TWO ESSAYS ON AMBIGUITY AND STOCK RETURN VOLATILITY

A Dissertation

by

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ABSTRACT

This dissertation includes two essays on ambiguity and stock return volatility. The first essay focuses on the degree of ambiguity in the firm news, and studies the impact of ambiguous information regarding dividends and earnings on stock prices. Two proxies are constructed for firm-level ambiguity, measuring qualitative and uncertain aspects of news. The central finding is that stock prices react more strongly to bad news than good news. In addition to the asymmetric effect documented, the magnitude of this effect is larger as news becomes more ambiguous. Results are robust to alternative explanations. Taken together, these findings provide empirical evidence consistent with the theory of ambiguity aversion, and show that firm-specific ambiguity matters for financial decision making.

The second essay, coauthored with Hwagyun Kim, studies the idiosyncratic volatility (IVOL) puzzle. Recent studies find stock returns are negatively related to IVOL. We find that aggregate variables known to explain stock market volatility affect the IVOL and portfolio returns sorted by IVOL. Macroeconomic volatilities, yield spreads, dividend yield, trading volume and common factors of earnings forecast dispersions are important drivers of IVOL. Macro factors produce the negative pattern, consistent with theories of intertemporal hedging demand. Teasing out the common IVOL part, the residual IVOL is positively and significantly related to stock returns and the idiosyncratic portions of earnings forecast dispersions. This is consistent with ambiguity aversion and incomplete market hypotheses.

DEDICATION

To my family.

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1. INTRODUCTION

This dissertation includes two essays on ambiguity and stock return volatility. The first essay, "In the Face of Ambiguity: Investors' Reactions to News", focuses on ambiguity in the news. Two proxies from the firm news are used to test the hypotheses of how investors react to ambiguous information based on the theory of Epstein and Schneider (2008). The first proxy uses the idea that soft information is harder to interpret than hard information, and the second proxy focuses on the frequency of vague and uncertain words used in the corporate news. As Epstein and Schneider (2008) point out in their model, when the information has a particular type of uncertainty, Knightian uncertainty or ambiguity, ambiguity-averse agents treat bad news as more relevant and precise than good news. Therefore they react to the information asymmetrically - they respond more strongly to bad news than good news. Consistent with their theory, I find the asymmetry effect. Investors react 25.2 bps more to bad news than good news. Besides, as news becomes more ambiguous, the asymmetry effect is larger. It suggests that investors place more weight on bad news than good news, which is consistent with the theory of ambiguity aversion.

The second essay, "Ambiguity, Macro Factors, and Stock Return Volatility", coauthored with Hwagyun Kim, focuses on the idiosyncratic volatility (IVOL) puzzle. Ang, Hodrick, Xing, and Zhang (2006) find that monthly stock returns are negatively related to the idiosyncratic volatility in the previous month. We study the extent to which idiosyncratic volatility measured by Ang, Hodrick, Xing, and Zhang (2006) are decomposed into common and idiosyncratic parts, using observable macroeconomic and firm-specific variables, and thus examine whether this measured volatility is a proxy for idiosyncratic risk or uncertainty. We find that IVOL can be explained by aggregate variables known to explain stock market volatility, and the negative relation between IVOL and stock returns mainly comes from aggregate variables. Teasing out the common IVOL part, the residual IVOL is positively priced, as suggested by incomplete market hypotheses and ambiguity aversion theory.

2. IN THE FACE OF AMBIGUITY: INVESTORS' REACTIONS TO NEWS

2.1 Introduction

Investors are surrounded by a variety of information nowadays, from economy-wide news to corporate earnings reports. They make use of all types of information available to estimate key variables of their interest. But not always do they feel certain as to how to interpret information precisely, especially when the information itself is ambiguous. Can we quantify the degree of ambiguity in the news? If so, more importantly, how would investors process news with ambiguous value?

As Epstein and Schneider (2008) point out in their model, when the information has a particular type of uncertainty, Knightian uncertainty or ambiguity, ambiguity-averse agents treat bad news as more relevant and precise than good news. Therefore they react to the information in an asymmetric way - they respond more strongly to bad news than good news. Besides, investors respond to firm-specific information as well as macroeconomic information so that asset prices reflect idiosyncratic risks. A key obstacle to test this model is the measurement of ambiguity. Typical proxies are used at the macro level, such as VIX or variance risk premium. This paper uses two proxies of firm-level ambiguity and tests the asymmetric effect documented in Epstein and Schneider (2008).

The paper first lays out the theory of Epstein and Schneider (2008). At each period, an ambiguity-averse agent observes an ambiguous and noisy signal. When the investor receives a signal, she is concerned about the ambiguity of the signal over time. She cannot interpret the signal precisely and makes decisions under the worst case scenario. When the news is good, she will regard it as less relevant with low precision, whereas bad news is viewed as more informative with high accuracy. Thus the investor places more weight on bad news than good news. This setup offers two hypotheses: (1) Investors react more to bad news than good news of the same magnitude, producing an asymmetric response to the news, and (2) the magnitude of the asymmetric effect increases with the level of ambiguity.

To test these hypotheses, we hand collected all dividend and earnings-related news of S&P 500 firms between 2000 and 2015 from a global news database from Dow Jones Factiva. The first ambiguity proxy measures the qualitative aspect of the news. Intuitively, soft information is harder to interpret and process than hard information. Investors can easily analyze numbers in an earnings report or annual report based on their experience or past data, whereas soft information such as opinions or rumors about a firm is more subject to differential interpretation. Also, the language used in the news also matters. If a piece of news uses too many vague or uncertain words such as “maybe", “could be" or “possibly", the news content is less clear to investors and admits more ambiguous interpretation. Thus, the second proxy of ambiguity measures the uncertain aspect of the news. Results show these two proxies do not overlap with each other perfectly. Instead, they capture different aspects of the source of the ambiguity.

The main finding in this paper is that in the two-day window around the news, stock returns increase 13 bps to a unit of good news, but decrease 38.2 bps to a unit of bad news, producing an asymmetric effect of 25.2 bps. This result is robust to controlling for other variables that could also affect the stock return. The logical next question is whether the extent of the asymmetric effect becomes larger when the news is more ambiguous. With the two proxies for firm-level ambiguity included in regressions, the finding shows that investors give a higher weight on bad news than good news when the ambiguity proxy is larger. In this case, the asymmetric effect ranges from 31.7 bps to 37.8 bps depending on different proxies used in the analysis. The paper also explores difference sources of the news. Compared to press releases and conference transcripts provided directly from the firm, other news such as commentaries or opinions of journalists needs more judgment of the news quality. Results are robust in the subsample with the exclusion of press releases and transcripts. Overall, the results are consistent with the theory of ambiguity aversion that investors are pessimistic and act cautiously when facing ambiguous information.

To rule out other forces that lead to the documented asymmetric response, we consider several alternative explanations. The ambiguity proxies in the paper could be related to macro variables.

First, the firm level ambiguity can be a reflection of macro-level uncertainty. To measure the economy-wide ambiguity, we follow Williams (2015) and use the change in VIX over the two-day period immediately preceding the two-day news day window. However, controlling for the change in VIX, investors still react more to bad news than good news as the information becomes more ambiguous, suggesting that the observed asymmetry is not due to macro-level uncertainty. Second, it is possible that market sentiment is the driving force behind the asymmetric response. Baker and Wurgler (2006) construct the investor sentiment index and find that investors overreact in high sentiment periods and underreact in low sentiment periods. Mian and Sankaraguruswamy (2012) find that investors react more (less) strongly to good news than bad news when market sentiment is high (low). To consider this explanation, we control for the Baker and Wurgler (2006) sentiment measure and find that results are robust. The third alternative explanation is that the market reacts more to bad news than good news when the market valuation is high, as suggested by Conrad, Cornell, and Landsman (2002). With the measure of state risk controlled, results of this paper remain robust. Fourth, ambiguity proxies used in the paper may reflect the economic uncertainty. The main results are robust after controlling the economic policy uncertainty index in the empirical settings.

It is also possible that if management on average delays the release of bad news once it is accumulated and withheld up to a certain threshold, but privately leaks and quickly reveals good news, then investors will react more to bad news disclosures than to good news ones as Kothari et al. (2009) find. They hypothesize that when there is high information asymmetry between managers and investors, managers are better able to withhold bad news. Moreover, when managers' wealth is more tied to the firm value, managers have more incentive to delay their wealth loss after the bad news disclosure. With proxies of information asymmetry and manager ownership incentives included, the remain results rarely change.

Another possible explanation is that a loss-averse investor becomes more (less) loss-averse if the prior gain is negative (positive), and this state-dependent nature of preference may produce an asymmetric response to good and bad news under certain market conditions consistent with the prospect theory. To check the robustness of the main result to this explanation, past returns and a dummy variable indicating the sign of past stock performance are added to the empirical models, and asymmetric responses are still quite significant both economically and statistically. Last, the empirical results may be sensitive and related to short-sale constraints. Using proxies for short-sale constraints, short interest and institutional ownership, we find the main empirical results still stand firm and significant. In addition to ruling out possible explanations, the paper tests the relation between return volatility and ambiguity measures. The result shows that return volatility is positively associated with ambiguity in the news, which is consistent with the ambiguity aversion theory and intuition.

This paper builds on the literature that links ambiguity in the economy and asset prices. The simple model follows Epstein and Schneider (2008), Kim (2015), and Zhou (2015), who investigate how ambiguity-averse investors process ambiguous information. Gilboa and Schmeidler (1989) argue that ambiguity-averse decision makers will make decisions when their utilities are maximized in the worst case scenario, i.e., max-min expected utility. Hansen and Sargent (2001) and related work use robust control theory to explore ambiguity aversion. Jeong, Kim, and Park (2015) find that ambiguity aversion is vital in explaining the market equity premium using a multiple-priors continuous-time model. With regard to the literature on ambiguous information, Leippold, Trojani, and Vanini (2008) study asset prices under learning and ambiguous information about the expected dividend growth, and their model is successful in matching the equity premium, the interest rate, and the excess volatility. Illeditsch (2011) focuses on ambiguous signal precision and its impact on optimal portfolios and equilibrium asset prices. Kim (2015) studies the impact of ambiguous information regarding future interest rates on bond prices. The closest studies to this paper are Williams (2015) and Zhou (2015). Williams (2015) uses VIX as a proxy for ambiguity to test individual stock asymmetric responses to earning news. Zhou (2015) constructs a variance risk premium series as a measure of ambiguity to test aggregate stock market reaction. In these two papers, ambiguity proxy is macro-uncertainty related, and when the economy is in the uncertainty state, people will find it hard to interpret information. An integral and novel part of this research is the construction of proxies for information ambiguity at the firm level. By doing so, this paper contributes to the literature that focuses on testing its effect on individual stocks and providing empirical evidence consistent with the theory.

This paper is also related to the studies on textual analysis in finance and accounting; see Loughran and McDonald (2016) for a survey. Loughran and McDonald (2011) create six different word lists (positive, negative, uncertainty, litigious, strong modal and weak modal) by exploring words in a broad cross-section of 10-Ks. Many papers use these lists to measure the tone of newspaper articles, and others use uncertain word lists to measure the vagueness in the disclosure. Dzielínski et al.(2016) examine the use of vague words in earnings conference calls. Du (2015) measures the usage of ambiguous words in the Management's Discussion and Analysis section of annual and quarterly reports. von Beschwitz, Chuprinin, and Massa (2017) study how qualitative news can affect short sellers' trading by measuring the proportion of numbers used across all media articles. One contribution of this paper in this regard is that it attempts to quantify both uncertain and qualitative aspects of news, and applies this to ambiguity-based models. Given the rarity of the measures of firm-specific ambiguity, this paper can shed light on how ambiguity plays a role in firm decisions.

The rest of the paper is organized as follows. Section 2.2 reviews the model. Section 2.3 describes the data and proposes information ambiguity measures. Section 2.4 presents empirical results and robustness tests. The paper concludes in Section 2.5.

2.2 Theoretical Motivation and Research Design

This section develops a simple asset pricing model based on Epstein and Schneider (2008) to motivate the empirical study that follows. Suppose that Ω is a state space and one element $s_t \in \Omega$ prevails every period. The representative investor is assumed to be ambiguity-averse, and she has information of the history $s^t \equiv \{s_0, \dots s_t\}$ at each time t. Given a history s^t, her preference over consumption c is presented by a utility function U_t recursively

$$U_t(c; s^t) = \max_{c} \min_{p_t \in P_t(s^t)} E^{p_t}[u(c_t) + \beta U_{t+1}(c; s^t, s_{t+1})], \tag{2.1}$$

where $u(\cdot)$, c_t and β are the notations for a concave utility function, consumption at time t, and the time discount factor, respectively. As in Epstein and Schneider (2008), $P_t(s^t)$ represents conditional beliefs about the next observation s_{t+1}. When the investor is ambiguity-averse and faces a range of probability measures, she will choose the one that leads to the lowest expected utility.

2.2.1 Setup

To begin with, based on the setting of infinite horizon in Epstein and Schneider (2008), the dividends of some assets is specified as

$$d_{t+1} = \kappa\overline{d} + (1-\kappa)d_t + u_{t+1}, \tag{2.2}$$

which is revealed at time $t+1$. $\overline{d}$ is the mean dividend, $\kappa \in (0,1)$ and u_{t+1} is a normal, mean-zero shock.

At time t, the agent observes an ambiguous and noisy signal s_t on next period's shock (u_{t+1}):

$$s_t = u_{t+1} + \epsilon_t^s + \eta_{t-1}\nu_t. \tag{2.3}$$

$\epsilon_t^s \sim N(0, \sigma_s^2)$ is a normal, mean-zero shock. The news is ambiguous to the investor as she only knows that the variance ϵ_t^s is within the interval $[\underline{\sigma_s^2}, \overline{\sigma_s^2}]$. As an extension to Epstein and Schneider (2008), $\eta_{t-1}\nu_t$ is included in the signal process. Kim (2015) suggests that $\eta_{t-1}\nu_t$ is a time-varying, but unambiguous noise to create time-varying ambiguity. Here $\nu_t \sim N(0,1)$ and η_t is a Markov process. Intuitively, when the investor receives a signal, she is concerned about the existence of the signal over time. Thus she cannot interpret the signal precisely.

Based on the signal received, the investor updates expectation about the dividend shock in the Bayesian fashion

$$\begin{aligned} E(u_{t+1}|s_t) &= E(u_{t+1}) + \frac{Cov(u_{t+1}, s_t)}{Var(s_t)}(s_t - E(s_t)) \\ &= \frac{\sigma_u^2}{\sigma_u^2 + \sigma_s^2 + \eta_{t-1}^2} s_t. \end{aligned} \tag{2.4}$$

Denote $\overline{\gamma_t} \equiv \frac{\sigma_u^2}{\sigma_u^2+\underline{\sigma_s^2}+\eta_{t-1}^2}$ and $\underline{\gamma_t} \equiv \frac{\sigma_u^2}{\sigma_u^2+\overline{\sigma_s^2}+\eta_{t-1}^2}$. Under ambiguity, $\overline{\gamma_t}$ is larger than $\underline{\gamma_t}$. $\overline{\gamma_t}$ and $\underline{\gamma_t}$ provide the upper and lower bounds on information content, respectively. The information will be more ambiguous as $\overline{\gamma_t} - \underline{\gamma_t}$ increases.

2.2.2 Asset Prices

In this subsection, we assume a risk-neutral yet ambiguity-averse investor in the model to focus on the effect of ambiguity. In addition, a discount factor β is defined as $\frac{1}{1+r}$ with r being a risk-free rate.

2.2.2.1 Unambiguous News Benchmark

When news is unambiguous, the investor knows the true variance and does not need to choose its distribution. That is, $\underline{\sigma_s^2} = \underline{\sigma_s^2} = \sigma_s^2$ under this scenario. It is straightforward to derive the price after the arrival of the news:

$$q_t = \frac{\overline{d}}{r} + \frac{1-\kappa}{r+\kappa}(d_t - \overline{d}) + \frac{1}{r+\kappa}\gamma_t s_t. \tag{2.5}$$

From Equation 2.5, the investor reacts the same magnitude to both good news and bad news, producing the symmetrical effect.

2.2.2.2 Ambiguity News

Now assume an ambiguous signal arrives. The price of the asset after the arrival of the signal is computed as

$$\begin{aligned} q_t &= \min_{(\sigma_{s,t}^2, \sigma_{s,t+1}^2) \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]^2} \beta E_t[q_{t+1} + d_{t+1}] \\ &= \begin{cases} \frac{\overline{d}}{r} + \frac{1-\kappa}{r+\kappa}(d_t - \overline{d}) + \frac{1}{r+\kappa}\underline{\gamma_t} s_t - (\overline{\gamma_t} - \underline{\gamma_t})\frac{\sigma_u}{r\sqrt{2\pi\underline{\gamma_t}}}, & \text{if } s_t \geq 0 \\ \frac{\overline{d}}{r} + \frac{1-\kappa}{r+\kappa}(d_t - \overline{d}) + \frac{1}{r+\kappa}\overline{\gamma_t} s_t - (\overline{\gamma_t} - \underline{\gamma_t})\frac{\sigma_u}{r\sqrt{2\pi\underline{\gamma_t}}}, & \text{otherwise} \end{cases} \end{aligned} \tag{2.6}$$

Consistent with Epstein and Schneider (2008), the first two terms reflect the present value of dividends. The third term captures the asymmetric response to ambiguous information. The fourth term is the present value of ambiguity premium for future ambiguous news. Compared the third term across different news types, the stock price decreases for a negative piece of news more than the stock price increases for a positive piece of news with the same magnitude, producing the asymmetric effect given $\overline{\gamma_t} > \underline{\gamma_t}$. Intuitively, the ambiguity-averse investor makes decisions under the worst case scenario. So when new is good, she will regard it as less relevant with low precision whereas the bad news is viewed as more informative with high precision. Thus the investor places more weight on bad news than good news. Moreover, as $\overline{\sigma_s^2} - \underline{\sigma_s^2}$ increases, the investor feels more ambiguous about the signal, which leads to an increase in $\overline{\gamma_t} - \underline{\gamma_t}$. With the greater ambiguity, the asymmetric effect also increases.

2.2.3 Hypotheses and Research Design

Two hypotheses can be directly derived from the model above.

Hypothesis 1: When a piece of news about the dividend shock arrives, investors react more strongly to bad news than good news of the same magnitude. Thus the response to the news is asymmetric.

Hypothesis 2: The asymmetric effect is driven by the variation of ambiguity in the information. The magnitude of the asymmetric effect enlarges with the greater ambiguity.

To test Hypothesis 1, the regression to be estimated is [1]

$$Ret_{it} = \beta_0 + \beta_1 Goodnews_{it} + \beta_2 Badnews_{it} + Controls_{it} + \delta_i + \gamma_t + \epsilon_{it}. \tag{2.7}$$

This specification allows for differential responses to good and bad news. $Goodnews$ $(Badnews)$ is equal to the new tone measure when the measure $>$ $(<)$ 0 and 0 otherwise, which will be explained in details in next section. β_1 measures the response to good news and β_2 represents the response to bad news. Based on Hypothesis 1, the magnitude of β_1 is expected to be smaller than β_2.

[1] This methodology follows Conrad (2002). Williams (2015) also uses the same specification.

The following specification is used to test the second hypothesis,

$$\begin{aligned} Ret_{it} = \beta_0 &+ \beta_1 Goodnews_{it} + \beta_2 Badnews_{it} + \beta_3 Ambiguity_{it} \\ &+ \beta_4 Goodnews_{it} * Ambiguity_{it} + \beta_5 Badnews_{it} * Ambiguity_{it} \\ &+ Controls_{it} + \delta_i + \gamma_t + \epsilon_{it}. \end{aligned} \tag{2.8}$$

$Ambiguity$ is the proxy for firm-level ambiguity introduced in details later. Interaction terms between news tone and ambiguity proxies are included in this specification. The incremental sign on interaction terms indicates whether investors respond more following an increase in ambiguity. Based on Hypothesis 2, the sign on β_4 is expected to be negative than or equal to 0 whereas β_5 is expected to be greater than 0. The other interest in (2.8) is the overall effect. The magnitude of $\beta_1 + \beta_4$ is expected to be less than that of $\beta_2 + \beta_5$, and the difference in the magnitude of total coefficients will be tested.

2.3 Data

This section introduces data used in the paper. From the theory presented in the previous section, ambiguity aversion can be tested based on whether the news is good or bad. Also, the theory implies that ambiguity contained in the news is associated with the uncertain degrees of accuracy when news about a firm is available. Based on these observations, a few empirical proxies for ambiguity are constructed.

2.3.1 News Data

The empirical analysis in the paper uses public news from Factiva. Factiva is a subsidiary of Dow Jones & Company and provides access to more than 32,000 news sources worldwide. To focus on news directly linked to firm fundamental, all dividend- and earnings-related news of S&P 500 companies from 2000 to 2015 are manually collected. According to Factiva[2], dividends news includes dividend announcements, dividend increases or reduction, and any other dividend-related news. Earnings news contains earnings announcements, preliminary and unaudited results when

[2] https://www.dowjones.com/products/factiva/

specific figures are given, earnings restatements and profitability indicator ratios, earnings surprise and reported sales figures. There is also another type of news related to earnings news, i.e., earnings projections. It covers earnings or revenue projections, as well as profit warnings announced by a public company in advance of its earnings announcements [3].

This paper uses articles in English categorized under “Dow Jones News Wire" for each S&P 500 firm[4]. Each article downloaded from Factiva contains a number of data elements. It includes headline and content of the news, the number of words in the news, the publication date and time, the name of the source (e.g., *Dow Jones Institutional News*) and the author of the news (if applicable). An example of articles collected is given in the Appendix. Some filters are imposed to eliminate irrelevant stories. Each article has to occur while the firm is a constituent of the S&P 500 index. In addition, each story should contain at least 20 words, and it mentions the firm's official name at least once within the headline and the leading paragraph which is the first two paragraphs of an article, and the firm's common name at least twice within the full article. Suggested by Shleifer (1986), stock price increases after a firm is included in the S&P index. Therefore, all articles in the first week after the inclusion in the index are excluded. The final sample consists of 59,076 unique qualifying news stories for 718 firms[5].

2.3.2 Good News versus Bad News Using News Tone

Each article in the sample is classified as good, bad, or neutral. Following Tetlock et al. (2008), the primary measure for news tone is defined as

$$adjusted\_net\_tone = \frac{No.\ of\ positive\ words - No.\ of\ negative\ words}{No.\ of\ positive\ words + No.\ of\ negative\ words}. \tag{2.9}$$

[3] To be included in the sample, an article should have a subject code of C1512, C151 or C152 which correspond to dividends, earnings and earnings projections respectively based on Factiva Intelligent Indexing Subject Code. An article also has to have "dividend(s)" or "earning(s)" in its headline or leading paragraph. An article can contain information on both dividends and earnings based on this criteria.

[4] See Tetlock et al. (2008) for detailed methods of finding firms' name used in the media.

[5] Unreported results show that 19.8% of articles in the final sample contains information about dividends, 86.2% of articles are earnings-related, and 46.8% of articles talk about earnings projections.

Positive and negative words are based on the Loughran and McDonald (2011) Dictionary[6]. This dictionary is created based on a large sample of 10-Ks during 1994 to 2008, containing six different word lists (*Positive, Negative, Uncertainty, Litigious, Strong Modal and Weak Modal*). According to Loughran and McDonald (2011), this dictionary has the most interpretation of a word in financial communication compared with standard dictionaries. To be specific, 353 words in the dictionary are identified as positive words, and there exist 2,337 negative words, suggesting that expressions may be more sophisticated in describing negative situations [7].

When $adjusted\_net\_tone$ of each article is larger (smaller) than 0, the news is classified as positive (negative) news. By construction, an article is neutral when $adjusted\_net\_tone$ is 0. As a robustness check, the other measure net_tone of an article is constructed as

$$net\_tone = \frac{No.\ of\ positive\ words - No.\ of\ negative\ words}{No.\ of\ total\ words}. \tag{2.10}$$

2.3.3 Ambiguity Proxies

Tangible (hard) information is easier to interpret rather than intangible (soft) information. The intuition is line with Epstein and Schneider (2008) and Beschwitz, Chuprinin, and Massa (2017) that quantitative news is less subjective to differential interpretation. Investors can learn from historical data and experience to help them understand the quantitative news. On the other hand, soft information such as opinions, commentaries, and rumors about a firm can be interpreted differently by optimists and pessimists. As a measure of the qualitative (soft) aspects of the news, the first proxy is constructed as

$$AMB^{numseq} = 1 - \frac{Numbers}{No.\ of\ total\ words}. \tag{2.11}$$

[6]https://www3.nd.edu/ mcdonald/Word_Lists.html

[7]See Appendix Table A.13 for a subset of words in each category.

$Numbers$ in the measure is based on numeric sequences, which is a sequence of symbol 0-9 bordered by any non-alphanumeric symbol [8]. An additional measure is constructed as

$$AMB^{numsym} = 1 - \frac{Number\ Symbols}{No.\ of\ total\ symbols}, \tag{2.12}$$

where $Number\ Symbols$ is the number of numeric symbols in an article. In the empirical analysis, AMB^{numseq} is used as the primary measure, and AMB^{numsym} is used for robustness check[9]

In addition to the qualitative aspect, the language used in the news also matters in that ambiguous and vague content in the news can affect the precision of the information. If a piece of news includes many vague or uncertain words such as “maybe", “could be" or “possibly", the news content is less clear to investors and admits more ambiguous interpretation. Du (2015) measures ambiguity ratio of soft information as the percentage of uncertainty and weak modal words in the annual and quarterly reports. Dzieliński, Wagner, and Zeckhauser (2016) proxy manager vagueness on the conference call by the use of uncertain words. Motivated by these papers, the second measure in the public news is defined as follows.

$$AMB^{netunc} = \frac{No.\ of\ uncertain\ words - No.\ of\ certain\ words}{No.\ of\ total\ words}. \tag{2.13}$$

Uncertain words are defined as Loughran and McDonald (2011), and they focus on the general notion of imprecision. Certain words are “strong modal" words in Loughran and McDonald (2011). “Strong modal" words are created with an emphasis on the level of confidence. In total, there are 297 uncertain words, and the list of “strong modal" contains 19 words. Examples of each category are given below.

Uncertain words: risk, approximately, believe, roughly, might, etc.

Strong modal words: will, best, highest, must, clearly, etc.

Prior research in textual analysis use the Harvard word lists produced by General Inquirer

[8]For example: $10,000, 6.6% or 200.

[9]An illustrative example: I have 10 apples. $AMB^{numseq} = 1 - \frac{1}{4}$, $AMB^{numsym} = 1 - \frac{2}{13}$.

(GI)[10]. This dictionary has 175 words indicating "a feeling of sureness, certainty and firmness", and 132 words "denoting feelings of uncertainty, doubt and vagueness". As a robustness check, lists of uncertain words and certain words are constructed from the overlap words in Loughran and McDonald (2011) list and the GI category. Words lists of the combination of Loughran and McDonald (2011) list and the GI category are also used to measure the ambiguity. In the main analyses, lists in Loughran and McDonald (2011) are used to constructed ambiguity proxies, and lists from the alternative dictionaries are tested as robustness checks.

Following Loughran and McDonald (2011), the paper accounts for simple negation for positive, negative, uncertain and certain words[11]. Loughran and Mcdonald (2016) suggest identifying the proportions of the most frequently used words for research using words classifications given that certain words can potentially have a larger impact according to Zipf's law. Figure A.1 and Figure A.2 show the plots the frequency of top 25 frequently occurring positive, negative, uncertain, and certain words. These popular words seem to alleviate the concern that misclassification drives the results. For uncertain words used in the news, the top 3 words are "could", "may" and "nearly". These words account for 27% of the total uncertain words count.

2.3.4 Other Variables

The key dependent variable is the two-day $(t, t+1)$ cumulative abnormal return adjusted for a six-factor model - Fama and French (2015) five factors and momentum factor over news day t. For each firm in the sample, stock data is from Center for Research in Security Prices (CRSP) database and financial accounting data from Compustat. Firm size ($Size$) is defined as a firm's market equity value. Illiquidity ($Illiquidity$) is measured as in Amihud (2002). In addition, other variables include the average level of VIX over the week prior to the news (VIX_lag) and return over the prior month ($Return\_lag$).

Specification (2.7) and specification (2.8) will be estimated using daily observations for each firm. Given multiple news occurrences at the same day, all news related variables within each

[10] http://www.wjh.harvard.edu/ inquirer/

[11] Simple negation is taken to be observations of one of six words (no, not, none, neither, never, nobody) occurring within three words preceding a word.

day are averaged by using news article in the trading window from 9:35 am to 15:55 pm for each firm. For news article occurring outside the trading window, they are classified as news of the next trading window.

To measure daily news tone of firm i at certain day t ($adjusted\_net\_tone_{it}$), all news tones at that day are averaged. Overall, key independent variables at each day are defined as

$$Goodnews_{it}(Badnews_{it}) = \begin{cases} adjusted\_net\_tone_{it}, & \text{if } adjusted\_net\_tone_{it} > (<)\, 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.14}$$

Firm (Industry) effects and year effects are included in the regression. To allow observations in the same firm at the same week to be correlated, standard errors are clustered at firm-week level. All firm-level variables are winsorized at 1% and 99% cutoffs to eliminate outliers. News tone measures and ambiguity measures are log transformed when included in the regressions[12] Except for stock returns, all variables are normalized. Stock returns are reported in percentage. The definitions of variables are given below.

2.3.5 Summary Statistics

The sample consists of 36,968 daily observations. Panel A in Table A.2 reports summary statistics at the news level. The sample contains more bad news than good news. The mean (median) of news tone is -8.03% (0.000%). Around 8% of the words are numbers, and 0.44% of the words are uncertain words. On average, there are 2 articles for a firm at each day. Panel C of Table A.2 reports summary statistics across good news and bad news. To alleviate the concern that good news capture relative good news and bad news measures extreme bad ones, in the main analysis news tone measures for each news type are normalized by its group standard deviation respectively. As it shows in Table A.2, bad news and good news differ in the ambiguity proxies. Though the magnitudes of differences are not large, it still indicates that bad news tends to be more ambiguous. Table A.3 reports the correlation among news variables. The news tone is negatively

[12] Since some variables values are negative, a formula $sign(X) * log(1 + |x|)$ is used for log tranformation.

correlated with each of the information ambiguity measures weakly . AMB^{numseq} is associated with AMB^{netunc} with a correlation of 10.31%, suggesting that they measure different aspects of news with some commonality.

2.4 Main Findings

2.4.1 The Asymmetric Response to News

In Section 2.2, Hypothesis 1 implies the existence of the asymmetric effect. To verify if this effect prevails, Table A.4 presents the results from specification (2.7). Column (1) shows that one standard deviation more (log) bad news lowers the stock cumulative abnormal return by 38.2 bps whereas one standard deviation more (log) good news increases the return by 13 bps; both coefficients are significantly different from zero. In addition, from the test of asymmetry, the difference of 25.2 bps between the two is significantly different from zero at the 1% level, suggesting an asymmetry of the price reaction to the news. After adding other control variables, column (2) shows that the asymmetric effect is robust, and the extent of the effect is significantly different from zero. When industry fixed effects is included in the specification, the results are robust as shown in column (3) and column (4).

Given the finding that bad news is likely to be more ambiguous news as shown in Table A.2, it is possible that the asymmetric effect is driven by the ambiguity in the news in lieu of the news tone being bad. This correlation may result from firms who have an incentive to create ambiguity in case of bad news to cloud investors' perception. It is subtle, but if investors are aware of this tendency, investors simply react to bad news more to cope with added uncertainty. Investors still dislike ambiguity, but in this case, they have suspicions regarding the quality of information because it is likely to be worse than reported. In an attempt to identify different channels of ambiguity, several robustness checks are performed. Table A.5 reports the regression results adding the ambiguity proxies. Column (1) includes the qualitative measure (AMB^{numseq}), and the magnitude of the asymmetric effect is 26.4 bps, which is similar to that in Table A.4. Column (2) controls for another uncertainty measure (AMB^{netunc}), and the result is robust.

Regarding the direct effect of ambiguity or uncertainty, one interesting finding in this table is that one unit of (log) AMB^{numseq} decreases return by 12.3 bps whereas AMB^{netunc} increases return by 4.7 bps. Different responses to ambiguity proxies may be due to various aspects these proxies measure. To test this conjecture, Column (3) in Table A.5 presents the results controlling for both AMB^{numseq} and AMB^{netunc}. First, the asymmetric effect of 27.4 bps is significantly different from zero. Second, similar to Column (1) and Column (2), the coefficient on AMB^{numseq} is -0.129 and significant at 1% level whereas the coefficient on AMB^{netunc} is 0.058 and significant at 1% level. Unreported results show that the two coefficients are significantly different from each other at 1% level. As can be seen from Table A.3 that the correlation between AMB^{numseq} and AMB^{netunc} is 10.31%, together these findings suggest the two measures capture different sources of ambiguity in the news. As a robustness test, another measure of news tone net_tone is used, and the results are robust as seen in Appendix A.14. Overall findings in Table A.4 and Table A.5 are consistent with Hypothesis 1, implying the existence of the asymmetric effect.

Does the extent of the asymmetric effect vary when the news is harder to interpret? Based on Hypothesis 2, ambiguity-averse investors would be more concerned about the information with greater ambiguity than the smaller ones. Therefore, the variation of ambiguity will drive the variation of the magnitude of the asymmetric effect. Table A.6 presents the results when interaction terms are included. Column (1) and column (3) report coefficients when firm fixed effects and year fixed effects are included, whereas column (2) and column (4) show results with industry fixed effect and year fixed effect. The total coefficients on good news are smaller than those on bad news overall. When the news contains more qualitative information, investors react 37.8 bps more to bad news than good news. As the news uses more uncertain words, the stock return increases by 11.7 bps to good news and decreases 43.4 bps to bad news. The asymmetric effects are statistically significant in both specifications. In addition, the coefficients on the interaction terms are also in line with the predictions. With the greater ambiguity in the news, investors place less weight on good news and treat it less precisely. On the other hand, the bad news is weighed more heavily. That is, the coefficient on $Goodnews * Ambiguity$ is less than or equal to 0, and the coefficient on $Badnews * Ambiguity$ is greater than 0. Across all columns, the coefficients on $Badnews * Ambiguity$ are positive and statistically significantly different from zero, suggesting that investors are more concerned with bad and more ambiguous news. However, none of the coefficients on $Goodnews * Ambiguity$ are significant at 10% level. Regarding the sign, they are negative in all columns. Appendix Table A.15 reports coefficients when an alternative qualitative proxy, AMB^{numsym} is included. Robust to the alternative qualitative measure, the variation in ambiguity measures drives the variation in the asymmetric effect. As an additional robustness check, the dependent variable in the specification is replaced with three-day $(t-1, t+1)$ cumulative abnormal return adjusted for Fama and French five-and-momentum-factor model over news day t and results are reported in appendix Table A.16. The overall asymmetric effect is bigger in a three-day window. Investors react 42.3 bps more to bad news when AMB^{numseq} is used, and the asymmetric effect is 34.9 bps after controlling for AMB^{netunc}.

It is possible that the ambiguity proxy AMB^{netunc}, and thus the main results are sensitive to how uncertain words and certain words are defined. To consider this possibility, we use three different word lists to construct the measure AMB^{netunc}, and Table A.7 reports investors responses to news following an increase in the usage of uncertain words. In column (1) and column (2), uncertain words and certain words are defined by the overlap of Loughran and McDonald (2011) list and the GI dictionary. It is worth noting that words related to risk ("risk","risks") are among the top 25 most frequently occurring uncertain and certain words as shown in A.2. Also "nearly", "approximately" and "roughly" are commonly used. One may question that these words are more related to risk or imprecision, rather than uncertainty and ambiguity. Therefore, column (3) and column (4) report results by using a modified list of the overlap dictionary excluding those words and their inflections. Column (5) and column (6) show the regression coefficients when uncertain words and certain words are defined by the combination of Loughran and McDonald (2011) list and the GI dictionary. Robust to different dictionaries or different fixed effects used, when more uncertain words are used in the news, investors react more strongly to bad news than good news. Overall, the findings in Table A.6 and A.7 suggest that investors place more weights on bad news as news is more ambiguous, which is consistent with Hypotheses 2.

2.4.2 Who Writes the News

Different types of news are covered in Factiva. It contains press releases and written reproduction of what was said orally at a press conference or on broadcast media. Other examples of news are in-depth analyses by the writer, columns, commentaries or opinions of the journalists, and insights into companies, etc. Compared with press releases and transcripts which are directly provided by firms, news from other sources needs more judgment from investors for its quality. If a piece of news comes from an unfamiliar media, or just reflects the opinion or conjecture of the news writer, it is difficult for investors fully process information since the reliability of the source is questionable to them. Hence, the main findings documented in the previous subsection are expected to be robust for news indirectly provided by the firm.

To shed light on how investors react to news from sources other than firms, we exclude press releases and transcripts from the sample[13]. Table A.8 reports the results in the subsample, and they are robust. When the news contains more soft information than hard information, stock return decreases 53.1 bps for bad news whereas it increases only 19.4 bps for good news, implying the existence of the asymmetric effect. The result is similar when more uncertain words are used, though the magnitude of the effect is smaller, and the result is robust when industry fixed effects is included. With the greater ambiguity in non-press release/transcripts type of news, investors act as more cautiously and conservatively. Although it is relatively coarse only to exclude press releases and transcripts, Table A.8 provides evidence that the main findings documented come from the news indirectly provided by the firm.

2.4.3 Robustness Checks

This section conducts robustness tests and investigates multiple alternative explanations studied by Williams (2015) and other related studies.

[13]Press Release has a subject code "npress" and a transcript has subject code "ntra" based on Factiva Intelligent Indexing Subject Code.

2.4.3.1 Macro or Micro

Williams (2015) uses the change in VIX over the two-day period immediately preceding the three-day news day window as a proxy for macro-level uncertain shocks. The paper finds more response to bad news than good news when the VIX increases prior to the news. Macro-level uncertainty can affect not only the decision process of investors but also the signal generation process. It is likely that news is more ambiguous when news writers are influenced by macro-level uncertainty. Therefore, the ambiguity in the news is merely a reflection of macro-level uncertainty. To rule out this explanation, two-day change in VIX (ΔVIX) is included in the regression as reported in column (1) of Table A.9 Panel A and column (1) of Table A.10 Panel A. To control for the potential effect of the announcement of dividend increases, we also include a dummy for dividend change. As similar in Table A.6, not only are the coefficients on $Badnews * Ambiguity$ interaction term significantly positive for any of the proxies used, but also the overall effects of good news are smaller than bad news. When the change in VIX is controlled, the asymmetric effect is 39.9 bps when AMB^{numseq} is included and it is 32.2 bps when AMB^{netunc} is used to measure ambiguity. In sum, it is unlikely that macro-level uncertainty is the driving force behind the results.

It is possible that investors respond asymmetrically due to investor sentiment. Baker and Wurgler (2006) construct the investor sentiment index and find that investors overreact in high sentiment periods and underreact in low sentiment periods. Mian and Sankaraguruswamy (2012) document that investors react more (less) strongly to good news than bad news when market sentiment is high (low). To consider this explanation, we include the Baker and Wurgler (2006) sentiment index, and it is interacted with both $Goodnews$ and $Badnews$. Table A.9 Panel A column (2) and Table A.10 Panel A column (2) report the result from inclusion of ambiguity proxies and interaction terms in the regression. The results are consistent with Hypothesis 2. The ambiguity-induced asymmetry ranges from 28.5 bps to 36.8 bps which are different from zero at 1% significance level. Therefore, the results are robust to the inclusion of investor sentiment.

The third alternative explanation is that the market reacts more to bad news than good news when the market valuation is high, as suggested by Conrad, Cornell, and Landsman (2002). When the market valuation is high, i.e., good times, bad news is unexpected and good news is expected, producing a larger effect on bad news and a smaller effect on good ones. Table A.9 Panel A column (3) and Table A.10 Panel A column (3) show the results from inclusion of market valuation proxy. Following Conrad et al. (2002), the relative price-to-earnings ratio ($DCAPE$) is constructed. It is the cyclically-adjusted price-to-earnings ratio from Robert Shiller's website subtract its previous 12-month average. Consistent with the predictions, the ambiguity-induced asymmetry ranges from 27.2 bps to 33.8 bps; both are significant at 1% level. The results indicate that the documented asymmetry effect is robust to the inclusion of the market condition variable.

Fourth, ambiguity in the news may reflect the overall economic uncertainty. Thus the economic policy uncertainty index ($EPUI$) constructed by Baker et al. (2016) is included in the regression. As shown in Table A.9 Panel A column (4) and Table A.10 Panel A column (4), the economic uncertainty cannot be the explanation of observed asymmetric response. Instead, the main results are still robust to controlling for this measure.

2.4.3.2 Bad News Withholding

Kothari et al. (2009) find that investors react more to bad news disclosures than to good news ones, suggesting management on average delays the release of bad news once it is accumulated and withheld up to a certain threshold, but privately leaks and quickly reveals good news. If this explanation is the main driving force of the results in Table A.6, then there should be an asymmetry between the magnitude of good news versus bad news. However, as shown in Table A.2 Panel C, the average magnitude of good new is 0.546 but the average bad news tone measure is 0.537, and their difference is statistically significant.

To rule out this possibility formally, Table A.9 Panel B and Table A.10 Panel B report the result by including proxies of information asymmetry and manager ownership incentives. As Kothari et al. (2009) argue, when there is high information asymmetry between managers and investors, managers are better able to withhold bad news. Moreover, when managers' wealth is more tied to the firm value, managers have more incentive to delay their wealth loss after the bad news disclosure.

Following Kothari et al. (2009), the manager ownership proxy is constructed as the fraction of total shares outstanding held by managers. As for information asymmetry proxies, four variables are considered: (1) market-to-book ratio, (2) annual stock volatility, (3) a dummy for high-tech industries, and (4) a dummy for regulated industries (other than financial institutions). Growth firms may have more information asymmetry than value firms. For firms with high return volatility and high-tech firms, they face more uncertainty, and thus increases information asymmetry. However, firms in regulated industries must timely disclose information to regulatory bodies, therefore reducing information asymmetry. As seen in Table A.9 Panel B and Table A.10 Panel B, the main results are robust to the inclusion of these variables. Therefore, the asymmetric reaction is more consistent with the ambiguity theory than with the withholding bad news hypothesis.

2.4.3.3 Additional Robustness Checks

Another economic mechanism related to the study comes from psychology and behavioral finance literature. According to Kahneman and Tversky (1979), Thaler and Johnson (1990), and Barberis, Huang, and Santos (2001), investors' risk preferences depend on changes in financial wealth and feature aversions to loss over financial wealth. Thus, risk aversion can vary over good and bad states of an economy according to this theory. Testable implications of this theory are that a loss-averse investor becomes more (less) loss-averse if the prior gain is negative (positive), and this state-dependent nature of preference may produce an asymmetric response to good and bad news under certain market conditions. To check the robustness of the main result to this explanation, past returns and a dummy variable indicating the sign of past stock performance are added to the empirical models, and Table A.9 Panel C column (1) and column (2), and Table A.10 Panel C column (1) and column (2) report the results. Again, asymmetric responses are still quite significant both economically and statistically.

Lastly, the empirical results may be sensitive and related to short-sale constraints. According to Diether, Malloy, and Scherbina (2002), stocks with high forecast dispersions tend to earn lower returns because reactions by pessimistic investors are restricted due to the existence of a short-sale constraint. This finding works against our finding in that bad news will have a less price reaction than it should be if short-sale constraints are binding. As proxies for short-sale constraints, short interest and institutional ownership are included in the empirical settings. The main empirical results shown in Table A.9 and A.10 still stand firm and significant.

Finally, Table A.11 reports the results controlling for all alternative explanations discussed above and their interactions with $Goodnews$ and $Badnews$. Though coefficients on the interaction term $Badnews{*}Ambiguity$ is insignificant when AMB^{netunc} is used, the documented asymmetric response is robust. To summarize, the evidence in Table A.9, A.10 and A.11 is consistent with the Hypothesis 2 that investors weight bad news more when the new is more ambiguous.

Before concluding the paper, Table A.12 displays relations between yearly return volatility on news day and the ambiguity measures used in this paper. The result shows that return volatility is positively affected by ambiguity in firm-specific news, again consistent with the theory and intuition. Return volatility is known to be highly persistent, and controlling for the lagged return volatility does not change the result.

In sum, results are robust to these alternative explanations. Consistent with Hypotheses 1 and 2, investors not only react more to bad news than good news but also even more strongly when news becomes more ambiguous.

2.5 Conclusion

This paper examines how investors respond to firm-specific news regarding dividends and earnings when they receive ambiguous news and cannot interpret it precisely. Given the rarity of measures of firm-specific ambiguity, the paper uses two proxies to quantify qualitative and uncertain aspects of news. The central finding is that stock returns response more strongly to bad news than good news. Furthermore, the magnitude of the asymmetric effect enlarges when news becomes more ambiguous as measured by ambiguity proxies. The documented asymmetric effect also prevails in the subsample excluding press releases and transcripts. In robustness checks, alternative explanations are investigated, and main results are robust.

In sum, the paper contributes to the literature by providing ambiguity proxies at the firm level, which are useful to future research in finance and accounting. Moreover, it shows empirical evidence consistent with the theory of ambiguity aversion, providing insights into how investors process information with uncertain value.

3. AMBIGUITY, MACRO FACTORS, AND STOCK RETURN VOLATILITY

3.1 Introduction

Is idiosyncratic return volatility associated with ambiguity or risk? If so, does it proxy for idiosyncratic risk or uncertainty? Idiosyncratic return volatility has been extensively discussed in the literature, yet the topic still provides challenging questions to many researchers and practitioners. Lintner (1965) points out that idiosyncratic volatility has a positive coefficient in cross-sectional regressions. Some theories imply a compensation for bearing idiosyncratic risk. For instance, Levy (1978), Merton (1987) and Malkiel and Xu (2002) suggest that firms with larger firm-specific volatilities require higher returns because of an incomplete market and resultant under-diversification. Lehmann (1990) finds a positive and statistically significant coefficient on idiosyncratic volatility using individual securities, and Goyal and Santa-Clara (2003) also report a positive link between average idiosyncratic volatility and the market return. Epstein and Schneider (2008) show that agents can demand a positive premium for holding stocks with high idiosyncratic volatility due to ambiguity or uncertainty aversion. Fu (2009) uses a parametric stochastic volatility model to find that expected idiosyncratic volatilities are positively related to expected returns. However, Ang, Hodrick, Xing, and Zhang (2006, 2009) (AHXZ hereafter) and many related papers find that monthly stock returns are negatively associated with the one-month lagged idiosyncratic volatilities, and the strong statistical significance of this negative relation has presented an important asset pricing puzzle (IVOL puzzle).

AHXZ (2006)'s results have attracted much attention since then. A large number of papers have been trying to solve the IVOL puzzle, which we review the literature in the next section. However, as mentioned early, a key question to be answered is whether or not the IVOL in AHXZ (2006) represents idiosyncratic risk and uncertainty of firms in that it is uncorrelated with aggregate variables. Panel (A) in Figure B.1 displays an empirical distribution of the ratio of IVOL to return volatility. According to the figure, AHXZ (2006)'s IVOL accounts for over 88% of return volatility on average, suggesting that the IVOL measure does not differ much from the total variations in return. Although it is possible that most of return volatility results from idiosyncratic fluctuations, this stylized fact naturally leads to a question whether those variables known to explain or predict return volatility could also explain IVOL.

In a pioneering study by Schwert (1989) and many studies that follow, aggregate variables including the volatilities of macroeconomic variables, NBER recession indicator, term spread and credit spread can explain or predict stock returns and return volatilities. In addition, the literature finds that aggregate cash-flow-to-price ratio, dividend-to-price ratio (dividend yield), leverage and trading volume serve as other determinants of return volatility. Further, aggregate volatility can affect stock return through uncertainty channels via the analyst forecast dispersion, according to Schwert (1989), Epstein and Schneider (2008), Kim, Lee, Park, and Yeo (2009), and Jeong, Kim, and Park (2015) etc.[1] By projecting IVOL of individual firms onto these aggregate variables known to explain or predict return volatility, we compute the empirical distribution of adjusted R^2 values to check if variations in IVOL are indeed associated with macroeconomic variables. Panel (B) of Figure B.1 shows that over 30% of IVOL variations come from those of macroeconomic variables on average, and adjusted R^2 are greater than 0 in more than 80% of cases, despite the fact that IVOL controls for the key asset pricing factors.[2]

Motivated by this, we disentangle IVOL into systematic and idiosyncratic fluctuations, and investigate their respective roles in accounting for the cross section of stock prices. In addition, we attempt to further dissect contributions from risk and uncertainty in determining the conditional means and volatilities of stock returns.

To produce concrete hypotheses, we write down an economic model and relate return volatility to the cross section of stock returns. In the setup, we incorporate ambiguity aversion into an asset pricing model with recursive preferences popularized by Epstein and Zin (1989, 1991) and Bansal and Yaron (2004). We attempt to distinguish risk and uncertainty as sources of return volatility,

[1]Uncertainty aversion or ambiguity aversion follows from Gilboa and Schmeidler (1989), Epstein and Wang (1994) and Hansen and Sargent (2001).

[2]The maximum adjusted R^2 value from the macroeconomic variables is around 90 %.

further disentangle those into common and idiosyncratic parts, and investigate roles of the different sources of return volatilities in explaining the cross sectional variations of returns. Our simple theory offers two main testable implications.

First, we show that if there exists a fraction of IVOL common to each asset, this part can generate a negative relation to the portfolio returns sorted by IVOL, because of intertemporal hedging motives as explained by Merton (1973). Cross-sectional stock returns are priced in response to systematic variations of return volatility. Merton (1973) develops an intertemporal capital asset pricing model (ICAPM), according to which a risk-averse investor prefers to hold assets that perform well when investment opportunities deteriorate, and the higher stock market volatility indicates that economic conditions get worsened.

Second, our model also suggests that ambiguity produces a positive link between expected return and return volatility for both systematic and idiosyncratic parts. Taken together, systematic components affecting the IVOL can have both positive and negative signs in their relation to expected returns. Therefore, the sign of the relation is an empirical concern, depending on the relative sizes of the effects from each source of return volatility. On the other hand, the idiosyncratic portion of IVOL will have a positive link to the expected returns.

To this end, we regress firm-level IVOL on those aggregate variable following Schwert (1989). For a proxy for macroeconomic uncertainty, we follow an asymptotic principal component method in Connor and Korajczyk (1986, 1988) to obtain common factors of analysts' EPS forecast dispersion and use first several common dispersion factors as our measure of aggregate uncertainty regarding future earnings. We refer to the fitted part of IVOL as the IVOL fitted by macroeconomic or aggregate variables (m-IVOL), and the unexplained part of IVOL as the residual IVOL (r-IVOL). By construction, the latter measure captures the extent to which IVOL is not induced by macro-level fluctuations, and the former describes systematic variations linked to macro shocks. In addition, we compute the product of each aggregate variable and its estimated regression coefficient as the partially fitted IVOL corresponding to the specific regressor to gauge the individual contribution toward explaining IVOL fluctuations. We then use the portfolio strategies that sort stocks on the size of this variable related to the components of IVOL at the end of each month and form quintile value-weighted portfolios in the following month. Finally, we construct zero cost portfolios based on the rankings to examine mean returns and alphas of these zero cost portfolios with respect to the Fama and French (1993) three-factor and Fama and French (2015) five-factor models.

Using common stock samples from the Center for Research in Security Prices (CRSP) database, we find that a nontrivial portion of IVOL comes from systematic variations, and it indeed affects stock returns through macroeconomic channels. The m-IVOL sorted stock returns are highly compatible with those based on IVOL. That is, the negative relation of the IVOL puzzle prevails when m-IVOL is instead used for sorting. On the other hand, the result based on the residual component of IVOL (r-IVOL) shows the opposite result. Zero cost portfolios sorted on r-IVOL has a *positive* and statistically significant mean return of 0.534$\%$ and an alpha of 0.549$\%$ per month. Therefore, the empirical findings are consistent with our model.

We also use regressions to test the explanatory power of these aggregate variables. We construct return-based factors by using returns to these zero investment portfolios sorted on the partially fitted IVOL by each aggregate variable. By augmenting a capital asset pricing model (CAPM) with our new return-based factors, we conduct time-series tests on zero cost IVOL portfolio. We show that some return-based factors are significant determinants of IVOL portfolios, and several models can price our portfolio correctly with insignificant abnormal return. We also present evidence that the IVOL puzzle cannot be solely driven by small stocks, business cycles, or skewness preferences in the sample.

Our empirical results have important implications on asset pricing theories. First, the existing measure of idiosyncratic volatility, or IVOL can be a summary statistic for broader and more complex volatility channels, rather than a proxy for purely idiosyncratic volatility. Second and related, because the negative relation between IVOL and stock returns mainly comes from aggregate variables, this anomaly is likely to come from macroeconomic volatilities, business cycles, aggregate uncertainty, or cash flow channels, rather than idiosyncratic variations of return volatility. Third, if idiosyncratic volatility refers to unsystematic part of firm risk, this can be positively priced, as suggested by Schwert (1989), Merton (1987), Epstein and Schneider (2008), and other related papers, according to the results from r-IVOL.

The rest of the paper is organized as follows. Section 3.2 reviews the related literature, and section 3.3 develops a simple economic model to motivate the study and write down testable hypotheses. Section 3.4 describes the data and our empirical strategy. Sections 3.5 and 3.6 present our main results with various robustness checks. Then, we conclude in section 3.7.

3.2 Related Literature

Our paper is related to an empirical literature on explanations of the IVOL puzzle. Bali and Cakici (2008) suggest that AHXZ (2006)'s results are sensitive to the research method and they are not robust. They show that the return differences between the lowest and highest idiosyncratic volatility quintile portfolios are sensitive to the idiosyncratic volatility breakpoints of the entire sample or sub-samples used. Another explanation attributes the IVOL puzzle to market frictions. Huang, Liu, Rhee, and Zhang (2010) illustrate that AHXZ (2006)'s results are driven by monthly stock return reversals and Fu (2009) has the same conclusion. Once controlling for the one-month return reversal effect likely driven by microstructure biases, the negative relation between idiosyncratic volatility and return is no longer significant. The third group of potential explanations of the IVOL puzzle is related to the lottery preference of investors. Doran, Jiang, and Peterson (2011) find in January individual investors prefer lottery-type stocks which have high idiosyncratic volatility because of a New Year's gambling preference. As a result, there will be a positive relation between idiosyncratic volatility and returns only in January and the negative relation between idiosyncratic volatility and returns exists in the rest of the year. Boyer, Mitton, and Vorkink (2010) show that the IVOL puzzle is consistent with the investor preference for positive skewness in stock returns. Bali, Cakici, and Whitelaw (2011) find that IVOL puzzle can be explained by the preference of extreme positive returns. The fourth group of explanations concerns firm's fundamentals. For example, Avramov, Chordia, Jostova, and Philipov (2013) show that many cross-sectional return anomalies, including the idiosyncratic volatility puzzle, exist only among financially distressed firms. Jiang, Xu, and Yao (2009) state that earnings shocks and selective information disclosure by firms matter for the IVOL puzzle, and Wong (2011) shows that stocks with high idiosyncratic volatility experience negative earnings shocks before and after portfolio formation, resulting in poor return performance of those stocks. Chen and Petkova (2012) suggest that growth options associated with average return variance can explain the IVOL puzzle. Stambaugh, Yu, and Yuan (2015) argue that short-sale constraints play an important role in explaining the puzzle. The alternative channels may work in part, but we show that the IVOL puzzle mainly comes from aggregate variations generating a negative relation with stock returns while the residual, or the idiosyncratic part of IVOL, is actually positively related to stock returns.

Our paper is related to the literature studying systematic fluctuations of IVOL. Campbell, Lettau, Malkiel, and Xu (2001), and Bekaert, Hodrick, and Zhang (2012) construct an aggregated IVOL index to examine the time-series and cross-sectional behaviors of the idiosyncratic variations of stock returns. Duarte, Kamara, Siegel, and Sun (2014) and Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2015) show that there is a strong factor structure in firms'idiosyncratic volatility, and in the cross-section shocks to the common factor in idiosyncratic volatility are priced. We share the spirit of extracting common variation from IVOL, yet we emphasize the role of observable, macroeconomic variables instead of latent factors. Indeed, we find that IVOLs have multiple common factors, and these common factors are in fact driven by macroeconomic variables, aggregate corporate variables and aggregate forecast dispersion. In addition, we show that the residual part of the IVOL, which we believe is close in spirit to idiosyncratic fluctuations of return volatility, is significantly and positively priced in the cross section.

This paper connects to the literature on the stock return volatility. Schwert (1989) analyzes a few macroeconomic factors which could be correlated to stock market volatility. He shows that though macroeconomic volatility can weakly predict stock volatility, financial leverage and trading volume growth seem to be important in affecting stock volatility. In this paper, we show that a part of systematic variation of IVOL is actually related to these factors that are known to explain or predict market volatility. Campbell, Lettau, Malkiel, and Xu (2001) study time-series behaviors of a weighted average of idiosyncratic volatilities of individual stocks for the US market, and find that idiosyncratic volatilities significantly increased. Investigating 23 international stock markets, Bekaert, Hodrick, and Zhang (2012) report that the upward trend disappears, if extending the period to 2008. They show that growth opportunity, market volatility, and some other macroeconomic variables are related to the aggregated IVOL index. We use those variables in our set of macroeconomic determinants of IVOL.

Finally, our paper is also related to the literature on the uncertainty via the forecast dispersion. Diether, Malloy, and Scherbina (2002), Johnson (2004), Anderson, Ghysels, and Juergens (2009), Gallmeyer, Jhang, and Kim (2015), Kim (2015), and many others show that uncertainty via the forecast dispersion should matter for asset pricing. We contribute to this strand of literature that analyst forecast dispersion may serve as a channel through which firm-specific risk and uncertainty affect expected return.

3.3 Theory and Hypotheses

In this section, we develop a simple continuous-time economic model to link return volatility to the cross section of returns. We attempt to distinguish risk and uncertainty as sources of return volatility via incorporating ambiguity aversion into an asset pricing model with recursive preferences. Recursive preference function in finance literature is popularized by Epstein and Zin (1989, 1991) and Bansal and Yaron (2004), and the model helps resolve several prominent asset pricing puzzles such as the equity premium puzzle. Bansal and Yaron (2004) and Kim, Lee, Park, and Yeo (2009) show that the setup produces a volatility channel to determine asset prices as well. In addition, uncertainty or ambiguity aversion can generate volatility channels of asset pricing, according to Chen and Epstein (2002), Epstein and Schneider (2008) and Jeong, Kim, and Park (2015). However, the existing literature did not separate roles of risk and uncertainty of return volatilities in explaining the cross section of stock returns, and we tackle this issue.

3.3.1 Setup

Following Jeong, Kim, and Park (2015), we begin by defining a standard d-dimensional Brownian motion $W_t = \left(W_t^1, ..., W_t^d\right)$ on $(\Omega, \mathcal{F}, P)$ and the Brownian filtration $(\mathcal{F}_t)_{0\leq t\leq T}$, where $\mathcal{F}_t$ is the σ-field generated by $(W_s^1, ..., W_s^d)_{s\leq t}$. The time horizon is $[0, T]$, where T is finite. Suppose that the representative investor does not know the true probability measure and has to select a subjective probability measure from the set of all priors $\mathfrak{P}$ which are uniformly absolutely continuous with respect to the true P in $\mathfrak{P}$. Duffie and Epstein (1992) show that for a fixed consumption process C and a probability measure $Q \in \mathfrak{P}$, there exists a utility process V_t^Q uniquely solving

$$V_t^Q = \mathbb{E}^Q\left[\int_t^T f(C_s, V_s^Q)ds \middle| \mathcal{F}_t\right], \quad 0 \leq t \leq T, \tag{3.1}$$

where $\mathbb{E}^Q(\cdot|\mathcal{F}_t)$ is the conditional expectation operator and $f(C, V)$ is called a normalized aggregator function linking current consumption and the future value. Using the martingale representation theorem, we write equation (3.1) in a differential form of

$$dV_t^Q = -f(C_t, V_t^Q)dt + \sigma_t^v dW_t^Q, \tag{3.2}$$

where $V_T^Q = 0$, (W_t^Q) is the standard Brownian motion under Q-measure, and σ_t^v is endogenously determined. From now on, we use the functional form of

$$f(C, V) = \frac{C^{1-\beta} - \gamma(\alpha V)^{\frac{1-\beta}{\alpha}}}{(1-\beta)(\alpha V)^{\frac{1-\beta}{\alpha}-1}} \tag{3.3}$$

for some $\gamma \geq 0$, $\beta \neq 1$, $\alpha \leq 1$. This can be regarded as the continuous-time version of a utility function introduced by Kreps and Porteus (1978), in which α and β measure the degree of relative risk aversion (RRA) and the elasticity of intertemporal substitution (EIS) respectively. Specifically, the RRA is measured by $(1 - \alpha)$, and the EIS is $1/\beta$. An important feature of the model is that the consumer chooses a probability measure from available priors. To be specific, we assume that the sets $\mathfrak{P}$ of measures are equivalent to P. This is constructed by specifying suitable densities.

We define a density generator to be an R^d-valued process $\theta = (\theta_t)$ for which the process z_t^θ is a P-martingale, where

$$dz_t^\theta = -z_t^\theta \theta_t \cdot dW_t, \tag{3.4}$$

$$z_0^\theta = 1. \tag{3.5}$$

θ generates a probability measure Q^θ on $(\Omega, \mathcal{F})$ equivalent to P, i.e., $\frac{dQ^\theta}{dP}|_{\mathcal{F}_t} = z_t^\theta$ for each t and $\frac{dQ^\theta}{dP} = z_T^\theta$.Thus, given a set Θ of density generators, the corresponding set of priors is

$$\mathfrak{P}^\Theta = \left\{ Q^\theta : \theta \in \Theta \text{ and } Q^\theta \text{ is defined by } \frac{dQ^\theta}{dP}|_{\mathcal{F}_t} = z_t^\theta \text{ for each } t \text{ and} \frac{dQ^\theta}{dP} = z_T^\theta \right\} \tag{3.6}$$

Following Chen and Epstein (2002) and Epstein and Schneider (2003, 2007), we assume rectangularity to attain dynamic consistency.[3] As Jeong, Kim, and Park (2015) argue, under this extra layer of uncertainty, which leads to the Ellsberg paradox (Ellsberg (1961)), the min-max type of value function

$$V_t = \min_{Q \in \mathcal{P}} V_t^Q, \quad 0 \le t \le T \tag{3.7}$$

is suggested by Gilboa and Schmeidler (1989). The multiple-priors recursive utility is given by the lower envelope of the utility process (V_t^Q), which is determined by the conditional expectation of future consumption and utility values. Chen and Epstein (2002) show that there exists a unique solution to equation (3.7) satisfying the dynamic consistency under certain conditions. Given the statistical setup, the Girsanov transformation lies at the heart of constructing a set of priors $\mathcal{P}$ on $(\Omega, \mathcal{F}_T)$. Further, we fix a parameter $\kappa = (\kappa_1, ..., \kappa_d)$ in R_+^d and take

$$\Theta_t(\cdot) = \left\{ y \in R^d : |y_i| \le \kappa_i \text{ for all } i \right\}, \tag{3.8}$$

[3] Dynamic consistency in this paper is defined in the following sense. If two consumption plans c and c' are the same up to a stopping time τ, and the value V_τ of c is weakly preferred to that of c' at τ almost surely, then $V_0(c) \ge V_0(c')$ almost surely with a strict inequality in the case that $P\{V_\tau(c) > V_\tau(c')\} > 0$ holds.

which is called $\kappa-$ignorance. Then, it is shown that

$$dV_t = [-f(C_t, V_t) + \kappa \cdot |\sigma_t|]\, dt + \sigma_t^v \cdot dW_t, \tag{3.9}$$

$$V_T = 0. \tag{3.10}$$

The intertemporal marginal rate of substitution or the stochastic discount factor, denoted as Λ is derived as

$$\Lambda_t = \exp\left[\int_0^t \left(-\gamma - \left(1 - \frac{\alpha}{1-\beta}\right) \frac{\left(C_s^{(1-\beta)} - \gamma\,(\alpha V_s)^{\frac{1-\beta}{\alpha}}\right)}{(\alpha V_s)^{\frac{1-\beta}{\alpha}}}\right) ds\right] C_t^{-\beta}\,(\alpha V_t)^{\frac{\beta-1}{\alpha}}\, z_t^{\kappa}. \tag{3.11}$$

In comparison with the conventional stochastic discount factor without ambiguity aversion, it is clear to see that ambiguity matters in equation (3.11). In the next subsection, we compute asset returns implied by this theoretical model.

3.3.2 Theoretical Asset Prices

We assume that there exist d assets in the economy and denote the vector of instantaneous conditional mean returns by $b = [b^1, ..., b^{d-1}, b^M]$ and the vector of returns by $R = [R_1, ..., R_{d-1}, R_M]$, and specify that the returns have the following forms: for $i = 1, ..., d-1$, and M,

$$dR_{it} = b_t^i dt + \phi_i s_t^d dW_t^d + s_t^i dW_t^i, \tag{3.12}$$

$$dR_{Mt} = b_t^M dt + s_t^d dW_t^d, \tag{3.13}$$

where ϕ_i measures the co-variation of an asset i with the common (i.e., macroeconomic) Brownian motion shock W^d and b_t is to be endogenously determined.

By construction, W^d refers to an aggregate shock and W^i, $i = 1, ...d-1$ stand for idiosyncratic shocks, and we assume that the aggregate stock market return (R_M) does not depend on individual Brownian motions. Extending the dimension of W^d to a multivariate vector is straightforward, and the convention that the asset M has W^d as the only Brownian motion shock reflects that the idiosyncratic shocks get diversified away in case of the aggregate stock market. In our empirical application, we use multiple macroeconomic variables.

Note that the conditional return variance $Var_t(dR_{it})$ is computed as $\phi_i^2(s_t^d)^2 + (s_t^i)^2$. Because the estimated portion of returns by pricing factors capture the drift term b_t^i for $i = 1, ..., d$, the conventional IVOL à la AHXZ (2006) is defined as $\phi_i^2(s_t^d)^2 + (s_t^i)^2$, netting out the contribution from the risk factors.

We argue that the more relevant idiosyncratic return variance under this setup should be $(s_t^i)^2$, obtained from further purging out the common component $(\phi_i^2(s_t^d)^2)$. The conventional definition of IVOL hinges upon the idea that idiosyncratic shocks are identifiable by controlling for the common pricing factors. However, the cross section of return volatilities can have a factor structure as well, as illustrated above. In this light, s_t^d measures a common, macroeconomic volatility component, and $(s_t^1, ..., s_t^{d-1})$ refers the idiosyncratic part of return volatility (IVOL).

To solve for the asset returns, we define that aggregate consumption process (C_t) as

$$\frac{dC_t}{C_t} = \mu_t^c dt + s_t^c \cdot dW_t, \tag{3.14}$$

where $s_t^c = \left[s_t^{1,c}, ..., s_t^{d-1,c}, s_t^{d,c}\right]$. Equation (3.14) indicates that consumption can depend on all d sources of shocks represented by $(W)_t$, and s_t^c refers to co-variations with each shock. Thus, the sources of consumption shocks include, but are not limited to the aggregate risk. This is because consumption depends on aggregate wealth, denoted as G, and the market can be incomplete so that the representative investor is subject to both aggregate and idiosyncratic shocks. It is well known that solving the model, for each $i = 1, ..., d-1, M$, we have

$$b_t^i - r_t^f = \left[\frac{\alpha\beta}{1-\beta} Cov_t\left(\frac{dC_t}{C_t}, dR_t^i\right) + \left(1 - \frac{\alpha}{1-\beta}\right) Cov_t\left(dR_t^G, dR_t^i\right)\right] + [\phi_i s_t^d, s_t^i] \cdot \theta_t^*, \tag{3.15}$$

where R_t^G represents the returns on aggregate wealth, and θ_t^* is the optimal choice of θ. According to Chen and Epstein (2002), θ_t^* is determined by setting $\theta_t^* = \kappa \otimes sgn\left(s_t^c\right)$ under a Markovian setting with κ-ignorance. Equation (3.15) states that the conditional mean component of the asset returns will be determined by an ambiguity premium associated with the market and idiosyncratic shocks as well as the conventional conditional covariations of returns with consumption growth and returns from the aggregate wealth.

Under the Markovian setting and $\kappa-$ignorance with the rectangularity assumption, we can write down (3.15) as follows:

$$b_t^i - r_t^f = \frac{\alpha\beta}{1-\beta} Cov_t\left(\frac{dC_t}{C_t}, dR_t^i\right) + \left(\frac{1-\beta-\alpha}{1-\beta}\right) Cov_t\left(dR_t^G, dR_t^i\right) \tag{3.16}$$
$$+ \kappa_d \phi_i sgn(s_t^{d,c}) s_t^d + \kappa_i sgn(s_t^{i,c}) s_t^i,$$

where $sgn\left(\cdot\right)$ is the sign function (i.e., positive or negative of the argument).

The conditional mean part of the asset returns computed in equation (3.16) describes that premiums for holding an asset i are due to risks from consumption growth, changes in aggregate wealth, and ambiguities from aggregate and idiosyncratic shocks in the economy. To better understand the relation between volatility and the expected returns, we now make some additional assumptions to identify the model of asset returns.

Assumption 1: $sgn(s_t^{d,c}) > 0$ and $sgn(s_t^{i,c}) > 0$ for all i and t.

Assumption 2: For each i, $sgn(s_t^{i,c})$ does not change over time, though it varies across assets.

Assumption 3: $\kappa_1 = ... = \kappa_{d-1} = \overline{\kappa}$.

Assumption 4 (Early Resolution of Uncertainty): $\alpha < 0$ and $0 < \beta < 1$.

Assumption 1 implies that the correlations between consumption and asset returns are positive. Although the magnitudes of covariance between consumption growth and stock returns are known to be small, the positive sign of the co-variations is well supported in data. For instance, sample correlation between aggregate consumption and the market return is known to be around 0.2 to 0.3, according to previous studies. Assumptions 2 and 3 are mainly for tractability and can be relaxed. In particular, Assumption 3 means that ambiguity boundary for an individual shock is the same across assets i. Although we suspect that the boundary (κ_i) can be bigger for assets with higher idiosyncratic volatilities (s_t^i), we take a conservative stance to assume that all idiosyncratic shocks can be equally ambiguous. Assumption 4 states a condition to guarantee early resolution of uncertainty. According to Epstein and Zin (1989) and more generally Brown and Kim (2013), if relative risk aversion is greater than the reciprocal of the elasticity of intertemporal substitution, the investor prefers early resolution of uncertainty. Bansal and Yaron (2004) show that this creates an important risk channel to resolve the equity premium puzzle. This hypothesis has been empirically tested by several studies, such as Bansal, Kiku, and Yaron (2010), Kim, Lee, Park, and Yeo (2009), and Jeong, Kim, and Park (2015) to show that data support the early resolution of uncertainty.

Then, for $i = 1, ..., d-1$, M, we have

$$dR_{it} = b_t^i dt + \phi_i s_t^d dW_t^d + s_t^i dW_t^i, \tag{3.17}$$

$$dR_{Mt} = b_t^M dt + s_t^d dW_t^d \tag{3.18}$$

with

$$b_t^i - r_t^f = \frac{\alpha\beta}{1-\beta} Cov_t\left(\frac{dC_t}{C_t}, dR_t^i\right) + \left(1 - \frac{\alpha}{1-\beta}\right) Cov_t\left(dR_t^G, dR_t^i\right) + \kappa_d \phi_i s_t^d + \overline{\kappa} s_t^i, \tag{3.19}$$

$$b_t^M - r_t^f = \frac{\alpha\beta}{1-\beta} Cov_t\left(\frac{dC_t}{C_t}, dR_t^M\right) + \left(1 - \frac{\alpha}{1-\beta}\right) Cov_t\left(dR_t^G, dR_t^M\right) + \kappa_d s_t^d. \tag{3.20}$$

Note that both idiosyncratic return volatility and systematic volatility affect expected returns of individual assets. The first part of the right hand side of equation (3.19) ($\frac{\alpha\beta}{1-\beta} Cov_t\left(dC_t/C_t, dR_t^i\right)$) refers to the terms related to the consumption CAPM. The second part shows the association between individual asset returns and aggregate wealth, which is known to be proxied by empirical asset pricing factors. Finally, ambiguity aversion affects the last two terms of the equation (3.19). It is clear that both resolution of uncertainty via long-run risk channel (α, β) and ambiguity aversion (κ_d, κ_i) determine expected returns through return volatilities. Jeong, Kim, and Park (2015) estimate versions of the model (3.19) for the aggregate stock market return to show that ambiguity aversion plays an instrumental role to explain the historic equity premium.

To check this more precisely, we exploit a property of the model that consumption-wealth ratio is a function of state variables. Denote the consumption-aggregate ratio by A_t, or $C_t = A_t G_t$ holds. Chen and Epstein (2002) show that A is a function of state variables, denoted as X, and the value function from equation (3.7) satisfies the following form $V = \Psi(A)G^{\alpha}/\alpha$ with $\Psi'(A) > 0$. Using Ito's lemma, we know that the following relation holds.

$$\frac{dC_t}{C_t} = \frac{dA_t}{A_t} + \frac{dG_t}{G_t} + \frac{dA_t}{A_t}\frac{dG_t}{G_t}. \tag{3.21}$$

Then, we can compute

$$b_t^i - r_t^f = (1-\alpha)\, Cov_t\left(dR_t^G, dR_t^i\right) + \frac{\alpha\beta}{1-\beta} Cov_t\left(\frac{dA_t}{A_t}, dR_t^i\right) + \kappa_d \phi_i s_t^d + \overline{\kappa} s_t^i. \tag{3.22}$$

To specify the process for A_t, we use Merton (1973)'s intertemporal capital asset pricing model (ICAPM), which assumes the state variable to be latent. In particular, The process for X determines the aggregate consumption-wealth ratio, and is defined as

$$dX_t = \kappa_x\left(\theta - X_t\right) dt + \sigma_x dW_t^x, \tag{3.23}$$

in which W^x is a standard Brownian motion and the correlation with W^d is denoted as $\rho_{dx} dt$.[4]

Then, using Stein's lemma , we can express the above equation as

$$b_t^i - r_t^f = (1-\alpha)\, Cov_t\left(dR_t^G, dR_t^i\right) + \left(\frac{\alpha\beta}{1-\beta}\right) A'(X_t)\left(\phi_i \rho_{dx} \sigma_x s_t^d\right) + \kappa_d \phi_i s_t^d + \overline{\kappa} s_t^i, \tag{3.24}$$

for $i = 1, ..., d-1$.

If the correlation ($\rho_{dx} dt$) is positive, this means that the state variable (X) tends to move in the same direction as the stock market return (dR^M). According to Lettau and Ludvigson (2001) and many related studies, it is well known that A and dR^M have a positive relation. Therefore, it is plausible to assume that the signs of $A'(X)$ and ρ_{dx} are the same. (i.e., $A'(X) > (<) 0$ and $\rho_{dx} > (<) 0$.) For instance, if X proxies for business cycle fluctuations, positive shocks to X can

[4]Extending the setup to include multiple state variables is straightforward and hence omitted.

increase both consumption and stock return simultaneously.

Equation (3.24) shows that premiums for holding assets can depend on multiple risk factors and return volatilities. In addition, aggregate return volatility and idiosyncratic return volatilities produce premiums due to both risk channels and uncertainty channels. The next subsection scrutinizes how these channels determine the cross section of stock returns.

3.3.3 Volatilities and Returns

We compare expected stock returns of high volatilities with those of low volatilities. Suppose that two assets H and L differ in that $\phi_H > \phi_L$ and $s_t^H > s_t^L$ hold. That is, although it is not necssary, it suffices to say that asset H has the higher IVOL than asset L in the sense of AHXZ (2006). Then, using equation (3.24), we can compute the expected returns of a zero-cost portfolio consisting of returns sorted by IVOL:

$$\begin{aligned} \mathbb{E}_t\left(dR_t^H - dR_t^L\right) = &(1-\alpha)\, Cov_t\left(dR_t^G, dR_t^H - dR_t^L\right) \\ &+ (\phi_H - \phi_L)\left(\frac{\alpha\beta}{1-\beta}\right) A'(X_t)\rho_{dx}\sigma_x s_t^d \\ &+ \kappa_d\left(\phi_H - \phi_L\right) s_t^d + \overline{\kappa}\left(s_t^H - s_t^L\right). \end{aligned} \tag{3.25}$$

Equation (3.25) states that the zero cost portfolio sorted by the size of IVOL will depend on risk factors associated with aggregate wealth, aggregate return volatilities, and the residual parts of the IVOL. It is important to note that the first component in the right-hand-side of equation (3.25) captures a conventional risk premium known to be captured by several empirical asset pricing factors such as the market, book-to-market, size, and momentum factors. Because risk aversion $(1-\alpha)$ is positive from Assumption 4, this term is positive, provided that the covariance term is positive.

The second term is related to the resolution of uncertainty as well as time-varying and stochastic investment opportunity set. From Assumption 4, $\alpha\beta/(1-\beta) < 0$ holds. Then, the sign of the second term is negative, because ϕ_H is greater than ϕ_L. That is, the contribution from the aggregate return volatility can lead to a negative relation to the cross-sectional portfolio, when investment opportunity set (X) co-moves with the aggregate consumption-wealth ratio. The last two terms are due to ambiguity aversion, and it is easy to infer that both terms are positive.

To summarize, our simple theory offers key testable hypotheses. First, if there exists a fraction of IVOL which is common to each asset, this part can generate a negative relation to the portfolio returns sorted by IVOL, from the intertemporal hedging demand. Second, ambiguity produces a positive link between expected returns and return volatilities for both systematic and idiosyncratic volatilities. In the next section, we empirically test the hypotheses.

3.4 Data

This section describes data series used and constructed in this paper. Table B.1 provides summary statistics of the data set, and Figures B.2 and B.3 provide time-series plots of several key variables in the data. Table B.1 consists of four panels. Panel A reports characteristics of stock returns: average return, return volatility, and return IVOL at firm-month level. Panel B shows summary statistics regarding aggregate variables used in the previous literature to explain stock market volatility. Panel C presents summary statistics about analysts forecast dispersions at firm level. We notice that the firm-month observations shrink in this case. It is mainly because analysts forecast dispersion data set in the Institutional Brokers' Estimate System (I/B/E/S) is not available until 1976. Panel D reports the average adjusted R^2 values from regressing firm-level forecast dispersions onto the common factors of forecast dispersions to measure the importance of the common variations of analyst forecast dispersions. In the below, we explain the data set in detail.

3.4.1 Estimating the Idiosyncratic Volatility

The stock data sample includes all common equities (share codes 10 or 11) on the NYSE, AMEX and NASDAQ in the Center for Research in Security Prices (CRSP) database. At least 17 daily observations are required. The sample period is from July 1963 to December 2012. Following AHXZ (2006)'s approach, we define idiosyncratic volatility (IVOL) as the standard deviation of residuals (ϵ_t^i) in the Fama and French (1993, 1996) regression (FF-3F) given as follows:

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \epsilon_t^i. \tag{3.26}$$

That is, in each month, IVOL is computed as the sample analogue of $\sqrt{Var(\epsilon_t^i)}$ using daily returns for each firm i in the CRSP database.

3.4.2 Aggregate Variables Related to Stock Return Volatility

Following Schwert (1989), we consider aggregate variables related to stock volatility. Macroeconomic variables including the volatility of the monetary base growth, inflation volatility and the volatility of industry production growth, the National Bureau of Economic Research (NBER) based recession indicators, credit spread and term spread can be important in explaining stock return volatility. The volatility of stock returns can result from the volatilities of inflation or money growth, especially if market participants perceive that the overall economy is uncertain about future direction of monetary policy and liquidity conditions. Similarly, real macroeconomic volatility can be correlated to stock return volatility, because common stocks are the claims on future firm performances, and the volatility of future profits is likely to change if aggregate real activity fluctuates over time.

In addition, we use aggregated corporate and financial variables, such as cash-flow-to-price ratio, dividend-to-price ratio, leverage, and trading volume. Cash-flow-to-price ratio and dividend-to-price ratio, known as variables predicting future returns, can explain return volatility, because these variables tend to forecast stock returns persistently with multiple horizons. If these predictors proxy for aggregate state variables which are closely linked to future expected returns over multiple periods, both returns and return volatilities can be connected via these forecasting variables.

Trading volume measures how actively financial transactions occur. Heterogeneous beliefs, arrival of new information, and market liquidity conditions can jointly affect the trading volume and return volatility, as pointed out by Schwert (1989). Emphasizing the role of macroeconomic fluctuations, we use the aggregated trading volume of stock market.

3.4.2.1 Macroeconomic Variables

Data of the monetary base and industry production index are from the Federal Reserve Board, and consumer price index (CPI) is from the Bureau of Labor Statistics. As in Schwert (1989), we estimate the volatility of the monetary base growth ($\Delta Mvol$), of the inflation ($INFLvol$) and of the industry production growth ($\Delta IPvol$) by the following procedures:

(i) Estimate a 12th-order autoregression with different monthly intercepts (D_t) for the growth rates X_t:

$$X_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{i=1}^{12} \beta_i X_{t-i} + \varepsilon_t. \tag{3.27}$$

and (ii) The absolute values of the fitted errors from (3.27), $|\hat{\varepsilon_t}|$, estimate the monthly volatility.

We also include NBER based Recession Indicators ($Recession_t$), which is equal to 1 in a recessionary period or 0 in an expansionary period. We calculate the credit spread between Moody's Baa corporate bond yield and Aaa yield ($Yield_t$) , and the term spread ($Term_t$) between 10-year Treasury rate and 1-year Treasury rate from the Federal Reserve Board.

3.4.2.2 Aggregated Corporate and Financial Variables

We use the CRSP/Compustat Merged Quarterly Data set and calculate Cash-Flow-to-Price ratio (CP), Dividend-to-Price ratio (DP) and leverage (Lev) for each firm at the end of each fiscal quarter. Leverage is defined as the book value of long term debt divided by book value of assets. Given that our IVOL measure is computed at monthly frequency, we follow Irvine and Pontiff (2009) to produce monthly estimates of the above ratios. CP_{it} (DP_{it}, Lev_{it}) is the firm i's accounting ratio at time t. If time t does not correspond to the end of the firm's quarter, CP_{it} (DP_{it}, Lev_{it}) reflects either the quarterly accounting ratio that was reported in the previous month or the quarterly accounting ratio that was reported in the following month. After having monthly series of these ratios for each firm, we calculate the value weighted average among all firms for each month. Finally, we compute trading volume ($Tvlm_t$) as the value weighted average of firm level traded shares over total shares outstanding in each month.

3.4.3 Analysts Forecast Dispersion

Recent studies such as Diether, Malloy, and Scherbina (2002), Epstein and Schneider (2008), Kim (2015), and Jeong, Kim, and Park (2015) show close relations among return volatility, ambiguity, and analyst forecast dispersions. Based on this idea, we further decompose firm-level analyst forecast dispersions into common and idiosyncratic fluctuations in order to pair systematic and residual return volatilities to common and idiosyncratic components of forecast dispersions. For analysts forecast dispersion at firm level, we follow the procedure in Diether, Malloy, and Scherbina (2002). We use I/B/E/S for the data on analysts' earnings-per-share (EPS) 1Y (1 year) forecast. For each stock in CRSP, we calculate its dispersion as the standard deviation of EPS forecast divided by the absolute value of the mean EPS forecast. We then use the asymptotic principal component method in Connor and Korajczyk (1986, 1988) to obtain common factors of analyst forecast dispersion.

Each month we regress firm-level analyst forecast dispersion ($DISP_{it}$) on up to first ten common factors from the asymptotic principal component analysis and obtain adjusted R^2:

$$DISP_{it} = \alpha_i + \beta_i' F_t + u_{it}. \tag{3.28}$$

Panel D of Table B.1 reports adjusted R^2 using up to four common factors, which is also the total variance explained by common dispersion factors. We only include the first four factors because each additional common factor after the fourth factor only increases the explained variance by less than three percent.

We believe that analysts try to predict individual firms' earnings based on firms' likely responses to aggregate shocks as well as idiosyncratic shocks affecting earnings. Although the extent and amount of reactions of individual firms differ from each other, the the degree of co-movement will be stronger for those against aggregate shocks. This can be reflected upon the degree and commonality of uncertainty that analysts estimate as well. In this light, we use the first four common dispersion factors as our measure of aggregate analysts forecast dispersion. The first four factors explain slightly more than one quarter (27%) of the variation in total. Thus, the first impression is that there exist common variations of forecast dispersions, capturing uncertainty about earnings associated with macroeconomic fluctuations. In addition, a significant portion of forecast dispersion comes from idiosyncratic variations.

Panel (F) of Figure B.2 shows the time series plot of the first common factor. The first common factor of analyst dispersion is higher in early and mid-1980s, and becomes significantly lower in 1990s, correctly depicting the period of great moderation. Then, it shows some spikes in early 2000s, consistent with the period of credit crunch and the 9/11 tragic event. Then, it surges up since the period of financial crisis of 2007-2009 period. Overall, the common dispersion factor describes changes in macroeconomic level of uncertainty, consistent with other studies such as Kim, Lee, Park, and Yeo (2009).

3.5 Main Results

This section presents the main results of the paper. The next subsection reproduces the results by AHXZ (2006), extending the period. Then, we verify if the aggregate variables selected in the previous section can explain stock market volatility, reproducing and extending the results by Schwert (1989). In section A.4, IVOLs of individual stock returns are projected onto the macro factors to compute $m-$IVOL (common IVOL) and $r-$IVOL (residual IVOL) to analyze how these affect the cross section of stock returns. Finally, we compute factor-mimicking portfolios to analyze if the part of IVOL fitted by each aggregate variable plays a role in pricing the portfolio sorted by IVOL.

3.5.1 The Idiosyncratic Volatility Puzzle

Table B.2 reports monthly percentage returns of portfolios sorted by IVOL. In each month, we sort stocks into quintile value-weighted portfolios on the basis of idiosyncratic volatility computed using daily returns over the previous month. We hold these portfolios for one month and rebalance them at the end of each month. We examine the differences in both raw average returns and abnormal returns between the highest IVOL and lowest IVOL portfolio. Panel A replicates Table

VI of AHXZ (2006). The results are similar to their main findings. The quintile portfolio of stocks with the highest IVOL has a raw average return -1.050% lower than that with the lowest IVOL (-1.06% in AHXZ (2006)). The difference in CAPM alpha between the highest IVOL portfolio and the lowest IVOL portfolio is -1.375% per month (-1.38% in AHXZ (2006)). Fama-French 3-Factor (FF-3F) alpha difference between the highest IVOL portfolio and the lowest IVOL portfolio is -1.344% per month, which is also statistically significant (-1.31% in AHXZ (2006)).

In Panel B, we extend AHXZ (2006)'s sample period by twelve years to December 2012. Again, we obtain similar patterns, and the IVOL puzzle still exists. The difference in raw average returns is -0.870% per month. Both CAPM and FF-3F model are unable to price these portfolios correctly since the differences in alphas between the highest IVOL portfolio and the lowest IVOL portfolio are significantly negative. The difference in CAPM alpha between the highest IVOL portfolio and the lowest IVOL portfolio is -1.220% per month, with a t-statistic of -4.42. Further, FF-3F alpha difference between the highest IVOL portfolio and the lowest IVOL portfolio is -1.279% per month, with a t-statistic of -6.78. Panel C verifies if the IVOL puzzle prevails under different business cycle regimes, and Panel D reports the results excluding the penny stocks to see if the results are driven by micro-cap stocks, as argued by the existing papers. Both show that the IVOL puzzle is significant. Overall, the IVOL puzzle prevails significantly in our sample, consistent with the finding of Jiang, Xu, and Yao (2009).

3.5.2 Explaining Market Volatility

Do the aggregate variables introduced in section 3.4 matter to account for stock return volatility? We test the explanatory power of our candidate variables in explaining monthly market volatility. Market volatility ($MKTvol$) is measured as the standard deviation of excess market return within each month using daily returns. In Table B.3, we regress the logarithm market volatility ($Ln(MKTvol)$) on candidate variables (X_t) and obtain the estimates of coefficients (β) as shown in the following regression,

$$Ln(MKTvol)_t = \alpha + \beta_i' X_t + u_{it}. \tag{3.29}$$

Model 1 specification is due to Schwert (1989). We also run regressions using other macroeconomics variables and aggregate corporate variables as in Models 2, 3 and 4. The results in Model 1 are broadly consistent with the existing studies. For instance, the average level of volatility is lower in expansions and is higher in recessions. Adjusted R^2 under this specification is 0.1958, similar to Schwert (1989)'s finding of a R^2 of 0.208. In addition, credit spread ($Yield$), recession ($Recession$), dividend-to-price ratio (DP) and trading volume ($Tvlm$) are vital in explaining the market volatility. Moreover, Schwert (1989) suggests that although these aggregate variables explain fluctuations of market return volatility, macroeconomic uncertainty can play an important role in understanding time-varying and excessive return volatility observed in the data. Following this view, we augment Model 4 with aggregate dispersion factors and refers to those as Model 5 and Model 6. Table B.3 shows that the first common factor ($Disp_t^1$) and the third common factor ($Disp_t^3$) have significantly positive associations with the market volatility, although the second and fourth factors are insignificant. Adjusted R^2 under this specification is around 0.51, which is more than twice in comparison with that of Model 1. Thus, many factors affect stock market volatility, and the aggregate level of uncertainty can be an important determinant of return volatility.

3.5.3 Portfolios Sorted by IVOL Determinants

What drives the IVOL puzzle? Can aggregate variables known to explain market return volatility shed light on this anomaly? If so, what is the relation between stock return and the idiosyncratic volatility after netting out the macroeconomic effect? We scrutinize these issues, using portfolio-sorting strategies. Our empirical strategy is straightforward. In the first stage, we regress the time series of individual stock IVOL on candidate variables (X_t) and obtain the estimates of coefficients[5]:

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it}. \tag{3.30}$$

Second, we sort stocks on the size of $\hat{\gamma}_i^j X_t^j$ for the variable X_t^j at the end of each month and form quintile value-weighted portfolios based upon the sorting for the following month. Finally,

[5]Note that the coefficients α_i and γ_i' are time-invariant, and we use the same estimates in our sorting procedure to focus on the variations of X_t, rather than γ_i.

we construct a zero cost portfolio of buying the stock with the highest $\hat{\gamma}_i^j X_t^j$ ranking and shorting the stock with the lowest $\hat{\gamma}_i^j X_t^j$ ranking. We hold this portfolio for one month and re-balance it at the end of each month. Here we refer to $\hat{\gamma}_i^j X_t^j$ as the partially fitted IVOL related to variable X_t^j. In addition, we repeat the procedure for the whole fitted part of IVOL, $m-$IVOL, and the residual, $r-$IVOL as the sorting variable. This method serves two purposes in answering the questions raised above. First, studying the relations between return volatility and expected return has been one of the key problems in finance, and the theories state that the sign of this relation can be either positive or negative. By looking at the returns sorted by the IVOL coming from the individual variable X_t^j as well as all the variables as a whole, we can shed light on the volatility channels affecting the cross section of stock returns. Second, the residual component of IVOL ($r-$IVOL) is closer in spirit to the "idiosyncratic" part of return volatility. Thus, by analyzing the returns sorted by the $r-$IVOL, we investigate the effects of idiosyncratic volatility risk on returns, and compare those with the findings of the existing studies.

3.5.3.1 Macroeconomic Variables Related to IVOL

We now study the roles of the variables explaining stock market volatility in affecting the IVOL puzzle. To this end, Table B.4 shows both raw average returns and abnormal returns of zero cost portfolios formed by sorting stock returns using the aggregate variables. The fitted IVOL refers to the result sorted by all the explained part of IVOL by the macroeconomic variables. The result states that the significantly negative pattern emerges, consistent with AHXZ (2006). Thus, the IVOL puzzle is likely to come from macroeconomic fluctuations. Among ten variables, three of them seem to be important. Zero cost portfolios sorted on the partially fitted IVOL related to the term spread ($Term_t$), dividend-to-price ratio (DP_t) and the trading activity ($Tvlm_t$) have statistically significant negative raw mean returns of -0.238% ,-0.409% and -0.679% respectively, and alphas of -0.310%, -0.521% and -0.751% with respect to the Fama and French (1993) three-factor model respectively.

We also form portfolios sorted on the residual idiosyncratic volatility, $\hat{\varepsilon}_{it}$. Interestingly, the zero cost portfolio yields a positive mean return of 0.722% and an alpha of 0.668%, which are all statistically significant with Newey-West t-statistics of 3.09 and 2.92 respectively. This finding is in line with economic theories that there should be a positive relation between IVOL and expected returns. Especially, it is consistent with Merton (1987) that in an incomplete market setting, investors require higher returns for holding stocks with larger firm-specific variance and not being able to fully diversify their portfolios. In addition, ambiguity aversion can lead to a positive link as well, as shown by Epstein and Schneider (2008).

Overall, results from Table B.4 suggest that the IVOL puzzle is a result of combined forces. On one hand, the part of IVOL that is explained by aggregate variables, mainly the term spread, the dividend-to-price ratio and trading activity, generates the negative IVOL-return relation. In other words, IVOL computed by AHXZ (2006) is not truly idiosyncratic and it comes from systematic variations related to stock market volatility. Note that these variables are highly related to business cycle fluctuations which affect business opportunities. Thus, this result is consistent with the key implication of Merton's intertemporal capital asset pricing model (ICAPM): If return volatility varies due to changes in investment opportunities, hedging demand can explain the negative relation between expected returns and volatility.

On the other hand, $r-$IVOL, i.e., the residual part of IVOL is in fact positively associated with stock returns. By construction, $r-$IVOL is uncorrelated with the common fluctuations of IVOL, and the data set of portfolio returns sorted by $r-$IVOL provides a good laboratory to examine if an idiosyncratic risk or uncertainty is priced in the stock market. If there exists no market friction and complete market prevails, this type of risk and uncertainty should be diversified away. Our results imply that this is not the case.

3.5.3.2 Aggregate Analysts Forecast Dispersion

We consider another potential channel through which IVOL affects stock returns. We construct aggregate analysts' EPS forecast dispersion as a proxy for aggregate uncertainty related to economy-wide profitability as mentioned earlier. Again, we use portfolio sorting strategies to examine how partially fitted IVOL related to aggregate analysts forecast dispersion affects expected return. To this end, in Table B.5, we include all the aggregate variables in the equation (3.30), and sort stocks on the partially fitted IVOL as well as all the fitted IVOL.

Most notably, the common factors of earnings forecast dispersion matter in that the zero-cost portfolio constructed from the summation of the partially fitted IVOL related to each of the common factor yields significantly positive mean return and alpha at 1% level.[6] The channels through which forecast dispersions affect stock returns can be both positive or negative. Diether, Malloy, and Scherbina (2002) argue that there exists a negative relation between forecast dispersion and stock returns due to the existence of short sale constraints. On the other hand, existing literature focusing on ambiguity or uncertainty aversion claims a positive link based upon the notion of uncertainty-return tradeoff. In our case, we filter this channel through the lens of return volatility, and which effect dominates is an empirical concern. Thus, our result shows that a positive uncertainty premium exists for holding stocks, and this can weaken the negative relation between stock returns and return volatilities.

Regarding macroeconomic variables, similar to the result in Table B.4, Table B.5 shows that the total fitted IVOL shows a significantly negative IVOL effect, reproducing the AHXZ (2006)'s finding, and the portfolio returns sorted on $r-$IVOL are positive. The mean return from the fitted IVOL is around -1.37% for the mean return and -1.62% for the abnormal returns, which is quite comparable to the results in Table B.2. Volatility risks related to macroeconomic risks as a whole are priced negatively, suggesting that investors demand these firms to hedge against macroeconomic volatility risks. [7] For the latter, $r-$IVOL, the results are robust at 1% significance level, with a mean return of 0.534$\%$ and an alpha of 0.549$\%$. This finding implies that purely idiosyncratic risks price the cross-section of stock returns in a positive fashion.

Examining individual variables used to explain IVOL, most of the variables show negative relations. Some aggregate variables, such as money growth volatility, output growth volatility, recession, and the aggregate trading volume show negative relations, but their statistical significances are marginally significant or insignificant. Zero cost portfolios sorted on the partially fitted IVOL

[6]To conserve space, we did not report the results from cases with each common forecast dispersion factor included. Results are similar, and available upon request.

[7]We also construct a zero-cost portfolio from the summation of the macroeconomic variables, and mean return and alpha are significantly negative.

related to term spread ($Term_t$) and the dividend-to-price ratio (DP_t) remain robust in the sense that mean return are -0.233$\%$ and -0.312$\%$ respectively, which are all statistically significant, and alphas are also significant at 1$\%$ level. Moreover, mean return and abnormal return of the zero cost portfolio sorted on credit spread ($Yield_t$) becomes negative and statistically significant in this specification. It realizes a mean return of -0.350$\%$ with a t-statistic of -2.06, and an abnormal return of -0.537$\%$ at 1$\%$ significance level.

However, there also exist zero-cost portfolios that have opposite signs of mean return and alpha compared to Table B.4. For example, in Table B.4, zero cost portfolio sorted on the leverage ($Leverage_t$)-related fitted IVOL has marginally significant, negative returns. Nevertheless, in our full specification with uncertainty channel, the magnitude of returns and their t-statistics increase a lot. The mean return is 0.170$\%$ per month and the alpha is 0.218$\%$, which is statistically significant.

In sum, under the specifications used in Tables B.4 and B.5, it is evident that macroeconomic variables are capable of explaining the IVOL of each firm. The IVOL puzzle is driven mostly by the systematic variation related to risk priced in the market via the volatility channel. In addition, IVOL can affect stock returns through the uncertainty channel, proxied by aggregate forecast dispersion factors. However, aggregate uncertainty affects stock returns positively, generating positive uncertainty premiums. Regarding the effects of idiosyncratic risk, the residual part of IVOL is positively related to expected returns, as suggested by Merton (1987) and Epstein and Schneider (2008).

3.5.4 Regression Results Using Factor-Mimicking Portfolios

So far, our results from portfolio strategies suggest that IVOL can be explained by some systematic variations related to both stock market volatility and aggregate uncertainty regarding future earnings. In this subsection, we use a return-based regression approach to test the explanatory power of these aggregate variables.

Given that our zero cost portfolios in Table B.4 and Table B.5 are directly sorted on the size of $\hat{\gamma}_i^j X_t^j$, or X_t^j-related fitted IVOL for each macro variable j, we can use returns to these zero investment portfolios as additional return-based factors. A zero investment portfolio sorted on

IVOL serves as our main test asset. We first test the CAPM model using this test asset. As shown in the first column of Table 6, CAPM model is unable to price this asset correctly in the sense that it would yield an abnormal return of -1.220% per month at 1% significance level.

Next, we augment the CAPM model with our return-based factors. We can see from Models 2 to Model 5 in Table B.6 that the time-series intercept $alpha$ decreases in both magnitude and t-statistics. The zero cost portfolio sorted on IVOL will earn an alpha around -0.25%, but this abnormal return is statistically insignificant under the models including the portfolios mimicking IVOL using macro variables. In fact, some return-based factors are significant determinants of IVOL portfolios. Credit spread ($Yield$), Cash-Flow-to-price (CP) and trading activity ($Tvlm$)-related factors have positive loadings while inflation ($INFLvol$), leverage (Lev) and aggregate dispersion ($Disp_t^1$) -related factors are negatively related to the portfolio return. In sum, the IVOL portfolio returns are well explained by the macroeconomic variables explaining the IVOL.

3.6 Robustness Checks and Discussions

In this section, we perform robustness tests. We begin with using alternative IVOL measures as argued by several authors. Next, we check if our results are robust to preferences about skewness. Then, we further discuss the associations between IVOL and uncertainty.

3.6.1 Alternative IVOL measures

As discussed in earlier sections, our IVOL measure is estimated using daily returns over the previous month. However, Bali and Cakici (2008) also consider another IVOL measure that is based on the previous 24 to 60 monthly returns, and Fu (2009) uses a generalized autoregressive conditional heteroskedasticity (GARCH) model. Inspired by their measures, we use monthly return data to compute IVOL as well. We resort to the following GARCH (1,1) model using monthly data and IVOL is estimated as the standard deviation of ϵ_t^i.

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \epsilon_t^i, \tag{3.31}$$

$$E((\epsilon_t^i)^2|\Omega_{t-1}) = \sigma_{it}^2 = \theta_0^i + \theta_1^i(\epsilon_{t-1}^i)^2 + \theta_2^i(\sigma_{t-1}^i)^2 \tag{3.32}$$

As before, in each month we sort stocks and form the zero cost portfolio based on this new IVOL measure over the previous month. Table B.7 reports the mean and abnormal return of the zero cost portfolio. Contrary to Bali and Cakici (2008)'s finding, there exists a negative and significant relation between this new IVOL measure and the expected returns, and IVOL puzzle still exists, according to the results in Model A.

To test the explanatory power of our return-based factors used in the previous section, we include them in Model B to re-estimate a new IVOL as the standard deviation of the residual term. As shown in Table B.7, the zero-cost portfolios sorted on these IVOL measures show that both the magnitude and the significance are significantly reduced by a large amount compared to Model A. As robustness checks, we also use GARCH(1,1) in Fama and French (2015) five-factor model with and without our return-based factors to estimate IVOLs. A very similar pattern arises, and our factor mimicking factor works reasonably well.

Thus far, we use the holding return data to estimate IVOL without distinguishing capital gains and cash flows. Next, we decompose the holding returns into two parts based on the following definition

$$Holding\ Period\ Return = \frac{P_{it}-P_{i,t-1}}{P_{i,t-1}} + \frac{D_{it}}{P_{i,t-1}}.$$

We denote $\frac{P_{it}-P_{i,t-1}}{P_{i,t-1}}$ as the capital gain and $\frac{D_{it}}{P_{i,t-1}}$ as the cash flow return. Accordingly, we could re-estimate our IVOL measures based on these two different returns, and check our main findings.

Table B.8 reports the results. First, we sort stocks on capital gain IVOL ($IVOLx$) and the cash flow return IVOL($IVOLr$) respectively, and form zero cost portfolios. As shown in the table, the zero cost portfolio sorted on $IVOLx$ has negative and significant raw and abnormal return while the one sorted on $IVOLr$ does not. It indicates that the IVOL puzzle mainly comes from capital gain or the return without dividend part. Then we regress the capital gain IVOL ($IVOLx$) on our aggregate variables, and obtain the fitted capital gain IVOL and the residual capital gain IVOL. Consistent with the main finding in Table B.5, the fitted capital gain IVOL generates the negative relation between the IVOL measure and the expected return, while the zero cost portfolio sorted on the residual capital gain IVOL has a positive and significant raw and abnormal return. Thus, our main findings remain robust.

3.6.2 Lottery and Skewness

One potential explanation of the IVOL puzzle is related to the lottery preference of investors. Doran, Jiang, and Peterson (2011) find stocks with strong lottery features typically have high idiosyncratic volatility, and outperform stocks with weak lottery features in January but not necessarily the other months. Their explanation is that because of a New Year's gambling preference, stock market gamblers chase after these stocks, inducing a positive relation between IVOL and the expected return only in January and the negative relation between IVOL and expected returns in the remainder of year. They suggest that the negative relation in non-January months suggests a correction of overpricing of the lottery-type stocks caused by investor preference of speculative features. Following Doran, Jiang, and Peterson (2011), we split our monthly return data into January returns and non-January returns. According to Table B.9, raw mean returns in January are strongly positive and negative in non-January months, consistent with the finding of Doran, Jiang, and Peterson (2011). However, when risk adjustment is made using Fama-French 3 factors, the effect becomes insignificant. More importantly, the r-IVOL effect prevails both in January and non-January months, showing a positive relation between IVOL and stock returns. In fact, both January and non-January effect are roughly the same, implying that the skewness channel is weak.

Related, Kapadia (2006) and Boyer, Mitton, and Vorkink (2010) show that the IVOL puzzle is consistent with investor preference for positive skewness in stock returns. They suggest IVOL as a proxy for skewness. Thus, a more skewed stock, hence higher IVOL stock is preferred, and requires a lower expected return. We measure skewness using daily returns, and each month we sort stocks first on their skewness into two groups and then on IVOL with each skewness group. Table B.10 reports the results. First, the IVOL effect exists in both low and high skewness group. Raw and abnormal return of the zero cost IVOL portfolio do not seem very differentiated between each group. In addition, our results are still robust, though the residual IVOL effect is somewhat weaker in the high skewness group. Overall, these additional explanations could not explain our findings. The IVOL puzzle is driven by the systematic variation via the volatility and uncertainty channels, and the residual IVOL is positively related to the expected return.

3.6.3 Uncertainty and Volatility

Finally, we discuss connections between uncertainty and return volatility. Our results show that the common fluctuations of IVOL are closely related to aggregate uncertainty, measured by common factors of analyst earnings forecast dispersions. Then, does uncertainty affect idiosyncratic fluctuations of IVOL ($r-$IVOL) as well? We suspect that $r-$IVOL is related more closely to firm-specific level of uncertainties, given that $m-$IVOL captures macroeconomic and common fluctuations. To answer this question, we compare $m-$IVOL and $r-$IVOL with the common and residual components of earnings forecast dispersions, respectively. We report results in Table B.11.

We compute the average sizes of the forecast dispersions for each decile of $m-$IVOL portfolios and $r-$IVOL portfolios, denoted as DISP. That is, we investigate whether uncertainty (DISP) leads to common or idiosyncratic fluctuations of IVOL. Table B.11 shows that a higher (lower) $m-$IVOL group has higher (lower) DISP, but a higher (lower) $r-$IVOL group features lower (higher) values of DISP. This implies that $m-$IVOL is positively correlated with uncertainty, but our measure of idiosyncratic risk ($r-$IVOL) is negatively correlated to uncertainty in earnings, which is puzzling.

To further investigate this, we decompose DISP into the common part ($D\hat{I}SP$) and the idiosyncratic part (Residual DISP). Panel A shows that the $m-$IVOL is positively associated with the aggregate level of uncertainty ($D\hat{I}SP$), consistent with our results in Tables 4 and 5. In addition, $m-$IVOL is not significantly related to the residual part of DISP. Taken together, we infer that $m-$IVOL measures aggregate uncertainty reasonably well, and macroeconomic uncertainty premium prevails through volatility channel.

On the other hand, Panel B shows that the residual portion of IVOL ($r-$IVOL) is negatively related to the overall forecast dispersion ($DISP$) or the fitted part of the dispersion ($D\hat{I}SP$), but positively associated with the residual part of the $DISP$. Firms that have higher idiosyncratic risks ($r-$IVOL) are those who are less exposed to aggregate uncertainty, yet more vulnerable to idiosyncratic uncertainty. Therefore, in conjunction with the results of Tables B.4 and B.5, this finding gives evidence that the positive relation between $r-$IVOL and stock returns can result from the channel of idiosyncratic risk and uncertainty being priced. Thus, the results strongly suggest that both common and idiosyncratic fluctuations of uncertainty play instrumental roles to explain the cross section of stock returns.

3.7 Conclusion

Ang, Hodrick, Xing, and Zhang (2006) find that monthly stock returns are negatively related to the idiosyncratic volatility in the previous month. They view this finding as something of a puzzle. In comparison with the cross-section of stock returns, the factor structure of the cross-section of stock return volatility is much less known. In this paper, we study the extent to which return volatilities are decomposed into common and idiosyncratic parts, using observable macroeconomic and firm-specific variables. This enables us to examine whether aggregate variables that are known to predict return-volatility and return-uncertainty relation can explain the systematic and firm-specific variations in individual return volatility. Using observable variables helps to interpret the results and reconcile alternative theories that seem to be at odds with each other. Our findings suggest that a recursive preference model with ambiguity aversion, incomplete market, and an intertemporal hedging motive is a good asset pricing model to study interactions between the cross-section of stock returns and the cross-section of return volatilities. Expanding this line of analysis to higher moments, especially skewness and kurtosis of stock returns is challenging but interesting venues to future research.

4. SUMMARY

In this dissertation, I study how ambiguity plays a role in the financial market, and how it is linked to stock return volatility. In the first essay, I measure the degree of ambiguous information regarding dividends and earnings on stock prices and study its impact on stock prices. The essay uses two proxies to quantify qualitative and uncertain aspects of news. The main finding is that stock returns response more strongly to bad news than good news. Furthermore, the magnitude of the asymmetric effect enlarges when news becomes more ambiguous as measured by ambiguity proxies. The essay contributes to the literature by providing ambiguity proxies at the firm level, which are useful to future research in finance and accounting. Moreover, it shows empirical evidence consistent with the theory of ambiguity aversion, providing insights into how investors process information with uncertain value.

In the second essay, "Ambiguity, Macro Factors, and Stock Return Volatility", coauthored with Hwagyun Kim, we study the extent to which return volatilities are decomposed into common and idiosyncratic parts, using observable macroeconomic and firm-specific variables. This enables us to examine whether aggregate variables that are known to predict return-volatility and return-uncertainty relation can explain the systematic and firm-specific variations in individual return volatility. We find that aggregate variables known to explain stock market volatility affect the IVOL and portfolio returns sorted by IVOL. Teasing out the common IVOL part, the residual IVOL is positively and significantly related to stock returns and the idiosyncratic portions of earnings forecast dispersions. Our findings suggest that a recursive preference model with ambiguity aversion, incomplete market, and an intertemporal hedging motive is a good asset pricing model to study interactions between the cross-section of stock returns and the cross-section of return volatilities. Expanding this line of analysis to higher moments, especially skewness and kurtosis of stock returns is challenging but interesting venues to future research.

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APPENDIX A

TABLES AND FIGURES FOR SECTION 2

A.1 Tables and Figures

Table A.1: Variable Definitions

This table defines all variables used in this paper.

Variables	Definition
$adjusted\_net\_tone$	$\frac{No.\ of\ positive\ words - No.\ of\ negative\ words}{No.\ of\ positive\ words + No.\ of\ negative\ words}$
net_tone	$\frac{No.\ of\ positive\ words - No.\ of\ negative\ words}{No.\ of\ total\ words}$
$Goodnews$	$adjusted\_net\_tone$ if $adjusted\_net\_tone > 0$, and 0 otherwise.
$Badnews$	$adjusted\_net\_tone$ if $adjusted\_net\_tone < 0$, and 0 otherwise.
AMB^{numseq}	$1 - \frac{No.\ of\ numeric\ sequence}{No.\ of\ total\ words}$
AMB^{numsym}	$1 - \frac{No.\ of\ numeric\ symbols}{No.\ of\ total\ words}$
AMB^{unc}	$\frac{No.\ of\ uncertain\ words}{No.\ of\ total\ words}$
CER	$\frac{No.\ of\ certain\ words}{No.\ of\ total\ words}$
AMB^{netunc}	AMB^{unc} - CER
$No.\ of\ Articles$	the number of articles about a firm each day
CAR	two-day (t,$t+1$) cumulative Fama and French (2015) five factors and momentum factor model adjusted return over the news day t
ΔVIX	two-day change in the VIX immediately preceding the news window (t,$t+1$)
VIX_lag	average level of VIX over the week prior to the news window (t,$t+1$)
$Size$	firm's market equity value
$Illiquidity$	Amihud (2002) illiquidity, $10^6 * \frac{\lvert return \rvert}{DollarVolume}$
$Return\_lag$	firm's return over the previous month leading up to the news window

Continued on next page

Table A.1 Continued

Variables	Definition
$Past\_Return\_Dummy$	a dummy variable equal to 1 if $Return\_lag$ is negative, and 0 otherwise
$Sentiment$	Baker and Wurgler (2006) Sentiment Index
$DCAPE$	relative price-to-earnings ratio; monthly change in cyclically-adjusted price-to-earnings ratio
$EPUI$	Baker et al. (2016) Economic Policy Uncertainty Index
$Short\ Interest$	shares held short divided by shares outstanding
$Institutional\ Ownership$	shares held by asset managers divided by shares outstanding
$Div\_Increase$	a dummy variable equal to 1 if the dividend change is positive during the news window (t,t+1), and 0 otherwise
MTB	market value of equity over the book value of equity
Vol_lag	standard deviation of daily stock returns in one-year period ending two months prior to the news window (t,t+1)
$High-tech$	a dummy of 1 if firms in high technology industries (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379 and 8731-8734)
$Reg.Ind$	a dummy of 1 if firms in regulated industries (SIC codes 4812-4813, 4833, 4841, 4811-4899, 4922-4924, 4931 and 4941)
$Insider$	the fraction of total shares outstanding held by managers.

Table A.2: Summary Statistics

This table reports summary statistics for variables used in the paper. News-related variables are constructed using Factiva, and stock data is from Center for Research in Security Prices (CRSP). Panel A reports news variables summary statistics at the news level and Panel C reports summary statistics across good and bad news. Definitions of good and bad news are from Tetlock et al. (2008). Panel B reports other variables. All variables are defined as in Table A.1. The sample is from Jan. 2000 to Dec. 2015.

Panel A: News Variables

Variables	No. of Observation	Mean	Median	Std. Dev.
$adjusted\_net\_tone$	59076	-0.080	0.000	0.579
net_tone	59076	-0.003	0.000	0.013
AMB^{numseq}	59076	0.922	0.927	0.038
AMB^{numsym}	59076	0.944	0.952	0.034
AMB^{unc}	59076	0.004	0.003	0.006
AMB^{netunc}	59076	0.001	0.000	0.007
STR	59076	0.003	0.001	0.005

Panel B: Other Variables

Variables	No. of Observation	Mean	Median	Std. Dev.
$No.\ of\ Articles$	36968	1.652	1.000	1.139
$CAR(\%)$	36968	-0.032	0.034	4.278
$Size(\$m)$	36968	43634	17055	65810
$Illiquidity$	36968	0.00019	0.00007	0.00035
$Return\_lag(\%)$	36968	0.580	0.952	8.093

Table A.2 Continued

Panel C: News Variables by Type

	Good News (n=12101)		Bad News (n=17932)		
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Diff.
$adjusted\_net\_tone$	0.546	0.339	-0.537	0.307	-1.082***
net_tone	0.008	0.006	-0.012	0.009	-0.021***
AMB^{numseq}	0.922	0.030	0.928	0.032	0.005***
AMB^{numsym}	0.944	0.027	0.950	0.028	0.006***
AMB^{unc}	0.004	0.005	0.005	0.006	0.001***
AMB^{netunc}	0.001	0.006	0.002	0.006	0.001***
STR	0.003	0.004	0.003	0.004	0.000***

Table A.3: Correlations among News Variables

This table reports correlation among news variables used in the paper. All variables are defined as in Table 1. The sample is from Jan. 2000 to Dec. 2015.

	$adjuseted\_net\_tone$	net_tone	AMB^{numseq}	AMB^{numsym}	AMB^{unc}	CER
net_tone	0.823	1				
AMB^{numseq}	-0.038	-0.091	1			
AMB^{numsym}	-0.059	-0.101	0.896	1		
AMB^{unc}	-0.086	-0.105	0.326	0.270	1	
CER	-0.009	-0.004	0.224	0.153	0.080	1
AMB^{netunc}	-0.062	-0.080	0.103	0.108	0.732	-0.621

Table A.4: Investors Responses to News

This Table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
$Goodnews$	0.130***	0.128***	0.135***	0.132***
	(6.24)	(6.14)	(6.77)	(6.61)
$Badnews$	0.382***	0.393***	0.383***	0.391***
	(17.57)	(18.12)	(17.87)	(18.37)
Controls:				
VIX_lag		0.005		0.029
		(0.11)		(0.62)
$Size$		-0.014		0.064**
		(-0.18)		(2.45)
$Illiquidity$		0.076		0.014
		(1.50)		(0.30)
$Return\_lag$		-0.116***		-0.099***
		(-3.65)		(-3.13)
$No.\ of\ Articles$		-0.081***		-0.078***
		(-3.16)		(-3.07)
Test of Asymmetry				
Goodnews - Badnews	-0.252***	-0.265***	-0.248***	-0.259***
Fixed Effects	F,Y	F,Y	I,Y	I,Y
N	36968	36968	36968	36968
adj. R^2	0.021	0.022	0.017	0.018

Table A.5: Investors Responses to News Incorporating Ambiguity Measures

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. Ambiguity proxies are included. AMB^{numseq} is the qualitative-based proxy and AMB^{netunc} is the uncertainty-based proxy. Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Goodnews$	0.125***	0.126***	0.122***	0.127***	0.130***	0.124***
	(6.00)	(5.98)	(5.80)	(6.38)	(6.45)	(6.16)
$Badnews$	0.389***	0.399***	0.396***	0.387***	0.397***	0.394***
	(17.92)	(18.07)	(17.94)	(18.15)	(18.27)	(18.15)
AMB^{numseq}	-0.123***		-0.129***	-0.132***		-0.138***
	(-5.19)		(-5.38)	(-5.65)		(-5.84)
AMB^{netunc}		0.047**	0.058***		0.044**	0.056***
		(2.26)	(2.79)		(2.19)	(2.79)
Controls:						
VIX_lag	0.007	0.006	0.007	0.032	0.030	0.033
	(0.14)	(0.12)	(0.15)	(0.68)	(0.62)	(0.70)
$Size$	-0.019	-0.014	-0.019	0.084***	0.064**	0.085***
	(-0.24)	(-0.18)	(-0.24)	(3.20)	(2.46)	(3.24)
$Illiquidity$	0.075	0.076	0.075	0.009	0.014	0.009
	(1.49)	(1.49)	(1.49)	(0.21)	(0.31)	(0.21)
$Return\_lag$	-0.119***	-0.116***	-0.119***	-0.103***	-0.099***	-0.103***
	(-3.74)	(-3.64)	(-3.73)	(-3.25)	(-3.12)	(-3.25)
$No.\ of\ Articles$	-0.085***	-0.083***	-0.088***	-0.081***	-0.080***	-0.083***
	(-3.30)	(-3.24)	(-3.41)	(-3.17)	(-3.15)	(-3.27)
Test of Asymmetry						
Goodnews - Badnews	-0.264***	-0.273***	-0.274***	-0.260***	-0.267***	-0.270***
Fixed Effects	F,Y	F,Y	F,Y	I,Y	I,Y	I,Y
N	36968	36968	36968	36968	36968	36968
adj. R^2	0.023	0.022	0.023	0.019	0.018	0.019

Table A.6: Investors Responses to News Following Changes in Ambiguity

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. Ambiguity proxies are included. AMB^{numseq} is the qualitative-based proxy and AMB^{netunc} is the uncertainty-based proxy. Other control variables are defined as in Table 1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
	AMB^{numseq}	AMB^{numseq}	AMB^{netunc}	AMB^{netunc}
$Goodnews$	0.120***	0.123***	0.122***	0.125***
	(5.75)	(6.20)	(5.70)	(6.11)
$Goodnews * Ambiguity$	-0.014	-0.009	-0.005	-0.019
	(-0.67)	(-0.41)	(-0.27)	(-0.97)
$Badnews$	0.403***	0.401***	0.400***	0.398***
	(18.34)	(18.60)	(18.01)	(18.26)
$Badnews * Ambiguity$	0.081***	0.083***	0.034*	0.031*
	(4.38)	(4.52)	(1.91)	(1.76)
$Ambiguity$	-0.033	-0.042	0.082***	0.082***
	(-1.00)	(-1.28)	(2.99)	(3.13)
Controls:				
VIX_lag	0.009	0.035	0.006	0.030
	(0.19)	(0.74)	(0.12)	(0.62)
$Size$	-0.025	0.086***	-0.014	0.065**
	(-0.32)	(3.26)	(-0.18)	(2.48)
$Illiquidity$	0.077	0.009	0.075	0.013
	(1.53)	(0.20)	(1.48)	(0.29)
$Return\_lag$	-0.123***	-0.107***	-0.116***	-0.099***
	(-3.88)	(-3.40)	(-3.65)	(-3.14)
$No.\ of\ Articles$	-0.085***	-0.081***	-0.086***	-0.083***
	(-3.33)	(-3.17)	(-3.33)	(-3.24)
Test of Asymmetry				
(Goodnews + Goodnews*Ambiguity)				
- (Badnews +Badnews*Ambiguity)	-0.378***	-0.370***	-0.317***	-0.323***
Fixed Effects	F,Y	I,Y	F,Y	I,Y
N	36968	36968	36968	36968
adj. R^2	0.024	0.020	0.023	0.018

Table A.7: Investors Responses to News Following Changes in Ambiguity: Alternative Ambiguity Dictionaries

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. AMB^{netunc} is the uncertainty-based proxy. In column (1) and (2), uncertain words and certain words are defined by the overlap of Loughran and McDonald (2011) list and the GI dictionary. Column (3) and (4) use a modified list of the overlap dictionary. Column (5) and (6) use a combined dictionary of Loughran and McDonald (2011) list and the GI dictionary for uncertain and certain words. Other control variables are defined as in Table 1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)					
	LM-GI Overlap		LM-GI Ovlap Modified		LM-GI Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
$Goodnews$	0.122***	0.126***	0.127***	0.131***	0.121***	0.125***
	(5.84)	(6.36)	(5.86)	(6.30)	(5.68)	(6.17)
$Goodnews * AMB^{netunc}$	-0.034*	-0.034*	0.006	0.004	-0.036*	-0.043**
	(-1.79)	(-1.93)	(0.28)	(0.19)	(-1.74)	(-2.20)
$Badnews$	0.396***	0.394***	0.392***	0.390***	0.400***	0.398***
	(18.25)	(18.50)	(18.01)	(18.26)	(18.09)	(18.30)
$Badnews * AMB^{netunc}$	0.036*	0.038**	0.033*	0.034*	0.039**	0.030*
	(1.83)	(1.98)	(1.70)	(1.80)	(2.14)	(1.68)
AMB^{netunc}	0.013	0.023	-0.021	-0.013	0.092***	0.081***
	(0.39)	(0.73)	(-0.62)	(-0.39)	(3.17)	(2.96)
Controls:						
VIX_lag	0.006	0.030	0.006	0.031	0.005	0.029
	(0.12)	(0.64)	(0.13)	(0.65)	(0.12)	(0.62)
$Size$	-0.015	0.068***	-0.016	0.069***	-0.014	0.064**
	(-0.20)	(2.59)	(-0.21)	(2.65)	(-0.18)	(2.47)
$Illiquidity$	0.076	0.013	0.076	0.012	0.075	0.013
	(1.51)	(0.28)	(1.50)	(0.26)	(1.49)	(0.29)
$Return\_lag$	-0.118***	-0.100***	-0.118***	-0.101***	-0.116***	-0.099***
	(-3.69)	(-3.17)	(-3.71)	(-3.19)	(-3.65)	(-3.14)
$No.\ of\ Articles$	-0.083***	-0.080***	-0.084***	-0.081***	-0.085***	-0.082***
	(-3.23)	(-3.13)	(-3.27)	(-3.16)	(-3.32)	(-3.20)
Test of Asymmetry						
(Goodnews + Goodnews*AMB^{netunc})						
- (Badnews + Badnews*AMB^{netunc})	-0.344***	-0.340***	-0.292***	-0.289***	-0.354***	-0.346***
Fixed Effects	F,Y	I,Y	F,Y	I,Y	F,Y	I,Y
N	36968	36968	36968	36968	36968	36968
adj. R^2	0.023	0.018	0.023	0.018	0.023	0.018

Table A.8: Investors Responses to Non Press Release News Following Changes in Ambiguity

This table reports the results from regressions of returns on firm news and control variables using non press release news. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to normalized news tone when news tone is larger (smaller) than 0, and 0 otherwise. Column (1)-(2) include AMB^{numseq}, the qualitative-based proxy. AMB^{netunc} is the uncertainty-based proxy and included in Column (3)-(4). Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
	AMB^{numseq}	AMB^{numseq}	AMB^{netunc}	AMB^{netunc}
$Goodnews$	0.185***	0.185***	0.191***	0.190***
	(6.71)	(6.85)	(6.98)	(7.08)
$Goodnews * Ambiguity$	0.009	0.016	0.019	0.007
	(0.40)	(0.70)	(0.80)	(0.29)
$Badnews$	0.428***	0.430***	0.419***	0.421***
	(17.09)	(17.33)	(16.92)	(17.18)
$Badnews * Ambiguity$	0.103***	0.106***	0.034*	0.035*
	(5.00)	(5.21)	(1.71)	(1.74)
$Ambiguity$	-0.032	-0.040	0.048	0.049
	(-0.86)	(-1.11)	(1.34)	(1.40)
Controls:				
VIX_lag	0.019	0.046	0.013	0.037
	(0.35)	(0.87)	(0.24)	(0.70)
$Size$	-0.021	0.091***	-0.008	0.067**
	(-0.25)	(2.91)	(-0.09)	(2.19)
$Illiquidity$	0.062	-0.000	0.058	0.003
	(1.08)	(-0.00)	(1.01)	(0.06)
$Return\_lag$	-0.141***	-0.126***	-0.131***	-0.115***
	(-3.85)	(-3.48)	(-3.57)	(-3.15)
$No.\ of\ Articles$	-0.119***	-0.116***	-0.116***	-0.115***
	(-4.15)	(-4.09)	(-4.02)	(-4.04)
Test of Asymmetry				
(Goodnews + Goodnews*Ambiguity)				
- (Badnews +Badnews*Ambiguity)	-0.337***	-0.335***	-0.243***	-0.259***
Fixed Effects	F,Y	I,Y	F,Y	I,Y
N	31509	31509	31509	31509
adj. R^2	0.027	0.023	0.026	0.022

Table A.9: Robustness Check: Investors Responses to News Following Changes in Qualitative-based Ambiguity Controlling Alternative Explanations

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. AMB^{numseq}, the qualitative-based proxy is included as the Ambiguity proxy. $Sentiment$ is the Baker and Wurgler (2006) sentiment index $DCAPE$ is the change in cyclical-adjusted price-to-earnings-ratio. $EPUI$ is the Economic Policy Uncertainty Index. MTB is the market-to-book ratio. Vol_lag is the past stock volatility. $Hi - tech$ is a dummy for High-tech firms. $Reg.Ind$ is a dummy for firms in regulated industries. $Insider$ is the fraction of stock shares held by managers. $Past\_Return$ is the firm's return over the previous month leading up to the news window. $Past\_Return\_Dummy$ is a dummy for negative $Past\ Return$. Other control variables are defined as in Table 1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

Table A.9 Continued

Panel A: Macro-level Explanations

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
	$Change\_in\_VIX$	$Sentiment$	$DCAPE$	$EPUI$
$Goodnews$	0.113***	0.136***	0.145***	0.136***
	(3.89)	(6.01)	(6.29)	(6.04)
$Goodnews * AMB^{numseq}$	-0.023	-0.017	-0.014	-0.021
	(-1.05)	(-0.76)	(-0.63)	(-0.97)
$Badnews$	0.404***	0.396***	0.387***	0.401***
	(13.47)	(17.51)	(17.66)	(17.94)
$Badnews * AMB^{numseq}$	0.085***	0.091***	0.082***	0.084***
	(4.52)	(4.72)	(4.32)	(4.43)
AMB^{numseq}	-0.017	-0.010	-0.020	-0.018
	(-0.51)	(-0.30)	(-0.60)	(-0.54)
$Alternative$	0.007	-0.156*	0.075	0.065
	(0.10)	(-1.93)	(1.09)	(1.44)
$Goodnews * Alternative$	0.039	0.050*	-0.059**	0.017
	(0.98)	(1.71)	(-1.97)	(0.66)
$Badnews * Alternative$	-0.001	0.026	-0.073***	0.022
	(-0.01)	(1.06)	(-2.95)	(0.92)
$Div\_Increase$	0.386***	0.362***	0.371***	0.372***
	(3.03)	(2.82)	(2.90)	(2.91)
$Goodnews * Div\_Increase$	-0.197***	-0.183***	-0.185***	-0.190***
	(-3.21)	(-2.95)	(-3.01)	(-3.10)
$Badnews * Div\_Increase$	-0.124	-0.090	-0.121	-0.128
	(-1.11)	(-0.82)	(-1.08)	(-1.16)
Other Controls (See Table 4)	Yes	Yes	Yes	Yes
Test of Asymmetry				
(Goodnews + Goodnews*AMB^{numseq})				
- (Badnews +Badnews*AMB^{numseq})	-0.399***	-0.368***	-0.338***	-0.370***
Fixed Effects	F,Y	F,Y	F,Y	F,Y
N	36741	35880	36968	36968
adj. R^2	0.024	0.024	0.025	0.024

Table A.9 Continued

Panel B: Withholding Bad News Explanations

	Dependent Variable CAR(0,+1)				
	(1)	(2)	(3)	(4)	(5)
	MTB	Vol_lag	$Hi-tech$	$Reg.Ind$	$Insider$
$Goodnews$	0.164***	0.153***	0.115***	0.158***	0.136***
	(6.11)	(5.72)	(5.15)	(6.11)	(5.83)
$Goodnews * AMB^{numseq}$	-0.027	-0.016	-0.024	-0.021	-0.022
	(-1.00)	(-0.76)	(-1.11)	(-0.95)	(-0.97)
$Badnews$	0.482***	0.386***	0.405***	0.441***	0.406***
	(17.24)	(17.72)	(17.70)	(17.03)	(17.31)
$Badnews * AMB^{numseq}$	0.107***	0.076***	0.085***	0.084***	0.089***
	(4.34)	(4.02)	(4.49)	(4.48)	(4.53)
AMB^{numseq}	-0.022	-0.035	-0.017	-0.021	-0.019
	(-0.54)	(-1.05)	(-0.49)	(-0.62)	(-0.56)
$Alternative$	-0.108**	0.261***	-0.279	-0.682***	0.133*
	(-2.13)	(3.47)	(-0.84)	(-3.10)	(1.81)
$Goodnews * Alternative$	0.077***	0.033	0.152*	-0.116***	-0.010
	(3.19)	(0.83)	(1.82)	(-2.68)	(-0.36)
$Badnews * Alternative$	-0.028	0.158***	-0.032	-0.174***	0.085***
	(-0.98)	(5.34)	(-0.40)	(-3.66)	(2.98)
$Div\_Increase$	0.264*	0.413***	0.371***	0.384***	0.347***
	(1.74)	(3.24)	(2.91)	(3.01)	(2.64)
$Goodnews * Div\_Increase$	-0.177**	-0.192***	-0.187***	-0.190***	-0.181***
	(-2.41)	(-3.14)	(-3.04)	(-3.10)	(-2.85)
$Badnews * Div\_Increase$	-0.304**	-0.070	-0.128	-0.126	-0.104
	(-2.24)	(-0.63)	(-1.15)	(-1.13)	(-0.91)
Other Controls (See Table 4)	Yes	Yes	Yes	Yes	Yes
Test of Asymmetry					
(Goodnews + Goodnews*AMB^{numseq})					
- (Badnews +Badnews*AMB^{numseq})	-0.452***	-0.325***	-0.399***	-0.388***	-0.381***
Fixed Effects	F,Y	F,Y	F,Y	F,Y	F,Y
N	27649	36925	36968	36968	34190
adj. R^2	0.029	0.026	0.024	0.025	0.025

Table A.9 Continued

Panel C: Other Explanations

	Dependent Variable CAR(0,+1)		
	(1)	(2)	(3)
	$Past\_Return$	$Past\_Return\_Dummy$	$Short\_Sale\_Constraint$
$Goodnews$	0.138***	0.113***	0.154***
	(6.19)	(4.19)	(6.84)
$Goodnews * AMB^{numseq}$	-0.019	-0.021	-0.011
	(-0.90)	(-0.99)	(-0.51)
$Badnews$	0.398***	0.349***	0.385***
	(17.95)	(12.22)	(16.99)
$Badnews * AMB^{numseq}$	0.081***	0.080***	0.083***
	(4.32)	(4.25)	(4.36)
AMB^{numseq}	-0.018	-0.018	-0.034
	(-0.54)	(-0.54)	(-1.01)
$Alternative$	-0.181***	0.220***	
	(-3.59)	(3.18)	
$Goodnews * Alternative$	-0.028	0.044	
	(-0.95)	(1.10)	
$Badnews * Alternative$	-0.057**	0.098**	
	(-2.12)	(2.35)	
$Div\_Increase$	0.373***	0.368***	0.364***
	(2.92)	(2.88)	(2.79)
$Goodnews * Div\_Increase$	-0.191***	-0.186***	-0.171***
	(-3.10)	(-3.03)	(-2.72)
$Badnews * Div\_Increase$	-0.126	-0.128	-0.099
	(-1.14)	(-1.16)	(-0.88)

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Table A.9 Continued

Panel C Continued

	Dependent Variable CAR(0,+1)		
	(1)	(2)	(3)
	$Past\_Return$	$Past\_Return\_Dummy$	$Short\_Sale\_Constraint$
Table Continued			
$Short\ Interest$			0.188***
			(2.93)
$Short\ Interest * Goodnews$			0.041
			(1.40)
$Short\ Interest * Badnews$			0.070**
			(2.36)
$Institutional\ Ownership$			0.057
			(0.86)
$Institutional\ Ownership * Goodnews$			0.033
			(1.41)
$Institutional\ Ownership * Badnews$			0.066***
			(2.81)
$Return\_lag$			-0.121***
			(-3.69)
Other Controls (See Table 4)	Yes	Yes	Yes
Test of Asymmetry			
(Goodnews + Goodnews*AMB^{numseq})			
- (Badnews +Badnews*AMB^{numseq})	-0.360***	-0.337***	-0.325***
Fixed Effects	F,Y	F,Y	F,Y
N	36968	36968	34387
adj. R^2	0.024	0.024	0.026

Table A.10: Robustness Check: Investors Responses to News Following Changes in Uncertainty-based Ambiguity Controlling Alternative Explanations

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. AMB^{netunc}, the uncertainty-based proxy is included as the Ambiguity proxy. $Sentiment$ is the Baker and Wurgler (2006) sentiment index $DCAPE$ is the change in cyclical-adjusted price-to-earnings-ratio. $EPUI$ is the Economic Policy Uncertainty Index. MTB is the market-to-book ratio. Vol_lag is the past stock volatility. $Hi - tech$ is a dummy for High-tech firms. $Reg.Ind$ is a dummy for firms in regulated industries. $Insider$ is the fraction of stock shares held by managers. $Past\_Return$ is the firm's return over the previous month leading up to the news window. $Past\_Return\_Dummy$ is a dummy for negative $Past\ Return$. Other control variables are defined as in Table 1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

Table A.10 Continued

Panel A: Macro-level Explanations

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
	$Change\_in\_VIX$	$Sentiment$	$DCAPE$	$EPUI$
$Goodnews$	0.117***	0.139***	0.147***	0.138***
	(3.94)	(5.96)	(6.21)	(5.99)
$Goodnews * AMB^{netunc}$	-0.006	0.000	0.001	-0.005
	(-0.29)	(0.02)	(0.05)	(-0.24)
$Badnews$	0.398***	0.390***	0.383***	0.397***
	(13.18)	(16.96)	(17.17)	(17.49)
$Badnews * AMB^{netunc}$	0.035*	0.034*	0.037**	0.032*
	(1.96)	(1.87)	(2.07)	(1.80)
AMB^{netunc}	0.082***	0.072**	0.078***	0.078***
	(2.98)	(2.54)	(2.84)	(2.83)
$Alternative$	0.011	-0.168**	0.089	0.066
	(0.16)	(-2.07)	(1.28)	(1.45)
$Goodnews * Alternative$	0.036	0.053*	-0.063**	0.020
	(0.92)	(1.83)	(-2.13)	(0.78)
$Badnews * Alternative$	0.003	0.023	-0.074***	0.024
	(0.07)	(0.95)	(-2.96)	(0.98)
$Div\_Increase$	0.383***	0.357***	0.371***	0.370***
	(3.07)	(2.85)	(2.98)	(2.97)
$Goodnews * Div\_Increase$	-0.181***	-0.169***	-0.173***	-0.176***
	(-3.03)	(-2.80)	(-2.89)	(-2.94)
$Goodnews * Div\_Increase$	-0.159	-0.130	-0.153	-0.162
	(-1.45)	(-1.20)	(-1.40)	(-1.49)
Other Controls (See Table 4)	Yes	Yes	Yes	Yes
Test of Asymmetry				
(Goodnews + Goodnews*AMB^{netunc})				
- (Badnews +Badnews*AMB^{netunc})	-0.322***	-0.285***	-0.272***	-0.296***
Fixed Effects	F,Y	F,Y	F,Y	F,Y
N	36741	35880	36968	36968
adj. R^2	0.023	0.023	0.024	0.023

Table A.10 Continued

Panel B: Withholding Bad News Explanations

	Dependent Variable CAR(0,+1)				
	(1)	(2)	(3)	(4)	(5)
	MTB	Vol_lag	$Hi-tech$	$Reg.Ind$	$Insider$
$Goodnews$	0.167***	0.156***	0.117***	0.160***	0.141***
	(6.05)	(5.73)	(5.09)	(6.02)	(5.89)
$Goodnews * AMB^{netunc}$	-0.008	0.000	-0.006	-0.003	-0.004
	(-0.31)	(0.01)	(-0.29)	(-0.16)	(-0.21)
$Badnews$	0.474***	0.382***	0.402***	0.436***	0.398***
	(16.66)	(17.23)	(17.31)	(16.57)	(16.78)
$Badnews * AMB^{netunc}$	0.038*	0.035*	0.034*	0.035*	0.020
	(1.65)	(1.94)	(1.87)	(1.96)	(1.07)
AMB^{netunc}	0.089***	0.067**	0.080***	0.080***	0.062**
	(2.63)	(2.44)	(2.92)	(2.90)	(2.12)
$Alternative$	-0.105**	0.244***	-0.266	-0.706***	0.134*
	(-2.08)	(3.24)	(-0.81)	(-3.20)	(1.82)
$Goodnews * Alternative$	0.075***	0.037	0.155*	-0.115***	-0.010
	(3.12)	(0.92)	(1.86)	(-2.64)	(-0.36)
$Badnews * Alternative$	-0.028	0.159***	-0.031	-0.171***	0.084***
	(-0.97)	(5.35)	(-0.40)	(-3.57)	(2.95)
$Div\_Increase$	0.263*	0.427***	0.368***	0.384***	0.348***
	(1.78)	(3.44)	(2.95)	(3.09)	(2.71)
$Goodnews * Div\_Increase$	-0.160**	-0.183***	-0.171***	-0.176***	-0.168***
	(-2.24)	(-3.07)	(-2.85)	(-2.94)	(-2.71)
$Badnews * Div\_Increase$	-0.342**	-0.097	-0.163	-0.160	-0.142
	(-2.57)	(-0.89)	(-1.49)	(-1.46)	(-1.26)
Other Controls (See Table 4)	Yes	Yes	Yes	Yes	Yes
Test of Asymmetry					
(Goodnews + Goodnews*AMB^{netunc})					
- (Badnews +Badnews*AMB^{netunc})	-0.353***	-0.261***	-0.325***	-0.314***	-0.281***
Fixed Effects	F,Y	F,Y	F,Y	F,Y	F,Y
N	27649	36925	36968	36968	34190
adj. R^2	0.028	0.025	0.023	0.024	0.024

Table A.10 Continued

Panel C: Other Explanations

	Dependent Variable CAR(0,+1)		
	(1)	(2)	(3)
	$Past\_Return$	$Past\_Return\_Dummy$	$Short\_Sale\_Constraint$
$Goodnews$	0.140***	0.115***	0.158***
	(6.10)	(4.16)	(6.83)
$Goodnews * AMB^{netunc}$	-0.005	-0.004	0.012
	(-0.24)	(-0.20)	(0.58)
$Badnews$	0.395***	0.342***	0.381***
	(17.48)	(11.83)	(16.56)
$Badnews * AMB^{netunc}$	0.033*	0.032*	0.016
	(1.82)	(1.80)	(0.91)
AMB^{netunc}	0.079***	0.079***	0.055**
	(2.86)	(2.85)	(1.96)
$Alternative$	-0.181***	0.221***	
	(-3.59)	(3.19)	
$Goodnews * Alternative$	-0.029	0.046	
	(-0.98)	(1.15)	
$Badnews * Alternative$	-0.063**	0.106**	
	(-2.33)	(2.54)	
$Div\_Increase$	0.372***	0.366***	0.377***
	(2.98)	(2.94)	(2.95)
$Goodnews * Div\_Increase$	-0.177***	-0.172***	-0.164***
	(-2.96)	(-2.87)	(-2.66)
$Badnews * Div\_Increase$	-0.159	-0.161	-0.134
	(-1.46)	(-1.48)	(-1.20)

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Table A.10 Continued

Panel C Continued

	Dependent Variable CAR(0,+1)		
	(1)	(2)	(3)
	$Past\_Return$	$Past\_Return\_Dummy$	$Short\_Sale\_Constraint$
Table Continued			
$Short\ Interest$			0.188***
			(2.94)
$Short\ Interest * Goodnews$			0.041
			(1.39)
$Short\ Interest * Badnews$			0.077***
			(2.61)
$Institutional\ Ownership$			0.046
			(0.69)
$Institutional\ Ownership * Goodnews$			0.034
			(1.47)
$Institutional\ Ownership * Badnews$			0.052**
			(2.20)
$Return\_lag$			-0.114***
			(-3.48)
Other Controls (See Table 4)	Yes	Yes	Yes
Test of Asymmetry (Goodnews + Goodnews*AMB^{netunc}) - (Badnews +Badnews*AMB^{netunc})	-0.293***	-0.263***	-0.227***
Fixed Effect	F,Y	F,Y	F,Y
N	36968	36968	34387
adj. R^2	0.023	0.023	0.025

Table A.11: Robustness Check: Investors Responses to News Following Changes in Ambiguity Controlling for All Explanations

This table reports the results from regressions of returns on firm news and control variables using different ambiguity measures. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to normalized news tone when news tone is larger (smaller) than 0, and 0 otherwise. Column (1)-(2) include AMB^{numseq}, the qualitative-based proxy. AMB^{netunc} is the uncertainty-based proxy and included in Column (3)-(4). Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	(1) AMB^{seq}	(2) AMB^{seq}	(3) AMB^{netunc}	(4) AMB^{netunc}
$Goodnews$	0.223***	0.210***	0.233***	0.221***
	(4.82)	(4.67)	(4.99)	(4.85)
$Goodnews * Ambiguity$	0.004	0.002	0.026	0.009
	(0.14)	(0.08)	(0.99)	(0.35)
$Badnews$	0.489***	0.488***	0.474***	0.473***
	(11.45)	(11.46)	(11.02)	(11.03)
$Badnews * Ambiguity$	0.110***	0.118***	0.026	0.024
	(4.13)	(4.41)	(1.07)	(0.97)
$Ambiguity$	-0.050	-0.051	0.036	0.030
	(-1.12)	(-1.16)	(0.98)	(0.87)
$Div\_Increase$	Yes	Yes	Yes	Yes
$Change\_in\_VIX$	Yes	Yes	Yes	Yes
$Sentiment$	Yes	Yes	Yes	Yes
$DCAPE$	Yes	Yes	Yes	Yes
$EPUI$	Yes	Yes	Yes	Yes
MTB	Yes	Yes	Yes	Yes
Vol_lag	Yes	Yes	Yes	Yes
$Hi-tech$	Yes	Yes	Yes	Yes
$Reg.Ind$	Yes	Yes	Yes	Yes
$Insider$	Yes	Yes	Yes	Yes
$Past\_Return$	Yes	Yes	Yes	Yes
$Short\ Interest$	Yes	Yes	Yes	Yes
$Institutional\ Ownership$	Yes	Yes	Yes	Yes
Other Controls (See Table 4)	Yes	Yes	Yes	Yes
Test of Asymmetry				
(Goodnews + Goodnews*Ambiguity)				
- (Badnews +Badnews*Ambiguity)	-0.372***	-0.394***	-0.241***	-0.267***
Fixed Effects	F,Y	I,Y	F,Y	I,Y
N	23378	23391	23378	23391
adj. R^2	0.037	0.031	0.035	0.029

Table A.12: Return Volatility and Ambiguity

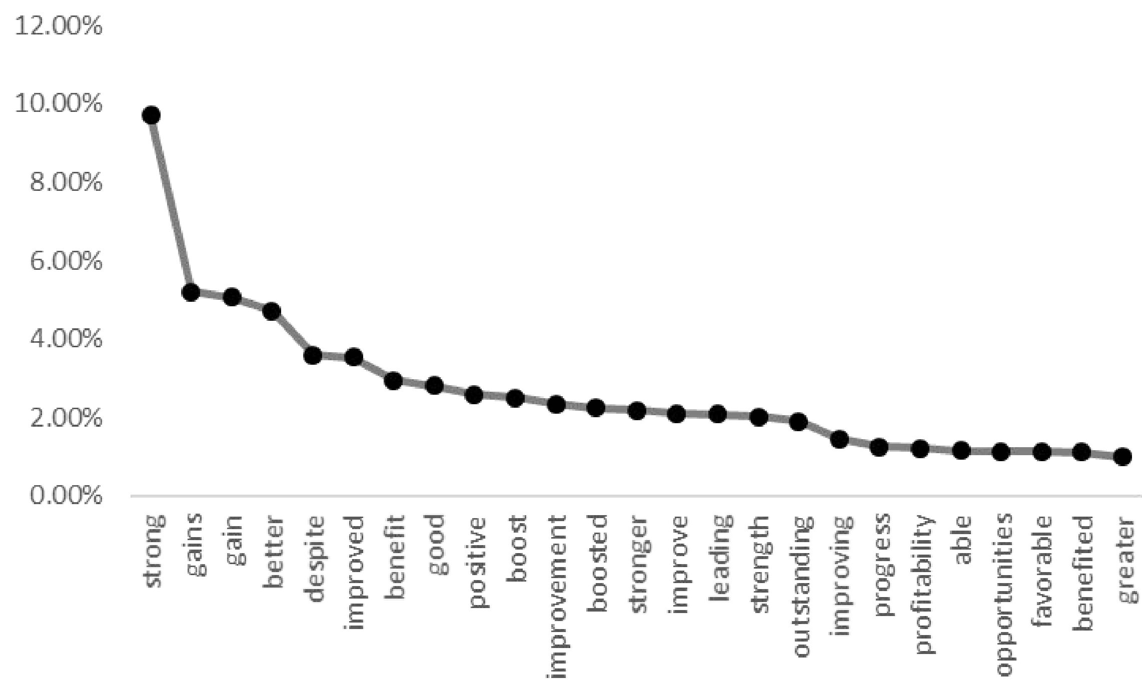
This tables reports the results from regressions of news-day return volatility on firm ambiguity measures and control variables. Dependent variables are annual stock return volatility for all news day in that year. Column (1) includes AMB^{numseq}, the qualitative-based proxy. AMB^{netunc} is the uncertainty-based proxy and included in Column (2). Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-year level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable Return Volatility on News-Day		
	(1)	(2)	(3)
AMB^{numseq}	0.113***		0.110***
	(4.81)		(4.68)
AMB^{netunc}		0.240**	0.195
		(2.01)	(1.62)
$Annual\_volatility\_lag$	0.741***	0.772***	0.737***
	(8.35)	(8.73)	(8.33)
$Size$	-0.004***	-0.004***	-0.004***
	(-4.52)	(-4.85)	(-4.55)
Fixed Effects	F,Y	F,Y	F,Y
N	5943	5943	5943
adj. R^2	0.365	0.362	0.365

Figure A.1: Top 25 Most Frequently Occurring Positive and Negative Words

This figure shows the most frequently occurring positive and negative words defined in Loughran and McDonald (2011).

(a) Positive Words



(b) Negative Words

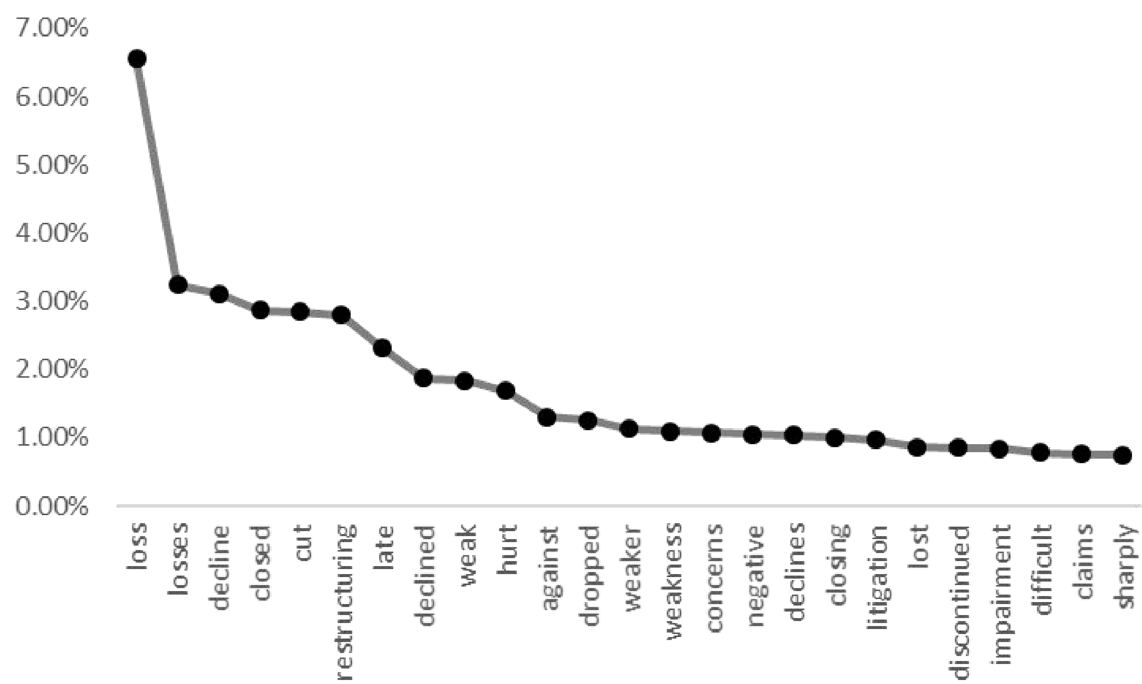
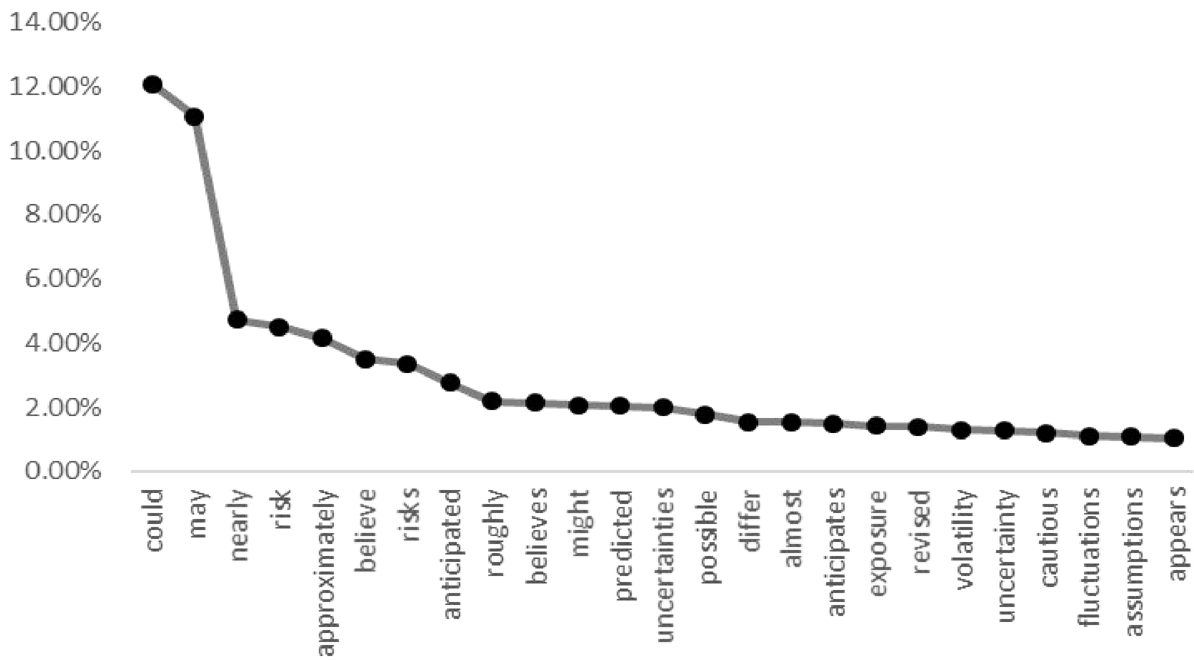


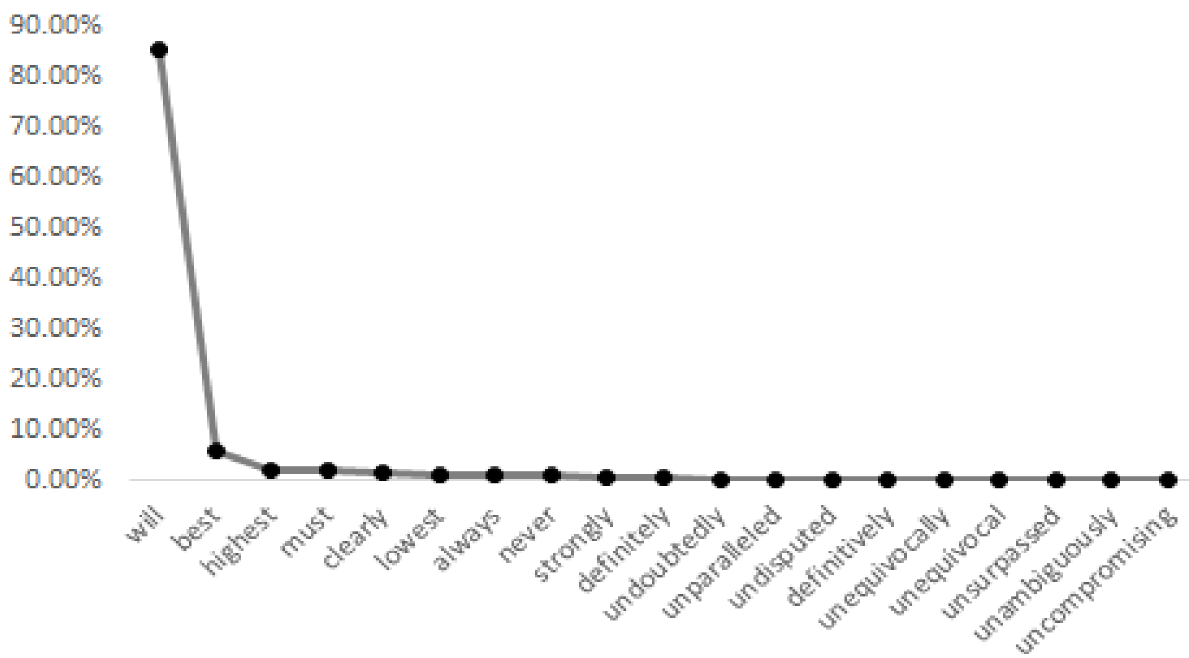
Figure A.2: Top 25 Most Frequently Occurring Uncertain and Certain Words

This figure shows the most frequently occurring uncertain and certain words defined in Loughran and McDonald (2011).

(a) Uncertain Words



(b) Certain (Strong Modal) Words



A.2 Appendix for Section 2

Table A.13: Example of Words List

This table lists top 30 most frequently occurring words in the sample for positive, negative and uncertain category in Loughran and McDonald (2011). Complete lists for certain words are shown in the last two columns.

Positive	Negative	Uncertain	Certain
strong	loss	could	will
gains	losses	may	best
gain	decline	nearly	highest
better	closed	risk	must
despite	cut	approximately	clearly
improved	restructuring	believe	lowest
benefit	late	risks	always
good	declined	anticipated	never
positive	weak	roughly	strongly
boost	hurt	believes	definitely
improvement	against	might	undoubtedly
boosted	dropped	predicted	unparalleled
stronger	weaker	uncertainties	undisputed
improve	weakness	possible	definitively
leading	concerns	differ	unequivocally
strength	negative	almost	unequivocal
outstanding	declines	anticipates	unsurpassed
improving	closing	exposure	unambiguously
progress	litigation	revised	uncompromising
profitability	lost	volatility	
able	discontinued	uncertainty	
opportunities	impairment	cautious	
favorable	difficult	fluctuations	
benefited	claims	assumptions	
greater	sharply	appears	
effective	poor	pending	
gained	slowdown	probably	
improvements	warned	anticipate	
highest	problems	preliminary	
profitable	slow	intangible	

Table A.14: Investors Responses to News Incorporating Ambiguity Measures: Alternative Tone Measure

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to net_tone when net_tone is larger (smaller) than 0, and 0 otherwise. Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)			
	(1)	(2)	(3)	(4)
$Goodnews$	0.197***	0.198***	0.190***	0.190***
	(7.92)	(7.98)	(7.95)	(7.94)
$Badnews$	0.527***	0.545***	0.534***	0.547***
	(18.42)	(19.07)	(18.88)	(19.48)
Controls:				
VIX_lag		0.006		0.031
		(0.13)		(0.66)
$Size$		-0.035		0.067**
		(-0.45)		(2.58)
$Illiquidity$		0.085*		0.022
		(1.68)		(0.49)
$Return\_lag$		-0.129***		-0.113***
		(-4.06)		(-3.57)
$No. of\ Articles$		-0.082***		-0.079***
		(-3.22)		(-3.11)
Test of Asymmetry				
Goodnews - Badnews	-0.330***	-0.347***	-0.344***	-0.357***
Fixed Effect	F,Y	F,Y	I,Y	I,Y
N	36968	36968	36968	36968
adj. R^2	0.024	0.025	0.020	0.021

Table A.15: Investors Responses to News Following Changes in Ambiguity: Alternative Ambiguity Measure

This table reports the results from regressions of returns on firm news and control variables. Dependent variables are two-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to $adjuseted\_net\_tone$ when $adjuseted\_net\_tone$ is larger (smaller) than 0, and 0 otherwise. AMB^{numsym} is the alternative qualitative-based proxy and included. Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(0,+1)	
	(1)	(2)
	AMB^{numsym}	AMB^{numsym}
$Goodnews$	0.132***	0.136***
	(6.05)	(6.48)
$Goodnews * Ambiguity$	0.0405*	0.0422*
	(1.82)	(1.93)
$Badnews$	0.397***	0.395***
	(17.83)	(18.07)
$Badnews * Ambiguity$	0.107***	0.113***
	(5.69)	(6.03)
$Ambiguity$	-0.0175	-0.0157
	(-0.54)	(-0.49)
Controls:		
VIX_lag	0.00877	0.0343
	(0.19)	(0.73)
$Size$	-0.0273	0.0788***
	(-0.35)	(3.00)
$Illiquidity$	0.0768	0.0100
	(1.53)	(0.22)
$Return\_lag$	-0.126***	-0.110***
	(-3.95)	(-3.47)
$No. of\ Articles$	-0.0826***	-0.0782***
	(-3.23)	(-3.08)
Test of Asymmetry		
(Goodnews + Goodnews*Ambiguity)		
- (Badnews + Badnews*Ambiguity)	-0.332***	-0.330***
Fixed Effects	F,Y	I,Y
N	36968	36968
adj. R^2	0.024	0.020

Table A.16: Investors Responses to News Following Changes in Ambiguity: 3-Day Event Window

This table reports the results from regressions of returns on firm news and control variables using different ambiguity measures. Dependent variables are three-day cumulative abnormal returns over every news day. Goodnews (Badnews) is equal to normalized news tone when news tone is larger (smaller) than 0, and 0 otherwise. Column (1)-(2) include AMB^{numseq}, the qualitative-based proxy. AMB^{netunc} is the uncertainty-based proxy and included in Column (3)-(4). Other control variables are defined as in Table A.1. FE is fixed effects, and N is the number of observations. All standard errors are clustered at firm-week level, and the t-statistics are reported in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The sample is from Jan. 2000 to Dec. 2015.

	Dependent Variable CAR(-1,+1)			
	(1)	(2)	(3)	(4)
	AMB^{numseq}	AMB^{numseq}	AMB^{netunc}	AMB^{netunc}
$Goodnews$	0.132***	0.131***	0.136***	0.136***
	(5.63)	(5.87)	(5.71)	(5.93)
$Goodnews * Ambiguity$	-0.019	-0.013	-0.007	-0.021
	(-0.79)	(-0.57)	(-0.31)	(-0.94)
$Badnews$	0.451***	0.448***	0.448***	0.446***
	(18.53)	(18.75)	(18.33)	(18.55)
$Badnews * Ambiguity$	0.085***	0.084***	0.030	0.027
	(4.06)	(4.05)	(1.51)	(1.38)
$Ambiguity$	-0.071*	-0.079**	0.075**	0.076***
	(-1.90)	(-2.14)	(2.41)	(2.59)
Controls:				
VIX_lag	0.122**	0.152***	0.118**	0.145***
	(2.28)	(2.83)	(2.20)	(2.71)
$Size$	-0.044	0.113***	-0.032	0.085***
	(-0.49)	(3.74)	(-0.35)	(2.87)
$Illiquidity$	0.087	0.014	0.086	0.019
	(1.63)	(0.29)	(1.59)	(0.40)
$Return\_lag$	0.285***	0.301***	0.293***	0.310***
	(7.79)	(8.26)	(8.00)	(8.49)
$No.\ of\ Articles$	-0.081***	-0.077***	-0.080***	-0.078***
	(-3.04)	(-2.90)	(-2.97)	(-2.91)
Test of Asymmetry				
(Goodnews + Goodnews*Ambiguity)				
- (Badnews +Badnews*Ambiguity)	-0.423***	-0.414***	-0.349***	-0.358***
Fixed Effects	F,Y	I,Y	F,Y	I,Y
N	36968	36968	36968	36968
adj. R^2	0.029	0.025	0.028	0.023

An Example of News Covered in Factiva

Sherwin-Williams Earnings -3: Street Sees 2002 EPS $2.01

241 words

22 October 2002

09:54

Dow Jones News Service

English

Sherwin-Williams warned that weak domestic economic activity, which hurt 2001 sales and profits, remains sluggish.

Specifically, the domestic manufacturing sector continues to delay maintenance spending, hurting industrial maintenance sales. In addition, low domestic factory output that is slowing the economic recovery is affecting product finishes and automotive original equipment manufacturer sales.

The company expects fourth-quarter sales to rise about 2.5% to 3.5% from year-ago sales of about $1.13 billion. This growth would put fourth-quarter sales between about $1.16 billion and $1.17 billion.

As a result, annual sales are expected to be 2.4% and 2.8% higher than last year's roughly $5.07 billion in sales. Full-year sales would, therefore, come to between roughly $5.19 billion and $5.21 billion.

Achieving anticipated sales would result in earnings of $2.00 to $2.06 a share, excluding the effect of adopting of SFAS 142. After adding back goodwill amortization expense to 2001 net income would have been $1.83 a share.

For 2002, First Call expects Sherwin-Williams to earn $2.01 a share, on about $5.18 billion in sales.

Sherwin-Williams said it has reduced its working capital to levels that it plans to maintain in line with its sales performance, while remaining poised for any increase in customer demand.

-Carrie Kocik; Dow Jones Newswires; 201-938-5388

APPENDIX B

TABLES AND FIGURES FOR SECTION 3

Table B.1: Summary Statistics of Variables

Panels A through D report summary statistics for monthly variables used in the paper. Panel A presents those related to stock returns, which are available from the CRSP database. In particular, Idiosyncratic volatility (IVOL) is measured relative to the Fama and French (1993) model, following Ang, Hodrick, Xing, and Zhang (2006). Panel B displays the summary statistics of the variables used to link to stock return volatility. The first group refers to macroeconomic variables, which are calculated based on Schwert (1989). Volatility of the monetary base growth ($\Delta Mvol$), of the industry production growth ($\Delta IPvol$) and of the CPI change ($INFLvol$) are estimated from equation (3.27). Recession Indicator (Recession) is equal to 1 in a recessionary period or 0 in an expansionary period. Credit spread (Yield) is the spread between Moody's Baa corporate bond yield and Aaa yield from the Federal Reserve Board. Term spread (Term) is the spread between 10-year treasury bond and 1-year treasury bond yield from the Federal Reserve Board. The second group (Corporate) contains corporate variables which are obtained from the CRSP-Compustat Merged database. ME is the firm market value in millions. BE/ME is the book to market ratio, CP refers to the Cash flow to Price ratio, and DP refers to the Dividend to Price ratio. Leverage (Lev) refers to the book value of long term debt divided by book assets. Trading Volume (Tvlm) is the ratio of the number of shares traded over total shares outstanding. Panels C and D refer to the data on analyst forecast dispersion. Analysts forecast dispersion is from I/B/E/S Merged database and is the standard deviation of earnings forecasts divided by the absolute value of the mean earnings forecast. The sample period is July 1963 to December 2012. Panel D reports the averages of adjusted R^2 explained by the common dispersion factors. Each month we regress firm-level analyst forecast dispersion ($Disp_{it}$) on up to first ten common factors from the asymptotic principal component analysis and obtain adjusted R^2

$$Disp_{it} = \alpha_i + \beta_i' F_t + u_{it},$$

where F_t are common factors obtained from asymptotic principle component analysis. $Disp_{it}$ is the standard deviation of EPS forecast divided by the absolute value of the mean EPS forecast.

Panel A: Return Characteristics

	Number of Observations	Mean	Median	Std. Dev.
Return	2880109	0.011	0.000	0.183
Return Volatility	2843406	0.033	0.026	0.031
IVOL	2843104	0.029	0.022	0.029

Table B.1 Continued

Panel B: Variables Related to Stock Market Volatility

	Variables	Number of Obs.	Mean	Median	Std. Dev.
Macro	MKTvol	595	0.009	0.007	0.005
	ΔMvol	551	0.005	0.003	0.009
	ΔIPvol	595	0.007	0.006	0.002
	INFLvol	595	0.002	0.002	0.000
	Recession	595	0.139	0.000	0.347
	Yield	595	0.011	0.009	0.005
	Term	595	0.010	0.009	0.012
Corporate	ME (in millions)	2445597	1325.217	89.200	8934.640
	BE/ME	2436642	0.959	0.348	28.801
	CP	1909502	-0.002	0.008	0.297
	DP	2288756	0.001	0.000	0.030
	Lev	2142579	0.059	0.039	0.087
	Tvlm	2558468	0.092	0.041	0.212

Panel C: Analysts Forecast Dispersion

	Number of Obs.	Mean	Median	Std. Dev.
Analysts Forecast Dispersion	1133678	0.210	0.046	1.338

Panel D: Average Explained Variance by Common Dispersion Factors

Number of factors	1	2	3	4
Average Adjusted R^2	0.124	0.195	0.238	0.270

Table B.2: Portfolios Sorted by Idiosyncratic Volatility Relative to Fama French 3 Factors

This table replicates the Table 6 of Ang, Hodrick, Xing, and Zhang (2006) and shows some robustness checks. In each month, we sort stocks based on IVOL relative to the Fama and French (1993) model. Portfolios are formed every month based on IVOL over the previous month. IVOL Ranking 1 (5) refers to the portfolio of stocks with the lowest (highest) IVOL. The statistics in the columns labeled Mean and Std. Dev. are measured in monthly percentage and apply only to total returns. The row "5-1" refers to the difference in monthly returns (alphas) between portfolio with the highest IVOL and portfolio with the lowest IVOL. The Alpha reports constants to the capital asset pricing model (CAPM) and the Fama and French (1993) three-factor model (FF-3F), respectively. For Panel C, we split our samples into recession period and expansion period according to NBER Recession Indicator. For Panel D, we restrict our samples with prices above $1. Robust Newey and West (1987) t-statistics are reported in square brackets. The sample period is July 1963 to December 2012.

Panel A: July 1963 to December 2000

IVOL Ranking	Mean	Std.Dev.	CAPM Alpha	FF-3F Alpha
1	1.036	3.785	0.097	0.034
			[1.35]	[0.72]
2	1.126	4.685	0.071	0.058
			[1.53]	[1.05]
3	1.214	5.824	0.043	0.069
			[0.42]	[0.90]
4	0.820	7.134	-0.441	-0.389
			[-2.59]	[-3.81]
5	-0.014	8.134	-1.278	-1.310
			[-4.95]	[-8.00]
5-1	-1.050		-1.375	-1.344
	[-3.08]		[-4.37]	[-7.06]

Panel B: July 1963 to December 2012

IVOL Ranking	Mean	Std.Dev.	CAPM Alpha	FF-3F Alpha
1	0.887	3.780	0.101	0.061
			[1.78]	[1.46]
2	0.941	4.921	0.0332	0.006
			[0.78]	[0.13]
3	1.030	6.094	0.022	0.024
			[0.25]	[0.35]
4	0.694	7.653	-0.413	-0.412
			[-2.54]	[-3.64]
5	0.016	8.818	-1.119	-1.218
			[-4.83]	[-7.44]
5-1	-0.870		-1.220	-1.279
	[-2.70]		[-4.42]	[-6.78]

Table B.2 continued

Panel C: IVOL Puzzle with Business Cycles

	H-L sorted on	FF-3F Alpha in Recession (NBER Recession=1)	FF-3F Alpha in Expansion (NBER Recession=0)
IVOL	$IVOL_{it}$	-2.264	-1.007
		[-2.71]	[-5.78]

Panel D: IVOL Puzzle Excluding Penny Stocks

	H-L sorted on	FF-3F Alpha
IVOL	$IVOL_{it}$	-1.106
		[-6.48]

Table B.3: Explaining Market Return Volatility

This table describes the determinants of the market return volatility. We use the following regression to obtain coefficient estimates

$$Ln(MKTvol) = \alpha + \beta_i' X_t + u_{it}.$$

Dependent variable is the log of market volatility ($MKTvol$). It is the standard deviation of excess market return within each month. The vector of right hand side variables, denoted as X are the logarithm of the variables defined in Table B.1. Robust Newey and West (1987) t-statistics are reported in square brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
α	-2.763	-3.092	-2.396	-2.682	5.263	6.129
	[-1.78]	[-2.15]	[-1.86]	[-1.97]	[2.99]	[3.09]
$\hat{\beta}_{\Delta Mvol}$	0.100	0.034	0.024	0.026	0.043	0.021
	[4.24]	[1.47]	[1.00]	[1.10]	[1.97]	[0.92]
$\hat{\beta}_{\Delta IPvol}$	0.081	0.070	0.080	0.066	0.058	0.102
	[1.29]	[1.40]	[1.53]	[1.34]	[1.32]	[2.24]
$\hat{\beta}_{INFLvol}$	0.116	-0.064	-0.030	-0.048	-0.065	-0.069
	[1.08]	[-0.69]	[-0.30]	[-0.50]	[-1.03]	[-1.03]
$\hat{\beta}_{Recession}$	0.387	0.222	0.278	0.250	0.212	0.206
	[3.85]	[3.15]	[3.70]	[3.39]	[2.60]	[2.50]
$\hat{\beta}_{Yield}$		0.360	0.415	0.409	0.171	0.234
		[3.35]	[3.88]	[3.76]	[1.66]	[2.25]
$\hat{\beta}_{Term}$						-0.011
						[-0.40]
$\hat{\beta}_{CP}$		-0.226		-0.088	-0.047	-0.045
		[-2.09]		[-0.76]	[-0.54]	[-0.52]
$\hat{\beta}_{DP}$			-0.302	-0.250	0.025	-0.041
			[-2.64]	[-1.98]	[0.20]	[-0.33]
$\hat{\beta}_{Lev}$	-1.020	-0.491	0.026	-0.051	2.447	2.913
	[-1.87]	[-1.04]	[0.06]	[-0.11]	[4.28]	[4.46]
$\hat{\beta}_{Tvlm}$		0.208	0.225	0.200	0.624	0.649
		[3.64]	[4.44]	[3.54]	[5.90]	[5.33]
$\hat{\beta}_{Disp1}$					4.166	4.100
					[2.86]	[2.65]
$\hat{\beta}_{Disp2}$					-0.192	-0.316
					[-0.24]	[-0.40]
$\hat{\beta}_{Disp3}$					6.130	5.527
					[7.60]	[5.99]
$\hat{\beta}_{Disp4}$					-0.294	-0.415
					[-0.46]	[-0.65]
$AdjR^2$	0.1958	0.3355	0.3797	0.3428	0.4705	0.5156

Table B.4: Portfolios Sorted on Macroeconomic Determinants of Return Volatilities

This table shows portfolio returns sorted by the part of the IVOL fitted by macroeconomic variables and the residual part of the IVOL. We first regress the time series of individual stock IVOL on candidate variables (X_t) and obtain coefficients estimates

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t)$ and are defined in Table B.1. We then sort stocks based on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and form zero cost portfolios (H-L). These portfolios are held for one month. The table reports zero cost portfolios mean return and alpha with respect to the Fama and French (1993) three-factor model in percentage. Robust Newey and West (1987) t-statistics are reported in square brackets.

	H-L sorted on	Mean Return	FF-3F Alpha
Fitted IVOL	$IV\hat{O}L_{it}$	-1.646	-2.063
		[-3.59]	[-6.42]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.722	0.668
		[3.09]	[2.92]
Aggregate Variables Explaining IVOL	$\hat{\gamma}_1^i \Delta Mvol_t$	0.112	0.017
		[0.65]	[0.08]
	$\hat{\gamma}_2^i \Delta IPvol_t$	0.039	-0.123
		[0.26]	[-0.86]
	$\hat{\gamma}_3^i INFLvol_t$	0.246	0.049
		[1.26]	[0.27]
	$\hat{\gamma}_4^i Recession_t$	-0.041	-0.228
		[-0.10]	[-0.51]
	$\hat{\gamma}_5^i Yield_t$	0.043	-0.044
		[0.21]	[-0.22]
	$\hat{\gamma}_6^i Term_t$	-0.238	-0.310
		[-1.81]	[-2.22]
	$\hat{\gamma}_7^i CP_t$	0.242	0.246
		[1.46]	[1.14]
	$\hat{\gamma}_8^i DP_t$	-0.409	-0.521
		[-3.65]	[-4.71]
	$\hat{\gamma}_9^i Lev_t$	-0.223	-0.357
		[-1.18]	[-1.93]
	$\hat{\gamma}_{10}^i Tvlm_t$	-0.679	-0.751
		[-3.98]	[-4.30]

Table B.5: Portfolios Sorted on IVOL Fitted by Macroeconomic Variables and the Common Factors of Analyst Forecast Dispersions

This table shows portfolio returns sorted by the part of the IVOL fitted by macroeconomic variables, the common factors of analyst forecast dispersions and the residual part of the IVOL. We first regress the time series of individual stock IVOL on candidate variables (X_t) and obtain coefficients estimates

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, Disp_t^1, Disp_t^2, Disp_t^3, Disp_t^4)$ and are defined in Table B.1. We then sort stocks based on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and form zero cost portfolios (H-L). These portfolios are held for one month. The table reports zero cost portfolios mean return and alpha with respect to the Fama and French (1993) three-factor model in percentage. The last two rows report the results from sorting stocks based on the size of the sum of contributions to return volatilities by macroeconomic variables ($MacV$) and common components of analyst dispersions, respectively. Robust Newey and West (1987) t-statistics are reported in square brackets.

	H-L sorted on	Mean Return	FF-3F Alpha
Fitted IVOL	$IV\hat{O}L_{it}$	-1.374	-1.617
		[-2.84]	[-4.03]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.534	0.549
		[2.13]	[2.22]
Aggregate Variables Explaining IVOL	$\hat{\gamma}_1^i \Delta Mvol_t$	-0.133	-0.288
		[-0.90]	[-1.48]
	$\hat{\gamma}_2^i \Delta IPvol_t$	-0.094	-0.130
		[-0.93]	[-1.21]
	$\hat{\gamma}_3^i INFLvol_t$	0.342	0.285
		[1.93]	[1.84]
	$\hat{\gamma}_4^i Recession_t$	-0.269	-0.317
		[-0.81]	[-0.90]
	$\hat{\gamma}_5^i Yield_t$	-0.350	-0.537
		[-2.06]	[-2.67]
	$\hat{\gamma}_6^i Term_t$	-0.233	-0.328
		[-1.92]	[-2.66]
	$\hat{\gamma}_7^i CP_t$	0.037	0.081
		[0.35]	[0.70]
	$\hat{\gamma}_8^i DP_t$	-0.312	-0.346
		[-2.44]	[-2.89]
	$\hat{\gamma}_9^i Lev_t$	0.170	0.218
		[1.37]	[2.08]
	$\hat{\gamma}_{10}^i Tvlm_t$	-0.180	-0.275
		[-1.15]	[-2.00]
	SUM($\hat{\gamma}^i Disp_t^j$)	0.290	0.232
		[2.40]	[2.02]

Table B.6: IVOL Zero Cost Portfolios Analysis

This table reports the coefficient estimates of the following regression

$$R_t^{HighIvol} - R_t^{LowIvol} = \alpha + b_x' R_t^{\gamma X} + \epsilon_{it}.$$

$R_t^{\gamma X}$ is the vector of factor-mimicking, zero-cost portfolio returns, constructed from first running the regression

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, \{Disp_t^j\}_{j=1}^{j=4})$ are defined in Table B.1. We then sort stocks on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and $R_t^{\gamma X}$ is computed as the stock return with the largest size of $\hat{\gamma}_i^j X_t^j$ minus the stock return with the smallest size of $\hat{\gamma}_i^j X_t^j$. Robust Newey and West (1987) t-statistics are reported in square brackets.

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
α	-1.220	-0.272	-0.278	-0.254	-0.250
	[-4.42]	[-1.14]	[-1.15]	[-1.01]	[-1.00]
b_{mktex}	0.771	0.148	0.144	0.152	0.164
	[7.43]	[2.10]	[2.08]	[2.12]	[2.33]
$b_{\Delta Mvol}$				0.020	0.046
				[0.15]	[0.34]
$b_{\Delta IPvol}$		-0.095	-0.082		-0.129
		[-0.81]	[-0.68]		[-1.11]
$b_{INFLvol}$		-0.634	-0.638	-0.649	-0.651
		[-5.46]	[-5.36]	[-5.35]	[-5.39]
b_{Yield}		0.442	0.450	0.446	0.454
		[3.38]	[3.54]	[3.85]	[3.87]
b_{Term}		-0.091	-0.082	-0.109	-0.111
		[-0.93]	[-0.86]	[-1.11]	[-1.15]
b_{CP}		0.250	0.249	0.266	0.253
		[2.11]	[2.10]	[2.14]	[2.06]
b_{DP}			-0.052	-0.026	0.008
			[-0.44]	[-0.22]	[0.06]
b_{Lev}		-0.917	-0.926	-0.927	-0.937
		[-6.80]	[-7.19]	[-7.77]	[-7.58]
b_{Tvlm}		0.741	0.756	0.751	0.729
		[8.21]	[7.55]	[7.67]	[7.18]
b_{Disp1}		-0.271	-0.272	-0.218	-0.209
		[-2.49]	[-2.51]	[-1.01]	[-2.01]

Table B.7: Portfolios Sorted by Alternative IVOL Measures

This table shows portfolio returns sorted by alternative IVOL measures. In each month, we use monthly data to compute IVOL as the standard deviation of ϵ_t^i by estimating the following GARCH(1,1) models

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \epsilon_t^i \text{ (A)}$$

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + b_x' R_t^{\gamma X} + \epsilon_t^i \text{ (B)}$$

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \epsilon_t^i \text{ (C)}$$

$$R_t^i - R_f = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + b_x' R_t^{\gamma X} + \epsilon_t^i \text{ (D)} ,$$

$$\epsilon_t^i \sim N(0, \sigma_{it}^2)$$

$R_t^{\gamma X}$ is constructed from first running the regression $IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it}$, where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, \{Disp_t^j\}_{j=1}^{j=4})$ and are defined in Table B.1. In each month, we sort stocks based on these alternative IVOL measures and portfolios are formed every month based on IVOL over the previous month. The table reports zero cost portfolios mean return in percentage. Robust Newey and West (1987) t-statistics are reported in square brackets.

Model	H-L sorted on	Raw Mean Return
A	$IVOL_{it}$	-0.843
		[-2.40]
B	$IVOL_{it}$	-0.658
		[-1.73]
C	$IVOL_{it}$	-0.772
		[-2.20]
D	$IVOL_{it}$	-0.555
		[-1.52]

Table B.8: Portfolios Sorted by Decomposed IVOL Measures

This table shows portfolio returns sorted by decomposed IVOL measures. We use either the daily return without dividends to calculate capital gain IVOL ($IVOLx$), or the difference between holding return and capital gain to calculate cash flow IVOL ($IVOLr$). Next we regress the time series of $IVOLx$ or $IVOLr$ on candidate variables (X_t) and obtain coefficients estimates

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, \{Disp_t^j\}_{j=1}^{j=4})$ and are defined in Table B.1. We then sort stocks based on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and form zero cost portfolios (H-L). These portfolios are held for one month. The table reports zero cost portfolios mean returns and alphas with respect to the Fama and French (1993) three-factor model in percentage. Robust Newey and West (1987) t-statistics are reported in square brackets.

	H-L sorted on	Raw Mean Return	FF-3F Alpha
Capital Gain IVOL	$IVOLx_{it}$	-0.888	-1.298
		[-2.77]	[-6.86]
Fitted Capital Gain IVOL	$IV\hat{O}Lx_{it}$	-1.460	-1.707
		[-3.00]	[-4.25]
Residual Capital Gain IVOL	$\hat{\varepsilon}_{xit}$	0.602	0.619
		[2.38]	[2.49]
Cash Flow IVOL	$IVOLr_{it}$	0.011	-0.341
		[0.01]	[-0.44]
Fitted Cash Flow IVOL	$IV\hat{O}Lr_{it}$	-0.365	-0.353
		[-2.13]	[-2.15]
Residual Cash Flow IVOL	$\hat{\varepsilon}_{rit}$	0.068	0.064
		[0.30]	[0.35]

Table B.9: Lottery Preference: January and Non-January Month

This table shows portfolio returns sorted by IVOL, the fitted IVOL and residual IVOL in January and non-January month. We split our monthly return data into January returns and non-January returns. Next we regress the time series of $IVOL$ on candidate variables (X_t) and obtain coefficients estimates for each subsample

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, \{Disp_t^j\}_{j=1}^{j=4})$ and are defined in Table B.1. We then sort stocks based on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and form zero cost portfolios (H-L). These portfolios are held for one month. The table reports zero cost portfolios mean returns and alphas with respect to the Fama and French (1993) three-factor model in percentage. Robust Newey and West (1987) t-statistics are reported in square brackets.

Panel A: January returns

	H-L sorted on	Raw Mean Return	FF-3F Alpha
IVOL	$IVOL_{it}$	3.353	-0.034
		[3.18]	[-0.05]
Fitted IVOL	$IV\hat{O}L_{it}$	1.641	0.325
		[2.09]	[0.40]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.579	0.396
		[1.64]	[2.22]

Panel B: Non-January returns

	H-L sorted on	Raw Mean Return	FF-3F Alpha
IVOL	$IVOL_{it}$	-1.251	-1.412
		[-3.71]	[-7.35]
Fitted IVOL	$IV\hat{O}L_{it}$	-1.758	-1.880
		[-3.35]	[-4.39]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.469	0.464
		[1.93]	[1.89]

Table B.10: Portfolios Sorted by IVOL Determinants with Skewness

This table shows portfolio returns sorted by IVOL, the fitted IVOL and residual IVOL with return skewness. Each month we sort stocks first on their skewness into two groups. Next we regress the time series of $IVOL$ on candidate variables (X_t) and obtain coefficients estimates

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Yield_t, CP_t, DP_t, Lev_t, Tvlm_t, Disp_t)$ and are defined in Table B.1. We then sort stocks based on the size of $\hat{\gamma}_i^j X_t^j$ over the previous month and form zero cost portfolios (H-L) within each skewness group. These portfolios are held for one month. The table reports zero cost portfolios mean returns and alphas with respect to the Fama and French (1993) three-factor model in percentage. Robust Newey and West (1987) t-statistics are reported in square brackets.

Panel A: Low Skewness Group

	H-L sorted on	Raw Mean Return	FF-3F Alpha
IVOL	$IVOL_{it}$	-0.755	-1.178
		[-2.48]	[-6.69]
Fitted IVOL	$IV\hat{O}L_{it}$	-1.752	-2.009
		[-4.31]	[-5.59]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.852	0.867
		[3.79]	[3.70]

Panel B: High Skewness Group

	H-L sorted on	Raw Mean Return	FF-3F Alpha
IVOL	$IVOL_{it}$	-0.933	-1.316
		[-2.80]	[-5.93]
Fitted IVOL	$IV\hat{O}L_{it}$	-1.383	-1.628
		[-2.86]	[-4.16]
Residual IVOL	$\hat{\varepsilon}_{it}$	0.478	0.469
		[1.72]	[1.77]

Table B.11: IVOL and Uncertainty

This table shows the analyst dispersion, the fitted dispersion and the idiosyncratic part of the dispersion of portfolios sorted on IVOL, the fitted IVOL (m-IVOL) or the residual IVOL (r-IVOL). We regress the time series of $IVOL$ on candidate variables (X_t) and obtain coefficients estimates

$$IVOL_{it} = \alpha_i + \gamma_i' X_t + \varepsilon_{it},$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Recession_t, Term_t, Yield_t, CP_t, DP_t, Lev_t, Tvlm_t, \{Disp_t^j\}_{j=1}^{j=4})$ and are defined in Table B.1. The fitted part is the fitted IVOL (m-IVOL) and the residual ε_{it} is the residual IVOL (r-ivol). We regress firm-level analyst forecast dispersion (DISP) on up to first ten common factors from the asymptotic principal component analysis

$$DISP_{it} = \alpha_i + \beta_i' F_t + u_{it},$$

where F_t are common factors obtained from asymptotic principal component analysis. $D\hat{I}SP$ is the fitted part of the dispersion and u_{it} is the idiosyncratic part of the dispersion (residual DISP). Robust Newey and West (1987) t-statistics are reported in square brackets.

Panel A: Dispersions of Portfolios Sorted on the fitted IVOL (m-IVOL)

m-IVOL Rank	DISP	$D\hat{I}SP$	Residual DISP
1 (Low)	0.039	0.04	-0.001
2	0.066	0.066	0
3	0.092	0.099	-0.008
4	0.113	0.123	-0.01
5	0.147	0.155	-0.007
6	0.179	0.182	-0.002
7	0.21	0.235	-0.023
8	0.267	0.27	0
9	0.323	0.328	-0.003
10 (High)	0.457	0.469	-0.008
High-Low	0.418	0.429	-0.008
t-statistics	[14.12]	[15.94]	[-0.55]

Panel B: Dispersions of Portfolios Sorted on residual IVOL (r-IVOL)

r-IVOL Rank	DISP	$D\hat{I}SP$	Residual DISP
1 (Low)	0.235	0.267	-0.03
2	0.138	0.154	-0.016
3	0.102	0.108	-0.005
4	0.087	0.092	-0.004
5	0.072	0.079	-0.006
6	0.07	0.078	-0.008
7	0.079	0.08	0
8	0.095	0.096	-0.001
9	0.135	0.123	0.013
10 (High)	0.181	0.175	0.006
High-Low	-0.055	-0.092	0.036
t-statistics	[-2.89]	[-5.82]	[2.25]

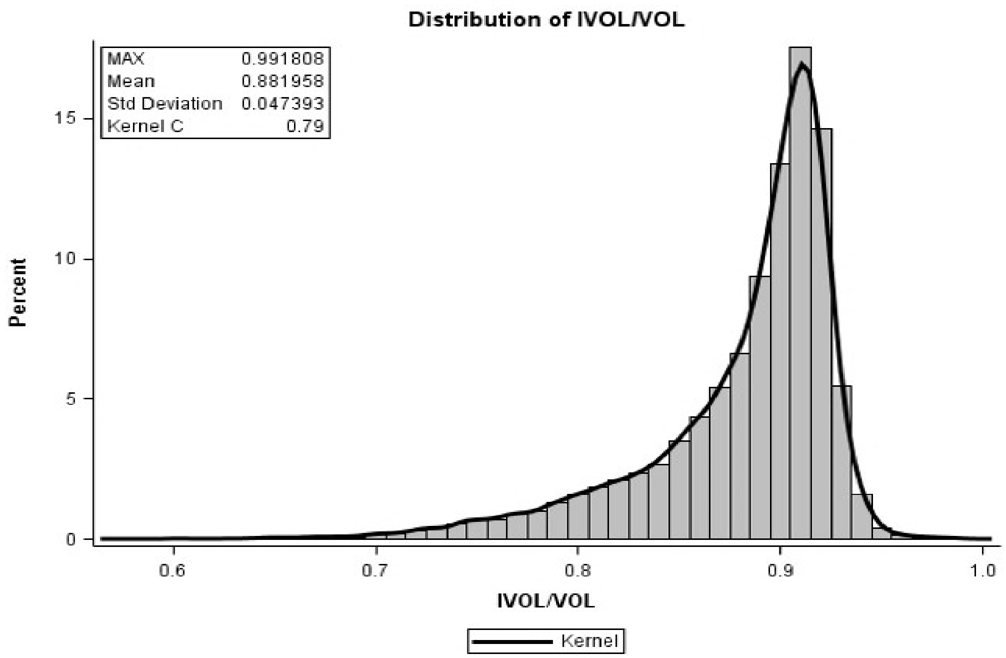
Figure B.1: Distribution Figures

In Panel A, the distribution of IVOL/VOL is plotted. Each month we calculate the ratio of IVOL to return volatility (IVOL/VOL) for each firm. We then average ratios to obtain firm level IVOL/VOL.
In Panel B, we first regress individual firm IVOL on market volatility ($MKTvol$)

$$IVOL_{it} = \alpha_i + \beta_i MKTvol_t + \gamma' X_t + u_{it}$$

where $X_t = (\Delta Mvol_t, \Delta IPvol_t, INFLvol_t, Yield_t, Term_t, CP_t, DP_t, Lev_t, Tvlm_t, Disp_t^1, Disp_t^2, Disp_t^3, Disp_t^4)$ and are defined in Table B.1, and plot the distribution of adjusted R^2.

(a) Panel A



(b) Panel B

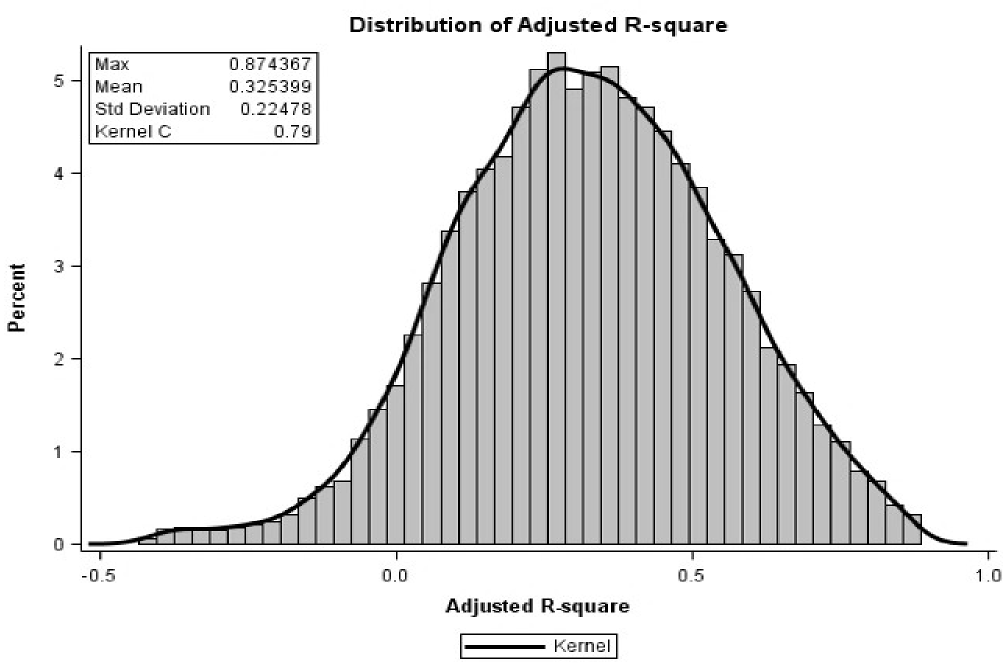
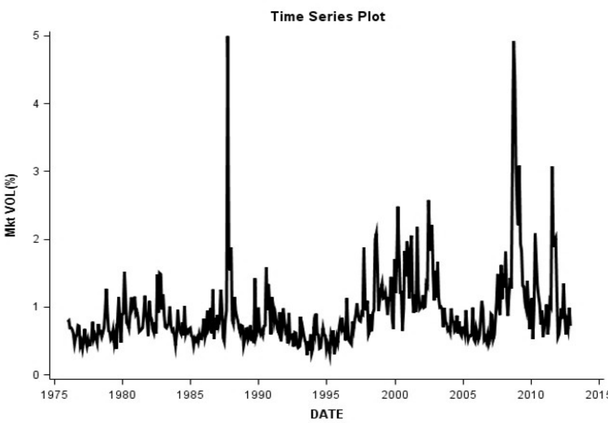


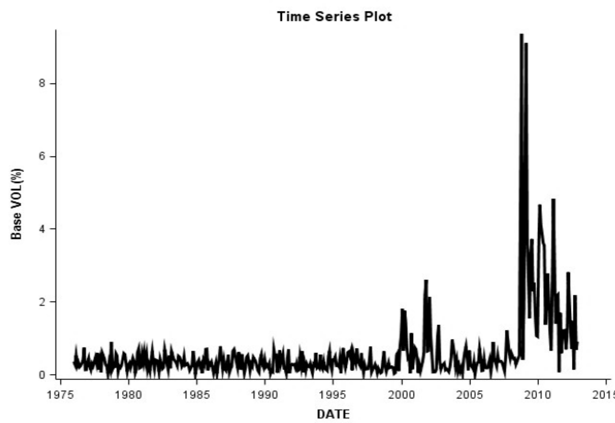
Figure B.2: Time Series Plot of Macro Variables

This figure shows the times series plot of macro variables. Market Volatility is the standard deviation of excess market return within each month. Volatility of the monetary base growth, of the industry production growth and of the CPI change are estimated from equation (3.27). Yield is the spread between Moody's Baa corporate bond yield and Aaa yield from the Federal Reserve Board. Term is the spread between 10-year Treasury rate and 1-year Treasury rate from the Federal Reserve Board. The first common factor of analysts forecast dispersion is obtained from asymptotic principle component analysis.

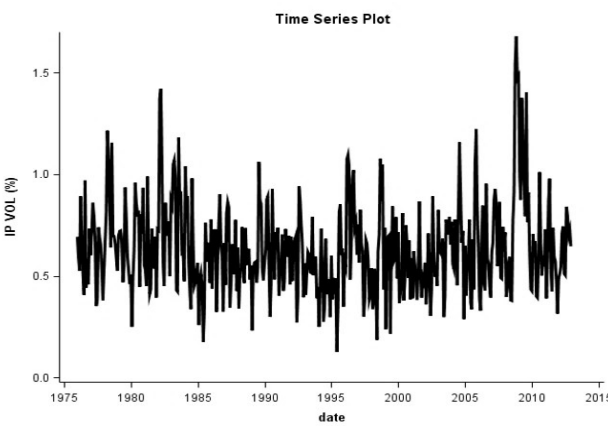
(a) Panel A Market Volatility



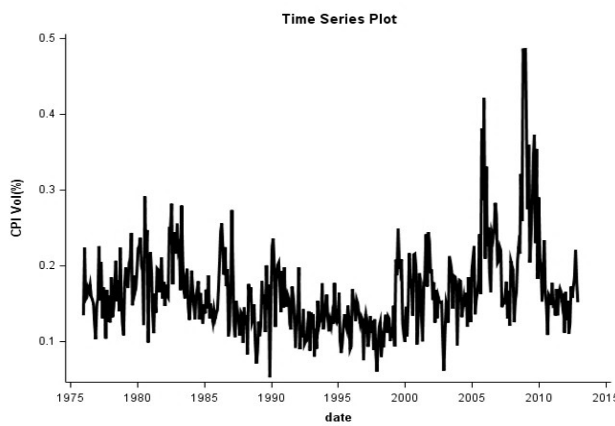
(b) Panel B Monetary Base Growth Volatility



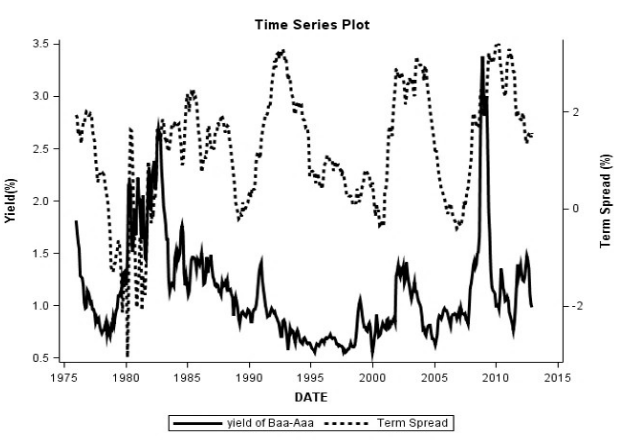
(c) Panel C Industry Production Growth Volatility



(d) Panel D Inflation Volatility



(e) Panel E Yield Spread and Term Spread



(f) Panel F The First Common Dispersion Factor

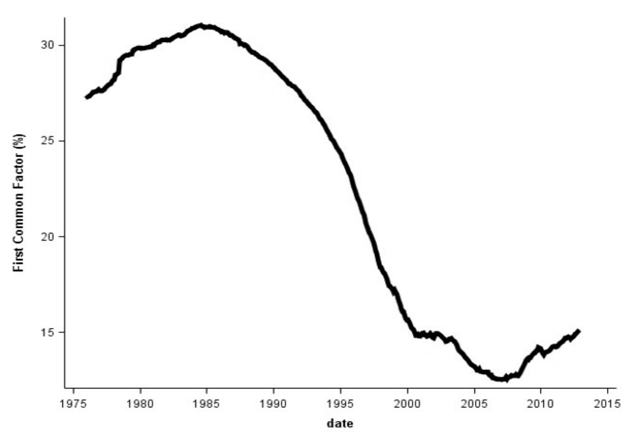
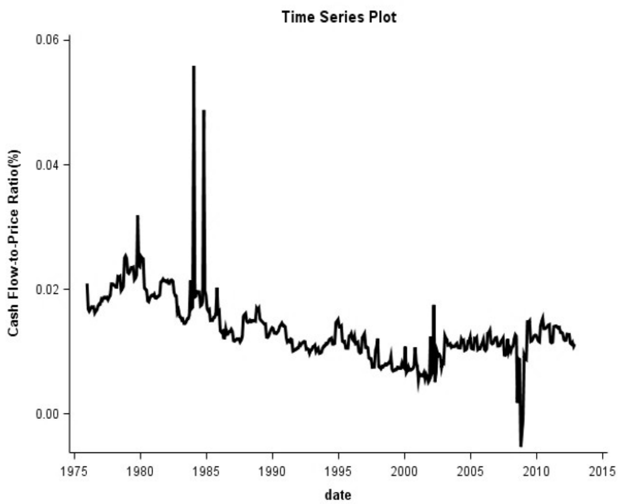


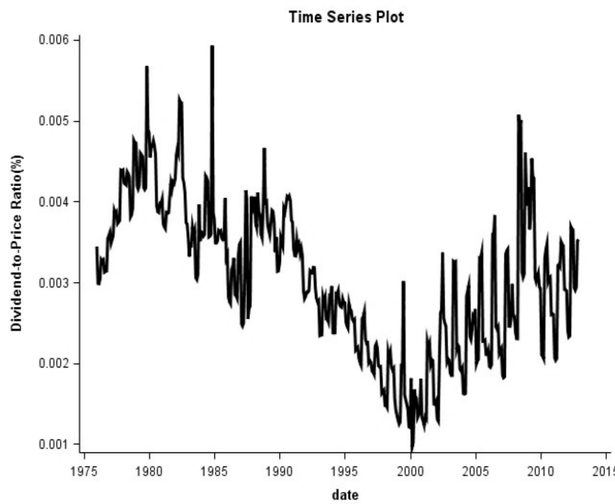
Figure B.3: Time Series Plot of Aggregate Corporate Variables

This figure shows the times series plot of aggregate corporate variables. They are value weighted average of firm level cash-flow-to-price-ratio, dividend-to-price ratio, leverage and trading volume. Leverage refers to the book value of long term debt divided by book assets. Trading Volume is the ratio of the number of shares traded over total shares outstanding.

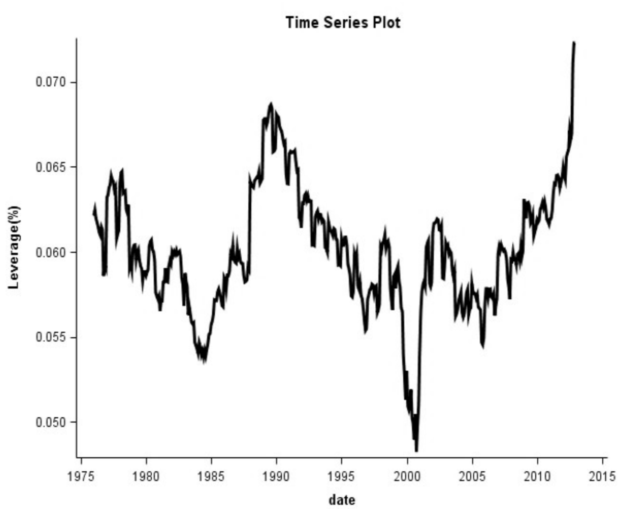
(a) Panel A Cash-Flow-to-Price Ratio



(b) Panel B Dividend-to-Price Ratio



(c) Panel C Leverage



(d) Panel D Trading Volume