment index and its orthogonalized counterpart are denoted as *BW* and $BW^{\perp}$, respectively, while the new sentimentalized IVOLs are denoted as *BW*IVOL* and $BW^{\perp}$**IVOL*.

Similarly, we provide the time-series summary statistics and autocorrelations for *BW*IVOL* and $BW^{\perp}$**IVOL* in Table 4. The mean and standard deviation of *BW*IVOL* and $BW^{\perp}$**IVOL*, both vale-weighted and equal-weighted, are lower than those of *SENTA*IVOL* and $SENTA^{\perp}$**IVOL*. Autocorrelations of all lags show persistence in value-weighted series but not in equal-weighted series.

[TABLE 4]

[7] The investor sentiment data are proposed in the study of Baker and Wurgler (2015), which are updated and available from this website https://pages.stern.nyu.edu/~jwurgler/.

To investigating the pricing effect, we run time-series regressions for *H-L* portfolios sorted on *BW*IVOL* and *BW⊥*IVOL* and record the alphas (in percentages) in Table 5. We also take into account the sentiment effect from *BW* (*BW⊥*), as shown in Equation (6). All alphas are comparable to previous alphas for *SENTA*IVOL* and *SENTA⊥*IVOL* in Table 2, though not statistically significant. The absence of positive alphas for equal-weighted *BW⊥*IVOL* indicates the influence brought by size.

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t$$
$$+\beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t$$
$$+\beta_{BW}\, BW_t\ (\beta_{BW^{\perp}} BW_t^{\perp}) + \epsilon_t \qquad (6)$$

[TABLE 5]

When we compare the results in Table 3 and Table 6 from cross-sectional Fama-MacBeth regressions with a 60-month rolling window (Equation (7) and (8)), we see that the leading role of idiosyncratic volatility in its highest quintile is stronger to *BW* and *BW⊥* as the coefficients become significantly positive. This could be due to a difference in sentiment extraction between HJTZ (2015) and Baker and Wurgler (2006), with the latter retaining more irrelevant information. Statistically, the positive coefficient of 0.0880 at 10% significance level (the coefficient of 0.0730) in the lowest *BW* (*BW⊥*) and highest *IVOL* double-sorted quintile, is to the opposite of the previous negative coefficient for *SENTA*IVOL* (*SENTA⊥*IVOL*), resulting in the overall insignificance rather than the negative significance in the lowest *BW*IVOL* (*BW⊥*IVOL*) quintile. While the coefficient of 0.1039 (0.1010) at 5% significance level is stronger in the highest *BW* (*BW⊥*) and highest *IVOL* double-sorted quintile than the positive but insignificant coefficient for *SENTA*IVOL* (*SENTA⊥*IVOL*), rendering the overall significant positivity in the highest *BW*IVOL* (*BW⊥*IVOL*) quintile.

When idiosyncratic volatility is lower, however, the results for *BW*IVOL* (*BW⊥*IVOL*) and *SENTA*IVOL* (*SENTA⊥*IVOL*) are similar.

$$XRET_{i,t} = \alpha_i + \beta_{BW*IVOL,i} BW * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i} BW_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (7)$$

$$XRET_{i,t} = \alpha_i + \beta_{BW^{\perp}*IVOL,i} BW^{\perp} * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i^{\perp}} BW_{t-1}^{\perp} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (8)$$

[TABLE 6]

5.2 *Different exclusion schemes for IVOL*

During the sample period from July 1965 to December 2020, the monthly total number of stocks listed in NYSE, AMEX and NASDAQ varies largely. Figure 1 shows that the monthly total number of stocks listed varies largely from the lowest 2,083 stocks in July 1965 to the highest 7,660 stocks in January 1998. The monthly number of stocks listed in NYSE/AMEX/NASDAQ experiences 3 stages. In the first stage from the beginning of the sample period to November 1972, the number of listed stocks keeps stable, increasing steadily from 2,083 to 2,517. In the second stage from December 1972, the number of stocks listed meets a sudden surge to over 5,300 and then grows with almost 1,000 stocks increase in every 10 years. In January 2009, the monthly number of listed stocks drops from its maximum point of 7,660 to 4,345, corresponding to the financial crisis during this stage.

[FIGURE 1]

In the related literature, the exclusion scheme of stocks with how many trading days in a month is chosen arbitrarily. Excluding stock with less than 5 trading days in a month is used in the previous sections as this scheme is implemented often in literature (Pollet and

Wilson, 2010; Chen and Petkova, 2012), which we adopted in our previous main empirical section. Further, following Bali and Cakici (2008), the selection of stock exclusion schemes affects the direction of the idiosyncratic volatility-return correlation.

In Figure 2, when including stocks with at least 5 and 10 trading days in a month inside the whole sample period, the monthly numbers of excluded stocks are incomparable and grow steadily. However, when including stocks with at least 11 and 15 trading days in a month, the number of excluded stocks suddenly increases from around 20 to 2,906 for 11 trading days and to 2,911 for 15 trading days in December 1972. This beginning time of excluded stocks surge is correspondent with the second stage of the blooming number of listed stocks. It is also one year earlier than the NBER U.S. business contraction starting in November 1973. Voluminous stocks met illiquidity in that cycle, thus a 11-day exclusion scheme is considered. The number of stocks excluded shows huge difference between the 10-day exclusion scheme and the 11-day exclusion scheme. To corroborate our results, excluding stocks with less than 10 and 11 trading days in a month is also chosen since there is a significant distinction in the number of excluded stocks between 10-day exclusion and 11-day exclusion.

[FIGURE 2]

We then reconstruct the sentimentalized IVOL as *SENTA*IVOL10* (*SENTA*$^{\perp}$**IVOL10*), *SENTA*IVOL11* (*SENTA*$^{\perp}$**IVOL11*), *BW*IVOL10* (*BW*$^{\perp}$**IVOL10*) and *BW*IVOL11* (*BW*$^{\perp}$**IVOL11*) by taking the product between both version of investor sentiment index and *IVOL10, IVOL11* respectively. Stocks with fewer than 10 trading days and 11 trading days in a month are excluded to calculate *IVOL10* and *IVOL11* separately, since the monthly standard deviation of the residuals with respect to the Fama-French three factor model based on daily stock returns. *IVOL10* and *IVOL11* are scaled by timing the square root of the number of days in each month. The time-series summary statistics and autocorrelations are presented in Table A.1 of the Online Appendix. After excluding stocks with less than 10 trading days in a month, 24,699 stocks, which are identified by the PERMNO, are left in the sample. Altogether, the cross-sectional sample has 3,167,699 observations. As for the exclusion of stocks with less than 11 trading days in a month, the number of stocks identified by PERMNO is 24,689 while the total number of observations is 3,162,838. Mean and standard deviation of both the value-weighted and the equal-weighted series across schemes are comparable to previous statistics under the 5-day exclusion. For autocorrelations, all series under both 10-day and 11-day exclusion schemes share the similar pattern as *SENTA*IVOL* and *BW*IVOL*. Specifically, the equal-weighted autocorrelations are still irregular.

To provide thorough robustness checks, we rerun previous analyses under 10-day and 11-day exclusion schemes. The time-series alphas of zero-investment portfolios under 10-day and 11-day exclusion schemes (Table A.2 of the Online Appendix), as well as the Fama-MacBeth regression loadings for sorted portfolios (Table A.3 of the Online Appendix), are reported in our Appendices. When we compare these results to our previous main results based on the 5-day exclusion, we discover that by excluding stocks differently, the pricing ability of sentimentalized IVOL is intact.

5.3 Controlling for size

To scrutinize the interaction of the sentimentalized IVOL with firm size, we conduct a double-sorting on size of only NYSE stocks and then the sentimentalized IVOL. We also value-weight each portfolio by the market capitalization. It has become common practice to use NYSE breakpoints since Fama and French (1992). This rules out the influence brought by small size stocks, as seen in Bali and Cakici (2008). Within each of the 25 portfolios, we run

Fama-MacBeth regressions with a 60-month rolling window. The results for the (orthogonalized) sentimentalized IVOLs using either HJTZ (2015) sentiment index aligned or the Baker and Wurgler (2006) sentiment index under all 5-, 10- and 11-day exclusions are presented in the Appendices (Table A.4 of the Online Appendix).

For *SENTA*IVOLs*, the strongest pricing ability is concentrated in the smallest stocks. However, for $SENTA^{\perp}*IVOLs$, *BW*IVOLs* and $BW^{\perp}*IVOLs$, the stocks with the smallest size and the most sentimentalized IVOL have the strongest pricing ability. Inferring from the above findings, stocks with a smaller market capitalization and extreme sentimentalized IVOL have a stronger pricing effect. In addition to NYSE stocks, we rank all stocks based on market capitalization. Our results are unaffected, though unreported.

5.4 Controlling for book-to-market ratios

To better understand the pricing role of the sentimentalized IVOL, we double sort the entire sample monthly according to the book-to-market ratios and the sentimentalized IVOL. The 25 portfolios are then value-weighted. A cross-sectional Fama-MacBeth regression with a 60-month rolling window is run within each portfolio. As shown in the Appendices (Table A.5 of the Online Appendix), *SENTA*IVOLs* ($SENTA^{\perp}*IVOLs$) negatively predict stock returns, with the exception of those across the highest *SENTA*IVOLs* ($SENTA^{\perp}*IVOLs$) quintiles.

5.5 NBER business cycles

We test for the influence from NBER business cycles to the pricing ability of our joint characteristic, sentimentalized IVOL under 5-, 10- and 11-day exclusions. While the orthogonalized sentiment index has already excluded the macroeconomic effects, we focus on *SENTA*IVOL* and *BW*IVOL* with the addition of the NBER dummy into the cross-sectional regressions. The monthly dummy variable NBER represents periods of expansion and recession provided by the National Bureau of Economic Research. The expansionary period is 0 while the recessionary period is 1. The results of all the regressions are not affected either by the NBER expansion or the recession periods, although the NBER dummy is negatively significant at 1% level.

6. Further analysis

Following Baker and Wurgler (2006), in this section we test the earnings announcement effects for each characteristic decile using the interaction of investor sentiment and idiosyncratic volatility, the sentimentalized IVOL. If there are systematic errors in earnings expectations, we would find that the cumulative abnormal return around the earnings announcements inclines to be related with the interaction sentimentalized IVOL.

Specifically, we collect quarterly earnings announcement dates from the merged CRSP-Compustat database, which is available from January 1971. We calculate the cumulative abnormal return (*CAR*) over the value-weighted market index for each firm-quarter observation through trading days *t-1* to *t+1*. The quarterly series of earnings announcement effects is then merged into our original sample from the previous year-end sentimentalized IVOL. The final merged sample covers 12,778 stocks identified by PERMNO comparing to 24,721 stocks in the original sample. We sort the merged sample into deciles according to the (orthogonalized) sentimentalized IVOLs using either HJTZ (2015) sentiment index aligned or Baker and Wurgler (2006) sentiment index under all 5-, 10- and 11-day exclusion schemes. We regress *CAR* on lagged (orthogonalized) sentimentalized IVOL, lagged *IVOL*, and lagged (orthogonalized) sentiment index and report coefficient β_1 from Equations (9) and (10) in Table 7 across each characteristic decile under 5-day, 10-day, and 11-day exclusions.

$$CAR_{X_{it}=Decile,t} = \alpha + \beta_1 SENTA * IVOL_{t-1}(\beta_1 SENTA^{\perp} * IVOL_{t-1}) + \beta_2 IVOL_{t-1} + \beta_3 SENTA_{t-1}(\beta_3 SENTA^{\perp}_{t-1}) + \varepsilon_t \quad (9)$$

$$CAR_{X_{it}=Decile,t} = \alpha + \beta_1 BW * IVOL_{t-1}(\beta_1 BW^{\perp} * IVOL_{t-1}) + \beta_2 IVOL_{t-1} + \beta_3 BW_{t-1}(\beta_3 BW^{\perp}_{t-1}) + \varepsilon_t \quad (10)$$

[TABLE 7]

Table 7 provides a lower bound for expectational errors of earnings. The results are similar across exclusion schemes. For all deciles, the variation is comparable to the trend of Fama-MacBeth regression loadings when sorted on the correspondent sentimentalized IVOL in Table 3, 6 and A.3. The earnings announcement effect is significantly and negatively related to $SENTA*IVOLs$ ($SENTA^{\perp}*IVOLs$) in the highest $SENTA*IVOL$ ($SENTA^{\perp}*IVOL$) decile, and to $BW*IVOLs$ in the lowest $BW*IVOL$ decile but is significantly and positively related to $BW^{\perp}*IVOLs$ in the highest $BW^{\perp}*IVOL$ decile. The above results suggest the potential power of sentimentalized IVOL in the correction of earnings announcement errors.

7. Conclusion

Erroneous stochastic beliefs and the limits to arbitrage are two sources hindering rational arbitrageurs' price correction behavior towards the fundamental value (De Long et al., 1990). In this paper, we explore whether the cross-section of expected returns is a joint function of arbitrage risk and investor sentiment (i.e., the effect of sentimentalized IVOL on expected returns). We use the closed-end fund discount rate, share turnover, IPO volume, IPO first-day returns, dividend premium and equity share in new issues to obtain the investor sentiment measure. Arbitrage risk is proxied by idiosyncratic volatility (IVOL), that is the standard deviation of the monthly residuals to the Fama-French three factor model scaled by the square root of the number of trading days in the month.

We perform a battery of analyses and discover that the one-month lag of the joint factor between IVOL and the investor sentiment index exerts a significant effect on cross-sectional stock returns, shifting from negative to positive. Combining the two factors is fruitful. However, the combination is unbalanced across different periods. The power of sentiment dominates during lower IVOL periods while the effect of IVOL takes over when it reaches to its own maximum. Moreover, the influence of the sentimentalized IVOL also varies with its components. With respect to portfolios double-sorted on the sentiment and IVOL, we further show that although stocks with a lower sentiment positively affect their return, the negative impact of stocks with the highest IVOL is more pronounced in our sample, rendering the overall negative pricing interaction to be found inside stocks with the lowest sentimentalized IVOL, and vice versa.

Our empirical results hold up to the substitution of the Baker and Wurgler (2006) sentiment index and different exclusions of stocks during factor construction and are unaffected by the NBER business cycles. At least as a lower bound, our interaction sentimentalized IVOL negatively reflects the errors in earnings expectations in the highest characteristic decile conditional on *SENTA*IVOLs* ($SENTA^{\perp}$**IVOLs*) and in the lowest decile conditional on *BW*IVOLs* while it does so positively in the highest $BW^{\perp}$**IVOL* deciles. For double-sorted portfolios, the joint effect is more significant for stocks with smaller sizes but not for those with higher book-to-market ratios.

Our study provides strong evidence that the cross-section of expected returns is sensitive to the sentimentalized IVOL. In particular, the sensitivity described above varies with the components of sentimentalized IVOL in their sorted portfolios. Future research may investigate questions such as, to what extent the sentimentalized IVOL affects specific investment fund portfolios and whether this effect differs in other countries' assets, than U.S. stocks.

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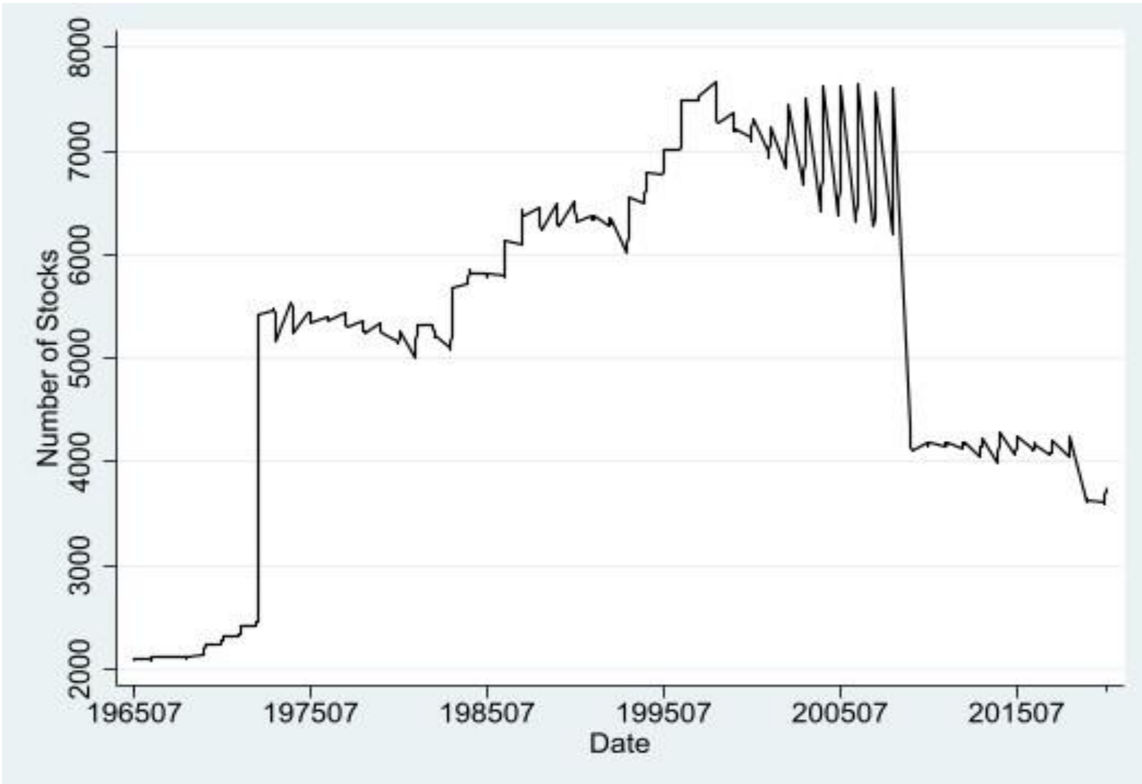
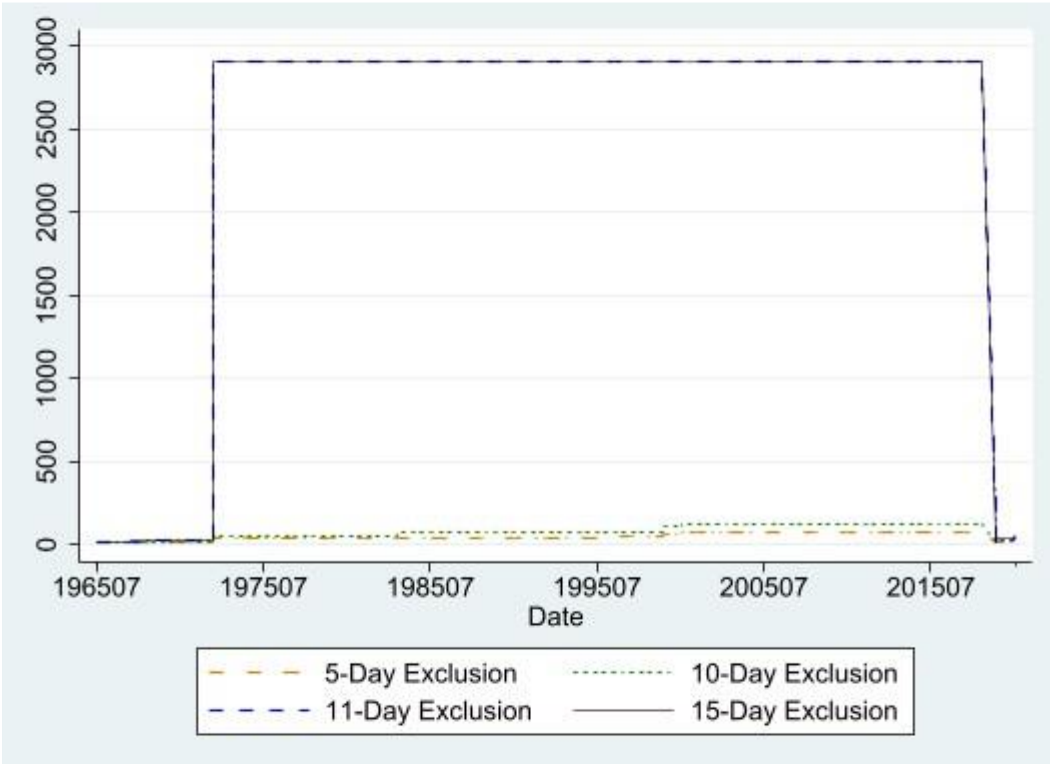
Figure 1. The Monthly Number of Listed Stocks



This figure plots the monthly number of stocks listed in NYSE/AMEX/NASDAQ from July 1965 to December 2020. The lowest number of stocks is in July 1965 with 2,083 stocks and the highest number of stocks is in January 1998 with 7,660 stocks.

Figure 2. The Monthly Excluded Stocks



This figure plots the number of excluded stocks in each month from July 1965 to December 2020. The highest solid line represents for the number of stocks excluded if with less than 15 trading days in a month. The second highest dashed blue line is for the number of excluded stocks if with less than 11 trading days in a month. The green tight dotted line is for the number of excluded stocks with less than 10 trading days in a month. The lowest yellow line is for the number of excluded stocks with less than 5 trading days in a month.

Table 1. Descriptive Statistics of Sentimentalized Idiosyncratic Volatilities

Panel A Value-Weighted Sentimentalized Idiosyncratic Volatilities											
	Obs.	No. of Stocks	Mean	S.D.							
SENTA*IVOL	3,177,422	24,721	0.0059	0.0668							
SENTA$^{\perp}$*IVOL			0.0055	0.0632							
	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
SENTA*IVOL	0.9738	0.9462	0.9188	0.8864	0.8429	0.7949	0.7498	0.7018	0.6495	0.5990	0.5474
SENTA$^{\perp}$*IVOL	0.9580	0.9196	0.8789	0.8305	0.7739	0.7152	0.6609	0.6053	0.5554	0.5036	0.4546
Panel B Equal-Weighted Sentimentalized Idiosyncratic Volatilities											
	Obs.	No. of Stocks	Mean	S.D.							
SENTA*IVOL	3,177,422	24,721	4.63E-11	3.70E-09							
SENTA$^{\perp}$*IVOL			6.25E-11	3.45E-09							
	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
SENTA*IVOL	-0.0574	-0.0679	0.1749	-0.0518	-0.102	0.0441	-0.04	-0.1756	-0.032	-0.0866	-0.0669
SENTA$^{\perp}$*IVOL	-0.0824	-0.0292	0.1493	-0.0249	-0.1048	0.0421	0.0008	-0.1479	-0.0312	-0.0468	-0.0745

This table reports means, standard deviations (S.D.) and autocorrelations of the interaction characteristic, sentimentalized IVOL (*SENTA*IVOL* and *SENT$^{\perp}$*IVOL*) over the period from July 1965 to December 2020. *IVOL* is computed from daily cross-sectional stock returns under 5-day exclusion of the Fama-French three factor model (Equation (1)). The total number of observations and the number of stocks identified by the unique PERMNO under 5-day exclusion are reported as well. *SENTA*IVOL* (*SENTA$^{\perp}$*IVOL*) is the product between *IVOL*, and the investor's sentiment index aligned, *SENTA*, (the orthogonalized investor's sentiment index aligned, *SENTA$^{\perp}$*) accessed from Professor Zhou's website. In panel A, the value-weighted *SENTA*IVOL* (*SENTA$^{\perp}$*IVOL*) is taken every month across all stocks within the sample period based on their market capitalization. In panel B, equal-weighted *SENTA*IVOL* (*SENTA$^{\perp}$*IVOL*) is taken every month across all stocks within the sample period.

Table 2. Time-series Alphas of High Minus Low Portfolios

	VW			EW		
	(1)	(2)	(3)	(1)	(2)	(3)
	H-L	+SENTA	+SENTA⊥	H-L	+SENTA	+SENTA⊥
Sorted on						
SENTA*IVOL	-0.0446**	-0.0421**		-0.0558***	-0.0512***	
	[-2.49]	[-2.29]		[-3.15]	[-2.79]	
SENTA⊥*IVOL	-0.0369**		-0.0350**	-0.0441***		-0.0412**
	[-2.08]		[-1.95]	[-2.50]		[-2.29]

This table displays value-weighted and equal-weighted time-series alphas (in percentages) on zero-investment portfolios (*H-L*) sorted on the sentimentalized IVOL (*SENTA*IVOL* and *SENTA⊥*IVOL*). The sample period is from July 1965 to December 2020. All coefficients are multiplied by 100. *IVOL* is computed from daily cross-sectional stock returns under 5-day exclusion of the Fama-French three factor model (Equation (1)). *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *SENTA*IVOL* (*SENTA⊥*IVOL*) is the product between *IVOL*, and *SENTA* (*SENTA⊥*). We construct the *H-L* portfolios by taking the difference between returns on the highest and the lowest sorted quintiles. We regress the *H-L* returns on the following two specifications,

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST\_Rev} ST\_Rev_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \epsilon_t \quad (2)$$

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \beta_{SENTA}\, SENTA_t\ (+\beta_{SENTA^{\perp}} SENTA_t^{\perp}) + \epsilon_t. \quad (3)$$

According to Equation (2), the regression (1) for each *H-L* portfolio contains Fama and French (1993) three factors, plus the momentum factor *MOM*, the short-term reversal factor *ST_Rev*, the profitability factor *RMW*, the investment factor *CMA* and the liquidity factor *PS*. The above factors are accessed from Professor French's data library and Professor Stambaugh's personal website. The excess market return RET_M is calculated by subtracting risk-free rate which is the monthly T-bill return compounded from a simple daily rate from Ibbotson and Associates Inc. *HML* stands for the returns on high book-to-market ratio stocks minus low book-to-market ratio stocks while *SMB* stands for the returns on small market capitalization stocks minus big market capitalization stocks. *MOM* is the difference between the average return on the two high prior (2-12 month) return portfolios and the two low prior (2-12 month) return portfolios. *ST_Rev* is the difference between the average return on the two high prior (1 month) return portfolios and the two low prior (1 month) return portfolios. *RMW* is the return on robust operating profitability stocks minus weak operating profitability stocks. *CMA* is the return on conservative stocks minus aggressive stocks. *PS* is the liquidity factor from Pastor and Stambaugh (2003). As indicated in the Equation (3), in addition to the above factors, *SENTA* (*SENTA⊥*) is included into the regression (2) and (3), respectively. Newey-West (1987) robust t-statistics are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Fama-MacBeth Regressions for Sorted Portfolios

*Panel A Fama-MacBeth Regression Loadings of SENTA*IVOL*							
Sorted on	IVOL	SENTA	SENTA*IVOL				
Low	-0.0063	-0.1432***	-0.0484***				
	[-0.76]	[-4.16]	[-3.99]				
High	-0.0270*	0.1208***	0.0151				
	[-1.92]	[3.12]	[1.39]				
Double-Sorted on		IVOL					
		Low	2	3	4	High	
SENTA	Low	0.0371**	0.0780***	0.0951***	0.0961***	-0.1582***	
		[1.99]	[3.29]	[3.62]	[3.44]	[-3.47]	
	High	-0.0768**	-0.3080***	-0.3860***	-0.4867***	0.0286	
		[-2.17]	[-6.33]	[-7.87]	[-8.36]	[0.57]	
*Panel B Fama-MacBeth Regression Loadings of SENTA⊥*IVOL*							
Sorted on	IVOL	SENTA⊥	SENTA⊥*IVOL				
Low	-0.0014*	-0.1888***	-0.0351***				
	[-1.85]	[-4.81]	[-3.13]				
High	-0.0139	0.1032***	0.0074				
	[-1.06]	[2.83]	[0.74]				
Double-Sorted on		IVOL					
		Low	2	3	4	High	
SENTA⊥	Low	0.0017	0.0950**	0.1565***	0.1689***	-0.1020**	
		[0.08]	[2.51]	[3.33]	[3.71]	[-2.16]	
	High	-0.0740**	-0.2613***	-0.3415***	-0.4260***	0.0430	
		[-2.44]	[-6.42]	[-7.39]	[-8.52]	[0.97]	

This table reports the cross-sectional loadings of single-sorted and double-sorted portfolios for Fama-MacBeth regressions. Monthly *IVOL* is computed as the standard deviation of residuals scaled by the square root of the number of trading days in the month with regard to the Fama-French three factor model based on daily stock returns (Equation (1)). Stocks with less than 5 trading days in a month are excluded. *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *SENTA*IVOL* (*SENTA⊥*IVOL*) is the product between *IVOL*, and *SENTA* (*SENTA⊥*). All regressions are performed using 60-month rolling windows. All coefficients are multiplied by 100. The sample period is from July 1965 to December 2020. We regress the excess stock returns (*XRET*) on the one-month lag of *SENTA*IVOL* (*SENTA⊥*IVOL*), controlling for the one-month lag of *IVOL*, one-month lag of *SENTA* (*SENTA⊥*) , the market beta (*BETA*), the one-month lag of stock return (RET_{t-1}), the near-term lagged return ($RET_{t-2,t-12}$), the log of market capitalization (*lnSIZE*) and the log of the book-to-market ratio (*lnBE/ME*), as shown in the following Equations (4) and (5),

$$XRET_{i,t} = \alpha_i + \beta_{SENTA*IVOL,i} SENTA * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{SENTA,i} SENTA_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (4)$$

$$XRET_{i,t} = \alpha_i + \beta_{SENTA^{\perp}*IVOL,i} SENTA^{\perp} * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{SENTA,i^{\perp}} SENTA^{\perp}_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t.} \quad (5)$$

In Panel A, our sample is first monthly single-sorted by *IVOL, SENTA,* and *SENTA*IVOL*, respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *SENTA* and then by *IVOL*. Loadings across *IVOL* quintiles inside the lowest and the highest *SENTA* quintiles are presented. In Panel B, our sample is first monthly single-sorted by *IVOL*, *SENTA⊥*, and *SENTA⊥*IVOL*, respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *SENTA⊥* and then by *IVOL*. Loadings across *IVOL* quintiles inside the lowest and the highest *SENTA⊥* quintiles are presented. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

Table 4. Descriptive Statistics of Sentimentalized Idiosyncratic Volatilities (BW Sentiment)

Panel A Value-Weighted Sentimentalized Idiosyncratic Volatilities											
	Mean	S.D.									
BW*IVOL	-0.0031	0.0595									
BW⊥*IVOL	-0.0038	0.0608									
	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
BW*IVOL	0.9728	0.9442	0.9147	0.8813	0.8459	0.8077	0.7683	0.7256	0.6834	0.6380	0.5862
BW⊥*IVOL	0.9666	0.9333	0.9031	0.8679	0.8295	0.7923	0.7538	0.7132	0.6732	0.6289	0.5786
Panel B Equal-Weighted Sentimentalized Idiosyncratic Volatilities											
	Mean	S.D.									
BW*IVOL	-2.17E-10	3.19E-09									
BW⊥*IVOL	-2.34E-10	3.20E*09									
	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
BW*IVOL	-0.0181	0.0468	0.0987	0.0578	-0.0013	-0.0496	-0.0602	-0.0933	0.0704	-0.1743	-0.0577
BW⊥*IVOL	-0.0344	0.0535	0.0727	0.0435	-0.0138	-0.0386	-0.0475	-0.0999	0.0723	-0.1642	-0.0596

This table reports means, standard deviations (S.D.) and autocorrelations of the interaction characteristic, sentimentalized IVOL (*BW*IVOL* and *BW⊥*IVOL*) over the period from July 1965 to December 2020. IVOL is computed from daily cross-sectional stock returns under 5-day exclusion of the Fama-French three factor model (Equation (1)). *BW*IVOL* (*BW⊥*IVOL*) is the product between *IVOL*, and the investor's sentiment index, *BW*, (the orthogonalized investor's sentiment index, *BW⊥*) accessed from Professor Wurgler's website. In panel A, value-weighted *BW*IVOL* (*BW⊥*IVOL*) is taken every month across all stocks within the sample period based on their market capitalization. In panel B, equal-weighted *BW*IVOL* (*BW⊥*IVOL*) is taken every month across all stocks within the sample period.

Table 5. Time-series Alphas of High Minus Low Portfolios (BW Sentiment)

	VW			EW		
	H-L	+BW	+BW⊥	H-L	+BW	+BW⊥
Sorted on						
BW*IVOL	-0.0239	-0.0226		-0.0034	-0.0017	
	[-1.40]	[-1.33]		[-0.19]	[-0.10]	
BW⊥*IVOL	-0.0096		-0.0095	0.0118		0.0121
	[-0.56]		[-0.55]	[0.68]		[0.70]

This table displays value-weighted and equal-weighted time-series alphas (in percentages) on zero-investment portfolios (*H-L*) sorted on the sentimentalized IVOL (*BW*IVOL* and *BW⊥*IVOL*). The sample period is from July 1965 to December 2020. All coefficients are multiplied by 100. *IVOL5* is computed from daily cross-sectional stock returns under 5-day exclusion of the Fama-French three factor model (Equation (1)). *BW* (*BW⊥*) is the investor's sentiment index (the orthogonalized investor's sentiment index), accessed from Professor Wurgler's website. *BW*IVOL* (*BW⊥*IVOL*) is the product between *IVOL*, and *BW* (*BW⊥*). We construct the *H-L* portfolios by taking the difference between returns on the highest and the lowest sorted quintiles. We regress the *H-L* returns on the following two specifications,

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST\_Rev} ST\_Rev_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \epsilon_t \quad (2)$$

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \beta_{BW}\, BW_t\ (+\beta_{BW^{\perp}} BW_t^{\perp}) + \epsilon_t. \quad (6)$$

According to Equation (2), the regression (1) for each *H-L* portfolio contains Fama and French (1993) three factors, plus the momentum factor *MOM*, the short-term reversal factor *ST_Rev*, the profitability factor *RMW*, the investment factor *CMA* and the liquidity factor *PS*. The above factors are accessed from Professor French's data library and Professor Stambaugh's personal website. The excess market return RET_M is calculated by subtracting risk-free rate which is the monthly T-bill return compounded from a simple daily rate from Ibbotson and Associates Inc. *HML* stands for the returns on high book-to-market ratio stocks minus low book-to-market ratio stocks while *SMB* stands for the returns on small market capitalization stocks minus big market capitalization stocks. *MOM* is the difference between the average return on the two high prior (2-12 month) return portfolios and the two low prior (2-12 month) return portfolios. *ST_Rev* is the difference between the average return on the two high prior (1 month) return portfolios and the two low prior (1 month) return portfolios. *RMW* is the return on robust operating profitability stocks minus weak operating profitability stocks. *CMA* is the return on conservative stocks minus aggressive stocks. *PS* is the liquidity factor from Pastor and Stambaugh (2003). As indicated in the Equation (6), in addition to the above factors, *BW* (*BW⊥*) is included into the regression (2) and (3), respectively. Newey-West (1987) robust t-statistics are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Fama-MacBeth Regressions for Sorted Portfolios (BW Sentiment)

*Panel A Fama-MacBeth Regression Loadings of BW*IVOL*

Sorted on	IVOL	BW	BW*IVOL
Low	-0.0083	-0.2348***	-0.0017
	[-0.95]	[-4.95]	[-0.16]
High	0.0374***	0.1237***	0.0307***
	[2.99]	[3.18]	[2.87]

Double-Sorted on		IVOL Low	2	3	4	High
BW	Low	0.0522	0.3075***	0.4818***	0.5669***	0.0880*
		[1.53]	[5.67]	[7.43]	[8.52]	[1.82]
	High	-0.0895***	-0.2353***	-0.2886***	-0.3031***	0.1039**
		[-3.12]	[-6.22]	[-7.04]	[-6.77]	[2.47]

*Panel B Fama-MacBeth Regression Loadings of BW⊥*IVOL*

Sorted on	IVOL	BW⊥	BW⊥*IVOL
Low	-0.0130	-0.1930***	-0.0041
	[-1.41]	[-4.00]	[-0.37]
High	0.0370***	0.1083***	0.0279**
	[2.85]	[2.77]	[2.43]

Double-Sorted on		IVOL Low	2	3	4	High
BW⊥	Low	0.0254	0.2636***	0.4237***	0.5134***	0.0730
		[0.66]	[5.44]	[7.44]	[8.13]	[1.46]
	High	-0.0843***	-0.2258***	-0.2506***	-0.2607***	0.1010**
		[-3.06]	[-5.80]	[-6.73]	[-6.07]	[2.44]

This table reports the cross-sectional loadings of single-sorted and double-sorted portfolios for Fama-MacBeth regressions. Monthly *IVOL* is computed as the standard deviation of residuals scaled by the square root of the number of trading days in the month with regard to the Fama-French three factor model based on daily stock returns (Equation (1)). Stocks with less than 5 trading days in a month are excluded. *BW* (*BW⊥*) is the investor's sentiment index (the orthogonalized investor's sentiment index), accessed from Professor Wurgler's website. *BW*IVOL* (*BW⊥*IVOL*) is the product between *IVOL*, and *BW* (*BW⊥*). All regressions are performed using 60-month rolling windows. All coefficients are multiplied by 100. The sample period is from July 1965 to December 2020. We regress the excess stock returns (*XRET*) on the one-month lag of *BW*IVOL* (*BW⊥*IVOL*), controlling for the one-month lag of *IVOL*, one-month lag of *BW* (*BW⊥*), the market beta (*BETA*), the one-month lag of stock return (RET_{t-1}), the near-term lagged return ($RET_{t-2,t-12}$), the log of market capitalization (*lnSIZE*) and the log of the book-to-market ratio (*lnBE/ME*), as shown in the following Equations (7) and (8),

$$XRET_{i,t} = \alpha_i + \beta_{BW*IVOL,i} BW * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i} BW_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (7)$$

$$XRET_{i,t} = \alpha_i + \beta_{BW^{\perp}*IVOL,i} BW^{\perp} * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i^{\perp}} BW^{\perp}_{t-1} \beta_{controls} + Controls_t + \epsilon_{i,t.} \quad (8)$$

In Panel A, our sample is first monthly single-sorted by *IVOL, BW*, and *BW*IVOL*, respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *BW* and then by *IVOL*. Loadings across *IVOL* quintiles inside the lowest and the highest *BW* quintiles are presented. In Panel B, our sample is first monthly single-sorted by *IVOL, BW⊥*, and *BW⊥*IVOL*, respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *BW⊥* and then by *IVOL*. Loadings across *IVOL* quintiles inside the lowest and the highest *BW⊥* quintiles are presented. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

Table 7. Earnings Announcement Effects, 1971-2020

	Decile									
	1	2	3	4	5	6	7	8	9	10
SENTA*IVOL	-0.3621	0.0126	-0.4135	0.5809	0.2953	-1.0145	-0.1387**	1.3046**	-0.0810	-1.4773***
SENTA⊥*IVOL	0.2163	-1.8432	-0.4208	-0.4903	-0.2694	-0.3485	-0.4693	1.6887***	0.6259	-1.3633***
BW*IVOL	-1.5233**	-1.1377	-2.1398**	-1.0596	-0.5830	-1.2849	-1.4961	1.2004	2.3365***	0.8370
BW⊥*IVOL	-0.6546	-0.9616	-2.4097***	-1.6261*	-1.2644	-1.4800	-1.0718	1.5529*	2.7178***	1.5590***
SENTA*IVOL10	-0.3468	0.0587	-0.4171	0.5489	0.2861	-0.9997	-1.2831**	1.2509**	-0.1146	-1.4833***
SENTA⊥*IVOL10	0.2349	-1.8899**	-0.3792	-0.6042	-0.1447	-0.4234	-0.4190	1.6183***	0.6080	-1.3752***
BW*IVOL10	-1.5477**	-1.1421	-2.1117**	-1.0806	-0.6253	-1.2999	-1.5200	1.3449	2.1502***	0.8086
BW⊥*IVOL10	-0.6687	-0.9855	-2.2744***	-1.7385**	-1.3523	-1.4354	-1.0571	1.6211*	2.5489***	1.5444**
SENTA*IVOL11	-0.3459	0.0435	-0.4227	0.5457	0.2752	-1.0100	-1.2707**	1.2436**	-0.1620	-1.4735***
SENTA⊥*IVOL11	0.1973	-1.9038**	-0.3314	-0.5752	-0.2082	-0.3612	-0.4883	1.6434***	0.5603	-1.3686***
BW*IVOL11	-1.5459**	-1.1482	2.1611**	-1.1286	-0.6207	-1.2957	-1.5521	1.3496	2.1547***	0.8165
BW⊥*IVOL11	-0.6361	-1.0055	-2.2446***	-1.7815**	-1.3480	-1.4717	-1.0608	1.6346*	2.5204***	1.5667***

This table reports the coefficient β_1 in Equations (9) and (10) for quarterly earnings announcement effects. All coefficients are multiplied by 100. The dependent variable is the cumulative abnormal return (*CAR*) over the value-weighted market index for each firm-quarter observation through trading days *t-1* to *t+1*. Quarterly cumulative abnormal returns are matched to previous year-end (orthogonalized) sentimentalized IVOLs in the original sample. The merged sample covers the period from January 1971 to December 2020 and is sorted into deciles according to the (orthogonalized) sentimentalized IVOL. Monthly *IVOL* is computed as the standard deviation of residuals scaled by the square root of the number of trading days in the month with regard to the Fama-French three factor model based on daily stock returns (Equation (1)). *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *SENTA*IVOL* (*SENTA⊥*IVOL*) is the product between *IVOL*, and *SENTA* (*SENTA⊥*). *BW* (*BW⊥*) is the investor's sentiment index (the orthogonalized investor's sentiment index), accessed from Professor Wurgler's website. *BW*IVOL* (*BW⊥*IVOL*) is the product between *IVOL*, and *BW* (*BW⊥*). Stocks with less than 5 trading days, 10 trading days, and 11 trading days in a month are excluded. Heteroskedasticity-robust *p*-values are in brackets. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

$$CAR_{X_{it}=Decile,t} = \alpha + \beta_1 SENTA * IVOL_{t-1}(\beta_1 SENTA^{\perp} * IVOL_{t-1}) + \beta_2 IVOL_{t-1}$$
$$+\beta_3 SENTA_{t-1}(\beta_3 SENTA_{t-1}^{\perp}) + \varepsilon_t \tag{9}$$
$$CAR_{X_{it}=Decile,t} = \alpha + \beta_1 BW * IVOL_{t-1}(\beta_1 BW^{\perp} * IVOL_{t-1}) + \beta_2 IVOL_{t-1}$$
$$+\beta_3 BW_{t-1}(\beta_3 BW_{t-1}^{\perp}) + \varepsilon_t \tag{10}$$

Online Appendix

Table A.1. Descriptive Statistics of Sentimentalized Idiosyncratic Volatilities (10-day and 11-day Exclusions)

Panel A Value-Weighted Sentimentalized Idiosyncratic Volatilities

	Obs.	No. of Stocks	Mean	S.D.		Mean	S.D.
SENTA*IVOL10	3,167,699	24,699	0.0059	0.0669	BW*IVOL10	-0.0031	0.0596
SENTA$^{\perp}$*IVOL10			0.0054	0.0633	BW$^{\perp}$*IVOL10	-0.0039	0.0608
SENTA*IVOL11	3,162,838	24,689	0.0059	0.0669	BW*IVOL11	-0.0031	0.0596
SENTA$^{\perp}$*IVOL11			0.0054	0.0633	BW$^{\perp}$*IVOL11	-0.0038	0.0608

	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
SENTA*IVOL10	0.9739	0.9463	0.9189	0.8866	0.8431	0.7952	0.75	0.7021	0.6499	0.5993	0.5477
SENTA$^{\perp}$*IVOL10	0.9581	0.9198	0.8791	0.8308	0.7742	0.7155	0.6613	0.6057	0.5558	0.504	0.4568
SENTA*IVOL11	0.9739	0.9464	0.919	0.8867	0.8433	0.7953	0.7502	0.7022	0.6499	0.5994	0.5478
SENTA$^{\perp}$*IVOL11	0.9581	0.9199	0.8792	0.8309	0.7744	0.7157	0.6614	0.6058	0.5559	0.5040	0.4568
BW*IVOL10	0.9729	0.9444	0.9149	0.8815	0.8462	0.8080	0.7686	0.7259	0.6836	0.6383	0.5866
BW$^{\perp}$*IVOL10	0.9667	0.9335	0.9033	0.8681	0.8297	0.7926	0.7540	0.7134	0.6735	0.6291	0.5789
BW*IVOL11	0.9729	0.9443	0.9149	0.8816	0.8463	0.8081	0.7688	0.7261	0.6839	0.6386	0.5869
BW$^{\perp}$*IVOL11	0.9667	0.9334	0.9033	0.8681	0.8299	0.7928	0.7545	0.7138	0.6739	0.6297	0.5796

Panel B Equal-Weighted Sentimentalized Idiosyncratic Volatilities

	Obs.	No. of Stocks	Mean	S.D.		Mean	S.D.
SENTA*IVOL10	3,167,699	24,699	-1.46E-10	3.05E-09	BW*IVOL10	-4.57E-11	2.89E-09
SENTA$^{\perp}$*IVOL10			-3.15E-11	2.90E-09	BW$^{\perp}$*IVOL10	-2.18E-11	2.97E-09
SENTA*IVOL11	3,162,838	24,689	-5.74E-11	3.47E-09	BW*IVOL11	-6.12E-11	3.06E-09
SENTA$^{\perp}$*IVOL11			-4.73E-11	3.25E-09	BW$^{\perp}$*IVOL11	-7.02E-11	3.07E-09

	Autocorrelations										
	1	2	3	4	5	6	7	8	9	10	11
SENTA*IVOL10	0.0181	-0.0741	-0.1043	-0.1761	0.1071	0.1347	0.0787	-0.0092	-0.0307	-0.0243	0.0629
SENTA$^{\perp}$*IVOL10	0.0562	-0.0452	-0.0486	-0.1716	0.0628	0.0750	0.0337	0.0213	-0.0059	0.0104	0.0487
SENTA*IVOL11	-0.1032	0.0256	0.1447	0.0150	-0.0855	0.0542	-0.0233	-0.1069	0.1000	-0.0049	0.0569
SENTA$^{\perp}$*IVOL11	-0.1188	-0.0038	0.1554	0.0153	-0.0801	0.0812	-0.0083	-0.0910	0.0722	0.0284	0.0178
BW*IVOL10	-0.0270	0.0164	-0.0547	-0.0432	0.0616	0.0707	0.0890	-0.0685	-0.0861	0.0262	0.0222
BW$^{\perp}$*IVOL10	-0.0365	0.0155	-0.0376	-0.0472	0.0593	0.0519	0.0834	-0.0700	-0.1021	0.0333	0.0278
BW*IVOL11	-0.1121	0.0593	0.0823	0.0555	0.0003	-0.0591	0.0871	-0.1241	0.0148	0.0509	0.0345
BW$^{\perp}$*IVOL11	-0.1107	0.0383	0.1001	0.0565	-0.0095	-0.0699	0.0961	-0.1265	0.0047	0.0561	0.0253

This table reports means, standard deviations (S.D.) and autocorrelations of the interaction characteristic, sentimentalized IVOL, over the period from July 1965 to December 2020. *IVOL10* and *IVOL11* is computed from daily cross-sectional stock returns under 10-day and 11-day exclusions of the Fama-French three factor model (Equation (1)). The total number of observations and the number of stocks identified by the unique PERMNO under 10-day and 11-day exclusions are reported as well. *SENTA*IVOL10* (*SENTA*IVOL11*) is the product between *IVOL10* (*IVOL*11) and the investor's sentiment index aligned (*SENTA*). *SENTA*$^{\perp}$**IVOL10* (*SENTA*$^{\perp}$**IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index aligned (*SENTA*$^{\perp}$). The (orthogonalized) sentiment index aligned, *SENTA* and *SENTA*$^{\perp}$, are accessed from Professor Zhou's website. *BW*IVOL10* (*BW*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the investor's sentiment index from Baker and Wurgler (2006) (*BW*). *BW*$^{\perp}$**IVOL10* (*BW*$^{\perp}$**IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index from Baker and Wurgler (2006) (*BW*$^{\perp}$). The (orthogonalized) sentiment index, *BW* and *BW*$^{\perp}$, are accessed from Professor Wurgler's website. In Panel A, value-weighted sentimentalized IVOL is taken every month across all stocks within the sample period based on their market capitalization. In Panel B, equal-weighted sentimentalized IVOL is taken every month across all stocks within the sample period.

Table A.2 Time-series Alphas of High Minus Low Portfolios (10-day and 11-day Exclusions)

	VW			EW		
	H-L	+SENTA	+SENTA⊥	H-L	+SENTA	+SENTA⊥
*Panel A SENTA*IVOL10 & SENTA⊥*IVOL10*						
Sorted on						
SENTA*IVOL10	-0.0443**	-0.0418**		-0.0576***	-0.0529***	
	[-2.46]	[-2.27]		[-3.27]	[-2.91]	
SENTA⊥*IVOL10	-0.0371**		-0.0352**	-0.0457***		-0.0427**
	[-2.09]		[-1.96]	[-2.60]		[-2.39]
*Panel B SENTA*IVOL11 & SENTA⊥*IVOL11*						
Sorted on						
SENTA*IVOL11	-0.0447**	-0.0422**		-0.0577***	-0.0529***	
	[-2.49]	[-2.30]		[-3.27]	[-2.91]	
SENTA⊥*IVOL11	-0.0370**		-0.0351*	-0.0456***		-0.0426**
	[-2.08]		[-1.95]	[-2.59]		[-2.38]

	VW			EW		
	H-L	+BW	+BW⊥	H-L	+BW	+BW⊥
*Panel C BW*IVOL10 & BW⊥*IVOL10*						
Sorted on						
BW*IVOL10	-0.0235	-0.0223		-0.0061	-0.0044	
	[-1.37]	[-1.30]		[-0.35]	[-0.25]	
BW⊥*IVOL10	-0.0093		-0.0092	0.0098		0.0101
	[-0.54]		[-0.54]	[0.57]		[0.59]
*Panel D BW*IVOL11 & BW⊥*IVOL11*						
Sorted on						
BW*IVOL11	-0.0238	-0.0225		-0.0062	-0.0045	
	[-1.39]	[-1.32]		[-0.35]	[-0.25]	
BW⊥*IVOL11	-0.0094		-0.0093	0.0099		0.0101
	[-0.55]		[-0.54]	[0.57]		[0.59]

This table displays value-weighted and equal-weighted time-series alphas (in percentages) on zero-investment portfolios (*H-L*) sorted on the sentimentalized IVOL. The sample period is from July 1965 to December 2020. All coefficients are multiplied by 100. *IVOL10* and *IVOL11* is computed from daily cross-sectional stock returns under 10-day and 11-day exclusions of the Fama-French three factor model (Equation (1)). *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *BW* (*BW⊥*) is the sentiment index accessed from Professor Wurgler's website. *SENTA*IVOL10* (*SENTA*IVOL11*) is the product between *IVOL10* (*IVOL*11) and the investor's sentiment index aligned (*SENTA*). *SENTA⊥*IVOL10* (*SENTA⊥*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index aligned (*SENTA⊥*). *BW*IVOL10* (*BW*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the investor's sentiment index from Baker and Wurgler (2006) (*BW*). *BW⊥*IVOL10* (*BW⊥*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index from Baker and Wurgler (2006) (*BW⊥*). We construct the *H-L* portfolios by taking the difference between returns on the highest and the lowest sorted quintiles. We regress the *H-L* returns on the following three specifications,

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST\_Rev} ST\_Rev_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \epsilon_t \quad (2)$$

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \beta_{SENTA}\, SENTA_t \,(+\beta_{SENTA^{\perp}} SENTA_t^{\perp}) + \epsilon_t. \quad (3)$$

$$(H-L)_t = \alpha + \beta_M RET_{M.t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_{ST_{Rev}} ST_{Rev_t} + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{PS} PS_t + \beta_{BW}\, BW_t \,(+\beta_{BW^{\perp}} BW_t^{\perp}) + \epsilon_t. \quad (6)$$

According to Equation (2), the regression (1) for each *H-L* portfolio contains Fama and French (1993) three factors, plus the momentum factor *MOM*, the short-term reversal factor *ST_Rev*, the profitability factor *RMW*, the investment factor *CMA* and the liquidity factor *PS*. The above factors are accessed from Professor French's data library and Professor Stambaugh's personal website. The excess market return RET_M is calculated by subtracting risk-free rate which is the monthly T-bill return compounded from a simple daily rate from Ibbotson and Associates Inc. *HML* stands for the returns on high book-to-market ratio stocks minus low book-to-market ratio stocks while *SMB* stands for the returns on small market capitalization stocks minus big market capitalization stocks. *MOM* is the difference between the average return on the two high prior (2-12 month) return portfolios and the two low prior (2-12 month) return portfolios. *ST_Rev* is the difference between the average return on the two high prior (1 month) return portfolios and the two low prior (1 month) return portfolios. *RMW* is the return on robust operating profitability stocks minus weak operating profitability stocks. *CMA* is the return on conservative stocks minus aggressive stocks. *PS* is the liquidity factor from Pastor and Stambaugh (2003). As indicated in the Equations (3) and (6), in addition to the above factors, *SENTA* ($SENTA^{\perp}$) or *BW* ($BW^{\perp}$) is included into the regressions (2) and (3), respectively. Newey-West (1987) robust t-statistics are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3. Fama-MacBeth Regression for Sorted Portfolios (10-day and 11-day Exclusions)

Panel A Fama-MacBeth Regression Loadings under 10-day Exclusion						
SENTA*IVOL10						
Sorted on	IVOL10	SENTA	SENTA*IVOL10			
Low	-0.0134*	-0.1417***	-0.0509***			
	[-1.76]	[-4.17]	[-4.35]			
High	-0.0266*	0.1215***	0.0110			
	[-1.90]	[3.13]	[1.03]			
Double-Sorted on				IVOL10		
		Low	2	3	4	High
SENTA	Low	0.0230*	0.0847***	0.1001***	0.0950***	-0.1540***
		[1.75]	[3.56]	[3.69]	[3.70]	[-3.47]
	High	-0.0934***	-0.3010***	-0.3872***	-0.4833***	0.0261
		[-2.78]	[-6.21]	[-7.91]	[-8.35]	[0.52]
SENTA⊥*IVOL10						
Sorted on	IVOL10	SENTA⊥	SENTA⊥*IVOL10			
Low	-0.0140*	-0.1906***	-0.0380***			
	[-1.89]	[-4.85]	[-3.42]			
High	-0.0148	0.1039***	0.0093			
	[-1.12]	[2.84]	[0.92]			
Double-Sorted on				IVOL10		
		Low	2	3	4	High
SENTA⊥	Low	0.0132	0.1258***	0.1501***	0.1667***	-0.1047**
		[0.65]	[3.26]	[3.25]	[3.64]	[-2.22]
	High	-0.0859***	-0.2600***	-0.3418***	-0.4255***	0.0412
		[-2.88]	[-6.40]	[-7.47]	[-8.52]	[0.92]
BW*IVOL10						
Sorted on	IVOL10	BW	BW*IVOL10			
Low	-0.0053	-0.2342***	0.0015			
	[-0.62]	[-4.91]	[0.14]			
High	0.0376***	0.1271***	0.0310***			
	[3.02]	[3.24]	[2.88]			
Double-Sorted on				IVOL10		
		Low	2	3	4	High
BW	Low	0.0526	0.3208***	0.4802***	0.5679***	0.0893*
		[1.52]	[6.01]	[7.40]	[8.47]	[1.86]
	High	-0.0749***	-0.2285***	-0.2883***	-0.3003***	0.1035**
		[-2.78]	[-6.08]	[-7.05]	[-6.93]	[2.47]
BW⊥*IVOL10						
Sorted on	IVOL10	BW⊥	BW⊥*IVOL10			
Low	-0.0104	-0.1933***	-0.0005			
	[-1.15]	[-4.00]	[-0.05]			
High	0.0380***	0.1124***	0.0283**			
	[2.93]	[2.85]	[2.44]			
Double-Sorted on				IVOL10		
		Low	2	3	4	High
BW⊥	Low	0.0220	0.2769***	0.4134***	0.5137***	0.0748
		[0.57]	[5.82]	[7.43]	[8.09]	[1.50]
	High	-0.0703***	-0.2175***	-0.2558***	-0.2583***	0.1046**
		[-2.73]	[-5.64]	[-6.81]	[-6.23]	[2.51]
Panel B Fama-MacBeth Regression Loadings under 11-day Exclusions						
SENTA*IVOL11						
Sorted on	IVOL11	SENTA	SENTA*IVOL11			
Low	-0.0134*	-0.1416***	-0.0508***			
	[-1.78]	[-4.17]	[-4.34]			
High	-0.0262*	0.1219***	0.0113			
	[-1.87]	[3.14]	[1.06]			
Double-Sorted on				IVOL11		

		Low	2	3	4	High
SENTA	Low	0.0223*	0.0898***	0.1007***	0.0953***	-0.1540***
		[1.71]	[3.71]	[3.71]	[3.70]	[-3.47]
	High	-0.0927***	-0.3005***	-0.3855***	-0.4842***	0.0280
		[-2.78]	[-6.19]	[-7.91]	[-8.36]	[0.56]
SENTA⊥*IVOL11						
Sorted on	IVOL11	SENTA⊥	SENTA⊥*IVOL11			
Low	-0.0136*	-0.1903***	-0.0377***			
	[-1.84]	[-4.85]	[-3.38]			
High	-0.0145	0.1042***	0.0099			
	[-1.10]	[2.84]	[0.97]			
Double-Sorted on				IVOL11		
		Low	2	3	4	High
SENTA⊥	Low	0.0139	0.1262***	0.1502***	0.1690***	-0.1048**
		[0.68]	[3.29]	[3.26]	[3.67]	[-2.23]
	High	-0.0853***	-0.2595***	-0.3406***	-0.4272***	0.0429
		[-2.86]	[-6.37]	[-7.46]	[-8.54]	[0.96]
BW*IVOL11						
Sorted on	IVOL11	BW	BW*IVOL11			
Low	-0.0052	-0.2343***	0.0014			
	[-0.60]	[-4.91]	[0.13]			
High	0.0373***	0.1275***	0.0307***			
	[3.00]	[3.24]	[2.84]			
Double-Sorted on				IVOL11		
		Low	2	3	4	High
BW	Low	0.0522	0.3133***	0.4811***	0.5704***	0.0871*
		[1.49]	[5.80]	[7.41]	[8.48]	[1.81]
	High	-0.0737***	-0.2297***	-0.2873***	-0.3011***	0.1043**
		[-2.74]	[-6.08]	[-7.05]	[-6.94]	[2.48]
BW⊥*IVOL11						
Sorted on	IVOL11	BW⊥	BW⊥*IVOL11			
Low	-0.0068	-0.1933***	-0.0009			
	[-0.83]	[-4.00]	[-0.08]			
High	0.0378***	0.1129***	0.0318***			
	[2.91]	[2.86]	[2.92]			
Double-Sorted on				IVOL11		
		Low	2	3	4	High
BW⊥	Low	0.0402	0.2712***	0.4240***	0.5182***	0.0723
		[1.23]	[5.62]	[7.46]	[8.09]	[1.45]
	High	-0.0693***	-0.2182***	-0.2548***	-0.2584***	0.1059**
		[-2.69]	[-5.63]	[-6.79]	[-6.23]	[2.53]

This table reports the cross-sectional loadings of single-sorted and double-sorted portfolios for Fama-MacBeth regressions. *IVOL10* and *IVOL11* is computed from daily cross-sectional stock returns under 10-day and 11-day exclusions of the Fama-French three factor model (Equation (1)). *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *BW* (*BW⊥*) is the sentiment index accessed from Professor Wurgler's website. *SENTA*IVOL10* (*SENTA*IVOL11*) is the product between *IVOL10* (*IVOL*11), and the investor's sentiment index aligned (*SENTA*). *SENTA⊥*IVOL10* (*SENTA⊥*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index aligned (*SENTA⊥*). *BW*IVOL10* (*BW*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the investor's sentiment index from Baker and Wurgler (2006) (*BW*). *BW⊥*IVOL10* (*BW⊥*IVOL11*) is the product between *IVOL10* (*IVOL11*) and the orthogonalized investor's sentiment index from Baker and Wurgler (2006) (*BW⊥*). All regressions are performed using 60-month rolling windows. All coefficients are multiplied by 100. The sample period is from July 1965 to December 2020. We regress the excess stock returns (*XRET*) on the one-month lag of *SENTA*IVOL* (*SENTA⊥*IVOL*), controlling for the one-month lag of *IVOL*, one-month lag of *SENTA* (*SENTA⊥*), the market beta (*BETA*), the one-month lag of stock return (RET_{t-1}), the near-term lagged return ($RET_{t-2,t-12}$), the log of market capitalization (*lnSIZE*) and the log of the book-to-market ratio (*lnBE/ME*), as shown in the following Equations (4) and (5),

$$XRET_{i,t} = \alpha_i + \beta_{SENTA*IVOL,i} SENTA * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{SENTA,i} SENTA_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (4)$$

$$XRET_{i,t} = \alpha_i + \beta_{SENTA^{\perp}*IVOL,i} SENTA^{\perp} * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{SENTA,i^{\perp}} SENTA^{\perp}_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t.} \quad (5)$$

As shown in Equations (7) and (8), we regress the excess stock returns (*XRET*) on the one-month lag of *BW*IVOL* (*BW⊥*IVOL*), controlling for the one-month lag of *IVOL*, one-month lag of *BW* (*BW⊥*), with other cross-sectional control variables,

$$XRET_{i,t} = \alpha_i + \beta_{BW*IVOL,i} BW * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i} BW_{t-1} + \beta_{controls} Controls_t + \epsilon_{i,t} \quad (7)$$

$$XRET_{i,t} = \alpha_i + \beta_{BW^{\perp}*IVOL,i} BW^{\perp} * IVOL_{i,t-1} + \beta_{IVOL,i} IVOL_{i,t-1} + \beta_{BW,i^{\perp}} BW^{\perp}_{t-1} \beta_{controls} + Controls_t + \epsilon_{i,t.} \quad (8)$$

Panel A presents results under 10-day exclusion. The sample is first monthly single-sorted by *IVOL10*, *SENTA*(*SENTA⊥*) or *BW* (*BW⊥*), *SENTA*IVOL10* (*SENTA⊥*IVOL10*) or *BW*IVOL10* (*BW⊥*IVOL10*), respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *SENTA* (*SENTA⊥*) or *BW* (*BW⊥*) and then by *IVOL10.* Loadings across *IVOL10* quintiles inside the lowest and the highest *SENTA* (*SENTA⊥*) or *BW* (*BW⊥*) quintiles are presented. Panel B records results under 11-day exclusion. The sample is first monthly single-sorted by *IVOL11*, *SENTA*(*SENTA⊥*) or *BW* (*BW⊥*), *SENTA*IVOL11* (*SENTA⊥*IVOL11*) or *BW*IVOL11* (*BW⊥*IVOL11*), respectively, into quintiles. The loadings for the lowest and the highest sorted portfolios are reported. Next, the sample is double-sorted monthly by *SENTA* (*SENTA⊥*) or *BW* (*BW⊥*) and then by *IVOL11.* Loadings across *IVOL11* quintiles inside the lowest and the highest *SENTA* (*SENTA⊥*) or *BW* (*BW⊥*) quintiles are presented. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

Table A.4. Fama-MacBeth Regression Loadings for Size Portfolios

Panel A Fama-MacBeth Regression Loadings under 5-day Exclusion

		Low	2	3	4	High	Low	2	3	4	High
Double-Sorted on		SENTA*IVOL					SENTA$^{\perp}$*IVOL				
SIZE	Low	-0.0829***	-0.0720***	-0.0931***	-0.0761***	0.0061	-0.0574***	-0.0441**	-0.0601***	-0.0578***	0.0049
		[-5.59]	[-4.33]	[-5.04]	[-4.45]	[0.46]	[-4.19]	[-2.51]	[-3.17]	[-3.37]	[0.40]
	2	0.0225	-0.0495*	-0.0322	-0.0916***	-0.0166	0.0141	-0.0157	-0.0293	-0.0806**	0.0103
		[0.90]	[-1.87]	[-1.12]	[-3.37]	[-0.52]	[0.55]	[-0.62]	[-0.92]	[-2.35]	[0.33]
	3	0.0404	-0.0248	-0.0380*	-0.0298	-0.0336	0.0455*	0.0606**	-0.0157	-0.0407	-0.0557**
		[1.34]	[-0.97]	[-1.65]	[-1.15]	[-1.21]	[1.80]	[2.10]	[-0.54]	[-1.49]	[-2.05]
	4	-0.0007	0.0202	0.0172	0.0042	0.0225	-0.0461	-0.0221	0.0105	0.0343	0.0009
		[-0.02]	[0.70]	[0.57]	[0.15]	[0.69]	[-1.60]	[-0.77]	[0.31]	[1.09]	[0.03]
	High	0.0062	0.0132	-0.0392	0.0381	0.0145	-0.0679**	-0.0694**	-0.0491	-0.0213	0.0712**
		[0.24]	[0.45]	[-1.34]	[1.40]	[0.32]	[-2.03]	[-2.30]	[-1.52]	[-0.71]	[2.22]
		BW*IVOL					BW$^{\perp}$*IVOL				
SIZE	Low	-0.0106	0.0537**	0.0377	0.0159	0.0534***	-0.0088	0.0482**	0.0401*	0.0216	0.0865**
		[-0.72]	[2.40]	[1.61]	[0.82]	[4.02]	[-0.57]	[2.30]	[1.76]	[1.20]	[2.48]
	2	0.1382***	0.1357***	0.0260	0.0497	0.0152	0.1226***	0.1113***	0.0218	0.0296	0.0285
		[3.59]	[4.25]	[0.76]	[1.50]	[0.48]	[3.27]	[3.82]	[0.65]	[0.95]	[0.91]
	3	0.0340	0.0923**	-0.0252	0.0309	-0.0157	-0.0154	0.0738*	-0.0350	0.0367	-0.0117
		[0.85]	[2.42]	[-0.72]	[0.96]	[-0.50]	[-0.37]	[1.94]	[-1.00]	[1.22]	[-0.37]
	4	-0.0161	0.0613*	0.0440	-0.0080	-0.0216	-0.0320	0.0424	-0.0087	-0.0154	-0.0018
		[-0.49]	[1.96]	[1.23]	[-0.23]	[-0.63]	[-1.00]	[1.33]	[-0.25]	[-0.43]	[-0.05]
	High	-0.0595*	-0.0430	0.0013	-0.0366	0.0458	-0.0612*	-0.0646**	-0.0226	-0.0315	0.0314
		[-1.69]	[-1.47]	[0.04]	[-1.07]	[1.22]	[-1.92]	[-2.32]	[-0.69]	[-0.97]	[0.87]

Panel B Fama-MacBeth Regression Loadings under 10-day Exclusion

		Low	2	3	4	High	Low	2	3	4	High
Double-Sorted on		SENTA*IVOL10					SENTA$^{\perp}$*IVOL10				
SIZE	Low	-0.0837***	-0.0725***	-0.0937***	-0.0749***	0.0035	-0.0610***	-0.0439**	-0.0621***	-0.0570***	0.0102
		[-5.75]	[-4.43]	[-5.10]	[-4.35]	[0.27]	[-4.49]	[-2.51]	[-3.29]	[-3.27]	[0.87]
	2	0.0176	-0.0551**	-0.0383	-0.0861***	-0.0192	0.0082	-0.0192	-0.0323	-0.0640**	0.0075
		[0.70]	[-2.11]	[-1.37]	[-3.05]	[-0.61]	[0.31]	[-0.77]	[-1.02]	[-2.00]	[0.25]
	3	0.0412	-0.0272	-0.0380*	-0.0277	-0.0360	0.0453*	0.0558*	-0.0153	-0.0342	-0.0534**
		[1.35]	[-1.06]	[-1.66]	[-1.04]	[-1.30]	[1.75]	[1.91]	[-0.52]	[-1.24]	[-2.01]
	4	-0.0049	0.0145	0.0295	0.0079	0.0230	-0.0447	-0.0277	0.0118	0.0361	0.0022
		[-0.19]	[0.51]	[0.96]	[0.28]	[0.72]	[-1.55]	[-0.98]	[0.34]	[1.14]	[0.07]
	High	0.0116	0.0106	-0.0368	0.0348	0.0133	-0.0642*	-0.0724**	-0.0477	-0.0237	0.0708**
		[0.44]	[0.36]	[-1.27]	[1.28]	[0.30]	[-1.93]	[-2.42]	[-1.48]	[-0.79]	[2.23]
		BW*IVOL10					BW$^{\perp}$*IVOL10				
SIZE	Low	-0.0067	0.0537**	0.0385	0.0172	0.0553***	-0.0035	0.0482**	0.0382*	0.0224	0.0914**
		[-0.46]	[2.41]	[1.64]	[0.89]	[4.24]	[-0.23]	[2.30]	[1.68]	[1.26]	[2.41]
	2	0.1379***	0.1328***	0.0212	0.0661**	0.0162	0.1211***	0.1127***	0.0151	0.0453	0.0304
		[3.57]	[4.18]	[0.61]	[2.06]	[0.51]	[3.28]	[3.86]	[0.45]	[1.48]	[0.98]
	3	0.0363	0.0869**	-0.0242	0.0323	-0.0209	-0.0123	0.0690*	-0.0341	0.0393	-0.0182
		[0.94]	[2.30]	[-0.70]	[0.99]	[-0.66]	[-0.31]	[1.82]	[-0.99]	[1.28]	[-0.57]
	4	-0.0205	0.0605*	0.0322	-0.0019	-0.0239	-0.0360	0.0417	-0.0172	-0.0071	-0.0055

		[-0.65]	[1.91]	[0.88]	[-0.05]	[-0.70]	[-1.20]	[1.29]	[-0.48]	[-0.20]	[-0.15]
	High	-0.0551	-0.0429	-0.0012	-0.0369	0.0432	-0.0625**	-0.0641**	-0.0253	-0.0304	0.0293
		[-1.57]	[-1.47]	[-0.03]	[-1.09]	[1.15]	[-1.96]	[-2.30]	[-0.78]	[-0.94]	[0.81]

Panel C Fama-MacBeth Regression Loadings under 11-day Exclusion

		Low	2	3	4	High	Low	2	3	4	High
Double-Sorted on		SENTA*IVOL11					SENTA⊥*IVOL11				
SIZE	Low	-0.0837***	-0.0721***	-0.0934***	-0.0733***	0.0034	-0.0609***	-0.0436**	-0.0621***	-0.0574***	0.0106
		[-5.76]	[-4.41]	[-5.07]	[-4.21]	[0.26]	[-4.49]	[-2.50]	[-3.29]	[-3.28]	[0.90]
	2	0.0176	-0.0516*	-0.0390	-0.0854***	-0.0208	0.0094	-0.0160	-0.0333	-0.0656**	0.0077
		[0.69]	[-1.95]	[-1.38]	[-3.03]	[-0.67]	[0.35]	[-0.64]	[-1.04]	[-2.05]	[0.25]
	3	0.0379	-0.0274	-0.0318	-0.0239	-0.0338	0.0471*	0.0570*	-0.0132	-0.0382	-0.0528**
		[1.24]	[-1.06]	[-1.44]	[-0.93]	[-1.22]	[1.84]	[1.94]	[-0.45]	[-1.40]	[-1.99]
	4	-0.0004	0.0151	0.0298	0.0077	0.0238	-0.0437	-0.0274	0.0121	0.0369	0.0010
		[-0.02]	[0.53]	[0.97]	[0.27]	[0.74]	[-1.52]	[-0.97]	[0.35]	[1.16]	[0.03]
	High	0.0093	0.0106	-0.0342	0.0355	0.0139	-0.0667**	-0.0695**	-0.0467	-0.0245	0.0709**
		[0.36]	[0.36]	[-1.18]	[1.30]	[0.31]	[-2.01]	[-2.31]	[-1.45]	[-0.81]	[2.23]
		BW*IVOL11					BW⊥*IVOL11				
SIZE	Low	-0.0066	0.0535**	0.0384	0.0152	0.0539***	-0.0033	0.0477**	0.0398*	0.0219	0.0554***
		[-0.46]	[2.40]	[1.64]	[0.79]	[4.13]	[-0.22]	[2.28]	[1.73]	[1.22]	[4.14]
	2	0.1386***	0.1337***	0.0220	0.0665**	0.0171	0.1205***	0.1135***	0.0165	0.0456	0.0318
		[3.58]	[4.20]	[0.64]	[2.07]	[0.54]	[3.26]	[3.87]	[0.49]	[1.49]	[1.03]
	3	0.0428	0.0862**	-0.0269	0.0337	-0.0208	-0.0074	0.0678*	-0.0326	0.0400	-0.0169
		[1.09]	[2.29]	[-0.77]	[1.05]	[-0.66]	[-0.18]	[1.79]	[-0.95]	[1.33]	[-0.53]
	4	-0.0220	0.0602*	0.0345	-0.0022	-0.0237	-0.0366	0.0411	-0.0143	-0.0077	-0.0056
		[-0.70]	[1.89]	[0.94]	[-0.06]	[-0.70]	[-1.21]	[1.27]	[-0.40]	[-0.22]	[-0.16]
	High	-0.0541	-0.0439	-0.0021	-0.0383	0.0433	-0.0626**	-0.0650**	-0.0258	-0.0319	0.0295
		[-1.54]	[-1.50]	[-0.06]	[-1.12]	[1.15]	[-1.96]	[-2.33]	[-0.79]	[-0.98]	[0.81]

This table shows the cross-sectional loadings of Fama-MacBeth regressions for portfolios that have been double-sorted by size and sentimentalized IVOL. SIZE is the stock market capitalization using NYSE breakpoints. *IVOL*, *IVOL10* and *IVOL11* are computed from daily cross-sectional stock returns under 5-day, 10-day and 11-day exclusions of the Fama-French three factor model (Equation (1)). *SENTA* (*SENTA⊥*) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *BW* (*BW⊥*) is the sentiment index accessed from Professor Wurgler's website. *SENTA*IVOL* (*SENTA*IVOL10* and *SENTA*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11), and the investor's sentiment index aligned (*SENTA*). *SENTA⊥*IVOL* (*SENTA⊥*IVOL10* and *SENTA⊥*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11) and the orthogonalized investor's sentiment index aligned (*SENTA⊥*). *BW*IVOL* (*BW*IVOL10* and *BW*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11) and the investor's sentiment index from Baker and Wurgler (2006) (*BW). BW⊥*IVOL* (*BW⊥*IVOL10* and *BW⊥*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11) and the orthogonalized investor's sentiment index from Baker and Wurgler (2006) (*BW⊥*). All regressions are run with a 60-month rolling window. Every coefficient is multiplied by 100. The sample period is from July 1965 to December 2020. In each of the 25 double-sorted portfolios, we perform Equations (4) and (5) for *SENTA*IVOLs* (*SENTA⊥*IVOLs*) and Equations (7) and (8) for *BW*IVOLs* (*BW⊥*IVOLs*). Panel A, B and C contain results under 5-day, 10-day and 11-day exclusions, respectively. *** denotes $p<0.01$, ** denotes $p<0.05$, and * denotes $p<0.1$.

Table A.5. Fama-MacBeth Regression Loadings for Book-to-Market Ratio Portfolios

Panel A Fama-MacBeth Regression Loadings under 5-day Exclusion

Double-Sorted on		Low	2	3	4	High	Low	2	3	4	High
		SENTA*IVOL					SENTA$^{\perp}$*IVOL				
lnBEME	Low	-0.0798***	-0.0463***	-0.0705***	-00690***	0.0030	-0.0432**	-0.0491***	-0.0576***	-0.0572***	-0.0054
		[-4.68]	[-3.28]	[-3.82]	[-4.09]	[0.17]	[-2.45]	[-3.49]	[-3.10]	[-3.22]	[-0.31]
	2	-0.0485***	-0.0305*	-0.0475***	-0.0669***	-0.0397**	-0.0457***	-0.0174	-0.0127	-0.0282	-0.0195
		[-3.14]	[-1.85]	[-3.34]	[-3.47]	[-2.41]	[-2.72]	[-0.98]	[-0.76]	[-1.30]	[-1.20]
	3	-0.0586***	-0.0222	-0.0863***	-0.0934***	0.0215	-0.0305**	-0.0073	-0.0489***	-0.0804***	0.0177
		[-3.74]	[-1.61]	[-5.11]	[-5.09]	[1.07]	[-2.11]	[-0.42]	[-2.67]	[-4.05]	[0.96]
	4	-0.0117	-0.0439**	-0.0307*	-0.0723***	-0.0047	-0.0150	-0.0240	-0.0235	-0.0712***	-0.0023
		[-0.69]	[-2.15]	[-1.73]	[-3.66]	[-0.27]	[-0.87]	[-1.24]	[-1.05]	[-4.26]	[-0.12]
	High	-0.0689***	-0.0656***	-0.0863***	-0.0771***	0.0146	-0.0624***	-0.0311*	-0.0637***	-0.0734***	0.0150
		[-4.08]	[-3.86]	[-3.58]	[-3.97}	[1.10]	[-2.71]	[-1.70]	[-2.67]	[-3.95]	[1.17]
		BW*IVOL					BW$^{\perp}$*IVOL				
lnBEME	Low	-0.0266	0.0286	0.0184	-0.0100	0.0482**	-0.0253	0.0353*	0.0226	-0.0059	0.0478**
		[-1.44]	[1.42]	[0.94]	[-0.54]	[2.45]	[-1.37]	[1.71]	[1.20]	[-0.31]	[2.40]
	2	0.0139	0.0532**	0.0446**	0.0269	0.0137	0.0090	0.0362	0.0399*	0.0387**	0.0070
		[0.66]	[2.31]	[2.22]	[1.37]	[0.76]	[0.45]	[1.57]	[1.95]	[2.24]	[0.40]
	3	0.0314*	.0492**	0.0383	-0.0212	0.0542**	0.0250	0.0360	0.0424*	-0.0233	0.0467**
		[1.67]	[2.07]	[1.55]	[-1.01]	[2.44]	[1.38]	[1.51]	[1.79]	[-1.21]	[2.04]
	4	0.0310	0.0767***	0.0557**	-0.0175	-0.0288	0.0196	0.0741***	0.0450*	-0.0047	-0.0270
		[1.58]	[2.87]	[2.05]	[-0.77]	[-1.49]	[1.08]	[3.03]	[1.77]	[-0.19]	[-1.32]
	High	-0.0271*	0.0469**	0.0391*	-0.0087	0.0471***	-0.0301**	0.0415*	0.0312	-0.0139	0.0315*
		[-1.89]	[2.02]	[1.78]	[-0.46]	[3.55]	[-2.08]	[1.87]	[1.47]	[-0.78]	[1.95]

Panel B Fama-MacBeth Regression Loadings under 10-day Exclusion

Double-Sorted on		Low	2	3	4	High	Low	2	3	4	High
		SENTA*IVOL10					SENTA$^{\perp}$*IVOL10				
lnBEME	Low	-0.0766***	-0.0472***	-0.0683***	-0.0677***	-0.0022	-0.0407**	-0.0503***	-0.0582***	-0.0580***	-0.0026
		[-4.62]	[-3.40]	[-3.72]	[-4.03]	[-0.13]	[-2.32]	[-3.64]	[-3.14]	[-3.31]	[-0.16]
	2	-0.0509***	-0.0297*	-0.0492***	-0.0675***	-0.0368**	-0.0481***	-0.0178	-0.0158	-0.0272	-0.0187
		[-3.34]	[-1.79]	[-3.49]	[-3.48]	[-2.26]	[-2.87]	[-0.99]	[-0.95]	[-1.25]	[-1.15]
	3	-0.0632***	-0.0209	-0.0775***	-0.0941***	0.0199	-0.0383***	-0.0071	-0.0410**	-0.0743***	0.0130
		[-4.04]	[-1.53]	[-4.67]	[-5.07]	[1.00]	[-2.65]	[-0.41]	[-2.31]	[-3.90]	[0.71]
	4	-0.0126	-0.0510***	-0.0295*	-0.0707***	-0.0050	-0.0160	-0.0231	-0.0242	-0.0700***	0.0014
		[-0.74]	[-2.62]	[-1.68]	[-3.56]	[-0.28]	[-0.92]	[-1.20]	[-1.09]	[-4.19]	[0.08]
	High	-0.0666***	-0.0544***	-0.0689***	-0.0719***	0.0205	-0.0794***	-0.0207	-0.0524***	-0.0604***	0.0210*
		[-4.73]	[-3.38]	[-3.89]	[-3.73]	[1.56]	[-5.09]	[-1.18]	[-2.83]	[-3.37]	[1.68]
		BW*IVOL10					BW$^{\perp}$*IVOL10				
lnBEME	Low	-0.0224	0.0276	0.0162	-0.0100	0.0501***	-0.0200	0.0343*	0.0211	-0.0056	0.0499**
		[-1.23]	[1.39]	[0.84]	[-0.54]	[2.60]	[-1.09]	[1.68]	[1.13]	[-0.30]	[2.54]
	2	0.0196	0.0544**	0.0408**	0.0290	0.0149	0.0166	0.0376	0.0362*	0.0390**	0.0093
		[0.92]	[2.35]	[2.03]	[1.46]	[0.82]	[0.83]	[1.62]	[1.77]	[2.22]	[0.53]
	3	0.0290	0.0508**	0.0415*	-0.0242	0.0497**	0.0233	0.0380	0.0443*	-0.0285	0.0473**
		[1.53]	[2.14]	[1.68]	[-1.14]	[2.26]	[1.27]	[1.59]	[1.86]	[-1.44]	[2.03]
	4	0.0310	0.0781***	0.0553**	-0.0136	-0.0288	0.0190	0.0740***	0.0423*	-0.0014	-0.0274

		[1.58]	[2.95]	[2.03]	[-0.62]	[-1.50]	[1.05]	[3.06]	[1.65]	[-0.06]	[-1.34]
	High	-0.0230*	0.0562***	0.0333	-0.0033	0.0479***	-0.0261*	0.0453**	0.0237	-0.0144	0.0301*
		[-1.74]	[2.57]	[1.53]	[-0.17]	[3.76]	[-1.94]	[2.23]	[1.15]	[-0.81]	[1.88]

Panel C Fama-MacBeth Regression Loadings under 11-day Exclusion

		Low	2	3	4	High	Low	2	3	4	High
Double-Sorted on		SENTA*IVOL11					$SENTA^{\perp}$*IVOL11				
lnBEME	Low	-0.0771***	-0.0477***	-0.0678***	-0.0670***	-0.0014	-0.0414**	-0.0508***	-0.0565***	-0.0570***	-0.0010
		[-4.67]	[-3.42]	[-3.68]	[-3.97]	[-0.08]	[-2.36]	[-3.67]	[-3.06]	[-3.26]	[-0.06]
	2	-0.0515***	-0.0310*	-0.0474***	-0.0680***	-0.0366**	-0.0483***	-0.0191	-0.0161	-0.0280	-0.0193
		[-3.41]	[-1.85]	[-3.31]	[-3.52]	[-2.25]	[-2.89]	[-1.06]	[-0.97]	[-1.29]	[-1.19]
	3	-0.0637***	-0.0209	-0.0755***	-0.0944***	0.0197	-0.0373***	-0.0063	-0.0409**	-0.0743***	0.0115
		[-4.04]	[-1.52]	[-4.52]	[-5.03]	[0.97]	[-2.60]	[-0.36]	[-2.31]	[-3.86]	[0.63]
	4	-0.0120	-0.0503***	-0.0296*	-0.0693***	-0.0054	-0.0156	-0.0245	-0.0240	-0.0688***	0.0033
		[-0.71]	[-2.57]	[-1.68]	[-3.47]	[-0.30]	[-0.90]	[-1.28]	[-1.08]	[-4.10]	[0.17]
	High	-0.0659***	-0.0536***	-0.0697***	-0.0718***	0.0209	-0.0785***	-0.0225	-0.0526***	-0.0604***	0.0252**
		[-4.70]	[-3.33]	[-3.90]	[-3.72]	[1.60]	[-5.08]	[-1.30]	[-2.86]	[-3.34]	[2.03]
		BW*IVOL11					$BW^{\perp}$*IVOL11				
lnBEME	Low	-0.0217	0.0278	0.0179	-0.0112	0.0501***	-0.0190	0.0354*	0.0228	-0.0070	0.0498**
		[-1.19]	[1.40]	[0.93]	[-0.62]	[2.61]	[-1.04]	[1.71]	[1.22]	[-0.38]	[2.54]
	2	0.0185	0.0544**	0.0403**	0.0280	0.0167	0.0158	0.0371	0.0355*	0.0369**	0.0104
		[0.87]	[2.36]	[2.00]	[1.40]	[0.92]	[0.79]	[1.60]	[1.74]	[2.10]	[0.60]
	3	0.0276	0.0525**	0.0411*	-0.0209	0.0489**	0.0220	0.0388	0.0434*	-0.0254	0.0477**
		[1.44]	[2.20]	[1.67]	[-0.98]	[2.21]	[1.19]	[1.62]	[1.83]	[-1.28]	[2.06]
	4	0.0310	0.0770***	0.0541**	-0.0144	-0.0279	0.0188	0.0739***	0.0404	-0.0002	-0.0264
		[1.57]	[2.91]	[2.00]	[-0.65]	[-1.46]	[1.03]	[3.06]	[1.59]	[-0.01]	[-1.30]
	High	-0.0227*	0.0566***	0.0357*	-0.0032	0.0459***	-0.0254*	0.0503**	0.0263	-0.0149	0.0373***
		[-1.74]	[2.58]	[1.65]	[-0.17]	[3.55]	[-1.90]	[2.40]	[1.28]	[-0.84]	[2.89]

This table shows the cross-sectional loadings of Fama-MacBeth regressions for portfolios that have been double-sorted by book-to-market ratio and sentimentalized IVOL. The log of the book-to-market ratio (*lnBE/ME*) is calculated following Fama and French (1992) by using the book value of equity from the previous fiscal year upon the market capitalization from the previous calendar year. *IVOL*, *IVOL10* and *IVOL11* are computed from daily cross-sectional stock returns under 5-day, 10-day and 11-day exclusions of the Fama-French three factor model (Equation (1)). *SENTA* ($SENTA^{\perp}$) is the investor's sentiment index aligned (the orthogonalized investor's sentiment index aligned), accessed from Professor Zhou's website. *BW* ($BW^{\perp}$) is the sentiment index accessed from Professor Wurgler's website. *SENTA*IVOL* (*SENTA*IVOL10* and *SENTA*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11), and the investor's sentiment index aligned (*SENTA*). $SENTA^{\perp}$*IVOL ($SENTA^{\perp}$*IVOL10 and $SENTA^{\perp}$*IVOL11) is the product between *IVOL* (*IVOL10 and IVOL*11) and the orthogonalized investor's sentiment index aligned ($SENTA^{\perp}$). *BW*IVOL* (*BW*IVOL10* and *BW*IVOL11*) is the product between *IVOL* (*IVOL10 and IVOL*11) and the investor's sentiment index from Baker and Wurgler (2006) (*BW*). $BW^{\perp}$*IVOL ($BW^{\perp}$*IVOL10 and $BW^{\perp}$*IVOL11) is the product between *IVOL* (*IVOL10 and IVOL*11) and the orthogonalized investor's sentiment index from Baker and Wurgler (2006) ($BW^{\perp}$). All regressions are run with a 60-month rolling window. Every coefficient is multiplied by 100. The sample period is from July 1965 to December 2020. In each of the 25 double-sorted portfolios, we perform Equation (4) and (5) for *SENTA*IVOLs* ($SENTA^{\perp}$*IVOLs) and Equation (7) and (8) for *BW*IVOLs* ($BW^{\perp}$*IVOLs). Panel A, B and C contain results under 5-day, 10-day and 11-day exclusions, respectively. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.