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► **To cite this version:**

Zhaobo Zhu, Wenjie Ding, Yi Jin, Dehua Shen. Dissecting the Idiosyncratic Volatility Puzzle: A Fundamental Analysis Approach. *Research in International Business and Finance*, 2023, 66. hal-04194180

**HAL Id: hal-04194180**

**<https://audencia.hal.science/hal-04194180v1>**

Submitted on 2 Sep 2023

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# Dissecting the Idiosyncratic Volatility Puzzle: A Fundamental Analysis Approach

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## **Acknowledgements**

We thank Min Chen, Jun Tu, Licheng Sun, and the seminar participants at Shenzhen University for their helpful comments. Dehua Shen would like to thank the support from the National Natural Science Foundation of China (Grant No. 72071141). Wenjie Ding would like to thank the support from the Young Scientists Fund of the National Natural Science Foundation of China (Grant No. 72203244).

# Dissecting the Idiosyncratic Volatility Puzzle: A Fundamental Analysis Approach

## Abstract

This paper argues fundamental information help resolve information uncertainty that leads to high idiosyncratic volatility premium. The IVOL-return relation is negative for stocks with poor fundamental strength but positive for stocks with strong fundamental strength. The arrival of fundamental news weakens the negative IVOL effect. Our findings are robust for alternative model specifications. Moreover, the negative IVOL effect dominates the positive IVOL effect due to arbitrage asymmetry that buying is easier than short selling stocks. Consistent with arbitrage asymmetry, the negative IVOL effect is stronger for stocks with low institutional ownership and following high investor sentiment. Overall, we provide a simple fundamental-based explanation for idiosyncratic volatility puzzle.

**JEL Classification:** G11, G12, G14

**Keywords:** Idiosyncratic Volatility; Fundamental Strength; Arbitrage Asymmetry

## 1. Introduction

Whether idiosyncratic volatility (IVOL) and stock returns positively or negatively correlates with each other is elusive in prior literature. Under the assumptions of frictionless markets and rational investors, classic asset pricing theories such as the CAPM predict that there exists neither a positive nor a negative relation between IVOL and average stock returns, which appears to be confirmed by some early studies such as Fama and MacBeth (1973). However, more recent empirical studies document contradictory evidence for this prediction. For example, Xu and Malkiel (2003) show evidence that IVOL is positively related to the stock return. In contrast, Ang, Hodrick, Xing, and Zhang (2006 and 2009) find a strong negative relation between IVOL and expected returns.

From a theoretical perspective, a positive IVOL-return relation is viable under alternative assumptions where markets are incomplete and investors hold undiversified portfolios (e.g., Levy, 1978; Merton, 1987; Barberis and Huang, 2001). However, to account for the observed negative relation, the current literature relies on explanations where individual investors are assumed to exhibit lottery-like preferences (Kumar, 2009; Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011).<sup>1</sup> Interestingly, Hou and Loh (2016) provide a comprehensive study that evaluates these potential explanations of the negative IVOL-return relation and concludes that none of them can fully explain the IVOL puzzle.

In this paper, we attempt to use a simple fundamental analysis approach to explain the

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<sup>1</sup> Evidence show that the negative IVOL-return relation is at least partially due to market frictions and imperfections such as short-term return reversal (Fu, 2009; Huang, Liu, Rhee, and Zhang, 2010; Goodell et al., 2021), illiquidity (Bali and Cakici, 2008; Han and Lesmond, 2011), short-sale constraints (Boehme, Danielsen, Kumar, and Sorescu, 2009), unpriced information risk (Johnson, 2004), investor inattention (Ang et al., 2009; George and Hwang, 2011; Hou and Loh, 2016; Hu, Li and Shen, 2020; Goodell et al., 2022), and earnings surprises (Jiang, Xu, and Yao, 2009; Wong, 2011; Chu, Li and Zhang, 2022).

elusive nature of the IVOL puzzle. Our motivation is intuitive and straightforward. High IVOL implies that investors have high divergence of opinion on the valuation of stocks possibly due to high information uncertainty for these stocks (e.g., Zhang, 2006). If so, then firms' most recently available fundamental information should help resolve such high information uncertainty.<sup>2</sup> Moreover, we argue that as fundamental information could either be good or bad, it enables us to differentiate the positive and negative IVOL-return relation. Stock prices are expected to increase (decrease) when high information uncertainty is resolved with the arrival of good (bad) news. Therefore, we expect a positive (negative) IVOL-return relation for stocks with strong (weak) fundamentals.

Furthermore, we expect that the negative IVOL effect for stocks with poor fundamentals is stronger than the positive IVOL effect for stocks with strong fundamentals in the absolute value due to arbitrage asymmetry. Stambaugh, Yu, and Yuan (2015) argue that buying is easier than shorting due to limits to arbitrage, which is the key component of arbitrage asymmetry. In our setting, for most investors, buying stocks with strong fundamental strength is easier and less risky than shorting stocks with poor fundamental strength in the formation period when information uncertainty is high, leading to a relatively weaker effect of the arrival of good news on the subsequent price change. Taken together, the negative IVOL effect dominates across all stocks.

In this paper, following Ang et al. (2006), we estimate the idiosyncratic volatility (IVOL) as the standard deviation of the residuals of daily return regression using the Carhart (1997) four-factor model. To measure a firm's quarterly fundamental strength, we employ the

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<sup>2</sup> Some recent studies show that fundamental strength could efficiently explain anomalies such as the book-to-market effect and short-term return reversals (Piotroski and So, 2012; Zhu, Sun, and Chen, 2019). However, the IVOL effect differs from these anomalies because both positive and negative IVOL-return relations coexist in the data.

composite fundamental index (FSCORE) first proposed by Piotroski (2000). We first confirm the negative IVOL-return pattern across all sample stocks in our sample period of 1985 to 2016.

Our empirical results show that the IVOL-return relation varies depending on the fundamental strength of stocks. To be more specific, we find that the IVOL-return relation for stocks with strong (poor) fundamental strength is positive (negative). This finding on the duality of the IVOL puzzle is robust when using different widely-accepted asset pricing models. The value-weighted return disparity between high and low IVOL quintile portfolios for stocks with poor fundamentals is -0.74% (t-value is -3.01), while the return disparity for stocks with strong fundamentals is 0.53% (t-value is 1.94) after adjusting for Fama-French five factors.<sup>3</sup> The negative (positive) IVOL-return relation conditional on weak (strong) fundamental strength is more pronounced in different subsamples of variables related to the IVOL puzzle. Furthermore, our additional test demonstrates that the difference in the IVOL-return disparity between fundamentally weak and strong firms retains its significance after controlling for alternative explanatory variables of the IVOL puzzle.

More specifically, consistent with our argument, the identification effect of fundamental strength is strongest for high-IVOL stocks. The value-weighted return disparity between stocks with strong fundamental strength and stocks with poor fundamental strength is 1.49% (t-value is 4.37) among high-IVOL stocks. In contrast, the return disparity is zero among low-IVOL stocks. Moreover, the return disparity varies monotonically across IVOL quintile portfolios. These findings suggest that the IVOL effect is mainly driven by high IVOL stocks and fundamental strength could efficiently identify high-IVOL stocks that have high

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<sup>3</sup> The results are more significant when calculating the abnormal return using the Fama and French (1993) three-factor model or the Carhart (1997) four-factor model.

future returns and those that have low future returns.

The explicit implication of our motivation is that the IVOL effect should be weakened by the arrival of the most recent financial-report fundamental information in the formation period.<sup>4</sup> We utilize the occurrence of quarterly earnings announcements (EA) to investigate whether the high IVOL is driven by information uncertainty. Our results confirm our argument. The *unconditional* IVOL effect is insignificant for stocks without quarterly EA in the formation period, while the IVOL effect is significant and has a larger magnitude for stocks with EA in the formation period. Moreover, the conditional IVOL effects show consistent results. The negative IVOL effect for stocks with poor fundamental strength becomes weaker and insignificant in the sample of stocks with EA. In contrast, the negative IVOL effect becomes stronger for stocks without EA.

Last, we test the implications of arbitrage asymmetry for the conditional IVOL effects in the cross-section and in the time-series. Existing studies show that stocks with low institutional ownership (IO) are more likely to have more binding short-sale constraints, so we expect that the negative IVOL effect among fundamentally weak firms is more pronounced for low-IO stocks. We find consistent results. High-IVOL stocks significantly underperform low-IVOL stocks by 1.61% in the subsample of low-IO stocks, while the underperformance is only 0.50% and insignificant.

Baker and Wurgler (2006), Stambaugh et al. (2015) and Jia, Shen and Zhang (2022), among others, argue that arbitrage costs and risk are higher when investors are excessively optimistic. Motivated by existing studies, we expect that the negative IVOL effect for stocks

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<sup>4</sup> The high IVOL for these stocks with the arrival of the most recent fundamental information in the formation month results from price reaction to the arrival of information. In contrast, the high IVOL for stocks without the most recent fundamental information is driven by information uncertainty.

with poor fundamental strength should also be stronger during periods in which investor sentiment is high. Our results are consistent with our predictions. For stocks with poor fundamental strength, the negative IVOL effect is more pronounced following high sentiment period.

This paper contributes to our better understanding of the IVOL puzzle from a novel perspective. Specifically, the firm fundamentals could efficiently identify the positive (negative) IVOL-return relation among stocks with strong (weak) fundamentals. Moreover, the negative IVOL-return relation dominates the positive relation because of arbitrage asymmetry. Our study provides new evidence on the debate on the relation between idiosyncratic volatility and expected returns in existing literature.

Our study also enriches existing studies on the role of the fundamental analysis approach in price discovery. Existing studies show that the firm fundamental information could significantly predict future returns (e.g., Yan and Zheng, 2017; Zhu, Sun, Yung, and Chen, 2020) and that firm fundamental strength could effectively explain some return anomalies such as value/glamour puzzle, short-term reversals, stock price crash risk, and the anchoring effect (e.g., Piotroski and So, 2012; Zhu, Sun, and Chen, 2019, 2023; Meng, Shen, and Xiong, 2023).

## **2. Related Literature Review**

Prior empirical studies find controversial evidence for the IVOL-return relationship. Based on the classic asset pricing theory (e.g., Markowitz, 1959; Merton, 1987), the idiosyncratic risk premiums are due to investor impediments to portfolio diversification. A strand of studies supports this positive IVOL-return relationship (e.g., Xu and Malkiel, 2003; Brockman et al.,



2022). Brockman et al. (2022) find a positive and significant IVOL-return relationship exists among firms from 57 countries from 1995 to 2016. However, the following empirical studies in this research topic find supportive evidence for the negative IVOL-return relation (e.g., Ang et al., 2006; Ang et al., 2009). The negative IVOL-return relation could not be fully explained by investors preference for lottery-like stocks (Hou and Loh, 2016; Hai et al., 2020).

To bridge the gap in the literature, Gu et al. (2019) investigate idiosyncratic volatility (IVOL) anomaly conditional on the analyst coverage and show a more pronounced negative IVOL-return relation in stocks without analyst coverage while a positive IVOL-return relation among stocks receiving analyst upgrades. They argue that analysts reduce information asymmetry and the upgrades are more quickly incorporated into the stock price, leading a positive IVOL-return relation. Stambaugh et al. (2015) conjecture that IVOL-return relation is conditional on the ex-ante mispricing of stock prices, that is, a positive IVOL-return relation exists among overpriced stocks while a negative IVOL-return relation exists among underpriced stocks. Inspired by this strand of studies, this paper aims to resolve the IVOL-return puzzle by conditional IVOL-return relation on the firm's fundamental strength.

Information asymmetry is closely associated with idiosyncratic volatility and IVOL-induced premium. High IVOL implies that investors have high divergence of opinion on the valuation of stocks possibly due to high information uncertainty for these stocks (e.g., Zhang, 2006). Yang et al. (2020) propose a novel information risk measure proxied with abnormal idiosyncratic volatility risk. Barber et al. (2013) show that earnings announcement premium is larger for countries with greatest IVOL increase around the time of earnings

announcements. Yang et al. (2020) also document that the abnormal idiosyncratic volatility prior to information events positively associates with informed trading, which leads to economically and statistically large cross-sectional future return disparity of high over low abnormal idiosyncratic volatility stocks.

The timely fundamental information disclosure lowers information uncertainty. For example, Boudoukh et al. (2019) find that fundamental information in news accounts for almost half of the variation in overnight idiosyncratic volatility. Caglayan et al. (2020) find that information disclosure and investor uncertainty avoidance degree reduce the country-level idiosyncratic risk. Li et al. (2021) use the 2012 Dividend Tax Reform in China as the natural experiment and report a negative association between the firms' dividend payout ratio and idiosyncratic volatility, because the reform reduce retail investors' trading and improves the stock price informativeness.

Fundamental information matters for the idiosyncratic volatility, but more importantly, recent literature also investigates whether the fundamental information affects the IVOL-return relationship. Khasawneh et al. (2021) show that both the fundamental-based and market-based news could explain the anomalous negative IVOL-return relation. However, the effect of information on IVOL-return relation is also inconclusive. For example, Brockman et al. (2022) find in their global sample that the positive IVOL-return relationship is attenuated by access to high quality information. While Gu et al. (2019) argue that when the good news about firm fundamentals is incorporated more quickly into stock prices due to higher analyst coverage, the alleviated information asymmetry leads to positive IVOL-return (Gu et al., 2019). To address the conflicting findings regarding the effect of

fundamental information on IVOL-return relation, this paper separate sample into high and low fundamental strength.

### **3. Data and Methodology**

We test our hypotheses using the common stocks (share code 10 and 11) listed on the NYSE, AMEX, and NASDAQ (exchange code 1, 2 and 3). The market activities data are from the Center for Research in Security Prices (CRSP). We adjust the returns of delisted stocks following Shumway (1997) and Shumway and Warther (1999). We exclude the stocks with prices lower than \$5 at each portfolio formation date to alleviate concerns about the penny stock effect. Fama-French factors are available on Kenneth French's webpage. Mispricing factors data are accessible from Robert Stambaugh's webpage. We obtain the quarterly financial statement data from the Compustat database. The quarterly institutional ownership (IO) data are obtained from Thomson-Reuters 13-f filings. To proxy for the monthly institutional ownership, we use the prior quarter's institutional ownership for the following three months. Following Nagel (2005), we assign 0 to the missing institutional ownership observations. Our sample period is from January 1985 to December 2016.

#### **3.1 Idiosyncratic Volatility**

This paper estimates idiosyncratic volatility following Ang et al. (2006) and Tan and Liu (2016). The regression equation is noted as Equation (1). We proxy IVOL as the standard deviation of the residuals in this regression. We require each month must at least have 15 daily returns available for the calculation of IVOL. In our unreported robustness tests, the results are robust when IVOL is computed based on the adjustment of Fama and French (1993) three factors.

$$R_{i,t} = a_{i,t} + \beta_1MKT_t + \beta_2SMB_t + \beta_3HML_t + \beta_4MOM_t + \varepsilon_{i,t} \quad (1)$$

### 3.2 Proxy for Firm Fundamentals

We employ Piotroski's (2000) FSCORE to proxy for the quarterly comprehensive fundamental strength of a firm.<sup>5</sup> The FSCORE is an aggregate index that is based on "nine binary signals designed to measure three different dimensions of the firm's fundamental condition: profitability, change in financial leverage/liquidity, and change in operational efficiency" (Piotroski and So, 2012). FSCORE has been widely employed as a fundamental strength measure in a strand of empirical studies, for example, Piotroski (2000), Piotroski and So (2012), and Choi and Sias (2012). The value of FSCORE ranges from 0 to 9.

To capture the timeliest fundamental information, we complement the Report Date of Quarterly Earnings (RDQ) from Compustat with the Securities and Exchange Commission (SEC) filing rules to construct the quarterly FSCORE. Listed firms are required by the SEC to disclose quarterly(annual) financial reports within 45/90 days after the end of the fiscal quarter/year, respectively. As for RDQ, it contains the earnings-related information which is usually disclosed by firms within one month past the fiscal quarter. In some cases, however, firms do not provide the balance sheet and cash flow information necessary to construct the quarterly FSCORE in the RDQ. Levi (2008) find that firms usually finish their 10-Q filings a few weeks later. As most public companies file their quarterly reports as early as possible to avoid negative outcomes, we assume that the fundamental strength information are accessible for investors in approximately two weeks after the RDQ.<sup>6</sup>

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<sup>5</sup> For the details of FSCORE measure construction, see the appendix of Piotroski and So (2012).

<sup>6</sup> We also conduct tests using the one-month information lag after the RDQ and our results do not alter when using alternative information lags.

### 3.3 Plausible Explanatory Variables for Idiosyncratic Volatility Puzzle

Following Hou and Loh (2016) and Li, Shen and Zhang (2018), we control for a set of plausible explanatory variables for the idiosyncratic volatility puzzle. These plausible explanatory variables include (1) lottery-preference characteristics such as the expected idiosyncratic skewness (EISKEW) and the maximum daily return (MAX); (2) variables related to market frictions such as the past one-month returns (REV) and illiquidity (ILLIQ); (3) variables related to earnings information such as the most recently standardized unexpected earnings (SUE); (4) variables related to mispricing and short-sale constraints such as the mispricing index for each stock in Stambaugh et al. (2015).

Boyer et al. (2010) build a cross-section model on expected idiosyncratic skewness, which is a contrarian predictor of future returns. EISKEW data for stocks are from Brian Boyer's website. The sample period is from 1988 to 2016. Bali et al. (2011) document that stocks that have high maximum daily returns (MAX) in prior month significantly underperform stocks with low MAX. Moreover, they show that non-lottery-like stocks have consistently lower skewness than lottery-like stocks. We use the maximum daily return of each stock in the past month as the first measure of the lottery feature.

Fu (2009) and Huang et al. (2010) show that the negative IVOL-return relationship becomes insignificant after controlling for the past one-month returns (i.e., the return in the IVOL formation month). The illiquidity is computed as the average of daily absolute return scaled by the average daily dollar trading volume in month  $t-1$  (Amihud, 2002).

We follow Chordia and Shivakumar (2006) to calculate the standardized unexpected earnings (SUE). SUE is the annual change in the quarterly earnings that are standardized using the standard deviation of these changes from the most recent eight quarters. In

addition, the financial information should be available within four months before the portfolio formation date.

We also control for the mispricing index MSCORE proposed by Stambaugh, Yu, and Yuan (2015). MSCORE is a complex mispricing index based on the 11 characteristics relevant to difficult-to-arbitrage in Stambaugh et al. (2015); a high MSCORE indicates overpricing.

## **4. Empirical Results**

### **4.1 Univariate Sort**

In this subsection, we first confirm the existence of the IVOL puzzle. Table 1 reports the results. We find that the portfolio of stocks with the lowest IVOL (P1) significantly outperforms the portfolio of stocks with the highest IVOL (P5) by an average return of 0.65% each month without adjusting for risk factors. The monthly outperformance is respectively 0.86%, 0.25%, and 0.20% after adjusting for the Fama-French three factors (FF3), Fama and French five factors (FF5), and Stambaugh and Yuan mispricing four factors (M4). A closer look at FF3- and FF5-adjusted return disparities suggests that the additional two fundamental-based factors (profitability and investment) could explain much of the IVOL puzzle, suggesting firm fundamentals has incremental explanatory power for the IVOL puzzle.

[Table 1]

However, the M4-factor adjusted abnormal alpha difference between high and low IVOL portfolios is not significant, even though the FF3- and FF5-adjusted abnormal alpha

differences are remarkable and salient.<sup>7</sup> Stambaugh et al. (2015) show that the negative relation between IVOL and returns only exists among overpriced stocks. They identify overpriced or underpriced stocks based on 11 asset pricing anomalies. Most of these anomalies are fundamental-based. Therefore, we expect firm fundamentals to explain much of the IVOL puzzle.

We find similar results based on value-weighted returns. Overall, the negative relation between IVOL and returns is significant when we do not control for fundamental factors, but the negative relation becomes weaker when we control for fundamental factors.<sup>8</sup> The results based on the adjustment of aggregate fundamental factors suggest that firm fundamentals seem promising to explain the IVOL puzzle. However, we are also interested in exploring whether and when a *positive* IVOL-return relationship is salient.

## 4.2 Bivariate Sorts

We further test how the IVOL-return relation varies conditional on the firm fundamental strength. Specifically, we examine the IVOL-return pattern within three groups of firms with high, middle, and low fundamental strength proxied by FSCORE, respectively. We assign stocks into 5×3 portfolio matrix independently sorted on IVOL and FSCORE.

Table 2 reports four main findings. First, the significantly *negative* relation between IVOL and subsequent returns mainly exists for stocks with poor fundamental strength (F1). For example, Panel A shows that the excess return disparity between high and low IVOL

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<sup>7</sup> An unreported table shows that the equal-weighted return disparity between high (P10) and low (P1) IVOL portfolios after controlling for M4 are significant at 10% level if we equally divide sample stock into 10 IVOL portfolios. Because we limit our sample to stocks with available quarterly FSCORE, the absolute return for IVOL puzzle is a little bit smaller than that in some papers with relatively small sample stocks.

<sup>8</sup> The fundamental factors refers to the investment and profitability factors in Fama-French five factors and mispricing factors in Stambaugh and Yu (2017).

portfolios is -1.10% for stocks with poor fundamental strength, which is remarkably larger than the unconditionally excess return disparity of -0.65% shown in Table 1. This finding is robust even after adjusting for Fama-French five factors and Stambaugh-Yuan mispricing factors. Specifically, the return disparity between high and low IVOL portfolios is -0.56% (t-value is -2.47%) even after controlling for mispricing factors. In contrast, unconditionally, Table 1 shows that the return disparity between P5 and P1 is insignificant after controlling for M4. A closer look at the results shows that the negative returns of the high IVOL portfolio contribute most to the negative IVOL-return pattern.

[Table 2]

Second, we find a (relatively weak) positive relation between IVOL and returns for stocks with strong fundamental strength (F3). The excess return of the IVOL long-short portfolio for stocks with strong fundamental strength (F3) is positive but insignificant. However, the positive abnormal return increases its magnitude and statistical significance when controlling for FF5. Moreover, the salient positive returns of the high IVOL leg contribute most to the positive IVOL-return relation. Though the significantly positive IVOL-return pattern becomes weaker after controlling for M4 based on value-weighted returns in Panel B, the magnitude of IVOL-return is equal in F1 and F3 portfolios in the absolute value. The return disparity is -0.49% in the F1 portfolio and it is 0.48% in the F3 portfolio. Overall, these findings provide strong evidence for the positive risk-return tradeoff, which is different from the IVOL puzzle interpreted by Ang et al. (2006).

Third, the IVOL return disparity within F1 portfolio is significantly smaller than that within F3 portfolio. For example, the FF5-adjusted IVOL return disparity is -0.63% (+0.39%) within F1 (F3) portfolio. The return disparity of 1.02% is significant with a t-value



of 5.56. We find robust results after controlling for M4 and based on value-weighted returns. These findings suggest that the IVOL-return relation depends on the firm fundamental strength. Motivated by Stambaugh et al. (2015), arbitrage asymmetry could explain why the negative IVOL effect among F1 stocks is stronger than the positive IOVL effect among F3 stocks because buying F3 stocks is easier and less risky than shorting F1 stocks. The key component of the arbitrage asymmetry is that “buying is easier than shorting for many equity investors” (Stambaugh, Yu, and Yuan, 2015). Therefore, the negative relation between IVOL and expected returns in the absolute value among stocks with weak fundamentals is stronger than the positive relation between IVOL and expected returns among stock with strong fundamentals due to arbitrage asymmetry, although the positive relation is also significant controlling for FF 5-factors and mispricing factors.

Fourth, consistent with our argument, the identification effect of fundamental strength is strongest for high-IVOL stocks. The value-weighted return disparity between stocks with strong fundamental strength and stocks with poor fundamental strength is 1.49% (t-value is 4.37) among high-IVOL stocks. In contrast, the return disparity is zero among low-IVOL stocks. Moreover, the return disparity varies monotonically across IVOL quintile portfolios. These findings suggest that the IVOL effect is mainly driven by high IVOL stocks and fundamental strength could efficiently identify high-IVOL stocks that have high future returns and those that have low future returns.

To summarize, empirical results strongly support our argument. High-IVOL stocks contribute to the IVOL puzzle. Firm fundamental strength could efficiently identify the positive IVOL effect for stocks with strong fundamental strength from the negative IVOL effect for stocks with poor fundamental strength. However, the negative IVOL effect is

stronger than the positive IVOL effect due to arbitrage asymmetry.

### 4.3 Triple Sorts

In this subsection, we examine whether the role of firm fundamentals in the IVOL puzzle is robust after controlling for some candidate variables that are related to the IVOL-return relation. Besides some candidate variables such as the expected idiosyncratic skewness (EISKEW), past one-month returns (REV), the maximum daily return over the past one-month (MAX), illiquidity (ILLIQ), the most recently standardized unexpected earnings (SUE) in Hou and Loh (2016), we also control for the mispricing score (MSCORE) in Stambaugh et al. (2015).

Because some control variables such as REV and MAX are highly correlated with the IVOL, we first follow the bivariate portfolio analysis method in Bali et al. (2011). First, we divide all sample stocks into ten control variable decile portfolios based on the measure of each control variable. Then, within each control variable decile portfolio, we further sort stocks into five IVOL quintile portfolios based on IVOL. We get 50 (10 x 5) portfolios. Next, we divide stocks into five portfolios in which each portfolio has a similar level of IVOL but different control variables. Bali et al. (2011) point out that such a procedure considers the dispersion of IVOL and controls for the control variable. In addition, we independently sort stocks based on a control variable or IVOL and FSCORE.

Table 3 reports the results based on value-weighted returns. We find that the relation between IVOL and returns is significantly negative for stocks with poor fundamentals (F1) in terms of excess or five-factor-adjusted returns after controlling for a set of control variables. For example, the IVOL long-short portfolio return disparity in F1 portfolio is

significant and has a value of -0.92% per month after controlling for EISKEW. However, the magnitude of the return disparity of IVOL long-short portfolio after controlling for EISKEW is smaller than the unconditional return disparity of -1.25% in Table 2. Consistent results hold for REV, MAX, ILLIQ, and MSCORE. The return disparity of IVOL long-short portfolio after controlling for SUE is still -1.23%. These results suggest that there is a negative relation between IVOL and returns for stocks with poor fundamentals even after controlling for some significantly related variables.

In addition, we document that the positive IVOL-return relation for stocks with strong fundamentals becomes stronger after controlling for these related variables, though the positive relation is still weak and insignificant in some cases. Unconditionally, Table 2 shows that the value-weighted excess return of IVOL long-short portfolio is 0.24% (t-value is 0.67), while the five-factor-adjusted return disparity is 0.53% (t-value is 1.94). Table 3 shows that the positive IVOL-return relation is significant only in the case of controlling for MAX in terms of excess returns. However, the positive relation is significant or marginally significant in the case of controlling for EISKEW, REV, ILLIQ, SUE, and MSCORE. Though the positive relation is weak and insignificant in many cases, the negative IVOL-return relation exists for stocks with strong fundamentals.

[Table 3]

To summarize, the role of fundamental strength in identifying the puzzling IVOL-return relations is robust after controlling for existing variables that are related to the IVOL effect. In particular, the negative IVOL effect is significant for stocks with poor fundamental strength, though the positive IVOL effect for stocks with strong fundamental strength is relatively weak or insignificant after controlling for some related variables. However, the

positive IVOL effect is economically and statistically significant for most control variables after controlling for Fama-French five factors.

#### 4.4 Fama-MacBeth Regressions

The above portfolio analyses provide strong evidence of the significant role of firm fundamentals in the IVOL-return relation. However, the portfolio analysis does not account for the effect of other plausible driven factors. In this subsection, we examine the role of firm fundamentals using the Fama-MacBeth (1973) regression method, and we control for a broad set of related control variables simultaneously.

$$R_{i,t+1} = a + \beta_1 IVOL_{i,t} + \beta_2 FSCORE_{i,t} + \beta_3 IVOL_{i,t} FSCORE_{i,t} + \beta_4 X_{i,t} + \beta_5 IVOL_{i,t} X_{i,t}, \quad (2)$$

where  $X$  refers to a set of control variables.

Table 4 reports the estimation of Equation (2). Following prior studies, the independent variables except the FSCORE and MSCORE are winsorized at their 1st and 99th percentiles. Model 1 shows that consistent with prior studies, the FSCORE positively and significantly predicts future returns and the IVOL negatively and significantly predicts future returns. The coefficients of IVOL is significantly negative in most regressions (i.e., regressions 1 to 7 in Table 4), indicating that the simple negative relation between IVOL and expected returns significantly exists. In addition, the coefficients of IVOL become insignificant in regressions that include variables such as mispricing factors, maximum daily returns, and the short-term reversal simultaneously (i.e., regressions 8 and 9 in Table 4). Because those variables are highly correlated with IVOL, it is not surprising that the coefficients of IVOL become insignificant.

Model 2 includes the interaction term of FSCORE and IVOL. A significant and positive

coefficient of the interaction term (FSCORE x IVOL) suggests that high IVOL stocks with low FSCORE have lower returns than high IVOL stocks with high FSCORE.

[Table 4]

Then we examine whether other control variables related to the IVOL-return relation could significantly affect the role of fundamental strength. Models 3 to 8 includes the expected idiosyncratic skewness (EISKEW), the maximum daily return (MAX), past one-month returns (REV), illiquidity (ILLIQ), the most recently standardized unexpected earnings (SUE), mispricing score (MSCORE), and their interaction with IVOL, respectively. In Table 4, the interaction terms of FSCORE and IVOL are significant and positive in Models 3 to 8. In contrast, the interaction terms of ESIKEW and IVOL, MAX and IVOL, and ILLIQ and IVOL are insignificant, suggesting that ESIKEW, MAX, and ILLIQ have no significant impact on the role of FSCORE in the IVOL-return relation.

In Model 9, we include all related control variables in one regression. We find that the interaction terms of FSCORE and IVOL are significant and positive, while other control variables such as EISKEW and ILLIQ have no significant effect. Overall, these results suggest that fundamental-related information provides incremental return predictability.

#### **4.5 The Arrival of Public Fundamental News**

If high IVOL is driven by high information uncertainty in the formation period, there are two implications. First, the unconditional IVOL effect should be weakened by the arrival of fundamental news because, to some extent, the most recent fundamental information could efficiently resolve the high information uncertainty for investors. Then we expect a weaker IVOL effect for stocks with the quarterly earnings announcements (EA) in the

formation period. In contrast, we expect a stronger IVOL effect for stocks without EA in the formation period. Second, the above argument applies to the fundamental-based conditional IVOL effect. More importantly, without earnings announcements, fundamental strength is expected to play a more significant role in identifying the puzzling IVOL effect.

The existing literature provides some direct and indirect evidence on the significant effect of the arrival of public fundamental information on the IVOL-return relation and variables related to the IVOL-return relation. Shi, Liu, and Ho (2016) show that the negative effect of IVOL on return is lowered by 50% by the arrival of public firm-level news. Bali et al. (2018) show that unusual firm-level news flow has a significant explanatory power on the negative relation between IVOL shocks and future returns. Nagel (2012) and Hameed and Mian (2015) show that short-term reversals are reduced by the arrival of public information. These studies suggest that the arrival of public fundamental information could mitigate the information uncertainty confronted by investors and then improve the price discovery process.

Table 5 reports the results. Panel A shows that unconditionally, the value-weighted raw return disparity (-0.53%) between high and low IVOL portfolios is not significant in the subsample that includes only stocks whose earnings announcements occur in the formation month. In contrast, the raw return disparity (-0.67%) is significant in the subsample that includes only stocks whose earnings announcements do not occur in the formation month. These results are consistent with our argument that the arrival of fundamental news could mitigate the information uncertainty that leads to negative IVOL effect.

[Table 5]

Panel B shows the FSCORE-based IVOL-return relation conditional on two earnings-

announcements subsamples. The findings are threefold. First, the IVOL-return relation is significant only for stocks whose earnings announcements do not occur in the formation month. The IVOL return disparity within F1 portfolio is significant only in the no-earnings-announcements subsample. Second, the positive IVOL-return relation for stocks with strong fundamentals (F3) is marginally significant only after controlling for five factors only in the no-earnings-announcements subsample. Last, the IVOL-return disparity between F1 and F3 portfolios is significant only in the no-earnings-announcements subsample. Overall, these results suggest that the arrival of public fundamental information weakens the role of fundamental strength in the IVOL puzzle. Alternatively, we can make use of firm fundamentals to reconcile the IVOL puzzle in the absence of public fundamental information.

#### **4.6 Institutional Ownership**

Though we show that both positive and negative IVOL-return relations coexist in the data, the negative IVOL effect for stocks with poor fundamental strength is stronger than the positive IVOL effect for stocks with strong fundamental strength. Motivated by Stambaugh et al. (2015), we argue that varying difficult-to-arbitrage level could explain why the negative IVOL effect dominates. In this subsection, we provide evidence to support that arbitrage asymmetry could explain the asymmetric IVOL effects.

Following prior studies such as Stambaugh et al. (2015) and Li, Shen and Zhang (2018), we use institutional ownership (IO) to measure short-sale constraints. Empirically, we examine the fundamental-based IVOL effect within IO subsamples. We first equally divide all sample stocks into three groups based on IO. Within each IO group, we independently sort stocks into 15 portfolios based on FSCORE and IVOL.

Table 6 reports the results after controlling for Fama-French five factors and Stambaugh-Yuan mispricing four factors. Consistent with findings in Stambaugh et al. (2015), the negative IVOL-return relation for stocks with poor fundamentals only exists in low-IO subsample. Moreover, the negative IVOL-return relation in low-IO subsample is more pronounced than that in Table 2. The IVOL return disparity for stocks with poor fundamentals is -1.01% in low-IO subsample, while the IVOL return disparity is -0.74%.

The IVOL return disparities for stocks with strong fundamentals are positive in both high and low-IO subsamples. The magnitude of return disparity in IO subsamples is close to that in all sample, though the return disparity is not significant. In fact, the positive IVOL-return disparity is larger in high-IO subsample than in low-IO subsample, though the difference is not significant. These findings suggest that IO has no significant effect on the positive IVOL-return relation for stocks with strong fundamentals.

[Table 6]

#### **4.7 Investor Sentiment**

To further support our argument, we investigate the IVOL-return relation in time series. Specifically, we expect to observe a stronger negative IVOL effect for stocks with poor fundamentals following high sentiment periods because stocks are more likely to be overpriced and arbitrage risk and cost are more likely to be high during high sentiment. Therefore, we use investor sentiment to identify the periods in which arbitrage asymmetry is more pronounced for the IVOL effect.

In a similar vein to Stambaugh, Yu, and Yuan (2012) and Jia, Shen and Zhang (2022), we define a high (low) sentiment month when the Baker-Wurgler sentiment index is above



(below) the sample median value. We then separately our sample into post high-sentiment and post low-sentiment periods and conduct the portfolio analysis for both subsamples.

Table 7 reports the value-weighted returns following high and low sentiment periods. There are three main findings. First, the negative IVOL-return relation within F1 portfolio is strengthened following high sentiment. Unconditionally, Panel B in Table 2 shows that the excess, FF5- and M4-adjusted return disparities between high and low IVOL portfolios within F1 portfolio are -1.25%, -0.74%, and -0.49%, respectively. In contrast, following high sentiment, the corresponding return disparities within F1 portfolio are -2.62%, -1.29%, and -1.20%, respectively. It is striking that the F1-based IVOL return disparity almost double following high sentiment.

[Table 7]

Second, the impact of sentiment on the positive IVOL-return relation is mixed depending on whether we control for pricing factors. Unconditionally, Panel B in Table 2 shows that the excess, FF5- and M4-adjusted return disparities between high and low IVOL portfolios within F3 portfolio are 0.24%, 0.53%, and 0.48%, respectively. In contrast, following high sentiment, the corresponding return disparities within F3 portfolio are -0.17%, 0.84%, and 0.59%, respectively. These results suggest that high sentiment weakens the positive IVOL-return relation without adjusting for factors, but it strengthens the positive relation when adjusting for factors.

Third, we find that the high IVOL portfolio (P5) contributes most to the negative IVOL-return relation within F1 portfolio, which is consistent with the argument in Stambaugh et al. (2015) that short selling is costlier and difficult than buying due to limits to arbitrage, leading to severe overpricing of stocks with high IVOL. We also find that the high

IVOL portfolio (P5) contributes most to the positive IVOL-return relation within F3 portfolio. High IVOL stocks with strong fundamental strength continue to experience high future returns, while high IVOL stocks with poor fundamental strength experience low future returns, suggesting that fundamental strength is essential in determining the future returns of high IVOL stocks.

#### **4.8 Size Effect**

It is well known that firms with poor fundamental strength tend to be smaller stocks and that smaller stocks tend to have higher IVOL. In addition, firm size is also a proxy for limits to arbitrage. Because firm size is related to both IVOL and fundamental strength, we are interested in investigating how the firm size affects the interaction of IVOL and FSCORE.

Table 8 reports the results. Among small stocks, the relation between IVOL and future returns is significant negative for stocks with poor fundamentals (F1). Moreover, the relation is also negative for stocks with strong fundamentals (F3), though it is not significant. In contrast, among large stocks, the excess returns and five-factor-adjusted returns of high-minus-low IVOL portfolio is marginally significant and negative for stocks with poor fundamentals (F1). The negative relation is insignificant after adjusting for mispricing four factors. It is obviously that the negative IVOL-return relation for stocks with poor fundamentals is weaker among large stocks than among small stocks. In addition, among large stocks, the relation between IVOL and returns is positive and significant for stocks with strong fundamentals after adjusting for five factors or mispricing four factors.

[Table 8]

In sum, these results show that the negative IVOL-return relation is more pronounced among small stocks and the positive IVOL-return relation exists only among large stocks. These results suggest that the risk-return tradeoff varies across stocks with different firm sizes. The positive risk-return relation mainly exists among large stocks with strong fundamentals, while the negative risk-return relation applies to both large and small stocks with poor fundamentals.

#### **4.9 FSCORE vs. MSCORE vs. SUE**

To some extent, this paper is in line with earnings-based explanations in Jiang et al. (2009) and Wong (2011). Our study is also similar to Stambaugh et al. (2015) as their mispricing index based on 11 market- and accounting-based anomalies could also reconcile negative and positive IVOL-return relations. However, our motivation and scope differ from theirs. We argue that fundamental information could resolve the information uncertainty that leads to the IVOL effect, while Stambaugh et al. (2015) ex-ante identify mispriced stocks from the perspective of arbitrage asymmetry. In addition, Jiang et al. (2009) and Wong (2011) simply link earnings to the negative IVOL effect. We differ from them in research focus and scope. In this subsection, we explicitly compare these candidate variables by controlling for each other.

Table 9 reports the value-weighted returns after adjusting for Fama-French five factors. Following the independent triple-sort in subsection 3.3, we have 30 sub-portfolios. Panel A compares FSCORE with SUE after controlling for each other. The results show that the IVOL-return relation is consistently and significantly negative in F1 portfolio in the subsamples of low and high SUE. The IVOL-return relation is positive in F3 portfolio in both SUE subsamples, though the relation is significant only in high SUE subsample.

Moreover, the IVOL-return disparity between F1 and F3 portfolios is consistently significant after controlling for SUE.

[Table 9]

In contrast, for stocks with poor fundamentals (F1), the IVOL-return relation is significantly negative among both stocks with high and low SUE. The return disparity is -0.92% (t-value is -2.99) and -0.79% (t-value is 2.02) among low and high SUE stocks, respectively. However, for stocks with strong fundamentals (F3), the IVOL-return relation is positive for stocks with high and low SUE. Specifically, the IVOL-return relation is significantly positive among high SUE stocks. Overall, these results suggest that the FSCORE-based IVOL-return relation is robust after controlling for SUE, but the SUE-based IVOL-return relation depends on FSCORE.

Panel B compares FSCORE with MSCORE after controlling for each other. We find that the positive F3-based IVOL-return relation is significant among underpriced stocks (MSCORE=1), and the negative F1-based IVOL-return relation is significant among overpriced stocks (MSCORE=3). Similarly, the positive IVOL-return relation among underpriced stocks is pronounced for stocks with strong fundamentals (F3), and the negative IVOL-return relation among overpriced stocks is significant for stocks with poor fundamentals (F1). These findings suggest that the mispricing index constructed in Stambaugh et al. (2015) does not outperform the simple non-parametric FSCORE in resolving the IVOL puzzle.

Overall, our empirical evidence shows that the negative (positive) IVOL-return relation among overpriced (underpriced) stocks is confined to stocks with weak (strong) fundamentals. Stocks with strong fundamentals may be overpriced, but these stocks are

more likely to have higher future returns than overpriced stocks with poor fundamentals. Therefore, joint consideration of firm fundamentals and mispricing could better identify future returns.

## 5. Conclusions

In this paper, we provide a simple fundamental-based explanation for the elusive and puzzling relations between IVOL and average stock returns. Our motivation is intuitive and straightforward. High IVOL could reflect that investors have high divergence of opinion on the valuation of stocks possibly due to high information uncertainty for these stocks. We argue that firms' most recently available fundamental information could help resolve such high information uncertainty. Moreover, we argue that firm fundamental information could help identify the positive IVOL-return relation from the negative IVOL-return relation because fundamental information could either be good or bad. Stock prices are expected to increase (decrease) when high information uncertainty is resolved with the arrival of good (bad) news. Therefore, we expect a positive (negative) IVOL-return relation for stocks with strong (weak) fundamentals.

Furthermore, we expect that the negative IVOL effect for stocks with poor fundamentals is stronger than the positive IVOL effect for stocks with strong fundamentals in the absolute value due to arbitrage asymmetry. Stambaugh et al. (2015) argue that buying is easier than shorting due to limits to arbitrage. In our setting, for most investors, buying stocks with strong fundamental strength is easier and less risky than shorting stocks with poor fundamental strength in the formation period when information uncertainty is high, leading to a relatively weaker effect of the arrival of good news on the subsequent price

change. Taken together, the negative IVOL effect dominates across all stocks.

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**Table 1: Returns of Portfolios Univariate-Sorted on Idiosyncratic Volatility**

This table presents average monthly equal- and value-weighted returns to portfolios sorted on idiosyncratic volatility in prior month. The idiosyncratic volatility (IVOL) is calculated as the standard deviation of the residuals from a regression of daily stock returns in month  $t-1$  on the Carhart four-factor model. We require at least 15 daily returns available for each stock to compute IVOL. Excess refers to average monthly returns in excess one-month T-bill; FF3 refers to Fama and French (1993) three-factor-adjusted returns; FF5 refers to Fama and French (2015) five-factor-adjusted returns; M4 refers to Stambaugh and Yuan (2017) mispricing factor-adjusted returns. P1 (P5) includes stocks with the smallest (largest) IVOL. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016. Newey-West (1987) adjusted t-statistics are in parentheses.

	Equal-Weighted				Value-Weighted			
	Excess	FF3	FF5	M4	Excess	FF3	FF5	M4
P1	0.86 (4.08)	0.23 (2.49)	0.01 (0.17)	0.03 (0.28)	0.81 (4.32)	0.25 (4.03)	0.03 (0.43)	-0.05 (-0.73)
P2	0.93 (3.57)	0.16 (2.05)	0.01 (0.21)	0.07 (0.85)	0.76 (3.15)	0.10 (1.22)	0.00 (-0.02)	0.04 (0.45)
P3	0.96 (3.20)	0.14 (1.87)	0.10 (1.43)	0.17 (2.49)	0.61 (2.00)	-0.12 (-1.30)	-0.06 (-0.63)	0.03 (0.37)
P4	0.73 (2.11)	-0.09 (-1.34)	0.03 (0.49)	0.07 (1.03)	0.62 (1.70)	-0.15 (-1.32)	0.07 (0.63)	0.09 (0.82)
P5	0.21 (0.52)	-0.63 (-5.73)	-0.24 (-2.69)	-0.17 (-1.40)	0.11 (0.27)	-0.68 (-3.45)	-0.23 (-1.36)	0.00 (-0.02)
P5 - P1	-0.65 (-2.28)	-0.86 (-5.04)	-0.25 (-2.18)	-0.20 (-1.11)	-0.69 (-2.07)	-0.93 (-3.94)	-0.26 (-1.30)	0.04 (0.19)

**Table 2: Returns of Portfolio Double-Sorted on IVOL and FSCORE**

This table presents average monthly equal- and value-weighted excess and factor-adjusted returns for portfolios double sorted on IVOL and FSCORE. P1 (P5) includes stocks with the smallest (largest) IVOL. F1 refers to the portfolio of stocks with FSCORE from 0 to 3; F2 refers to the portfolio of stocks with FSCORE from 4 to 6; F3 refers to the portfolio of stocks with FSCORE from 7 to 9. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016. Newey-West (1987) adjusted t-statistics are in parentheses.

Panel A: Equal-Weighted												
	Excess Return				FF5				M4			
	F1	F2	F3	F3 - F1	F1	F2	F3	F3 - F1	F1	F2	F3	F3 - F1
P1	0.59	0.86	0.98	0.39	-0.22	0.01	0.13	0.36	-0.19	0.03	0.13	0.31
	(2.52)	(4.08)	(4.69)	(3.96)	(-1.98)	(0.12)	(1.72)	(3.45)	(-1.49)	(0.26)	(1.35)	(2.93)
P2	0.69	0.88	1.16	0.47	-0.20	-0.03	0.22	0.42	-0.07	0.02	0.26	0.32
	(2.28)	(3.42)	(4.51)	(3.64)	(-1.76)	(-0.39)	(2.69)	(3.39)	(-0.54)	(0.21)	(2.54)	(2.49)
P3	0.43	0.96	1.29	0.86	-0.34	0.12	0.33	0.66	-0.16	0.19	0.30	0.46
	(1.28)	(3.22)	(4.32)	(5.37)	(-2.66)	(1.56)	(3.58)	(4.56)	(-1.18)	(2.73)	(3.15)	(3.11)
P4	0.19	0.72	1.30	1.11	-0.41	0.02	0.49	0.91	-0.29	0.05	0.46	0.74
	(0.48)	(2.08)	(4.14)	(5.92)	(-3.10)	(0.26)	(5.55)	(5.69)	(-2.00)	(0.73)	(4.38)	(4.47)
P5	-0.52	0.18	1.18	1.71	-0.85	-0.29	0.52	1.37	-0.75	-0.21	0.51	1.26
	(-1.09)	(0.45)	(3.25)	(7.12)	(-6.80)	(-2.65)	(3.61)	(7.41)	(-4.43)	(-1.54)	(3.21)	(5.92)
P5 - P1	-1.11	-0.68	0.20	1.31	-0.63	-0.30	0.39	1.02	-0.56	-0.24	0.39	0.95
	(-3.10)	(-2.46)	(0.84)	(5.90)	(-3.82)	(-2.22)	(2.44)	(5.56)	(-2.47)	(-1.22)	(2.12)	(4.53)

**Table 2: (continued)**

Panel B: Value-Weighted

	Excess Return				FF5				M4			
	F1	F2	F3	F3 - F1	F1	F2	F3	F3 - F1	F1	F2	F3	F3 - F1
P1	0.74 (3.28)	0.86 (4.61)	0.74 (3.85)	0.00 (0.02)	-0.08 (-0.62)	0.10 (1.35)	-0.08 (-1.06)	-0.01 (-0.03)	-0.10 (-0.71)	0.00 (-0.03)	-0.08 (-0.90)	0.02 (0.11)
P2	0.57 (1.96)	0.77 (3.16)	0.89 (3.50)	0.32 (1.59)	-0.23 (-1.48)	0.06 (0.67)	-0.07 (-0.47)	0.16 (0.78)	-0.18 (-1.05)	0.13 (1.31)	-0.18 (-1.30)	0.00 (0.01)
P3	0.39 (1.16)	0.65 (2.11)	0.73 (2.25)	0.34 (1.56)	-0.30 (-1.65)	0.03 (0.32)	-0.12 (-0.76)	0.18 (0.75)	-0.14 (-0.77)	0.08 (0.78)	-0.02 (-0.11)	0.12 (0.48)
P4	0.27 (0.63)	0.60 (1.55)	0.90 (2.57)	0.63 (2.49)	-0.36 (-1.81)	0.15 (1.19)	0.18 (0.96)	0.54 (2.10)	-0.16 (-0.77)	0.12 (0.88)	0.16 (0.83)	0.32 (1.18)
P5	-0.52 (-0.98)	0.00 (0.00)	0.97 (2.32)	1.49 (4.37)	-0.82 (-3.63)	-0.27 (-1.28)	0.45 (1.77)	1.26 (3.55)	-0.59 (-2.35)	-0.01 (-0.06)	0.39 (1.53)	0.99 (2.71)
P5 - P1	-1.25 (-2.91)	-0.87 (-2.48)	0.24 (0.67)	1.49 (4.01)	-0.74 (-3.01)	-0.37 (-1.49)	0.53 (1.94)	1.27 (3.38)	-0.49 (-1.80)	-0.01 (-0.04)	0.48 (1.55)	0.97 (2.43)

**Table 3: Returns of Portfolios Triple-Sorted on IVOL, FSCORE, and Control Variables**

This table presents average monthly value-weighted excess and factor-adjusted returns for portfolios triple sorted on IVOL, FSCORE, and control variables. At the end of each month, we first assign stocks into ten decile portfolios based on the measure of each control variable. Then, within each control variable decile portfolio, we further assign stocks into five quintile portfolios based on IVOL. Finally, we group stocks into five IVOL quintile portfolios in which each IVOL portfolio has same level of IVOL across ten control variable deciles. Control variables include the expected idiosyncratic skewness (EISKEW), past returns (REV), the maximum daily returns over the past month (MAX), illiquidity (ILLIQ), the standardized unexpected earnings (SUE), and mispricing score for each stock (MSCORE). P1 (P5) includes stocks with the smallest (largest) IVOL. F1 refers to the portfolio of stocks with FSCORE from 0 to 3; F3 refers to the portfolio of stocks with FSCORE from 7 to 9. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016 except for EISKEW (1988 to 2016). Newey-West (1987) adjusted t-statistics are in parentheses.

	Excess Return			FF5		
	F1	F3	F3 - F1	F1	F3	F3 - F1
<i>EISKEW</i>						
P1	0.76	0.73	-0.03	-0.06	-0.07	-0.01
P5	-0.17	1.01	1.18	-0.69	0.34	1.03
P5 - P1	-0.92	0.29	1.21	-0.63	0.41	1.04
	(-2.26)	(0.79)	(3.61)	(-2.32)	(1.67)	(2.98)
<i>REV</i>						
P1	0.63	0.64	0.01	-0.04	-0.14	-0.10
P5	-0.26	0.92	1.18	-0.82	0.31	1.14
P5 - P1	-0.89	0.28	1.16	-0.78	0.45	1.24
	(-2.54)	(0.84)	(3.59)	(-2.73)	(2.16)	(3.36)
<i>MAX</i>						
P1	0.67	0.65	-0.02	0.11	-0.06	-0.17
P5	0.03	1.11	1.08	-0.50	0.24	0.74
P5 - P1	-0.64	0.47	1.10	-0.61	0.30	0.90
	(-2.50)	(2.31)	(4.19)	(-2.35)	(1.57)	(2.88)
<i>ILLIQ</i>						
P1	0.75	0.70	-0.05	0.00	-0.10	-0.10
P5	-0.16	0.94	1.10	-0.55	0.33	0.88
P5 - P1	-0.91	0.25	1.15	-0.55	0.43	0.98
	(-2.29)	(0.76)	(3.70)	(-2.25)	(1.69)	(2.95)
<i>SUE</i>						
P1	0.78	0.72	-0.06	-0.04	-0.10	-0.06
P5	-0.44	1.10	1.55	-0.78	0.64	1.42
P5 - P1	-1.23	0.38	1.60	-0.75	0.73	1.48
	(-3.03)	(1.06)	(4.67)	(-3.00)	(2.49)	(3.91)
<i>MSCORE</i>						
P1	0.63	0.73	0.10	-0.17	-0.07	0.10
P5	-0.15	1.15	1.30	-0.70	0.57	1.27
P5 - P1	-0.78	0.42	1.20	-0.53	0.64	1.17
	(-2.24)	(1.26)	(3.65)	(-2.24)	(2.27)	(3.37)

**Table 4: Fama-MacBeth Regressions**

This table presents the average coefficients from the monthly cross-sectional regressions. The dependent variable is a stock's raw return in month  $t$ , and independent variables include a set of lagged variables at the end of month  $t-1$ . The independent variables include FSCORE with a score from 1 to 10, Carhart four-factor-adjusted idiosyncratic volatility (IVOL), the logarithm of market capitalization (ME), the logarithm of book-to-market ratio (BM), past 1one-month returns from month  $t-12$  to  $t-2$  (MOM), six variables related to the IVOL puzzle (the expected idiosyncratic skewness (EISKEW), the maximum daily returns (MAX), the past one-month returns (REV), illiquidity (ILLIQ), the standardized unexpected earnings (SUE), and mispricing score for each stock (MSCORE)), and the interaction terms between IVOL and these six variables. The sample period is from 1985 to 2016 except for EISKEW (1988 to 2016). Independent variables except FSCORE and MSCORE are trimmed at the one and 99% levels. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. Newey-West (1987) adjusted t-statistics are in parentheses.

	1	2	3	4	5	6	7	8	9
FSCORE	0.151 (7.79)	0.028 (1.31)	0.019 (0.84)	0.028 (1.34)	0.026 (1.22)	0.024 (1.14)	0.038 (1.82)	0.024 (1.14)	0.021 (0.93)
IVOL	-0.173 (-3.39)	-0.439 (-5.72)	-0.408 (-3.59)	-0.283 (-2.78)	-0.478 (-6.31)	-0.464 (-5.81)	-0.369 (-4.80)	-0.035 (-0.33)	0.016 (0.12)
IVOL x FSCORE		0.053 (4.92)	0.051 (4.55)	0.054 (4.84)	0.055 (5.19)	0.055 (5.13)	0.039 (3.72)	0.041 (3.81)	0.036 (3.35)
IVOL x EISKEW			0.009 (0.14)						
IVOL x MAX				-0.543 (-0.83)					
IVOL x REV					0.749 (3.84)				
IVOL x ILLIQ						-0.027 (-0.25)			
IVOL x SUE							0.054 (4.51)		
IVOL x MSCORE								-0.006 (-3.91)	
ME	-0.084 (-2.87)	-0.082 (-2.81)	-0.105 (-2.90)	-0.070 (-2.41)	-0.069 (-2.33)	-0.126 (-3.61)	-0.086 (-2.93)	-0.090 (-3.10)	-0.135 (-3.39)
BM	0.125 (1.64)	0.121 (1.58)	0.088 (1.11)	0.128 (1.70)	0.139 (1.75)	0.134 (1.79)	0.121 (1.58)	0.099 (1.33)	0.119 (1.52)
MOM	0.531 (2.53)	0.521 (2.49)	0.437 (1.94)	0.519 (2.49)	0.483 (2.16)	0.540 (2.60)	0.431 (2.09)	0.363 (1.77)	0.212 (0.92)
EISKEW			-0.159 (-0.93)						-0.140 (-0.84)
MAX				-2.183 (-0.80)					5.406 (1.75)
REV					-4.350				-5.389

									(-5.91)	
ILLIQ									-0.257	(-5.98)
									(-0.88)	(-1.61)
SUE									-0.026	-0.020
									(-1.00)	(-0.72)
MSCORE										-0.007
										(-2.03)
										(-2.11)
Adjusted R <sup>2</sup>	0.034	0.035	0.037	0.039	0.042	0.040	0.036	0.038	0.058	



**Table 5: The Role of Earnings Announcements in the IVOL Effect**

Panel A presents the average monthly value-weighted returns for portfolios sorted on IVOL conditional on whether quarterly earnings announcements occur in the formation month t-1. EA refers to the subsample in which quarterly earnings announcements occur in the formation month; NO EA refers to the subsample in which no earnings announcements occur in the formation month. Panel B presents the average monthly value-weighted returns for portfolios double sorted on IVOL and FSCORE conditional on whether quarterly earnings announcements occur in the formation month t-1. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. The sample period is from 1985 to 2016. Stocks with price less than \$5 at the end of formation periods are excluded. Newey-West (1987) adjusted t-statistics are in parentheses.

Panel A						
		EA			NO EA	
	Excess	FF5	M4	Excess	FF5	M4
P1	0.75	-0.15	-0.28	0.80	0.02	-0.05
P5	0.22	-0.32	-0.10	0.13	-0.20	-0.01
P5 - P1	-0.53	-0.17	0.18	-0.67	-0.22	0.04
	(-1.26)	(-0.48)	(0.52)	(-2.00)	(-1.07)	(0.15)
Panel B						
<i>EXCESS</i>		EA			NO EA	
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	0.18	0.89	0.65	0.78	0.75	-0.02
P5	-0.26	0.86	1.19	-0.52	0.97	1.49
P5 - P1	-0.44	0.03	0.53	-1.29	0.22	1.51
	(-0.80)	(0.07)	(0.84)	(-2.99)	(0.62)	(3.71)
<i>FF5</i>		EA			NO EA	
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.59	-0.30	0.27	-0.04	-0.07	-0.04
P5	-0.91	-0.08	0.88	-0.76	0.40	1.16
P5 - P1	-0.31	0.13	0.54	-0.72	0.47	1.20
	(-0.69)	(0.30)	(0.81)	(-2.66)	(1.67)	(2.97)
<i>M4</i>		EA			NO EA	
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.62	-0.40	0.17	-0.06	-0.07	-0.01
P5	-1.09	-0.02	1.06	-0.54	0.31	0.85
P5 - P1	-0.47	0.29	0.83	-0.48	0.38	0.87
	(-0.86)	(0.66)	(1.14)	(-1.61)	(1.17)	(1.97)

**Table 6: Institutional Ownership and the IVOL-Return Relation**

This table presents the average monthly value-weighted returns in excess of one-month T-bill and Fama-French five-factor-adjusted and mispricing four-factor-adjusted returns for portfolios independently sorted on IVOL and FSCORE in high and low institutional ownership (IO) subsamples. The high (low) IO subsample consists of one of third of stocks with the highest (lowest) IO. P1 (P5) includes stocks with the smallest (largest) IVOL. F1 refers to the portfolio of stocks with FSCORE from 0 to 3; F2 refers to the portfolio of stocks with FSCORE from 4 to 6; F3 refers to the portfolio of stocks with FSCORE from 7 to 9. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016 except for EISKEW (1988 to 2016). Newey-West (1987) adjusted t-statistics are in parentheses.

Excess Return						
	High-IO Sample			Low-IO Sample		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	0.73 (2.85)	0.75 (3.22)	0.03 (0.14)	0.65 (2.33)	1.00 (4.78)	0.35 (1.40)
P5	0.23 (0.43)	1.10 (2.26)	0.87 (2.09)	-0.96 (-1.49)	0.98 (1.90)	1.94 (3.90)
P5 - P1	-0.50 (-1.16)	0.34 (0.84)	0.84 (1.93)	-1.61 (-2.83)	-0.02 (-0.04)	1.60 (3.23)
FF5						
	High-IO Sample			Low-IO Sample		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.10 (-0.60)	-0.11 (-0.88)	-0.01 (-0.04)	-0.16 (-0.72)	0.22 (1.53)	0.38 (1.47)
P5	-0.26 (-0.79)	0.44 (1.24)	0.71 (1.54)	-1.17 (-3.68)	0.70 (1.69)	1.88 (3.41)
P5 - P1	-0.17 (-0.45)	0.55 (1.43)	0.71 (1.51)	-1.01 (-2.80)	0.49 (1.11)	1.50 (2.70)
M4						
	High-IO Sample			Low-IO Sample		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.03 (-0.18)	-0.10 (-0.68)	-0.07 (-0.3)	-0.09 (-0.39)	0.22 (1.44)	0.31 (1.14)
P5	0.15 (0.42)	0.44 (1.48)	0.28 (0.65)	-1.02 (-2.69)	0.62 (1.6)	1.63 (3.1)
P5 - P1	0.19 (0.46)	0.54 (1.54)	0.35 (0.72)	-0.92 (-2.08)	0.39 (0.98)	1.32 (2.41)

**Table 7: Investor Sentiment and the IVOL Effect**

This table presents the average monthly value-weighted returns to portfolios double sorted on IVOL and FSCORE conditional on investor sentiment. A month  $t$  is classified as a high (low) sentiment month if the Baker and Wurgler (2006) sentiment index in month  $t$  is above (below) the sample median value. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. The sample period is from 1985 to September 2015. Stocks with price less than \$5 at the end of formation periods are excluded. Newey-West (1987) adjusted t-statistics are in parentheses.

<i>EXCESS</i>	High Sentiment			Low Sentiment			High - Low Sentiment		
	F1	F3	F3 - F1	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	0.55	0.64	0.08	0.89	0.83	-0.06	-0.34	-0.20	0.14
P5	-2.06	0.46	2.52	0.91	1.47	0.56	-2.97	-1.01	1.96
P5 - P1	-2.62	-0.17	2.44	0.02	0.64	0.62	-2.64	-0.81	1.82
	(-4.70)	(-0.44)	(5.33)	(0.04)	(1.09)	(1.07)	(-3.37)	(-1.16)	(2.42)
<i>FF5</i>	High Sentiment			Low Sentiment			High - Low Sentiment		
	F1	F3	F3 - F1	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.14	-0.11	0.03	-0.06	-0.09	-0.03	-0.08	-0.02	0.06
P5	-1.43	0.73	2.16	-0.26	0.18	0.44	-1.17	0.55	1.72
P5 - P1	-1.29	0.84	2.13	-0.20	0.27	0.47	-1.09	0.57	1.66
	(-4.00)	(2.67)	(4.74)	(-0.51)	(0.70)	(0.83)	(-2.03)	(1.30)	(2.30)
<i>M4</i>	High Sentiment			Low Sentiment			High - Low Sentiment		
	F1	F3	F3 - F1	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.13	-0.06	0.06	-0.11	-0.13	-0.02	-0.02	0.06	0.08
P5	-1.32	0.52	1.85	0.01	0.26	0.24	-1.34	0.27	1.60
P5 - P1	-1.20	0.59	1.78	0.12	0.38	0.26	-1.32	0.20	1.52
	(-3.30)	(1.46)	(3.36)	(0.29)	(0.87)	(0.49)	(-2.43)	(0.36)	(2.08)

**Table 8: The IVOL-Return Relation in Subsamples of Large versus Small Stocks**

This table presents the average monthly value-weighted returns in excess of one-month T-bill and Fama-French five-factor-adjusted and mispricing four-factor-adjusted returns for portfolios independently sorted on IVOL and FSCORE in the subsamples of small versus large stocks. First, we divide all sample stocks into three groups based on the firms' market capitalization at the end of formation month. Within each size group, we divide stocks into five quintile portfolios based on firms' IVOL. P1 (P5) includes stocks with the smallest (largest) IVOL. F1 refers to the portfolio of stocks with FSCORE from 0 to 3; F2 refers to the portfolio of stocks with FSCORE from 4 to 6; F3 refers to the portfolio of stocks with FSCORE from 7 to 9. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016 except for EISKEW (1988 to 2016). Newey-West (1987) adjusted t-statistics are in parentheses.

Excess Return						
	Small Stocks			Large Stocks		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	0.21	1.40	1.19	0.77	0.69	-0.08
	(0.59)	(5.90)	(5.45)	(3.33)	(3.44)	(-0.48)
P5	-0.95	1.10	2.05	-0.01	1.02	1.02
	(-1.85)	(2.76)	(6.63)	(-0.01)	(2.59)	(3.20)
P5 - P1	-1.16	-0.30	0.85	-0.78	0.33	1.11
	(-3.26)	(-1.10)	(2.81)	(-1.90)	(0.97)	(3.31)
FF5						
	Small Stocks			Large Stocks		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.58	0.64	1.22	0.04	-0.14	-0.18
	(-2.75)	(5.07)	(5.69)	(0.25)	(-1.47)	(-1.02)
P5	-1.31	0.25	1.56	-0.44	0.47	0.91
	(-6.14)	(1.11)	(5.67)	(-1.81)	(1.72)	(2.40)
P5 - P1	-0.73	-0.38	0.34	-0.48	0.60	1.09
	(-2.67)	(-1.55)	(1.14)	(-1.73)	(2.13)	(2.74)
M4						
	Small Stocks			Large Stocks		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.49	0.62	1.11	0.07	-0.12	-0.19
	(-2.16)	(4.18)	(4.83)	(0.41)	(-1.11)	(-1.02)
P5	-1.32	0.24	1.56	-0.25	0.35	0.59
	(-5.06)	(1.08)	(5.28)	(-0.93)	(1.51)	(1.63)
P5 - P1	-0.83	-0.39	0.45	-0.32	0.47	0.79
	(-2.48)	(-1.51)	(1.36)	(-1.08)	(1.75)	(2.06)



**Table 9: FSCORE vs. MSCORE vs. SUE**

This table presents average monthly value-weighted Fama-French (2015) five factor-adjusted returns for portfolios triple sorted on IVOL, FSCORE, and control variables such as SUE and MSCORE. Panel A reports the results based on triple sorts on IVOL, FSCORE, and SUE. At the end of each month, we independently assign sample stocks into 3, 5, and 3 groups based on SUE, IVOL, and FSCORE, respectively. Finally, we get 30 sub-portfolios. SUE=1 refers to the portfolio of stocks with the lowest SUE, and SUE=3 refers to the portfolio of stocks with the highest SUE. Panel B reports the results based on triple sorts on IVOL, FSCORE, and MSCORE. MSCORE=1 refers to the portfolio of stocks with the smallest mispricing score, and MSCORE=3 refers to the portfolio of stocks with the largest mispricing score. Sample stocks includes common stocks listed in NYSE/AMEX/NASDAQ exchanges. Stocks with price less than \$5 at the end of formation periods are excluded. The sample period is from 1985 to 2016. Newey-West (1987) adjusted t-statistics are in parentheses.

Panel A: FSCORE vs. SUE						
	SUE=1			SUE=3		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	0.01	-0.22	-0.24	-0.17	-0.06	0.12
P5	-0.91	-0.12	0.79	-0.94	1.29	2.24
P5 - P1	-0.92	0.10	1.02	-0.77	1.35	2.12
	(-2.99)	(0.24)	(1.96)	(-1.98)	(3.12)	(3.45)
	FSCORE=1			FSCORE=3		
	S1	S3	S3 - S1	S1	S3	S3 - S1
P1	0.01	-0.18	-0.20	-0.24	-0.06	0.18
P5	-0.91	-0.97	-0.06	-0.16	1.29	1.45
P5 - P1	-0.92	-0.79	0.14	0.08	1.35	1.27
	(-2.99)	(-2.02)	(0.30)	(0.20)	(3.11)	(2.14)
Panel B: FSCORE vs. MSCORE						
	MSCORE=1			MSCORE=3		
	F1	F3	F3 - F1	F1	F3	F3 - F1
P1	-0.04	-0.19	-0.15	-0.17	-0.17	0.01
P5	-0.10	0.73	0.83	-1.32	-0.36	0.96
P5 - P1	-0.06	0.92	0.98	-1.15	-0.19	0.95
	(-0.14)	(2.80)	(1.91)	(-3.88)	(-0.54)	(1.94)
	FSCORE=1			FSCORE=3		
	M1	M3	M3 - M1	M1	M3	M3 - M1
P1	-0.04	-0.17	-0.14	-0.20	-0.17	0.04
P5	-0.10	-1.31	-1.22	0.70	-0.36	-1.06
P5 - P1	-0.06	-1.14	-1.08	0.90	-0.19	-1.09
	(-0.14)	(-3.84)	(-2.11)	(2.76)	(-0.54)	(-2.34)