Idiosyncratic Return Volatility, Uncertainty, and Asset Pricing Implications[ψ]

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Abstract

In this study, we decompose idiosyncratic stock return volatility (IVOL) into uncertainty and residual volatility, and find that the negative IVOL-return relation primarily comes from the uncertainty component. Further analysis indicates that firm uncertainty increases are associated with negative contemporaneous stock returns. High uncertainty firms also have lower firm values and higher expected returns, and exhibit more asymmetric price responses to good/bad market states. All of these are consistent with ambiguity aversion modeled by Epstein and Schneider (2008). Our study documents novel valuation and return patterns associated with the uncertainty content embedded in IVOL. Our findings suggest that uncertainty offers a new channel to explore the IVOL puzzle. It may also help interpret the common factor in IVOL documented in the recent literature.

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Idiosyncratic stock return volatility (IVOL) is often viewed as a measure for unsystematic risk in the finance literature. This notion makes it difficult to interpret the negative relation between IVOL and subsequent stock returns documented by Ang et al. (2006; the IVOL puzzle). A large literature has been dedicated to solving the IVOL puzzle.[1] Surprisingly, despite the frequent usage of IVOL as a proxy for information uncertainty,[2] few studies discuss the asset pricing implications of IVOL from the perspective of uncertainty. This study aims to fill this gap in the literature.

Employing the theoretical framework and the uncertainty measure developed by Barron et al. (1998), we decompose IVOL into two components: uncertainty and residual volatility. Interestingly, we find that the negative IVOL-return relation primarily comes from the uncertainty component. Consistent with ambiguity aversion modeled by Epstein and Schneider (2008), we find that uncertainty changes correlate negatively with contemporaneous stock returns, and that high uncertainty firms have lower valuations and higher expected returns. Further, high uncertainty stocks show more asymmetric price responses to good versus bad market states. As a result, the negative relation between uncertainty and stock returns concentrates in bad market states, such as periods of negative aggregate earnings news, increased market volatility, and negative stock market returns. Because the predictive power of IVOL on future returns mainly comes from uncertainty, we find that the returns of high IVOL stocks exhibit similar asymmetry and state dependence.

To the best of our knowledge, our paper is the first to show that the negative IVOL-return relation primarily comes from its embedded uncertainty content. Our findings suggest that IVOL embodies more than “unsystematic risk”, and the uncertainty content in IVOL has significant asset pricing implications. In addition to providing a new channel to explore the IVOL puzzle, this study

[1] Hou and Loh (2016) summarize recent literature and existing explanations for the IVOL puzzle.
[2] For example, see Jiang et al. (2005), and Rajgopal and Venkatachalam (2011).

is also the first to show that the IVOL-return relation is state dependent. High IVOL stocks earn small positive returns in good market states, but their returns suffer strong negative shocks in bad states. When good and bad states are pooled together, the negative relation dominates. Any alternative explanation of the IVOL puzzle would also need to account for this state dependence.

This paper builds on the prior literature that IVOL reflects information uncertainty. Pastor and Veronesi (2003) show that IVOL increases with uncertainty about a firm's profitability. Empirically, a number of studies use IVOL to measure uncertainty (e.g. Jiang et al. (2005), Rajgopal and Venkatachalam (2011)). Analyst forecast dispersion is another popular proxy for uncertainty (Jiang et al. (2005), Zhang (2006)), and high dispersion also yields lower future returns (Diether et al. (2002)). In a study closely related to ours, Barron et al. (2009) decompose analyst forecast dispersion into uncertainty and information asymmetry following the theoretical framework developed by Barron et al. (1998). They find that the negative dispersion-return relation comes from uncertainty.

Motivated by Barron et al. (2009), we first examine whether IVOL's effect on future returns can also be attributed to uncertainty. Specifically, we use analyst earnings forecasts to calculate the uncertainty measure developed by Barron et al. (1998) for each firm, and then regress IVOL on this uncertainty measure to decompose IVOL into uncertainty (UNC; regression predictions) and residual volatility (RES; regression residuals). After the decomposition, we sort firms into quintiles by UNC or RES every month, and measure the returns of the long-short arbitrage portfolios (high UNC/RES – low UNC/RES) in the following month.

Similar to Barron et al. (2009), we find that the negative IVOL-return relation primarily comes from uncertainty: While the uncertainty component consistently predicts large negative returns in the subsequent month, the residual component does not do so consistently and sometimes even yields significantly positive returns.

To identify the channel through which uncertainty affects returns, we consider two possible explanations: option value and ambiguity aversion. Johnson (2004) posits that uncertainty enhances the option value of a firm. Hence, high uncertainty firms have higher values today, which results in lower returns in the future. According to Johnson (2004), uncertainty increases should be accompanied by positive changes in contemporaneous prices. Alternatively, Epstein and Schneider (2008) suggest that investors are ambiguity averse and they respond to uncertainty as if they take a worst-case assessment of potential outcomes. According to Epstein and Schneider (2008), uncertainty innovations should be negatively associated with contemporaneous price changes, contrary to Johnson (2004).

We next observe the contemporaneous relation between uncertainty changes and stock returns. Firms are sorted into quintiles by the monthly change in uncertainty and the portfolio returns of the sorting month are measured. We find that uncertainty changes negatively correlate with contemporaneous stock returns, indicating ambiguity aversion. The result is consistent with Epstein and Schneider (2008), but inconsistent with Johnson (2004).

We further explore the asset pricing implications of uncertainty under ambiguity aversion modeled by Epstein and Schneider (2008). Epstein and Schneider posit that investors dislike ambiguity, so when they process news of uncertain quality, they assume the worst-case outcome. As a result, investors tend to underreact to good news and overreact to bad news, and this tendency is particularly strong when they trade stocks with poor information quality, such as high uncertainty stocks, or when aggregate uncertainty is high. We find empirical evidence consistent with these predictions: the prices of high uncertainty stocks decline more during periods of negative aggregate earnings news, heightened market uncertainty, or negative stock market returns (collectively, “bad market states”).

These asymmetric price responses to good/bad market states also manifest in IVOL, consistent with our earlier finding that IVOL’s predictive power of future stock returns mainly comes from the uncertainty component. Hence, although high IVOL stocks yield small gains in good market states, these small gains are outweighed by large losses in bad states. This imbalance leads to a negative average return when good and bad market states are analyzed together.

Throughout our analysis, we find that the size factor (SMB) in the Fama-French three-factor model (FF-3f; Fama and French (1993)) tends to lower the contrast between the good and bad market states exhibited by high uncertainty/IVOL stocks: in good states, the abnormal returns are less positive; but in bad states, the returns are also less negative. This seemingly puzzling result is in fact consistent with investor aversion to ambiguity. Specifically, small stocks tend to do well in good states, so high uncertainty/IVOL stocks underperform relative to small stocks in good states. In bad states, high uncertainty/IVOL stocks severely underperform, but because small stocks also tend to do poorly in bad states, the underperformance becomes less severe relative to small stocks.

The aforementioned interaction between size and uncertainty/IVOL indicates that although small firms tend to have high uncertainty and high return volatility, size and uncertainty/IVOL have distinct asset pricing implications. We further explore this distinction and find that limiting exposure to uncertainty or IVOL greatly enhances the abnormal returns associated with a size-based trading strategy (ca. 2-5 times), consistent with our earlier findings.

Overall, our results suggest that the uncertainty content in IVOL provides a promising channel to explore the IVOL puzzle. A recent study by Hou and Loh (2016) also attempts to explain the IVOL puzzle using uncertainty but does not find much success. Different from our study, Hou and Loh use analyst forecast dispersion to proxy for uncertainty. However, as shown by Barron et al. (1998), forecast dispersion reflects only the idiosyncratic portion of uncertainty arising from individual analysts' private beliefs and can be expressed as the product of total uncertainty (or simply "uncertainty") and information asymmetry (or lack of consensus). Although uncertainty yields negative returns in the subsequent month, information asymmetry does the opposite (Barron et al. (2009)). The countervailing effect from information asymmetry contributes to dispersion's low explanatory power of the IVOL anomaly shown in Hou and Loh (2016).

Our study also extends the findings in Barron et al. (2009). Similar to Barron et al., we find that uncertainty predicts negative returns in the following month, but we further investigate the asset pricing implications of uncertainty under ambiguity aversion. Besides, while Barron et al. only examine the contemporaneous relation between stock returns and the changes in forecast dispersion and its two components around earnings announcements, we study the more general relation between monthly changes in uncertainty and contemporaneous stock returns.[3] Our finding that monthly increases in uncertainty are associated with negative contemporaneous returns extends Barron et al. and provides empirical evidence that contradicts Johnson (2004).

Despite predicting return asymmetry in good versus bad market states, our uncertainty perspective is distinct from arbitrage asymmetry proposed by Stambaugh et al. (2015). Stambaugh et al. posit that high IVOL stocks are easier to buy but harder to short sell. This arbitrage asymmetry results in overpricing for high IVOL stocks on average and thus lower returns in the future. However, arbitrage asymmetry cannot explain why only the uncertainty component is

[3] Barron et al. (2009) focus their study on the changes in forecast dispersion and its two components (uncertainty and information asymmetry) around earnings announcements. They find that dispersion changes around earnings announcements primarily come from the changes in information asymmetry. Although both the increases in uncertainty and information asymmetry around earnings announcements are associated with negative contemporaneous returns, only the latter is statistically significant (see Table 5 in Barron et al. (2009)).

consistently associated with subsequent negative returns. In fact, we find that the majority of the IVOL variation comes from the residual volatility component, and IVOL shows a much stronger correlation with the residual component than with uncertainty (0.95 vs. 0.31). Further, we find that high IVOL firms have lower contemporaneous firm values and higher expected returns measured by the implied cost of capital (Hou et al (2012)), similar to high uncertainty firms. The finding is inconsistent with Stambaugh et al. (2015) who suggest that high IVOL firms should be overpriced on average, but consistent with ambiguity aversion under Epstein and Schneider (2008).

In addition to the IVOL puzzle, the uncertainty component may also help decipher the common factor in IVOL documented in the recent literature. Herskovic et al. (2016) find that the IVOLs of U.S. firms show a high degree of comovement that obeys a factor structure and that the innovations in the common factor correlate with those in aggregate cash flows. Herskovic et al. posit that this common factor proxies for aggregate cash flow risk that impacts household incomes. Our results may suggest an alternative interpretation that is more intuitive: the comovement in firm IVOLs may reflect market-wide uncertainty about the economy that affects all stocks. Although a detailed study is beyond the scope of this paper, we find that aggregate IVOL/uncertainty shows strong correlations with commonly used market uncertainty measures, such as GDP forecast dispersion and the implied volatility of the S&P 100 index options (VXO). It may be worthwhile for future research to explore the association between uncertainty and the common factor in IVOL.

Finally, our study adds to the growing literature in ambiguity. The ambiguity literature has achieved some success in explaining market-level anomalies, such as the equity premium puzzle and high stock return volatility (e.g., Leippold, Trojani, and Vanini (2008), Ju and Miao (2012)), but its applications to cross-sectional anomalies are still limited (Williams (2015)). If uncertainty quantifies differential price responses to good/bad market states, it may help explain some other return anomalies. In a contemporaneous study, Liang et al. (2018) show that uncertainty explains the majority or all of the profits associated with a momentum- or profitability-based trading strategy. Uncertainty may help summarize a subset of cross-sectional return anomalies.

The remainder of this paper is organized as follows. In the following section, we decompose IVOL into uncertainty and residual volatility, and observe their respective effects on future stock returns. Section 2 develops and tests hypotheses regarding uncertainty's asset pricing implications under ambiguity aversion. Section 3 investigates the interaction between size and uncertainty/IVOL. Section 4 summarizes the findings and discusses potential future research.

1. IVOL decomposition

1.1. Uncertainty component and future return

Uncertainty is distinct from risk although both result in outcomes the agents cannot perfectly control. Risk is often referred to as the "known unknown". The agents face risk if they know the possible outcomes and the probabilities of these outcomes in advance, such as rolling a dice. Uncertainty is the "unknown unknown" or the Knightian uncertainty (Knight (1921)). The agents face uncertainty if they do not know for sure the possible outcomes or the probabilities, such as the color of a ball randomly drawn from an urn containing balls with unspecified colors or quantifies (the Ellsberg paradox; Ellsberg (1961)). Therefore, uncertainty can be understood as parameter uncertainty (Pastor and Veronesi (2009)). For example, for an event following a normal distribution with mean μ and standard deviation σ, the agents face risk if they have precise knowledge of both μ and σ in advance; if instead the agents do not have precise knowledge of μ and σ, they face uncertainty.

Stock return volatility has often been used as a proxy for information uncertainty in the literature, along with analyst forecast dispersion (Pastor and Veronesi (2003), Jiang et al. (2005), Zhang (2006), Rajgopal and Venkatachalam (2011)). Similar to stock return volatility, Diether et al. (2002) also document a negative association between forecast dispersion and subsequent stock returns. Applying the theoretical framework developed by Barron et al. (1998), Barron et al. (2009) decompose analyst forecast dispersion into uncertainty and information asymmetry. They find that the negative dispersion-return relation comes only from the uncertainty component.

Motivated by the findings by Barron et al. (2009), we decompose IVOL into uncertainty and residual volatility by regressing IVOL on the uncertainty measure constructed from analyst forecasts following Barron et al. (1998, 2009). Specifically, an individual analyst's uncertainty is measured with the difference between his/her forecast (FC_i) and the reported earnings per share (EPS). The uncertainty measure V for a firm is the aggregate of individual uncertainty, calculated as the mean of the squared differences between individual analysts' forecasts and reported EPS as shown in the left portion of eq. (1).

$$Uncertainty\ (V) = \frac{\sum_{i=1}^{n}(FC_i - EPS)^2}{n} = SE + \left(1 - \frac{1}{n}\right)D \qquad (1)$$

$$Consensus\ forecast\ error\ (SE) = (EPS - \overline{FC})^2 \qquad (2)$$

$$Dispersion\ (D) = \frac{\sum_{i=1}^{n}(FC_i - \overline{FC})^2}{n-1} \qquad (3)$$

Barron et al. (1998) show that after some rearrangement, V can also be expressed as the sum of SE and $\left(1 - \frac{1}{n}\right)D$ as shown in the right portion of eq. (1). SE is consensus forecast error, measured by the squared error in the mean forecast relative to the reported EPS.[4] D is analyst forecast dispersion, measured with the standard deviation of analyst forecasts (FC_i). Barron et al. (1998) illustrate in their theoretical model that SE in the first term reflects uncertainty common to

[4] SE looks similar to the earnings surprise measure, but it is quite different. The earnings surprise, measured by actual EPS - consensus forecast, is directional and may be either positive or negative, but SE is non-directional and always positive because it is the square of the difference.

all analysts while D in the second term reflects idiosyncratic uncertainty arising from individual analysts' private beliefs. Under the framework of parameter uncertainty, SE in the first term can also be interpreted as analysts' uncertainty about where the mean is centered, and D in the second term their uncertainty about how dispersed the distribution is.

Hence, V in eq. (1) is a more appropriate measure for uncertainty than forecast dispersion D, the frequently used uncertainty proxy in the literature, because V contains both common and idiosyncratic components of uncertainty. Another intuitive way to illustrate the difference between V and D is that D is based on each forecast's deviation from the mean forecast, while V is based on each forecast's deviation from the actual EPS. When information uncertainty is high, not only would analysts' forecasts differ from one another, but the consensus forecast, or the common belief, would also likely deviate from the true value.

We first calculate V using monthly analyst forecasts of the current fiscal year's earnings (FY1) from I/B/E/S according to eq. (1). To make it more comparable to IVOL, we take the squared root of V and scale it by stock price to obtain the uncertainty measure in Barron et al. (1998, 2009) for each firm. We then regress monthly IVOL on this uncertainty measure to decompose IVOL into two components: uncertainty (UNC; predictions from the regression), and residual volatility (RES; residuals of the regression). Monthly IVOL is obtained by regressing daily stock returns from CRSP against the Fama-French three factors and then taking the square root of the variance of the residuals, following Ang et al. (2006). The I/B/E/S coverage of FY1 earnings forecasts becomes more complete starting in 1983, so the IVOL decomposition and the UNC/RES series start in 1983. The descriptive statistics of firm-level variables used in the study are summarized in Appendix A.

In our first set of tests, we observe whether the uncertainty and residual volatility components exhibit different associations with future returns. In every month t, we sort stocks into quintiles according to uncertainty (UNC), residual volatility (RES), or IVOL, and then measure the returns of the long-short arbitrage portfolios (Q5 – Q1; high UNC/RES/IVOL – low UNC/RES/IVOL) in the subsequent month t+1. Table 1 reports the raw and adjusted returns of the arbitrage portfolios. Prior research finds that the abnormal returns of the arbitrage portfolio are sensitive to the portfolio weighting scheme, indicating potential interaction between IVOL and size (Bali and Cakici (2008)). Hence, in addition to the commonly used CAPM, Fama-French three-factor (Fama and French (1993); FF-3f), and Carhart four-factor (Carhart (1997); Carhart-4f) models, we also observe abnormal returns adjusted with the FF-3f or Carhart-4f model excluding the size factor (FF-3f ex. SMB; Carhart-4f ex. SMB).[5]

Table 1 Panel A summarizes the abnormal returns of the long-short arbitrage portfolios formed by sorting firms on UNC/RES/IVOL with an equal-weighting scheme. The uncertainty and residual components exhibit distinctive return patterns: In column (1), where firms are sorted by the uncertainty component UNC, all abnormal returns are negative and statistically significant at the 1% level. However, in column (2), where firms are sorted by the residual volatility component RES, only one out of six is negative, but statistically insignificant; moreover, three are even significantly positive. The results indicate that the negative IVOL-return relation primarily comes from the uncertainty component.

Columns (3) and (4) show the abnormal returns of sorting firms on IVOL. The difference between (3) and (4) is that column (4) includes all firms with available IVOL data, while column (3) includes only the subset of firms for which the IVOL decomposition can be performed. In other words, tests in columns (1)-(3) use the subset of firms that have analyst forecasts from I/B/E/S to

[5] The Fama-French three factors as well as the momentum factor are from Dr. Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

enable the IVOL decomposition. The tests in column (4) use the entire cross-section of CRSP firms. Nevertheless, the results in columns (3) and (4) are similar and comparable to those documented in the literature: the abnormal returns are weak and often insignificant under the equal-weighting scheme. Besides, Panel A also shows that size affects the magnitude of the abnormal returns. When the size factor (SMB) is removed from the FF-3f/Carhart-4f models, the abnormal returns tend to become less negative or more positive.

Table 1 Panel B reports the abnormal returns of the portfolios constructed with the value-weighting scheme. Similar to the patterns observed in Panel A, sorting firms by uncertainty yields significantly negative and sizable alphas (column (1)), but sorting firms by residual volatility does not do so consistently (column (2)). All six values are negative and significant at the 1% level in column (1), but only two out of six are significantly negative at the 5% level in column (2). The abnormal returns in column (4), where the full sample is used, have similar magnitude compared to that reported in the literature. In column (3), where the decomposition subsample is used, the abnormal returns are smaller.

Overall, the results in Table 1 indicate that the negative IVOL-return relation mainly comes from the uncertainty component embedded in IVOL, which also drives the negative association between forecast dispersion and returns (Barron et al. (2009)). The residual volatility component (the portion of IVOL that cannot be explained by uncertainty) has no consistent return predictive power. Interestingly, the residual component's lack of return predictive power actually fits the theory's description about IVOL (idiosyncratic risk should not predict returns).

1.2. Uncertainty change and contemporaneous return

The results in the previous section show that the negative IVOL-return relation arises primarily from uncertainty. Johnson (2004) offers an explanation for the negative association between uncertainty and future returns. He posits that uncertainty enhances the option value of a firm, which leads to a higher value today and lower returns in the future. According to Johnson (2004), an increase in uncertainty should result in a positive change in contemporaneous price, as discussed in Barron et al. (2009). We next test this conjecture.

In every month t, we calculate the change in uncertainty (dUNC) relative to the previous month t-1 for each firm, and sort firms into quintiles according to dUNC. The contemporaneous return in month t is then measured for the long-short portfolio (Q5 – Q1; high dUNC – low dUNC). Table 2 reports the abnormal returns of the long-short portfolio formed by sorting firms on contemporaneous uncertainty change, where column (1) and (2) correspond to equal- and value-weighted portfolios, respectively.

Contrary to Johnson (2004), both columns in Table 2 show significantly negative returns. The negative association between uncertainty increases and contemporaneous returns suggests that investors dislike heightened uncertainty, consistent with ambiguity aversion. According to Epstein and Schneider (2008), ambiguity-averse investors dislike uncertainty, so they tend to assume the worst-case scenario when facing uncertainty. Hence, an increase in uncertainty leads to lower contemporaneous returns.

2. Asset pricing implications of uncertainty under ambiguity aversion

The results in Section 1 show that the uncertainty component in IVOL has a significant effect on future returns, and IVOL's predictive power of subsequent stock returns mainly comes from the uncertainty component. Further, investors' responses to uncertainty increases are consistent with ambiguity aversion. In this section, we further explore the asset pricing implications of uncertainty under ambiguity aversion.

2.1. Testable hypotheses

Epstein and Schneider (2008) model the asset pricing implications of information uncertainty. They postulate the following:[6]

"When ambiguity-averse investors process news of uncertain quality, they act as if they take a worst-case assessment of quality. As a result, they react more strongly to bad news than to good news. They also dislike assets for which information quality is poor, especially when the underlying fundamentals are volatile."

Epstein and Schneider suggest that high uncertainty stocks are more susceptible to investor aversion to ambiguity, and these stocks tend to have more asymmetric price responses to good/bad news (underreaction to good news and overreaction to bad news). We propose two testable hypotheses and discuss the empirical results in the following subsection.

H1: High uncertainty firms are more susceptible to investor aversion to ambiguity, so the effect of asymmetric price responses to good/bad news should be more pronounced for high uncertainty stocks, i.e. the returns of high uncertainty stocks should suffer stronger negative shocks when market news is bad.

H2: The effect of investor aversion to ambiguity is stronger when the underlying fundamentals are volatile. Therefore, the returns of high uncertainty stocks should suffer stronger negative shocks when market uncertainty increases.

2.2. Empirical tests: H1 and H2

2.2.1. Baseline tests

To test H1 and H2, we first sort stocks into quintile portfolios based on the uncertainty component, UNC, in month t, and then measure the portfolio returns in the following month t+1, conditioning on the market news or market uncertainty in t+1. Epstein and Schneider (2008) do

[6] Equation (10) in Epstein and Schneider (2008; p. 197) best summarizes this hypothesis.

not suggest large firms to be more relevant than small firms in their model, and the results in the previous section show that the uncertainty component exhibits similar return characteristics in both equal-weighted and value-weighted portfolios, so we report returns from equal-weighted portfolios in the main tables for brevity. The value-weighted portfolios also yield qualitatively similar results, which will be discussed in Section 2.2.2.

In testing H1, we divide the return periods into two groups: (i) periods with positive market news; and (ii) periods with negative market news, and record portfolio returns separately. Market news is measured with aggregate forecast revision (AggRev). A return period t+1 is considered a period of positive (negative) market news if AggRev in month t+1 is positive (negative). AggRev is the equal-weighted mean of forecast revisions of firms in the sample, demeaned by the aggregate's average from the prior 12 months.[7] Firm forecast revision is calculated as analysts' mean EPS (earnings per share) forecast for the upcoming quarter, surveyed in month t+1, minus the mean EPS forecast for the same quarter surveyed in the previous month t, and then the difference is scaled by the firm's stock price from month t. Analyst forecasts are from I/B/E/S. Because the I/B/E/S coverage of quarterly EPS estimates starts in the second half of 1984, the AggRev series begins in 2H 1985 (after the 12 month demeaning). Our tests of H1 use a sample period of January 1986–December 2013.

Table 3 Panel A summarizes the test results of H1 with firms sorted on UNC. The cells in the table are the returns of the long-short arbitrage portfolio (Q5 – Q1; high UNC – low UNC), with or without pricing model adjustments. Epstein and Schneider (2008) are silent on the effects of pricing model adjustments, but it is possible for certain pricing factors to capture a portion of

[7] Analysts tend to start with more optimistic forecasts and then gradually revise them downward as the reporting time approaches. Demeaning with the prior-12-month mean removes this time trend. The results are similar if market news is measured with the value-weighted aggregate of forecast revisions.

the asymmetric price responses to positive/negative market news of high uncertainty stocks. Therefore, we first show the raw returns and then the abnormal returns (or alphas) based on the five pricing models used in Tables 1 and 2.

The results in columns (1) and (2) exhibit distinct patterns for periods of positive versus negative market news: The negative relation between uncertainty and subsequent returns shown in Table 1 concentrates in periods of negative market news. In periods of negative market news (column (2)), the long-short portfolio yields an average raw return of -1.890% that is statistically significant at the 1% level, but the return is only -0.138% and statistically insignificant in periods of positive market news (column (1)). The difference in returns between these two groups (negative market news – positive market news) is -1.752%, which is sizable and statistically significant at the 1% level (column (3)).

The abnormal returns of the long-short portfolio measured with the CAPM, FF-3f, and Carhart-4f models show a similar pattern, and the differences in the alphas between the two groups are all sizable (-1.543%, -1.005%, -1.129%) and statistically significant (column (3)). In the bottom two rows, when SMB is removed from the pricing models (FF-3f ex. SMB; Carhart-4f ex. SMB), the return differentials become greater in magnitude (-1.320%, -1.420%). In addition, the presence of the market factor (no factor vs. CAPM) also dampens the magnitude of the return differentials.

Because IVOL's predictive power of future returns primarily comes from the uncertainty component, in Panel B, we test whether the IVOL-return relation also exhibits asymmetry to good/bad market news. Indeed, we find similar results when we replace UNC with IVOL. Similar to Panel A, the negative alphas tend to concentrate in periods of negative market news. For periods of positive market news (column (1)), none of the alphas are negative; but for periods of negative news, all alphas are significantly negative (column (2)). The differences in returns between these two groups (negative market news – positive market news; column (3)) are all negative, sizable (ranging from -2.390% to -3.099%), and statistically significant at the 1% level.

Overall, the results in Table 3 are consistent with H1: High uncertainty stocks suffer stronger negative return shocks when market news is bad. Hence, the long-short return spreads between high and low uncertainty stocks are significantly more negative during periods of bad market news. This characteristics also carries through to IVOL because the long-short return spreads formed by sorting firms on IVOL also exhibit dependence on market news.

We next test H2 by dividing the return periods into periods of increased market uncertainty and periods of decreased market uncertainty. A return period t+1 is designated a period of increased (decreased) market uncertainty if the change in the implied volatility of the S&P 100 index options (dVXO) in month t+1 is positive (negative) compared to the previous month t. The test period starts in January 1986, when the VXO data first became available, and ends in December 2013.[8]

Similar to Table 3, we find that the negative UNC/IVOL-return relation concentrates in periods of increased market uncertainty, consistent with H2. In Table 4 Panel A, where firms are sorted on UNC, the long-short return spread is 0.636% (insignificant) in periods of decreased market uncertainty (column (1)) and -2.880% (1% significance) in periods of increased market uncertainty (column (2)). With pricing model adjustments, the alphas (significance level) are -0.625% (insignificant), -1.138% (5%), and -0.273% (insignificant) for CAPM, FF-3f, and Carhart-4f, respectively, for periods of decreased uncertainty. For periods of increased uncertainty, the

[8] The implied volatility of stock index options, such as the VXO or VIX, has been used in the literature to proxy for investor uncertainty about the economy (Bloom (2009), Jurado et al. (2015), Williams (2015)). VXO and VIX (implied volatility of the S&P 500 index options) are highly correlated, but VXO has a longer time series, so we use VXO in the study. VXO data are from the CBOE website: http://www.cboe.com/micro/vix/historical.aspx.

alphas are more negative: -2.547%, -2.472%, and -1.670%, respectively, all significant at the 1% level. The alpha differences between these two groups (increased uncertainty – decreased uncertainty; column (3)) are all sizable (-3.516%, -1.922%, -1.334%, -1.397%) and statistically significant. Similar to Table 3, the presence of the market or size factor dampens the contrast. In the bottom two rows, where SMB is excluded from the FF-3f/Carhart-4f models, the alpha differentials become greater in magnitude (-1.755%, -1.901%). The results are similar but with a slightly weaker contrast if firms are sorted by IVOL instead as shown in Panel B.

The results in Tables 3 and 4 indicate that stocks with high uncertainty suffer stronger negative return shocks during periods of negative market news or periods of increased market uncertainty, consistent with H1 and H2. Because the stock market aggregates information in the marketplace, market returns should reflect market news and market uncertainty. Indeed, we find that stock market returns, measured as the monthly returns of the CRSP index (CRSP-ew/-vw), are positively correlated with market news proxies (AggRev-ew/-vw) and negatively with the increase of market uncertainty (dVXO) as shown in Appendix B. Overall, the equal-weighted CRSP index return (CRSP-ew) exhibits higher correlations with AggRev and dVXO than its value-weighted counterpart. The correlations indicate that when the market conditions are adverse to high uncertainty stocks (negative market news or increased uncertainty), the stock market returns tend to be negative. Consequently, stock market returns can be viewed as a summary measure of market news and market uncertainty. Based on the results in Tables 3 and 4, high uncertainty stocks should also exhibit greater negative return shocks during periods of negative market returns.

In the next set of tests, we divide the return measurement periods into two groups: periods of positive market returns and periods of negative market returns. Market returns are measured with the returns of the CRSP equal-weighted index.[9] We report these results in Table 5. In Panel A/B, firms are sorted by UNC/IVOL respectively and the testing period starts in 1983 when analyst earnings forecasts from I/B/E/S become available for the IVOL decomposition.

Overall, the results in Table 5 are similar to those in Tables 3 and 4: the negative relation between UNC/IVOL and returns concentrates in periods of negative market returns. When firms are sorted by uncertainty (Panel A), the long-short strategy yields large and statistically significant (1% level) negative alphas in periods of negative market returns (column (2)): -3.922% (raw), -3.100% (CAPM), -2.815% (FF-3f), and -1.842% (Carhart-4f). In contrast, the strategy does not yield consistently negative alphas in periods of positive market returns (column (1)): 0.732% (raw), 0.086% (CAPM), -1.876% (FF 3f), and -0.542% (Carhart 4f). When SMB is excluded from the FF-3f/Carhart-4f models, alpha either shrinks in magnitude or switches signs (-0.118% / 1.025%) in periods of positive market returns (column (1)); in periods of negative market returns, alpha becomes more negative (-3.234% and -2.617; column (2)). The results are similar when firms are sorted by IVOL (Panel B).

Similar to previously observed, the results in Table 5 also indicate that the size factor SMB dampens the contrast between periods of positive/negative market returns. For example, in Panel A (UNC), the differences in alpha between the two groups (negative market returns – positive market returns) are all less than -3% when SMB is not present in the pricing models: -4.654% (raw), -3.186% (CAPM), -3.116% (FF-3f ex. SMB), and -3.642% (Carhart-4f ex. SMB). When SMB is present, the difference decreases in magnitude: -0.939% (FF-3f) and -1.300% (Carhart-4f). The reduced contrast comes from both the more negative alphas in periods of positive market returns and the less negative alphas in periods of negative market returns.

[9] The CRSP value-weighted index yields qualitatively similar but weaker results.

The effects of SMB on the long-short return spreads suggest that although high uncertainty stocks tend to be smaller in size, the effect of uncertainty on returns is distinct from that of size. In periods of positive market returns, small stocks tend to do well, so high uncertainty stocks perform worse relative to small stocks. In periods of negative market returns, high uncertainty stocks do badly, but because the prices of small stocks also tend to decline more in these periods, the underperformance of high uncertainty stocks does not look as bad relative to small stocks. Overall, the underperformance of high uncertainty stocks relative to small stocks is consistent with Epstein and Schneider (2008): the asymmetric price responses to good/bad shocks (underreaction to good and overreaction to bad) are stronger for stocks with high uncertainty. Similar patterns are also observed in Tables 3 and 4.

In addition to SMB, we also observe that the presence of the market factor in the CAPM model reduces the contrast between the good and bad market states. This is also consistent with high uncertainty stocks' asymmetric responses to good/bad market states: High uncertainty stocks have low CAPM betas in good states (underreaction to good news), and high CAPM betas in bad states (overreaction to bad news). Hence, the average beta overstates (understates) the true beta in good (bad) states, leading to a less positive (negative) abnormal returns in good (bad) market states under the CAPM.

Taken together, the results in Tables 3-5 show that high uncertainty stocks suffer greater negative return shocks during periods of negative market news, increased market uncertainty, or negative market returns (collectively bad or negative "market states"), consistent with H1 and H2. The IVOL-return relation also exhibits a similar state dependence.

2.2.2. Robustness checks

We conduct robustness checks with a different portfolio weighting scheme and with an extended sample period. The results are similar as shown in Appendices C-D. Appendix C repeats tests in Table 5 with value-weighted portfolios. Appendix D repeats the tests in Table 5 Panel B (sorting firms on IVOL) with an extended sample period January 1963 – December 2013 (UNC is not available before 1983). For brevity, we only report tests using market returns as the partitioning variable. The results are qualitatively similar if aggregate forecast revision or change in market uncertainty is used to partition the sample.

2.3. Arbitrage asymmetry, firm value, and expected return

In a recent study, Stambaugh, Yu, and Yuan (2015) posit that the negative IVOL-return relation arises from arbitrage asymmetry: High IVOL stocks are easier to buy but harder to short sell, resulting in greater overpricing than underpricing for high IVOL stocks and thus lower returns in the future. One might suspect our asymmetric results in good/bad market states stem from arbitrage asymmetry rather than uncertainty.

However, arbitrage asymmetry has difficulty explaining our results. First of all, it is unclear why only the uncertainty component in IVOL has return predictive power, not the residual volatility component. This becomes even more puzzling when in fact most of the IVOL variation comes from the residual component and IVOL has a much stronger correlation with the residual component than with uncertainty (0.95 vs. 0.31) as shown in Appendix A.

We next examine whether high IVOL firms are overpriced as posited by Stambaugh et al. (2015). Table 6 reports the results of regressing firm value on contemporaneous IVOL and uncertainty. Tobin's q, calculated with market value of equity plus book value of long term debt divided by total book value of assets, is the proxy for firm value, and log(q) is regressed against log(IVOL) or log (UNC). We also control for other firm characteristics that may affect valuation, such as systematic risk, size, leverage, investment, profitability, and growth opportunity, following

Rountree, Weston, and Allayannis (2008). The negative factor loading on IVOL indicates that high IVOL firms have lower values, inconsistent with Stambaugh et al. (2015). On the other hand, the negative loading on UNC is consistent with ambiguity aversion.

Lower valuations of high UNC/IVOL firms imply that investors require higher rates of returns for such firms, which seems to contradict the negative association between UNC/IVOL and the subsequent month's returns. Prior studies point out that realized returns are a noisy measure for expected returns (Elton (1999)). Leippold, Trojani, and Vanini (2008) also show that a severe downturn bias exists in the empirical relation between returns and return volatility, especially in the presence of ambiguity aversion. Hence, we estimate the implied cost of capital (ICC) following Hou, van Dijk and Zhang (2012) for firms sorting on UNC and IVOL to examine whether high UNC/IVOL firms have higher expected returns. As shown in Table 7, we find that the high UNC/IVOL quintiles have significantly higher implied costs of capital: the Q5-Q1 differences in ICC are all positive, ranging from 7.4% to 10.3% (5.2% to 7.6%) per annum for equal- (value-) weighted portfolios. These results indicate that high UNC/IVOL stocks have higher expected returns, consistent with their lower contemporaneous firm values shown in Table 6 and ambiguity aversion.

Lastly, because investor sentiment affects mispricing, Stambaugh et al. (2015) show that the negative IVOL-return relation is stronger following high sentiment periods. We also find that negative market returns tend to follow high sentiment periods.[10] It is possible that the stronger negative IVOL-return relation observed in periods of negative market returns comes from the correlation between market returns and lagged sentiment. Besides, market returns may also capture contemporaneous market sentiment. To address these concerns, we repeat the tests in Table 5,

[10] The correlation between market return (CRSP-ew(t+1)) and lagged sentiment (SENT(t)) is -0.12 (p-value < 0.01). The monthly sentiment data are from Dr. Jeffrey Wurgler's website.

including both lagged and contemporaneous market sentiment (sentiment(t) and sentiment(t+1)) as additional controls in the regressions. The results in Appendix E show that the contrast between positive and negative market return periods remains sharp. These results indicate that the stronger UNC/IVOL-return relation observed in periods of negative market returns does not stem from the correlation between investor sentiment and market returns.

2.4. Summary

Taken together, the results discussed in this section are consistent with the behavior of ambiguity-averse investors modeled by Epstein and Schneider (2008): Investors dislike stocks with high uncertainty, so they tend to underreact to good news and overreact to bad news when trading these stocks. Hence, high uncertainty firms have lower valuations and higher expected returns. They also experience more asymmetric price shocks in good versus bad market states. As a result, the negative uncertainty-return relation concentrates in bad market states.

In Section 1, we find that the negative IVOL-return relation is driven by the uncertainty component UNC embedded in IVOL. In this section, we also find that high IVOL stocks exhibit pricing characteristics similar to UNC: High IVOL stocks experience more asymmetric price responses to good/bad market states. Hence, the small gains in good market states are outweighed by large losses in bad market states, resulting in negative returns on average for high IVOL stocks.

Arbitrage asymmetry has difficulty explaining our findings. In particular, we find that high UNC/IVOL stocks have lower contemporaneous firm values and higher expected returns. These findings are consistent with ambiguity aversion, but inconsistent with arbitrage asymmetry.

The asset pricing implications of the uncertainty content in IVOL has not been separately studied in the prior literature. Our findings suggest that uncertainty has significant asset pricing implications. It provides a new channel for exploring the IVOL puzzle.

3. IVOL and size

The results in the previous sections suggest that there is interaction between IVOL and size. For example, in Tables 3-5, the presence of SMB dampens the contrast between the good and bad market states: the abnormal returns of the long-short arbitrage portfolio are less positive in good market states but also less negative in bad states. Because IVOL's predictive power of future return primarily comes from the uncertainty component, this result is consistent with ambiguity aversion. Specifically, small stocks perform well in good market states, so high UNC/IVOL stocks underperform relative to small stocks; in bad market states, high UNC/IVOL stocks suffer stronger negative shocks, but because small stocks also perform poorly, the underperformance becomes less severe.

These results indicate that size and UNC/IVOL have distinct asset pricing implications, although small firms tend to have high uncertainty and high return volatility. We next examine whether controlling for UNC or IVOL affects the profitability of a size-based trading strategy.

In the next set of tests, we independently sort firms by size and UNC (or IVOL) to form 3x3 portfolios in month t and record the returns for the nine portfolios in month t+1.[11] Table 8 summarizes the results. We also show returns from portfolios sorted on size only in the left column for comparison. In Panel A, where firms are double-sorted on size and UNC, the long-short portfolio based on the univariate sort by size yields an insignificant raw return spread of 0.235% for equal-weighted portfolios (Panel A1). In contrast, the diagonal long-short portfolio from the double sorts (small size, low UNC – big size, high UNC) yields an average spread of 1.081% that is statistically significant at the 1% level. The latter is 4.6 times of the former in magnitude. The results are similar with size and IVOL double sorts as shown in Panel B. The amplification is even

[11] If we double sort firms into 5x5 portfolios, some portfolios would have too few or even no observations in certain periods, so we sort firms into 3x3 portfolios instead.

more pronounced if the returns are adjusted with the CAPM model (Panels A3-A4; B3-B4).

That controlling for UNC/IVOL enhances the abnormal returns of a size-based trading strategy is consistent with the results discussed in previous sections: Although size and UNC/IVOL are highly correlated, high UNC/IVOL stocks have more asymmetric price responses to good/bad market states than small stocks due to the uncertainty component. Hence, high UNC/IVOL stocks tend to underperform relative to small stocks in both good and bad market states, and limiting UNC or IVOL exposure magnifies the abnormal returns associated with size. This offers a simple approach to enhance the profitability of a size-based trading strategy.[12]

4. Summary and Discussions

In this study, we decompose idiosyncratic stock return volatility into uncertainty and residual volatility, and find that the negative IVOL-return relation mainly comes from the uncertainty component. Further analysis indicates that firm uncertainty increases are associated with negative contemporaneous stock returns. High uncertainty stocks have lower firm values, and exhibit more asymmetric price responses to good/bad market states. All of these are consistent with investor ambiguity aversion modeled by Epstein and Schneider (2008).

Although IVOL is often used as a proxy for information uncertainty in the literature, the asset pricing implications of the uncertainty content embedded in IVOL have not been separately studied. Our study fills this void in the literature. Further, our findings that IVOL's predictive power of future returns mainly comes from uncertainty, and that similar to uncertainty, the IVOL-return relation exhibits state dependence suggest that uncertainty offers a promising channel to explore the IVOL puzzle.

Moreover, uncertainty may help interpret the common factor in IVOL documented in the

[12] A recent study by Asness et al. (2016) also finds that the profitability of a size-based trading strategy can be greatly enhanced if "quality" is controlled for, where idiosyncratic risk is one of the quality factors.

recent literature. Herskovic et al. (2016) find that firm IVOLs show strong comovement that obeys a factor structure and that the innovations in the common factor correlate with those in aggregate firm cash flows. Herskovic et al. conjecture that this common factor proxies for the risk of aggregate cash flows that influences household incomes. Our study suggests another uncertainty-based interpretation: the comovement in firm IVOLs may reflect market-wide uncertainty about the economy that affects all stocks.

Following Herskovic et al. (2016), we aggregate firm IVOLs and uncertainty in the cross-section, and find that aggregate IVOL/uncertainty shows strong correlations with market uncertainty proxies, such as GDP forecast dispersion and the implied volatility of the S&P 100 index options (VXO), as shown in Table 9. Although a detailed analysis is beyond the scope of this paper, it may be worthwhile for future research to investigate the connection between uncertainty and the common factor in IVOL.

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Table 1: Uncertainty and Residual Volatility Components in IVOL and Future Returns

This table tests how each of the two IVOL components (uncertainty and residual volatility) relates to future stock returns. The results indicate that only the uncertainty component (UNC, column (1)) consistently predicts negative returns in the subsequent month.

We first regress IVOL on the uncertainty measure constructed according to Barron et al. (1998, 2009) to decompose IVOL into the uncertainty (UNC) and residual volatility (RES) components. Then in every month t, firms are sorted by UNC, RES, or IVOL into quintile portfolios, and then the long-short (Q5 – Q1) portfolio is formed by longing quintile 5 (high UNC/RES/IVOL) and shorting quintile 1 (low UNC/RES/IVOL). The return of the long-short portfolio in subsequent month t+1 is then measured. Panels A and B show the returns of portfolios constructed with the equal- and value-weighting scheme respectively.

Column (3) includes only the subsample of firms whose earnings forecasts are available from I/B/E/S to enable the decomposition of IVOL. Column (4) includes all U.S. stocks listed on NYSE/Amex/Nasdaq whose IVOLs can be calculated from the daily returns in the CRSP database.

The cells in the table show the constant term (alpha) obtained by regressing the long-short portfolio returns against a constant (no factor), the market factor (CAPM), the Fama-French three factors (FF-3f), the Carhart four factors (Carhart-4f), the Fama-French three factors excluding the size factor SMB (FF-3f ex. SMB), and the Carhart four factors excluding SMB (Carhart-4f ex. SMB), respectively.

IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006). The uncertainty measure in Barron et al. (1998, 2009) is the squared root of [the mean of the squared differences between individual analysts' forecasts of FY1 EPS from I/B/E/S and reported EPS]/ price per share ([…] equals V in eq. (1)). UNC/RES (the uncertainty/residual volatility component in IVOL): the predictive/residual values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009).

Analysis period: January 1983 – December 2013 (February 1983 – December 2013 for returns; UNC/RES start in 1983). T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Equal-Weighted Portfolios

	(1)	(2)	(3)	(4)
Sorting variable	UNC	RES	IVOL (subsample)	IVOL (all)
Alpha (in %)	Q5 - Q1	Q5-Q1	Q5-Q1	Q5-Q1
No factor	-1.024***	0.431	-0.310	-0.197
	(3.65)	(1.22)	(0.80)	(0.50)
CAPM	-1.331***	-0.077	-0.888***	-0.619*
	(5.52)	(0.25)	(2.76)	(1.71)
FF-3f	-1.547***	0.307	-0.595***	-0.402
	(6.50)	(1.50)	(2.63)	(1.32)
Carhart-4f	-0.941***	0.679***	-0.109	0.050
	(4.66)	(3.04)	(0.47)	(0.15)
Factor models ex. SMB:				
FF-3f ex. SMB	-1.456***	0.437*	-0.440	-0.253
	(5.64)	(1.68)	(1.50)	(0.70)
Carhart-4f ex. SMB	-0.858***	0.795***	0.030	0.183
	(3.50)	(2.74)	(0.10)	(0.46)
Periods	371	371	371	371

Table 1: Uncertainty and Residual Volatility Components in IVOL and Future Returns (continued)

Panel B: Value-Weighted Portfolios

Sorting variable	(1) UNC	(2) RES	(3) IVOL (subsample)	(4) IVOL (all)
Alpha (in %)	Q5 - Q1	Q5-Q1	Q5-Q1	Q5-Q1
No factor	-0.715***	-0.209	-0.571	-1.106***
	(2.80)	(0.56)	(1.50)	(2.70)
CAPM	-1.065***	-0.777**	-1.172***	-1.636***
	(4.84)	(2.47)	(3.67)	(4.53)
FF-3f	-1.362***	-0.456**	-0.934***	-1.432***
	(6.87)	(2.18)	(4.29)	(5.48)
Carhart-4f	-0.970***	-0.169	-0.580***	-1.028***
	(5.56)	(0.78)	(2.67)	(3.99)
Factor models ex. SMB:				
FF-3f ex. SMB	-1.293***	-0.311	-0.774***	-1.249***
	(5.99)	(1.17)	(2.73)	(3.82)
Carhart-4f ex. SMB	-0.907***	-0.040	-0.438	-0.866***
	(4.47)	(0.15)	(1.52)	(2.59)
Periods	371	371	371	371

Table 2: Uncertainty Changes and Contemporaneous Returns

This table tests the relation between uncertainty changes and contemporaneous stock returns. The results show a negative relation, indicating ambiguity aversion. The results are consistent with Epstein and Schneider (2008) but inconsistent with Johnson (2004).

In every month t, the change of the uncertainty component of IVOL (dUNC) is calculated relative to last month t-1, and then firms are sorted by dUNC into quintile portfolios, and the long-short (Q5 – Q1) portfolio is formed by longing quintile 5 (high dUNC) and shorting quintile 1 (low dUNC). The contemporaneous return of the long-short portfolio in month t is then measured.

The cells in the table show the constant term (alpha) obtained by regressing the long-short portfolio returns against a constant (no factor), the market factor (CAPM), the Fama-French three factors (FF-3f), the Carhart four factors (Carhart-4f), the Fama-French three factors excluding the size factor SMB (FF-3f ex. SMB), and the Carhart four factors excluding SMB (Carhart-4f ex. SMB), respectively.

UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).

Analysis period: January 1983 – December 2013 (February 1983 – December 2013 for dUNC and returns; UNC starts in 1983). T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Sorting variable	dUNC	dUNC
Portfolio weighting	ew	vw
Alpha (in %)	Q5 - Q1	Q5-Q1
No factor	-7.466***	-4.819***
	(34.05)	(23.19)
CAPM	-7.461***	-4.874***
	(34.41)	(22.64)
FF-3f	-7.413***	-4.829***
	(33.74)	(21.47)
Carhart-4f	-7.437***	-4.856***
	(30.59)	(21.38)
Factor models ex. SMB:		
FF-3f ex. SMB	-7.446***	-4.836***
	(31.84)	(20.87)
Carhart-4f ex. SMB	-7.466***	-4.862***
	(29.67)	(21.08)
Periods	371	371

Table 3: Uncertainty/IVOL-Return Relation: Partition by Market News

This table tests the uncertainty/IVOL-return relation conditioning on market news. The results indicate that the negative relation between UNC/IVOL and subsequent stock returns concentrates in periods of negative market news.

In every month t, firms are sorted by uncertainty (UNC; Panel A) or IVOL (Panel B) into equal-weighted quintile portfolios, and then the long-short (Q5 – Q1) portfolio is formed by longing quintile 5 (high UNC/IVOL) and shorting quintile 1 (low UNC/IVOL). The return of the long-short portfolio in subsequent month t+1 is then measured. The return measurement periods are divided into two groups: positive (column (1)) or negative (column (2)) market news (AggRev) based on market news in the return measurement month t+1.

Market news is positive (negative) for month t+1 if the aggregate analyst forecast revision (AggRev) is positive (negative) in month t+1. Aggregate analyst forecast revision is the cross-sectional equal-weighted (ew) mean of firm forecast revisions demeaned by the ew-aggregate's mean from the prior 12 months. Firm forecast revision is calculated as analysts' mean EPS forecast for the upcoming quarter surveyed in month t+1 minus the mean EPS forecast for the same quarter surveyed in the previous month t, scaled by the firm's stock price from the previous month t.

UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).

The cells show the raw (no factor) or abnormal returns against the market factor (CAPM), the Fama-French three factors (FF-3f), the Carhart four factors (Carhart-4f), the Fama-French three factors excluding the size factor SMB (FF-3f ex. SMB), and the Carhart four factors excluding SMB (Carhart-4f ex. SMB), respectively. The Q5-Q1 spread becomes more negative in good states (column (1)) and less negative in bad states (column (2)) when SMB is included in the pricing model, consistent with high uncertainty stocks' asymmetric price responses to good/bad states.

Analysis period: January 1986 – December 2013 (AggRev starts in 1986). T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The results are similar with value-weighted portfolio returns (see discussions in Section 2.2.2).

Panel A: Uncertainty (UNC)

	(1)	(2)	(3)
Alpha (in %)	Positive AggRev Q5-Q1 (a)	Negative AggRev Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	-0.138	-1.890***	-1.752***
	(0.31)	(4.62)	(2.91)
CAPM	-0.552	-2.095***	-1.543***
	(1.48)	(5.95)	(3.01)
FF-3f	-1.010***	-2.016***	-1.005**
	(2.69)	(6.24)	(2.03)
Carhart-4f	-0.357	-1.486***	-1.129***
	(1.26)	(4.57)	(2.62)
Factor models ex. SMB:			
FF-3f ex. SMB	-0.778*	-2.099***	-1.320**
	(1.88)	(5.89)	(2.42)
Carhart-4f ex. SMB	-0.124	-1.544***	-1.420***
	(0.35)	(4.22)	(2.77)
Periods	182	153	--

Table 3: Uncertainty/IVOL-Return Relation: Partition by Market News (continued)

Panel B: IVOL

In Panel B, the test sample includes all U.S. stocks listed on NYSE/Amex/Nasdaq whose IVOLs can be calculated from the daily return data in the CRSP database. (Panel A includes only firms whose earnings forecasts are available from I/B/E/S to enable the IVOL decomposition.)

	(1)	(2)	(3)
Alpha (in %)	Positive AggRev Q5-Q1 (a)	Negative AggRev Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	1.274*	-1.487***	-2.761***
	(1.96)	(2.87)	(3.32)
CAPM	0.743	-1.762***	-2.505***
	(1.23)	(3.86)	(3.31)
FF-3f	0.801	-1.589***	-2.390***
	(1.64)	(4.07)	(3.82)
Carhart-4f	1.342***	-1.258***	-2.600***
	(2.78)	(2.89)	(4.00)
Factor models ex. SMB:			
FF-3f ex. SMB	1.260**	-1.663***	-2.923***
	(2.02)	(4.04)	(3.91)
Carhart-4f ex. SMB	1.788***	-1.311***	-3.099***
	(2.77)	(2.83)	(3.90)
Periods	182	153	--

Table 4: Uncertainty/IVOL-Return Relation: Partitioned by Market Uncertainty

This table tests the uncertainty/IVOL-return relation conditioned on the change in market uncertainty. The results indicate that the negative relation between uncertainty/IVOL and subsequent stock returns concentrates in periods of increased market uncertainty.

In every month t, firms are sorted by uncertainty (UNC; Panel A) or IVOL (Panel B) into equal-weighted quintile portfolios, and then the long-short (Q5 – Q1) portfolio is formed by longing quintile 5 (high UNC/IVOL) and shorting quintile 1 (low UNC/IVOL). The return of the long-short portfolio in subsequent month t+1 is then measured. The return measurement periods are divided into two groups: decrease (column (1)) or increase (column (2)) in market uncertainty based on the change in the implied volatility of S&P 100 index options (dVXO) in the return measurement month t+1. Monthly VXO data are from the CBOE website.

UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).

The cells show the raw (no factor) or abnormal returns against the market factor (CAPM), the Fama-French three factors (FF-3f), the Carhart four factors (Carhart-4f), the Fama-French three factors excluding the size factor SMB (FF-3f ex. SMB), and the Carhart four factors excluding SMB (Carhart-4f ex. SMB), respectively. The Q5-Q1 spread becomes more negative in good states (column (1)) and less negative in bad states (column (2)) when SMB is included in the pricing model, consistent with high uncertainty stocks' asymmetric price responses to good/bad states.

The analysis period is January 1986 – December 2013 (VXO starts in 1986). T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The results are similar with value-weighted portfolio returns (see discussions in Section 2.2.2).

Panel A: Uncertainty (UNC)

	(1)	(2)	(3)
Alpha (in %)	dVXO Decrease Q5-Q1 (a)	dVXO Increase Q5-Q1 (b)	Inc. - Dec. (b) - (a)
No factor	0.636	-2.880***	-3.516***
	(1.39)	(8.75)	(6.23)
CAPM	-0.625	-2.547***	-1.922***
	(1.63)	(7.76)	(3.81)
FF-3f	-1.138**	-2.472***	-1.334**
	(2.51)	(8.13)	(2.44)
Carhart-4f	-0.273	-1.670***	-1.397***
	(0.80)	(6.80)	(3.31)
Factor models ex. SMB:			
FF-3f ex. SMB	-0.800*	-2.555***	-1.755***
	(1.67)	(7.85)	(3.03)
Carhart-4f ex. SMB	0.064	-1.838***	-1.901***
	(0.15)	(6.45)	(3.76)
Periods	185	150	--

Table 4: Uncertainty/IVOL-Return Relation: Partitioned by Market Uncertainty (continued)

Panel B: IVOL

In Panel B, the test sample includes all U.S. stocks listed on NYSE/Amex/Nasdaq whose IVOLs can be calculated from the daily return data in the CRSP database. (Panel A includes only firms whose earnings forecasts are available from I/B/E/S to enable the IVOL decomposition.)

	(1)	(2)	(3)
	dVXO Decrease	dVXO Increase	Inc. - Dec.
Alpha (in %)	Q5-Q1 (a)	Q5-Q1 (b)	(b) - (a)
No factor	1.526**	-1.853***	-3.379***
	(2.59)	(3.09)	(4.02)
CAPM	0.235	-1.218**	-1.453
	(0.36)	(2.06)	(1.65)
FF-3f	-0.012	-0.980**	-0.968
	(0.02)	(2.26)	(1.34)
Carhart-4f	0.735	-0.563	-1.298*
	(1.22)	(1.18)	(1.69)
Factor models ex. SMB:			
FF-3f ex. SMB	0.510	-1.137**	-1.647**
	(0.78)	(2.23)	(1.98)
Carhart-4f ex. SMB	1.263*	-0.850	-2.112**
	(1.74)	(1.62)	(2.36)
Periods	185	150	--

Table 5: Uncertainty/IVOL -Return Relation: Partitioned by Market Returns

This table tests the uncertainty/IVOL-return relation conditioned on stock market returns. Similar to Tables 3 and 4, the results indicate that the negative relation between uncertainty/IVOL and subsequent stock returns concentrates in periods of negative market returns.

In every month t, firms are sorted by uncertainty (UNC; Panel A) or IVOL (Panel B) into equal-weighted quintile portfolios, and then the long-short (Q5 – Q1) portfolio is formed by longing quintile 5 (high UNC/IVOL) and shorting quintile 1 (low UNC/IVOL). The return of the long-short portfolio in subsequent month t+1 is then measured. The return measurement periods are divided into two groups: positive (column (1)) or negative (column (2)) market returns (MktRet) based on the return of the CRSP-equal weighted index in the return measurement month t+1.

UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).

The cells show the raw (no factor) or abnormal returns against the market factor (CAPM), the Fama-French three factors (FF-3f), the Carhart four factors (Carhart-4f), the Fama-French three factors excluding the size factor SMB (FF-3f ex. SMB), and the Carhart four factors excluding SMB (Carhart-4f ex. SMB), respectively. The Q5-Q1 spread becomes more negative in good states (column (1)) and less negative in bad states (column (2)) when SMB is included in the pricing model, consistent with high uncertainty stocks' asymmetric price responses to good/bad states.

The analysis period is January 1983 – December 2013 (UNC starts in 1983). T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The results are similar with value-weighted portfolio returns (see discussions in Section 2.2.2).

Panel A: Uncertainty (UNC)

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	0.732**	-3.922***	-4.654***
	(1.98)	(13.19)	(9.82)
CAPM	0.086	-3.100***	-3.186***
	(0.19)	(8.37)	(5.52)
FF-3f	-1.876***	-2.815***	-0.939
	(3.69)	(6.51)	(1.41)
Carhart-4f	-0.542	-1.842***	-1.300**
	(1.47)	(5.39)	(2.59)
Factor models ex. SMB:			
FF-3f ex. SMB	-0.118	-3.234***	-3.116***
	(0.25)	(8.58)	(5.10)
Carhart-4f ex. SMB	1.025**	-2.617***	-3.642***
	(2.45)	(8.28)	(6.95)
Periods	231	140	--

Table 5: Uncertainty/IVOL -Return Relation: Partitioned by Market Returns (continued)

Panel B: IVOL

In Panel B, the test sample includes all U.S. stocks listed on NYSE/Amex/Nasdaq whose IVOLs can be calculated from the daily return data in the CRSP database. (Panel A includes only firms whose earnings forecasts are available from I/B/E/S to enable the IVOL decomposition.)

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	2.669***	-4.924***	-7.593***
	(5.47)	(11.05)	(11.49)
CAPM	2.320***	-4.201***	-6.521***
	(3.48)	(8.40)	(7.82)
FF-3f	-0.183	-2.522***	-2.338***
	(0.30)	(4.67)	(2.88)
Carhart-4f	0.814	-1.991***	-2.805***
	(1.14)	(3.92)	(3.19)
Factor models ex. SMB:			
FF-3f ex. SMB	2.548***	-3.168***	-5.716***
	(3.49)	(7.25)	(6.71)
Carhart-4f ex. SMB	3.459***	-2.878***	-6.337***
	(4.39)	(6.38)	(6.98)
Periods	231	140	--

Table 6: Uncertainty/IVOL and Firm Value

This table reports estimates of regressing firm value (proxied by Tobin's q) against uncertainty or IVOL. The negative loading on uncertainty/IVOL indicates that high uncertainty/IVOL firms have lower values. The results are consistent with ambiguity aversion, but inconsistent with Stambaugh et al. (2015).

Tobin's q (q) is the proxy for firm value, measured as (equity market value in month t + book value of long-term debt)/book value of total assets. UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006). Firm value, UNC, and IVOL are all measured in month t (contemporaneously).

Control variables are measured following Rountree et al. (2008): SysRisk is beta multiplied by market risk. Beta is obtained by regressing returns from the previous 36 months against the CRSP value-weighted index. Market risk is the standard deviation of the daily returns of the CRSP value-weighted index in month t. Assets is a firm's total assets. Debt/Assets is the ratio of a firm's long-term debt to total assets. Capex/Sales, R&D/Sales, and Advertising/Sales are the respective expense to sales ratios. ROA is net income/total assets. Sales growth is the sales growth of the last fiscal year. Company financials are based on the previous fiscal year. Time and SIC 2-digit industry dmmies are included to control for time and industry effects. Standard errors are clustered on industry and time.

The analysis period is January 1983 – December 2013 (UNC starts in 1983).
T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Variable	Log(q)	Log(q)
Log(IVOL)	-0.334***	
	(-20.04)	
Log(UNC)		-1.469***
		(-14.09)
Log(SysRisk)	0.105***	0.032**
	(9.47)	(1.99)
Log(Assets)	-0.081***	-0.106***
	(-14.88)	(-19.10)
Debt/Assets	-0.003	-0.157***
	(-0.06)	(-2.75)
Capex/Sales	0.069**	0.007
	(2.51)	(0.20)
R&D/Sales	0.264***	0.286***
	(6.28)	(5.11)
Advertising/Sales	1.541***	1.547***
	(3.90)	(4.28)
ROA	0.152	0.651***
	(1.55)	(2.89)
Sales Growth	0.382***	0.347***
	(11.45)	(9.76)
Observations	1,129,048	621,831
R-squared	0.240	0.387

Table 7: Expected Returns: Implied Costs of Capital (ICCs)

This table reports the expected returns, measured with the implied costs of capital (ICCs), of IVOL and UNC quintiles and the long-short (Q5 – Q1) portfolios.

We infer the ICC (the discount rate) from a stock's contemporaneous price and earnings estimates following Hou, van Dijk and Zhang (2012). The ICC is calculated on a monthly basis, and winsorized at the 1% and 99% levels. We set the value to missing if it is greater than 50% or smaller than zero following Hou et al. (2012). Firms are sorted on IVOL/UNC; Q1 (Q5) is the lowest (highest) quintile.

UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006). UNC requires a firm to be covered by research analysts, so the IVOL sample contains more firms than the UNC sample.

Analysis period: January 1983 – December 2013. The ICC is estimated contemporaneously with IVOL/UNC (all from month t), so there are 372 monthly periods/observations in this analysis. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The standard errors and t-statistics are adjusted for autocorrelation.

Panel A: Equal Weighted

	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q5 - Q1	Obs.
VARIABLES	ICC	ICC	ICC	ICC	ICC	ICC	t-stat	
IVOL	0.137	0.148	0.168	0.195	0.240	0.103***	(8.45)	372
UNC	0.091	0.110	0.121	0.134	0.165	0.074***	(13.20)	372

Panel B: Value Weighted

	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q5 - Q1	Obs.
VARIABLES	ICC	ICC	ICC	ICC	ICC	ICC	t-stat	
IVOL	0.063	0.068	0.078	0.100	0.139	0.076***	(8.89)	372
UNC	0.052	0.067	0.073	0.083	0.104	0.052***	(13.37)	372

Table 8: Size and Uncertainty/IVOL

This table reports portfolio returns based on independent double sorts (3x3) of (i) size and uncertainty (UNC) (Panel A); and (ii) size and IVOL (Panel B). The results indicate that controlling for UNC or IVOL increases the profitability of a size-based trading strategy. Size is measured with equity market value. The tercile breakpoints are 30th and 70th percentiles. The top two panels report raw returns for equal-weighted (ew) and value-weighted (vw) portfolios. The bottom two panels report CAPM adjusted alphas.

Panel A: Size and Uncertainty (UNC) Double Sorts

Only firms with available size and UNC data are included in the analysis. Analysis period: January 1983 – December 2013. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A1	**ew**	**Raw returns**				
(%)	Size	Size/UNC Double Sort				
	Single Sort	Low UNC	2	High UNC	High - Low UNC	(t-stat)
Small	0.959	1.362	1.539	0.310	-1.053***	(-4.27)
2	0.738	0.969	1.129	-0.097	-1.066***	(-4.59)
Big	0.724	0.788	0.862	0.281	-0.507**	(-2.31)
Small - Big	**0.235**	0.574***	0.677***	0.03	**Diagonal**	**(t-stat)**
(t-stat)	**(1.28)**	(3.57)	(4.19)	(0.13)	**1.081*****	**(4.12)**

Panel A2	**vw**	**Raw returns**				
(%)	Size	Size/UNC Double Sort				
	Single Sort	Low UNC	2	High UNC	High - Low UNC	(t-stat)
Small	0.846	1.294	1.447	0.101	-1.192***	(-4.90)
2	0.735	0.933	1.083	-0.070	-1.003***	(-4.36)
Big	0.644	0.734	0.699	0.229	-0.505**	(-2.23)
Small - Big	**0.202**	0.559***	0.748***	-0.128	**Diagonal**	**(t-stat)**
(t-stat)	**(0.96)**	(2.93)	(3.98)	(-0.53)	**1.065*****	**(3.98)**

Panel A3	**ew**	**CAPM alphas**				
(%)	Size	Size/UNC Double Sort				
	Single Sort	Low UNC	2	High UNC	High - Low UNC	(t-stat)
Small	0.152	0.710	0.782	-0.578	-1.289***	(-5.83)
2	-0.068	0.285	0.346	-1.073	-1.358***	(-6.97)
Big	0.001	0.154	0.117	-0.649	-0.803***	(-4.35)
Small - Big	**0.151**	0.556***	0.665***	0.07	**Diagonal**	**(t-stat)**
(t-stat)	**(0.85)**	(3.37)	(4.05)	(0.33)	**1.359*****	**(5.61)**

Panel A4	**vw**	**CAPM alphas**				
(%)	Size	Size/UNC Double Sort				
	Single Sort	Low UNC	2	High UNC	High - Low UNC	(t-stat)
Small	0.026	0.629	0.670	-0.814	-1.443***	(-6.74)
2	-0.062	0.251	0.302	-1.044	-1.296***	(-6.68)
Big	-0.017	0.148	-0.009	-0.674	-0.822***	(-4.19)
Small - Big	**0.044**	0.482**	0.679***	-0.140	**Diagonal**	**(t-stat)**
(t-stat)	**(0.22)**	(2.49)	(3.51)	(-0.57)	**1.303*****	**(5.00)**

Table 8: Size and Uncertainty/IVOL (continued)

Panel B: Size and IVOL Double Sorts

Analysis period: January 1983 – December 2013. Different from Panel A, all firms with available size and IVOL data are included in the analysis in Panel B. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel B1	**ew**	**Raw returns**				
(%)	Size	Size/IVOL Double Sort				
	Single Sort	Low IVOL	2	High IVOL	High - Low IVOL	(t-stat)
Small	1.191	0.902	1.097	1.299	0.398	(1.22)
2	0.660	0.954	0.883	0.054	-0.901***	(-2.62)
Big	0.734	0.859	0.789	-0.260	-1.119***	(-2.82)
Small - Big	**0.457***	0.043	0.308	1.559***	**Diagonal**	**(t-stat)**
(t-stat)	**(1.94)**	(0.24)	(1.43)	(4.56)	**1.162*** **	**(2.62)**

Panel B2	**vw**	**Raw returns**				
(%)	Size	Size/IVOL Double Sort				
	Single Sort	Low IVOL	2	High IVOL	High - Low IVOL	(t-stat)
Small	0.871	0.793	1.025	0.764	-0.029	(-0.09)
2	0.648	0.966	0.832	-0.040	-1.006***	(-2.90)
Big	0.653	0.736	0.602	-0.250	-0.986***	(-2.54)
Small - Big	**0.218**	0.057	0.422*	1.014***	**Diagonal**	**(t-stat)**
(t-stat)	**(0.90)**	(0.31)	(1.93)	(2.92)	**1.043*** *	**(2.44)**

Panel B3	**ew**	**CAPM alphas**				
(%)	Size	Size/IVOL Double Sort				
	Single Sort	Low IVOL	2	High IVOL	High - Low IVOL	(t-stat)
Small	0.603	0.611	0.585	0.578	-0.034	(-0.12)
2	-0.076	0.475	0.143	-0.913	-1.388***	(-4.79)
Big	-0.001	0.301	-0.056	-1.398	-1.700***	(-5.10)
Small - Big	**0.604*** **	0.310***	0.641***	1.976***	**Diagonal**	**(t-stat)**
(t-stat)	**(2.64)**	(2.10)	(3.54)	(6.39)	**2.010*** **	**(6.23)**

Panel B4	**vw**	**CAPM alphas**				
(%)	Size	Size/IVOL Double Sort				
	Single Sort	Low IVOL	2	High IVOL	High - Low IVOL	(t-stat)
Small	0.269	0.496	0.484	0.005	-0.491*	(-1.73)
2	-0.105	0.457	0.062	-1.045	-1.502***	(-5.16)
Big	-0.006	0.179	-0.235	-1.356	-1.534***	(-4.56)
Small - Big	**0.274**	0.317*	0.719***	1.360***	**Diagonal**	**(t-stat)**
(t-stat)	**(1.14)**	(1.96)	(3.58)	(4.06)	**1.852*** **	**(5.63)**

Table 9: Aggregate IVOL/Uncertainty

This table reports the cross-correlations among aggregate IVOL/UNC, VXO, and GDP forecast dispersion. The results indicate that these four series are significantly correlated with one another.

IVOL (idiosyncratic return volatility): An individual stock's IVOL is first calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and finding the square root of the residual variance, following Ang et al. (2006). Then the monthly aggregate IVOL is obtained by taking the cross-sectional mean. Annual aggregate IVOL is the mean of the 12 monthly aggregate IVOLs.
UNC (the uncertainty component in IVOL): the predictive values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009; see Table 1 caption). Annual aggregate UNC is the mean of the 12 monthly aggregate UNCs.
VXO (implied volatility of S&P 100 index options): Monthly VXO data are from the Chicago Board Options Exchange (CBOE) website. Annual VXO is the mean of the 12 monthly values.
GDP (GDP forecast dispersion): The dispersion (difference between the 75th percentile and the 25th percentile) of quarterly real GDP forecasts is surveyed in mid-quarter for the current quarter's real GDP. Quarterly GDP forecast dispersions are averaged to obtain the annual GDP forecast dispersion. The data are from the Survey of Professional Forecasters database maintained by the Federal Reserve Bank of Philadelphia.

Analysis period: January 1986 – December 2013 (VXO starts in 1986). P-values are shown in parentheses (rounded to the second decimal point). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A	**Aggregate Level**		
	IVOL	UNC	VXO
UNC	0.36*		
	(0.06)		
VXO	0.45**	0.53***	
	(0.02)	(0.00)	
GDP	0.36*	0.83***	0.62***
	(0.06)	(0.00)	(0.00)

Panel B	**Change of the Aggregate Level**		
	IVOL	UNC	VXO
UNC	0.74***		
	(0.00)		
VXO	0.73***	0.66***	
	(0.00)	(0.00)	
GDP	0.68***	0.64***	0.65***
	(0.00)	(0.00)	(0.00)

Appendix A: Firm-Level Variables

This appendix reports the summary statistics of firm-level variables used in the study (Panel A1), and the cross-correlations between IVOL and its two components (UNC and RES; Panel A2).

IVOL (idiosyncratic return volatility): An individual stock's IVOL is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).
UNC/RES (the uncertainty/residual volatility component in IVOL): the predictive/residual values of regressing IVOL on the uncertainty measure of Barron et al. (1998, 2009).
Uncertainty measure (Barron et al.): the uncertainty measure in Barron et al. (1998, 2009) is the squared root of [the mean of the squared differences between individual analysts' forecasts of FY1 EPS from I/B/E/S and reported EPS] scaled by price per share ([…] equals V in eq. (1)).
Return: monthly stock returns (including dividends) from the CRSP database.

Sample period: January 1983 – December 2013 (UNC/RES/Uncertainty measure start in 1983).

A1: Summary Statistics (all in % except for N)

Statistics	IVOL	UNC	RES	Uncertainty Measure (Barron et al.)	Return
N	2,042,166	970,984	970,984	970,984	2,044,385
Mean	3.43	2.53	0.00	3.22	0.82
Standard Deviation	2.80	0.56	1.69	6.97	15.51
25th Percentile	1.58	2.30	-1.08	0.35	-7.02
50th Percentile	2.58	2.35	-0.42	0.99	0.00
75th Percentile	4.28	2.50	0.61	2.81	7.36

A2: Cross-Correlations (IVOL/UNC/RES)

	IVOL	UNC
UNC	0.31***	
	(0.00)	
RES	0.95***	0.00
	(0.00)	(1.00)

Appendix B: Correlation Matrix of Market Returns, Market News and Market Uncertainty

This appendix reports the cross-correlations among market returns, market news measures (aggregate forecast revisions; Aggrev-ew/-vw) and market uncertainty measure (VXO change; dVXO). The results indicate that stock market returns correlate positively with market news and negatively with market uncertainty.

CRSP-ew/-vw: The monthly returns of the CRSP equal-weighted (CRSP-ew) or value-weighted (CRSP-vw) index.

AggRev-ew/-vw: The monthly equal-weighted (AggRev-ew) or value-weighted (AggRev-vw) aggregate analyst forecast revisions. Aggregate analyst forecast revision is the cross-sectional ew/vw mean of firm forecast revisions demeaned by its own ew/vw-aggregate's mean from the prior 12 months. Firm forecast revision is calculated as analysts' mean EPS forecast for the upcoming quarter surveyed in month t+1 minus the mean EPS forecast for the same quarter surveyed in the previous month t, scaled by the firm's stock price from the previous month t.

dVXO: The monthly changes in VXO, the implied volatility of S&P 100 index options.

Analysis period: January 1986 – December 2013 (AggRev and dVXO start in 1986). P-values are shown in parentheses (rounded to the second decimal point). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRSP-ew	CRSP-vw	AggRev-ew	AggRev-vw
CRSP-vw	0.86***			
	(0.00)			
AggRev-ew	0.11**	0.06		
	(0.04)	(0.25)		
AggRev-vw	0.20***	0.14**	0.60***	
	(0.00)	(0.01)	(0.00)	
dVXO	-0.61***	-0.58***	0.06	-0.01
	(0.00)	(0.00)	(0.29)	(0.80)

Appendix C: Value-Weighted Portfolios

This appendix repeats tests in Table 5 with value-weighted portfolios. Long-short portfolios (Q5-Q1) are formed by sorting firms on the uncertainty component (UNC) in Panel C1, and by IVOL in Panel C2. Analysis period: January 1983 – December 2013.

Panel C1: Sorting on Uncertainty (UNC)

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	0.944***	-3.453***	-4.397***
	(3.14)	(9.63)	(9.40)
CAPM	0.086	-1.952***	-2.037***
	(0.22)	(4.95)	(3.72)
FF-3f	-1.407***	-2.101***	-0.694
	(3.64)	(4.74)	(1.18)
Carhart-4f	-0.654**	-1.119***	-0.466
	(2.07)	(3.28)	(1.00)
Factor models ex. SMB:			
FF-3f ex. SMB	-0.143	-2.485***	-2.342***
	(0.38)	(6.49)	(4.37)
Carhart-4f ex. SMB	0.514	-1.857***	-2.371***
	(1.59)	(5.96)	(5.29)
Periods	231	140	--

Panel C2: Sorting on IVOL

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	0.643**	-2.812***	-3.454***
	(2.51)	(10.65)	(9.40)
CAPM	0.336	-2.311***	-2.648***
	(1.03)	(6.86)	(5.63)
FF-3f	-0.928***	-2.256***	-1.329***
	(2.85)	(5.82)	(2.63)
Carhart-4f	-0.027	-1.439***	-1.412***
	(0.10)	(4.56)	(3.43)
Factor models ex. SMB:			
FF-3f ex. SMB	0.153	-2.469***	-2.623***
	(0.46)	(7.26)	(5.53)
Carhart-4f ex. SMB	0.921***	-1.935***	-2.856***
	(3.22)	(6.51)	(6.93)
Periods	231	140	--

Appendix D: Extended Sample Period (1963 – 2013)

This table repeats tests in Table 5 Panel B with an extended sample period (January 1963 – December 2013). Long-short portfolios (Q5-Q1) are sorted on IVOL.

Alpha (in %)	(1) Positive MktRet Q5-Q1 (a)	(2) Negative MktRet Q5-Q1 (b)	(3) Neg. - Pos. (b) - (a)
No factor	2.699***	-4.399***	-7.098***
	(7.69)	(14.29)	(15.21)
CAPM	1.941***	-3.583***	-5.523***
	(4.17)	(9.32)	(9.15)
FF-3f	-0.768**	-2.136***	-1.368**
	(2.02)	(5.48)	(2.51)
Carhart-4f	-0.096	-1.895***	-1.799***
	(0.20)	(5.08)	(2.93)
Factor models ex. SMB:			
FF-3f ex. SMB	2.075***	-3.076***	-5.151***
	(3.73)	(9.09)	(7.91)
Carhart-4f ex. SMB	2.756***	-2.993***	-5.749***
	(4.39)	(8.53)	(7.99)
Periods	375	236	--

Appendix E: Uncertainty/IVOL-Return Relation and Market Returns: Controlling for Sentiment

This appendix repeats the tests in Table 5 with both lagged (t) and contemporaneous (t+1) sentiment included as additional controls. The results are similar to those in Table 5, indicating that the asymmetric price responses of high uncertainty/IVOL stocks to positive versus negative market returns cannot be attributed to market sentiment.

In Panels E1 and E2, the long-short portfolios (Q5-Q1) are sorted on the uncertainty component (UNC) and IVOL respectively. Monthly sentiment data are from Dr. Jeffery Wurgler's website. Analysis period: January 1983 – December 2010 (sentiment data end in 2010).

Panel E1: Uncertainty (UNC)

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	0.942**	-3.871***	-4.813***
	(2.21)	(10.73)	(8.62)
CAPM	0.163	-3.141***	-3.304***
	(0.41)	(7.52)	(5.76)
FF-3f	-2.010***	-2.706***	-0.697
	(3.64)	(5.70)	(0.96)
Carhart-4f	-0.508	-1.945***	-1.437***
	(1.51)	(5.11)	(2.84)
Factor models ex. SMB:			
FF-3f ex. SMB	-0.103	-3.201***	-3.098***
	(0.26)	(7.69)	(5.37)
Carhart-4f ex. SMB	1.149***	-2.755***	-3.904***
	(3.12)	(7.79)	(7.66)
Periods	208	127	--

Appendix E: Uncertainty/IVOL-Return Relation and Market Returns: Controlling for Sentiment (continued)

Panel E2: IVOL

	(1)	(2)	(3)
Alpha (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
No factor	3.039***	-3.852***	-6.890***
	(5.75)	(8.09)	(9.69)
CAPM	2.282***	-3.299***	-5.581***
	(3.68)	(6.13)	(6.80)
FF-3f	-0.377	-2.230***	-1.852**
	(0.61)	(3.63)	(2.12)
Carhart-4f	0.740	-1.886***	-2.626***
	(1.12)	(3.25)	(2.98)
Factor models ex. SMB:			
FF-3f ex. SMB	2.586***	-3.001***	-5.587***
	(3.90)	(5.96)	(6.71)
Carhart-4f ex. SMB	3.588***	-2.834***	-6.422***
	(5.08)	(5.52)	(7.35)
Periods	208	127	--