Earnings Uncertainty and Attention

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Abstract

This paper explores the relationship between earnings uncertainty and attention to firm-specific information. I use the percentage of uncertain words in 10-K or 10-Q filings as the primary measure of ex ante earnings uncertainty. I find that, the earnings releases of high uncertainty firms are accompanied by higher Google search volume, higher Bloomberg readership, higher abnormal trading volume, and faster analyst response. Furthermore, I find evidence of larger underreaction of prices in low uncertainty firms suggesting that attention constraints play a role. The findings are consistent with attention constrained investors allocating more attention to high uncertainty firms.

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1 Introduction

Recent studies have shown that there are limits to investor attention. The attention constraints can explain a variety of behavior in the financial markets. For example, Peng and Xiong (2006) show that the attention constraints can explain co-movement (Barberis, Shleifer, and Wurgler, 2005) and style investing (Barberis and Shleifer, 2003). In addition, the constraints can also explain slow-moving capital (Duffie, 2010), underreaction to information (Cohen and Frazzini, 2008), under-diversification (Van Nieuwerburgh and Veldkamp, 2010), and the behavior of Mutual Fund managers (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). Complementing these studies, I explore the cross-sectional relationship between investor attention and earnings uncertainty.

Peng and Xiong (2006) present a model where an attention constrained investor allocates attention between market information and firm-specific information. The model predicts that the investor will allocate more attention to market information. The intuition is that, the investor can achieve a larger reduction in portfolio uncertainty when she pays more attention to market information. Extending that intuition, I hypothesize that the investors will pay more attention to high earnings uncertainty firms to achieve a larger reduction in portfolio uncertainty.[1,2] However, it is also plausible the investors might pay less attention to the high uncertainty firms if processing information about these firms is more taxing on their attention resources. This paper attempts to differentiate between these two contradicting

[1]In Internet Appendix A.1, I extend Peng and Xiong (2006) and model an investor who allocates attention between firms that differ in the uncertainty about future dividends. The model predicts that the investor would allocate more attention to high uncertainty firms.

[2]Positive relationship between uncertainty and attention is also mentioned in other fields. For example, the uncertainty of outcome hypothesis in sports states that the viewership is increasing in the uncertainty of outcome. It asserts that games that feature teams which are equally likely to win garner more viewership.(See Neale (1964)).

hypotheses and provide some clarity on the relationship.

I use the proportion of uncertain words in 10-K or 10-Q filings as the primary measure of ex ante earnings uncertainty. The uncertainty words are from Loughran and McDonald (2011) word list. The motivation for using this measure is Loughran and McDonald (2013), who propose the proportion of uncertain words in S-1 as a good proxy for ex ante uncertainty of firm value.[3] Furthermore, Loughran and McDonald (2011) document that the proportion of uncertain words in 10-Ks is positively related to return volatility in the year following the filing date.[4]

For comparison, I also use the historical earnings volatility as another measure of earnings uncertainty. Following Dichev and Tang (2009) and Cao and Narayanamoorthy (2012), I define earnings volatility as the standard deviation of income before extra-ordinary items, scaled by total assets. I use the data from the previous 8 quarters to construct earnings volatility. Earnings volatility is skewed. Therefore, in empirical tests, I follow the earnings volatility literature and use the decile ranking of earnings volatility as another measure.

First, I test whether the measures are effective in capturing uncertainty. I regress the earnings volatility in the 8 quarters following the earnings release on the uncertainty measures. I find that the coefficients on both the measures are positive and significant. The positive association between the uncertain tone and future earnings volatility suggests that firms use more uncertain language when they expect future earnings to be more volatile.[5]

[3]Loughran and McDonald (2013) note, "Our findings are consistent with the hypothesis that large amounts of uncertain text in an S-1 filing generally lead to more valuation uncertainty and, in turn, higher first-day returns, absolute offer price revisions, and subsequent return volatility."

[4]For the empirical tests in this paper, the positive relationship between uncertain words in filings and subsequent uncertainty is sufficient for uncertain words to be a reasonable proxy for earnings uncertainty.

[5]Graham et al. (2005) survey highlights that a majority of executives prefer smoother earnings. Therefore, it is unlikely that uncertain language in filings causes earnings volatility. Furthermore, the executives have incentives to highlight the potential volatility in future earnings to avoid any shareholder litigation.

Furthermore, I find that the stock return volatility during the month of earnings release increases with earnings uncertainty.[6] The findings suggest that the measures are reasonable proxies for uncertainty.

Then, I test for higher attention around earnings release by studying the retail investor attention captured by the Google search activity, the institutional investor attention captured by the Bloomberg readership, and the abnormal trading volume around the earnings release. I use panel regressions for these tests and control for the number of simultaneous announcements, Fridays, and the stock return volatility. I cluster the standard errors both by the firm and the release date to properly adjust for any time-series or cross-sectional correlation (Petersen, 2009). I also account for the industry (Fama and French, 1997) and quarter fixed effects.

The first measure of attention is the Google search activity during the week of earnings release. Da, Engelberg, and Gao (2011) observe that the Google search activity for a company's ticker symbol captures attention to a company. Following their study, I define abnormal search volume index (ASVI) as the difference between the natural logarithm of search volume index (SVI) during the week of earnings release and the natural logarithm of median SVI in the previous 8 weeks. I find a positive relationship between ASVI and earnings uncertainty. On average, the Google search activity during the earnings week is 22% higher. A two standard deviation increase in the fraction of uncertain words results in further 6% increase in the Google search activity or about 28% of the unconditional mean. Higher Google search activity suggests that more investors are seeking information about the high uncertainty firms.

[6] The volatility results are also consistent with Andrei and Hasler (2014) model which predicts that the stock return volatility increases with attention. The intuition is that, when attention is high investors immediately incorporate new information into prices and therefore return volatility increases.

The second measure of attention is the Bloomberg readership activity during the week of earnings release. Ben-Rephael, Da, and Israelsen (2017) note that the Google search activity is a better measure of retail investor attention. They propose the Bloomberg readership as a measure of institutional attention. I define the abnormal institutional attention (AIA) for a firm as the dummy variable that takes the value of 1 if the readership activity during the earnings week falls in the 94 percentile of activity in the previous 30 days. Unconditionally, 85% of firms see higher readership during the earnings week. In multivariate specification, I find that the uncertainty measures positively predict the institutional investor attention. A two standard deviation increase in the fraction of uncertain words results in 1.4% more firms seeing higher readership or about 10% of the firms which had lower readership.

I also use the abnormal trading volume around the earnings release as a measure of attention. Barber and Odean (2008) argue that abnormal trading volume is a reasonable measure of attention. Other studies that have used trading volume as an attention proxy include Hou, Xiong, and Peng (2009) and Gervais, Kaniel, and Mingelgrin (2001). I find a positive relationship between earnings uncertainty and abnormal volume during the announcement period. A two standard deviation increase in the fraction of uncertain words results in 13% higher trading volume. In the attention tests, uncertain tone does better than historical the earnings volatility in capturing attention. This can be attributed to the measure being more forward looking than the historical earnings volatility. In summary, the attention tests provide evidence that the investors pay more attention to stocks with high earnings uncertainty.

One alternate hypothesis is that the high uncertainty stocks might attract attention even in the absence of attention constraints. To rule out this hypothesis, I test for underreaction in low attention stocks. Recent studies document that in the presence of attention constraints, lower attention can result in underreaction of prices to information. For example, DellaVigna and Pollet (2009) provide evidence of larger underreaction to earnings on Fridays and Hirshleifer, Lim, and Teoh (2009) find larger underreaction on days with large number of simultaneous announcements. Underreaction is inconsistent with the rational Bayesian learning in the absence of constraints.

I test for underreaction in the low uncertainty stocks, which receive lower attention, by studying the initial and delayed price response to earnings. Cumulative abnormal returns around the earnings announcement (CAR[0,1]) is the measure of initial response, and the post-earnings announcement drift (CAR[2,60]) is the measure of delayed response. In low uncertainty stocks, the initial response of prices to earnings surprises is smaller and post-earnings announcement drift is larger. The higher post-earnings drift provides strong evidence of underreaction in the low uncertainty stocks. Rational Bayesian learning models without constraints cannot explain the drift. The evidence, therefore, is consistent with attention constraints playing a role.

Recent studies suggest that the analysts are also attention constrained (Driskill, Kirk, and Tucker, 2020). Therefore, I test whether the analysts pay more attention to high uncertainty firms by studying their responsiveness following an earnings release. I measure analyst responsiveness using the dummy variable (ONTIME) which takes the value of 1 if there is at least one analyst who revises the next quarter earnings estimate within a day of the current quarter earnings release. I find a positive relationship between ONTIME and uncertainty suggesting that the analysts respond faster (slower) to high (low) uncertainty firms. Faster analyst responsiveness in high uncertainty firms is consistent with them paying more attention. The slower response of analysts to the low uncertainty firms can also explain the higher post-earnings drift in those firms (Zhang, 2008).

I present a set of robustness checks to ensure that the results are robust to alternative explanations. The results are generally robust to adding stock volatility as a control for information uncertainty (Zhang, 2006), Friday dummy (DellaVigna and Pollet, 2009), and the decile rank of simultaneous announcements (Hirshleifer, Lim, and Teoh, 2009). The results are also robust to using alternative post-earnings announcement horizons. Furthermore, the positive relationship between uncertain tone and the speed of price response is present in both high and low complexity firms, suggesting that firm complexity does not explain the findings in the paper.

This study is related to the literature on attention to firm-specific news. Prior studies provide evidence of simultaneous events reducing attention to firm-specific news. I complement those studies by showing that the investors allocate more attention to high uncertainty stocks. I find that the low uncertainty stocks, which draw lower attention, underreact more. The underreaction is consistent with investors facing constraints when allocating attention. The findings are consistent with Benamar, Foucault, and Vega (2019) who use the information demand as a proxy for uncertainty [7]

I also contribute to the literature on textual analysis. Jegadeesh and Wu (2013) and Li (2010) study the information content in the text of filings.[8] Loughran and McDonald (2013) find that more uncertain words in IPO related filings affect the post IPO returns. I add to the literature by highlighting that the uncertain language in SEC filings can also capture the attention to subsequent firm information.

[7] More attention to high uncertainty stocks in addition to reducing the total uncertainty of the portfolio can also increase the trading profits as shown by Gargano and Rossi (2018).

[8] Loughran and McDonald (2016) survey the textual analysis literature in finance and accounting.

2 Data

I obtain the stock return data from the Center for Research in Security Prices (CRSP), financials from COMPUSTAT, the analyst EPS estimates and actuals from IBES, 10-K and 10-Q filings word counts from Bill McDonald website and the factor returns data from Kenneth French website.

I exclude firm-quarters where the price is lower than the absolute values of the actual quarterly EPS, the consensus EPS estimate, or the difference between the actual and estimated EPS, because these estimates are likely to be data errors. I exclude estimates posted more than 90 days before earnings announcement as they are likely to be stale estimates. I exclude penny stocks and firm-quarters in which an earnings announcement occurred on a Saturday or a Sunday. I only consider stocks with available market capitalization and book value information.

To accurately identify the earnings release date, I follow the procedure developed by DellaVigna and Pollet (2009). I exclude announcements for which IBES and COMPUSTAT release dates differ by more than five days. For the remaining announcements, if IBES and COMPUSTAT have different release dates, I consider the earliest date as the reporting date. DellaVigna and Pollet (2009) note that this procedure performs well beginning 1995. Therefore, the sample period in this study is from 1995 to 2018. The sample period for tests involving Google search activity is from 2004 to 2018 and Bloomberg data is from 2010 to 2018 due to reduced data availability.

2.1 Variables

2.1.1 Earnings Uncertainty Measures

EVOL: Earnings volatility is the standard deviation of quarterly income before extraordinary items, scaled by total assets, computed using data from the previous 8 quarters.

EVOLRANK: Decile rank of earnings volatility. Following the earnings volatility literature, I use EVOLRANK instead of EVOL as the earnings uncertainty measure.

% UNCERTAIN: Ratio of total uncertain words to the total word count in a 10-K or 10-Q filing in the previous quarter.[9] The uncertain words are from Loughran and McDonald (2011) word list. They include words such as ambiguous, arbitrarily, cautious, imprecise, etc.

2.1.2 Dependent Variables

FEVOL: Future earnings volatility is the natural logarithm of EVOL computed using the data from 8 quarters following the current quarter earnings release.

CSTOCKVOL: Current stock volatility in the month of earnings release date is computed as the sum of squared daily returns.

ASVI: Weekly search volume index (SVI) is the total google search for a keyword scaled by its time series average. Abnormal search volume index (ASVI) is the difference between natural logarithm of SVI during the earnings week and the natural logarithm of median SVI in the previous 8 weeks.

AIA: Weekly abnormal institutional attention (AIA) is the dummy variable that takes value 1 if the Bloomberg readership activity in a stock during the earnings week is in the 94

[9]If there are multiple filings in the previous quarter I use the earliest filing as the later ones tend to be amendments with less information. If there are multiple filings within the same filing date, I use the longest filing as it is likely to have more information.

percentile of the readership in the previous 30 days.

AVOL: Abnormal trading volume (AVOL[0,1]) in the earnings announcement period is the ratio of mean daily dollar trading volume during the earnings announcement period (days 0 and 1 relative to earnings release) to the mean trading volume 7 to 46 days before the earnings.

CAR: Cumulative abnormal returns is the buy and hold return of the stock minus the beta-adjusted buy and hold return of the market. The beta is computed using daily returns from 300 days to 45 days before the announcement. CAR[0,1] provides the initial price response to earnings and CAR[2,60] provides the delayed response or the post-earnings announcement drift (PEAD). Following prior literature, I exclude observations in the top and bottom 0.05% of CAR distributions.

ONTIME: Dummy variable that takes the value of 1 if there is at least one analyst who revises estimates within a day of the earnings announcement.

2.1.3 Controls

SURPRISE: Earnings surprise is the difference between the actual EPS in a quarter and the corresponding median consensus estimate scaled by the stock price before the announcement.

SRANK: Decile rank of earnings surprise.

ASRANK: Decile rank of absolute earnings surprise.

MCAP: The market capitalization of equity at the end of the previous June.

RSIZE: Decile rank of market capitalization.

BM: Book-to-Market calculated at the end of June, is the book equity for the last fiscal year-end in the previous calendar year divided by the market equity as of the previous

December.

RBM: Decile rank of book-to-market.

TURNOVER: The average of the previous 12 month turnover. Monthly turnover is the ratio of shares traded in a month to the total shares outstanding.

NUMEST: The number of EPS estimates available for the current quarter.

REPORTLAG: The number of days between the fiscal quarter end date and the earnings announcement date.

STOCKVOL: The sum of squared returns in the month before the earnings announcement date.

NREPORTS: Number of simultaneous announcements.

NRANK: Decile ranking of simultaneous announcements.

FRIDAY: Dummy variable for Fridays.

Following prior literature, in empirical tests, I use the decile ranking of earning surprises, size, book-to-market, and the number of simultaneous announcements.

3 Results

Table 1 reports the summary statistics. There are about 279,000 observations for the variables with the exception of ASVI, AIA, % UNCERTAIN, and ONTIME. The lower number of observations for % UNCERTAIN is because not all stocks have corresponding matches in the filings data. The lower ASVI and AIA observations are because the corresponding sample periods begin only from 2004 and 2010 respectively. The number of observations are lower for ONTIME because I require stocks to have at least one estimate for the next quarter EPS before the current quarter earnings release.

The mean immediate response (CAR[0,1]) and delayed response (CAR[2,60]) of prices to earnings is zero. This is because the average firm meets the analyst expectations and therefore has earnings surprise of zero.[10] In empirical tests, I express CAR measures in percentage terms for easier interpretation of results. However, there is over 20% and 100% increase in Google search activity and trading volume around earnings announcements. 85% of firms in the sample see higher institutional attention during announcements period. There is at least one analyst who responds within a day of the earnings for 70% of the firms.

The mean standard deviation of earnings is 3% relative to its assets. However, this variable is highly skewed. To address this, Dichev and Tang (2009) use earnings volatility deciles. Therefore, I follow them and use the decile ranking of earnings volatility in empirical tests. Uncertain words account for 1.2% of the total words in 10-K and 10-Q filings.

The average market capitalization is $5 Billion, the average book-to-market ratio is around 0.80, and the average number of EPS estimates is 5. There is a month delay between fiscal quarter end date and the earnings release. On a typical day, roughly 150 firms announce earnings simultaneously. Around 6% of announcements occur on Fridays, consistent with the numbers in DellaVigna and Pollet (2009).

3.1 Realized Earnings Volatility

I use % UNCERTAIN as the primary measure of earnings uncertainty. The motivation for % UNCERTAIN is Loughran and McDonald (2013), who propose the percentage of uncertain words in S-1 as a good proxy for ex ante uncertainty of firm value. I also use EVOLRANK as another measure for comparison. The motivation for EVOLRANK is Cao and Narayanamoorthy (2012), who use past earnings volatility groups as a measure of ex

[10] The difference between average CAR[0,1] in this paper and Ball and Kothari (1991) appears to be because of the different sample periods used.

ante earnings volatility.

I test whether these measures predict variation in future earnings. Earnings volatility is highly skewed, therefore I take the logarithm of future earnings volatility (FEVOL), computed from 8 quarters following the earnings release. I run a panel regression of FEVOL on measures of earnings uncertainty and controls. I cluster the standard errors both by the firm and the reporting date to control for any time series or cross-sectional correlation (Petersen, 2009).

Table 2 presents the results. The first column reports the results for EVOLRANK. The EVOLRANK coefficient is positive and significant. The second column reports the results for % UNCERTAIN. I find that the percent of uncertain words positively and significantly predicts future earnings volatility. This suggests that the firms use more uncertain language when they expect more earnings uncertainty in the future. Comparing the adjusted R^2 from the first two columns, I find that EVOLRANK explains a larger proportion of variance of future earnings volatility as compared to % UNCERTAIN. Because EVOLRANK is computed as the standard deviation of quarterly earnings, this measure will be higher for firms which are exposed to seasonality in their underlying business. Therefore, EVOLRANK can explain the variation in future realized earnings volatility better than % UNCERTAIN.

Columns three and four report the results for the specification with controls. The specifications also include industry and quarter fixed effects. The predictive power of both EVOLRANK and % UNCERTAIN continues to exist even after the addition of controls.[11] The findings suggest that both the measures have predictive power for future earnings volatility.

[11] In unreported results, I find that the coefficient on % UNCERTAIN continues to remain positive and significant after adding EVOLRANK as a control in the fourth specification.

3.2 Return Volatility

In this section, I test whether both the measures can explain the return volatility during earnings release month. I regress the stock volatility in the month of earnings release(CSTOCKVOL) on measures of earnings uncertainty. Table 3 presents the results. I use the volatility of the stock in the previous month (STOCKVOL) to control for persistence in volatility. The coefficients on the uncertainty measures, therefore, give the incremental effect of earnings uncertainty on volatility during earnings period. The coefficient are positive and significant. In columns three and four, the coefficients continue to remain positive and significant even after the addition of controls. The results show a strong association between earnings uncertainty and stock return volatility during earnings release. Loughran and McDonald (2011) also document a positive relationship between uncertain document tone and future return volatility. These return and earnings volatility tests provide comfort that % UNCERTAIN is a reasonable measure of earnings uncertainty.[12]

3.3 Google Search Activity

Da, Engelberg, and Gao (2011) propose the Google search activity for a firm ticker as a measure of attention to a firm. I use the ASVI during the week of the earnings release to capture investor attention. I regress ASVI on the earnings uncertainty measures. Table 4 presents the results. In the first column, the EVOLRANK coefficient is positive. There is 5.4% (9 x 0.006) higher Google search activity for firms in the highest decile of earnings volatility compared to the firms in the lowest decile. The second column shows a positive

[12]Andrei and Hasler (2014) study the relationship between attention, uncertainty, and stock volatility. Their model predicts that the stock return volatility increases with both attention and uncertainty. This is because when attention is high investors immediately incorporate new information into prices and therefore return volatility increases. The positive relationship documented here between uncertainty and volatility is consistent with more attention to high uncertainty stocks.

relationship between % UNCERTAIN and Google search activity. A two standard deviation increase in proportion of uncertain words results in 6% (2 x 0.4 x 0.075) increase in search activity around subsequent earnings. This is 28% of the unconditional mean (22%) and is economically significant.[13]

Columns three and four presents the results when adding controls to the specification. The relationship continues to be positive. EVOLRANK becomes insignificant after the addition of controls. However, the coefficient on % UNCERTAIN continues to remain significant. Loughran and McDonald (2013) provide evidence that the percent of uncertain words is a better measure of IPO underpricing than other commonly used measures. Similarly, the stronger performance of % UNCERTAIN when compared to EVOLRANK suggests that % UNCERTAIN is a better measure of the component of uncertainty that captures investor's attention.

Kothari, Li, and Short (2009) provide evidence that negative news can increase uncertainty in a firm. Consistent with the claim, Loughran and McDonald (2013) find that the fraction of weak modal words and negative words in S-1 filings are also correlated with future stock volatility. [14] I test whether attention increases with other document tone measures. Internet Appendix Table IA.1 presents the results. I find that the relationship is positive when using % NEGATIVE and % WEAKMODAL but is insignificant when using % POSITIVE. The findings are consistent with more investors paying attention to high earnings uncertainty firms.

[13]The increase in ASVI from 25 percentile to 75 percentile is only 21% from Table 1. The 6% increase is about 30% of interquartile range.

[14]The words such as *unexpected* and *unpredictable* overlap and appear in both negative and uncertain word lists.

3.4 Institutional Attention

Ben-Rephael, Da, and Israelsen (2017) propose Bloomberg readership as a measure of institutional attention. They argue that the Google search activity is a better measure of retail investor attention and that the AIA measure constructed from Bloomberg readership captures the institutional attention better. In this section I test the relationship between uncertainty and institutional attention.

I define the abnormal institutional attention (AIA) as the dummy variable that takes the value of 1 if the readership activity during the week of earnings release was in the 94 percentile of activity in the previous 30 days. From Table 1, about 85% of firms see higher readership during the week of earnings. The inter-quartile range is 0. This is because typically there is higher attention to firms around earnings announcement period than other periods as shown by Ben-Rephael, Da, and Israelsen (2017). This to some extent reduces the power of this test. I regress the AIA on measures of earnings uncertainty. Table 5 presents the results. In the univariate specifications in the first two columns, I find that the coefficient is negative. This is because uncertainty measures are higher for smaller firms and Ben-Rephael, Da, and Israelsen (2017) document a very strong positive association between larger firms and institutional attention. Therefore, univariate relationship is not a good measure of relationship between uncertainty and institutional attention.

In the third and fourth column, I add controls to the specification. In this multivariate analysis, the coefficients become positive and significant. A two standard deviation increase fraction of uncertain words results in 1.4% more firms seeing higher readership or about 10% of firms which had unconditional lower readership. The findings of multivariate tests suggest that institutional attention is also higher for high uncertainty firms.

3.5 Volume Response

It is intuitive that higher attention to an earnings release should be accompanied by higher trading volume. Prior studies including Hou et al. (2009), Barber and Odean (2008), and Gervais et al. (2001) have used trading volume as a proxy for investor attention. Abnormal trading volume (AVOL[0,1]) in the earnings announcement period is the ratio of the mean daily dollar trading volume during the earnings announcement period to the mean daily trading volume in 7 to 46 days before the earnings. I use abnormal trading volume instead of actual trading volumn to control for the possibility that high uncertainty stocks might typically have higher trading volume. Abnormal volume therefore captures the jump in trading volume which can be attributed to attention. Table 1 showed that there is a 100% increase in trading volume during the earnings announcement period, even though the average returns and surprises are zero. This is consistent with Kandel and Pearson (1995) who provide evidence of higher trading volume even in the absence of price change.

I regress AVOL[0,1] on the earnings uncertainty measures. I use absolute surprise decile rank (ASRANK) as a control. Table 6 presents the results. The coefficient on ASRANK is positive as the trading volume is typically higher both in firms with larger positive or negative surprises. In the first column, the coefficient on EVOLRANK is positive and significant suggesting that firms with higher historical earnings volatility see higher trading volume around subsequent earnings announcement. The second column presents evidence of higher trading volume in firms that use more uncertain language. A two standard deviation increase in the proportion of uncertain words increases the trading volume by 13%. In columns 3 and 4, the addition of controls reduces the respective coefficients. The coefficient on EVOLRANK becomes insignificant while the coefficient on % UNCERTAIN remains positive and significant. Similar to the Google search results, % UNCERTAIN performs better than

EVOLRANK in capturing the effect of attention. The findings are consistent with earnings uncertainty attracting attention and resulting in increased trading activity.[15]

3.6 Attention Constraints and Price Response to Earnings

The results so far show that there is higher attention to earnings of high uncertainty firms. However, it is quite plausible that this higher attention would have occurred even in the absence of attention constraints. In this section, I study whether attention constraints play a role by testing for underreaction in prices. Recent studies provide evidence of underreaction in the presence of attention constraints (DellaVigna and Pollet (2009), Hirshleifer et al. (2009), and Kottimukkalur (2019)). In the absence of attention constraints, low uncertainty firms, that receive lower attention, will not underreact to earnings. I test for underreaction by observing the immediate and delayed price response to earnings. Cumulative abnormal returns around the earnings announcement (CAR[0,1]) is the measure of initial response, and the post-earnings announcement drift (CAR[2,60]) is the measure of delayed response.

3.6.1 Immediate Price Response

The response of prices to earnings surprises is non-linear. Therefore, event studies in finance and accounting literature use surprise group ranks instead of the continuous measure of earnings surprise. I follow prior literature and regress CAR[0,1] on surprise decile rank of the firm, measures of earnings uncertainty and their interaction. Table 7 reports the results. The coefficient on SRANK is positive as the firms with positive surprises have positive abnormal returns in the announcement period. The first column reports the results

[15] I have used the decile ranking of historical earnings volatility following prior literature. Internet Appendix Table IA.2 presents the attention results when using log of earnings volatility instead of the decile ranking. The results are largely similar.

for EVOLRANK. The coefficient on EVOLRANK is negative and significant. This suggests that firms that have higher uncertainty typically earn lower returns around announcements.

The variable of interest is the interaction term (SRANK x EVOLRANK). This captures the relation between the sensitivity of immediate price response to surprises and earnings uncertainty. The interaction term coefficient is positive and significant. From the second column, I find that, the coefficient on the interaction term (SRANK x % UNCERTAIN) is also positive and significant. It is convenient to interpret the economic magnitude in terms of long-short extreme surprise portfolio returns. These extreme surprise portfolios are constructed by purchasing stocks in the largest surprise decile and short selling stocks in the smallest surprise decile. The estimates then imply that a two standard deviation increase in proportion of uncertain words results in 0.86 % (2 x 0.4 x 0.12 x 9) increase in returns for the long-short extreme surprise portfolio during the announcement period. The results show that the immediate response of prices is larger for high earnings uncertainty firms.

Columns three and four present the results when adding controls. In addition to the controls used in previous tests, I also add the interaction of controls and SRANK to the specification. The coefficient on the EVOLRANK interaction term becomes insignificant. The coefficient on the % UNCERTAIN interaction term, however, continues to remain positive and significant.

3.6.2 Delayed Price Response

Higher immediate response to high uncertainty firms alone cannot explain the attention constraints. Models of rational Bayesian learning also suggest larger(smaller) price response to earnings when prior uncertainty is high (low). However, these models in the absence of attention constraints imply that there would not be any drift in low uncertainty stocks following the initial price response. However, the models with attention constraints imply that there would be a stronger price drift following the initial price response, because the prices are slower to respond to news when attention is low. I test whether the drift is stronger in low uncertainty stocks in this section. I regress the CAR[2,60] on surprise ranks, uncertainty measures, and their interaction.

Table 8 presents the results for the delayed response. The coefficient on SRANK is positive. This is the post-earnings announcement drift (PEAD) documented in prior literature (Bernard and Thomas, 1989). In the first column, the coefficient on the interaction term (SRANK x EVOLRANK) is negative and significant. The results suggest that sensitivity of the PEAD to surprises is lower for high EVOLRANK firms. In terms of economic magnitude, the long-short extreme surprise portfolio earns 1.5% higher returns (6% annualized) in low EVOLRANK decile as compared to high EVOLRANK decile. The second column reports the results for % UNCERTAIN. The coefficient on the interaction term (SRANK x % UNCERTAIN) is negative and significant. In terms of economic magnitude this suggests that a two standard deviation decrease in proportion of uncertain words results in 1.8% higher returns (7.2% annualized) for the extreme surprises long-short portfolio. The results suggest that low uncertainty stocks underreact to earnings.

The magnitude of the interaction term coefficient in the delayed response specification is twice as that of the immediate response specification. This is consistent with prior literature where the magnitude of coefficient in immediate response is smaller than that of the delayed response (DellaVigna and Pollet (2009) and Hirshleifer et al. (2009)). The addition of controls to the specification in columns 3 and 4 does not affect the results. There is lower underreaction to earnings of firms using more uncertain language in their filings consistent with higher attention. Findings in tables 7 and 8 suggest that the underreaction of prices to earnings is more(less) severe in low(high) uncertainty firms. The delayed response results are consistent with attention constraints playing a role and are inconsistent with a rational Bayesian learning model without constraints.

I do robustness checks to ensure that the results are not due to the choice of post-earnings drift horizons. Internet Appendix Tables IA.3 and IA.4 report the delayed response regression results for different PEAD horizons for EVOLRANK and % UNCERTAIN respectively. The first four columns report the results for CAR[2,30], CAR[2,45], CAR[2,60], and CAR[2,75]. The interaction term coefficient is negative and significant across specifications for both EVOLRANK and % UNCERTAIN. The coefficient is also decreasing in horizon. The results suggest that the delayed response results are not affected by the choice of PEAD horizon.

I do subsample analysis to test whether the lower delayed response is concentrated in high complexity firms. Loughran and McDonald (2016) note that the file size is a good proxy for firm complexity. Therefore, I classify firms into high or low complexity firms based on whether the natural logarithm of net file size is above or below the median in the quarter. Internet Appendix Table IA.5 presents the results. Both low and high complexity firms see lower delayed response of prices to earnings when uncertainty is higher. The results show that the lower post-earnings drift is not concentrated in high complexity firms.

Then, I repeat the subsample analysis with market capitalization of firms. Internet Appendix Table IA.6 presents the results. I find that the lower delayed response is more pronounced in small firms suggesting that higher attention to high earnings uncertainty firms is primarily found in small firms. Therefore, higher attention to large firms is not driving the results. Furthermore, the coefficient is insignificant in the sample of large firms. This is because the PEAD is generally lower in large firms due to lower limits to arbitrage and higher attention in general.

This is not the first study to highlight the negative relationship between earnings volatility and the PEAD. Cao and Narayanamoorthy (2012) first documented this relationship. They note that the stocks with low earnings volatility have high earnings persistence and that the market underreacts to information in their earnings surprise. I complement their study by highlighting the attention as the channel through which the underreaction occurs.[16]

3.7 Analyst Responsiveness

Driskill, Kirk, and Tucker (2020) provide evidence that analysts are also subject to attention constraints. I study whether analysts pay more attention to high uncertainty firms by testing their responsiveness following earnings. I capture the responsiveness using a dummy variable (ONTIME) that takes value 1 if there is at least one analyst who revises next quarter estimates on the current quarter reporting date or the day after. This captures the idea that analyst revisions in the announcement period matter more for response of price to earnings.

Table 9 reports the results. Columns 1 and 2 report the result of regressing ONTIME on EVOLRANK and % UNCERTAIN respectively. The coefficients on the explanatory variables are positive and significant. There are 6% more firms with on time revisions in the high EVOLRANK decile as compared to the low EVOLRANK decile. Furthermore, a two standard deviation increase in uncertain language results in 12% increase in on time revisions. Columns 3 and 4 add controls to the specifications. The coefficients remain positive and significant. There is a strong positive relationship between prior earnings uncertainty and

[16] In Internet Appendix IA.7, I regress the delayed price response on SRANK, EVOLRANK, AVOL, and their interactions. I find the coefficient on triple interaction term (SRANK x EVOLRANK x AVOL) is negative and significant. However, the coefficient on double interaction term (SRANK x EVOLRANK) becomes insignificant. The post-earnings announcement drift is lower only in high earnings volatility that receive higher attention captured by abnormal trading volume. The results obtain even though earnings volatility loses its power in predicting abnormal trading volume in the multivariate specification. The findings support the claim that attention is the channel through which underreaction occurs in low earnings volatility stocks.

analyst responsiveness. The findings suggest that releases with higher earnings uncertainty are more likely to have on time revisions. The results are also consistent with Zhang (2008) who highlights the slower analyst responsiveness as a channel for stronger post-earnings announcement drift.

4 Conclusion

In this study, I explore how the investors allocate attention between firms having different uncertainty in earnings. I hypothesize that the investors will allocate more attention to high uncertainty firms. I test the hypothesis by using the fraction of uncertain (% UNCERTAIN) words in 10-K and 10-Q filings as a measure of ex ante earnings uncertainty. For robustness, I also use the historical earnings volatility as another measure. I find that, in empirical tests, % UNCERTAIN performs better than historical earnings volatility.

% UNCERTAIN predicts future earnings volatility suggesting that the firms use more uncertain language in the filings when they expect future earnings to be volatile. I find that the high uncertainty firms experience higher Google search activity, higher Bloomberg readership, and higher abnormal trading volume around earnings releases. The findings provide evidence of higher attention to high uncertainty firms.

To understand whether there are constraints to attention, I test for underreaction of prices. I find evidence of larger underreaction in low uncertainty firms. This is seen both in the lower initial response and the higher post-earnings announcement drift. Rational Bayesian learning models without attention constraints do not explain the underreaction suggesting that attention constraints play a role. I also find that the analysts are more responsive to earnings of high uncertainty firms . The findings are consistent with investors allocating more attention to high uncertainty firms in the presence of attention constraints.

This study contributes to the attention constraints literature by providing empirical evidence that uncertainty attracts attention in the cross-section of stocks. It also contributes to the literature on textual analysis by showing that the uncertain document tone is a better measure of ex ante earnings uncertainty in capturing attention.

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Table 1: Summary Statistics

The table presents the summary statistics of the variables used in the paper. ASVI is the abnormal search volume index in the week of earnings release. Abnormal institutional attention (AIA) is the dummy for Bloomberg readership. AVOL[0,1] is the abnormal trading volume during the announcement period. CAR[0,1] and CAR[2,60] are the cumulative abnormal returns. ONTIME is the dummy that is set to 1 if there is atleast one analyst who revises estimates during the announcement period. EVOL is the standard deviation of earnings before extra-ordinary items, scaled by total assets. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. SURPRISE is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. MCAP is the market capitalization (in $ millions) computed at the end of previous June. BM is the ratio of book value reported as of the fiscal year end in the previous calendar year divided by the market capitalization as of the previous December. TURNOVER is the average monthly turnover in the stock. NUMEST is the number of analyst estimates. REPORTLAG is the number of days between fiscal quarter end date and the earnings release date. STOCKVOL is the stock volatility computed as the sum of squared daily returns in the month before the announcement. NREPORTS is the number of simulataneous announcements. FRIDAY is the dummy variable for Fridays.

Variables	N	Mean	Std Dev	p25	p50	p75
ASVI	93,232	0.218	1.137	0.000	0.000	0.211
AIA	23,012	0.853	0.354	1	1	1
AVOL[0,1]	278,767	2.088	3.626	1.005	1.571	2.462
CAR[0,1]	278,854	0.000	0.080	-0.035	0.000	0.036
CAR[2,60]	278,854	0.002	0.218	-0.105	-0.006	0.090
ONTIME	144,731	0.714	0.452	0.000	1.000	1.000
EVOL	278,842	0.031	0.851	0.004	0.009	0.022
% UNCERTAIN	232,536	1.203	0.424	0.911	1.165	1.450
SURPRISE	278,854	-0.001	0.029	-0.001	0.000	0.002
MCAP	278,854	5,131	20,004	244	780	2,790
BM	278,854	0.810	8.164	0.280	0.500	0.816
TURNOVER	278,854	1.831	2.322	0.709	1.306	2.266
NUMEST	278,854	5	5	2	3	7
REPORTLAG	278,854	31	13	23	29	37
STOCKVOL	278,854	0.023	0.072	0.004	0.010	0.023
NREPORTS	278,854	148	98	63	133	229
FRIDAY	278,854	0.061	0.239	0.000	0.000	0.000

Table 2: Future Earnings Volatility

The table reports the results of regressing the natural logarithm of future earnings volatility on the measures of earnings uncertainty. FEVOL is the standard deviation of earnings before extra-ordinary items, scaled by total assets, computed using the data from 8 quarters following the earnings release. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are decile rankings of size (RSIZE), book-to-market (RBM), and number of simultaneous announcements (NRANK). Other controls include the turnover (TURNOVER), number of analyst estimates (NUMEST), the lag in days between quarter end and earnings announcement (REPORTLAG), stock volatility in the month before earnings announcement (STOCKVOL), and Friday Dummy (FRIDAY). Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Future Earnings Volatility(FEVOL)			
Variables	(1)	(2)	(3)	(4)
EVOLRANK	0.340***		0.222***	
	(0.004)		(0.003)	
% UNCERTAIN		0.351***		0.146***
		(0.025)		(0.019)
Constant	-6.265***	-5.198***		
	(0.024)	(0.032)		
Observations	274,316	230,226	264,768	222,007
Adjusted R-squared	0.425	0.010	0.531	0.435
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 3: Stock Volatility

The table reports the results of regressing the stock volatility on measures of earnings uncertainty.CSTOCKVOL is the stock volatility computed as the sum of squared daily returns during the month of the announcement date. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are decile rankings of size (RSIZE), book-to-market (RBM), and number of simultaneous announcements (NRANK). Other controls include the turnover (TURNOVER), number of analyst estimates (NUMEST), the lag in days between quarter end and earnings announcement (REPORTLAG), stock volatility in the month before earnings announcement (STOCKVOL), and Friday Dummy (FRIDAY). Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Stock Volatility(CSTOCKVOL)			
Variables	(1)	(2)	(3)	(4)
STOCKVOL	0.213***	0.233***	0.147***	0.146***
	(0.037)	(0.045)	(0.029)	(0.033)
EVOLRANK	0.004***		0.002***	
	(0.000)		(0.000)	
% UNCERTAIN		0.008***		0.005***
		(0.001)		(0.001)
Constant	0.007***	0.013***		
	(0.000)	(0.001)		
Observations	278,842	232,536	269,095	224,241
Adjusted R-squared	0.072	0.052	0.144	0.133
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 4: Google Search Activity Around Earnings Release

The table reports the results of regressing the abnormal search volume index (ASVI) during the week of earnings release on the measures of prior earnings uncertainty. Weekly search volume index (SVI) is the total google search for a keyword scaled by its time series average. Abnormal search volume index (ASVI) is the difference between natural logarithm of SVI during the earnings week and the natural logarithm of median SVI in the previous 8 weeks. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are decile rankings of size (RSIZE), book-to-market (RBM), and number of simultaneous announcements (NRANK). Other controls include the turnover (TURNOVER), number of analyst estimates (NUMEST), the lag in days between quarter end and earnings announcement (REPORTLAG), stock volatility in the month before earnings announcement (STOCKVOL), and Friday Dummy (FRIDAY). Also included are the industry and quarter fixed effects. Sample period is from 2004 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Abnormal Search Volume Index (ASVI)			
Variables	(1)	(2)	(3)	(4)
EVOLRANK	0.006***		0.002	
	(0.002)		(0.002)	
% UNCERTAIN		0.075***		0.048***
		(0.015)		(0.016)
Constant	0.189***	0.123***		
	(0.010)	(0.020)		
Observations	93,228	87,136	89,257	83,326
Adjusted R-squared	0.000	0.001	0.008	0.009
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 5: Institutional Attention Around Earnings Release

The table reports the results of regressing the abnormal institutional attention (AIA) during the week of earnings release on the measures of prior earnings uncertainty. Abnormal institutional attention (AIA) is a dummy variable that takes value 1 if the Bloomberg readership on any day during the week of earnings was above 94 percentile of the readership in the stock in prior 30 days. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are decile rankings of size (RSIZE), book-to-market (RBM), and number of simultaneous announcements (NRANK). Other controls include the turnover (TURNOVER), number of analyst estimates (NUMEST), the lag in days between quarter end and earnings announcement (REPORTLAG), stock volatility in the month before earnings announcement (STOCKVOL), and Friday Dummy (FRIDAY). Also included are the industry and quarter fixed effects. Sample period is from 2010 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Abnormal Institutional Attention (AIA)			
Variables	(1)	(2)	(3)	(4)
EVOLRANK	-0.003		0.005***	
	(0.002)		(0.002)	
% UNCERTAIN		-0.019*		0.016*
		(0.010)		(0.010)
Constant	0.865***	0.881***		
	(0.010)	(0.015)		
Observations	23,012	22,177	21,466	20,667
Adjusted R-squared	0.000	0.000	0.147	0.149
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 6: Trading Volume Response Around Earnings Releases

The table reports the results of regressing the abnormal volume around earnings release on measures of prior earnings uncertainty. Abnormal volume (AVOL[0,1]) is the average daily dollar trading volume during the earnings release period divided by the average trading volume in the 7 to 46 days before the earnings release. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. ASRANK is the decile rank of absolute earnings surprise. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, and FRIDAY. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Volume Response (AVOL [0,1])			
Variables	(1)	(2)	(3)	(4)
ASRANK	0.031***	0.044***	0.054***	0.055***
	(0.003)	(0.004)	(0.003)	(0.003)
EVOLRANK	0.047***		-0.000	
	(0.003)		(0.003)	
% UNCERTAIN		0.168***		0.048**
		(0.021)		(0.022)
Constant	1.739***	1.696***		
	(0.019)	(0.031)		
Observations	278,755	232,468	269,015	224,178
Adjusted R-squared	0.002	0.002	0.022	0.023
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 7: Immediate Price Response To Earnings Surprise

The table reports the results of regressing the immediate price response (CAR[0,1]) on surprise rank (SRANK), measures of earnings uncertainty, and their interaction. EVOLRANK is the decile ranking of earnings volatility (EVOL). % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Immediate Price Response (CAR[0,1])			
Variables	(1)	(2)	(3)	(4)
SRANK	0.750***	0.668***	1.201***	1.079***
	(0.015)	(0.024)	(0.037)	(0.045)
EVOLRANK	-0.134***		-0.081***	
	(0.013)		(0.016)	
SRANK x EVOLRANK	0.006**		-0.000	
	(0.003)		(0.003)	
% UNCERTAIN		-0.870***		-0.590***
		(0.097)		(0.107)
SRANK x % UNCERTAIN		0.123***		0.103***
		(0.019)		(0.020)
Constant	-2.882***	-2.601***		
	(0.071)	(0.120)		
Observations	278,842	232,536	269,095	224,241
Adjusted R-squared	0.079	0.082	0.086	0.091
Controls	No	No	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 8: Delayed Price Response To Earnings Surprise

The table reports the results of regressing the post-earnings announcement drift (CAR[2,60]) on surprise rank (SRANK), earnings uncertainty measures, and their interaction. EVOLRANK is the decile ranking of earnings volatility (EVOL). % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Delayed Price Response (CAR[2,60])			
Variables	(1)	(2)	(3)	(4)
SRANK	0.452***	0.644***	1.061***	1.105***
	(0.030)	(0.059)	(0.086)	(0.111)
EVOLRANK	-0.086**		-0.018	
	(0.041)		(0.038)	
SRANK x EVOLRANK	-0.018***		-0.028***	
	(0.006)		(0.007)	
% UNCERTAIN		0.733***		0.520*
		(0.281)		(0.272)
SRANK x % UNCERTAIN		-0.245***		-0.199***
		(0.047)		(0.048)
Constant	-1.101***	-2.325***		
	(0.185)	(0.367)		
Observations	278,842	232,536	269,095	224,241
Adjusted R-squared	0.003	0.002	0.047	0.048
Controls	No	No	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

Table 9: Analyst Responsiveness Around Earnings Releases

The table reports the results of regressing analyst responsiveness around earnings release on measures of prior earnings uncertainty. Analyst responsiveness measure (ONTIME) is the dummy variable which takes value 1 if there is atleast one analyst revising estimates for next quarter earnings within a day of the earnings release. EVOLRANK is the decile ranking of earnings volatility (EVOL). EVOL is computed as the standard deviation of earnings before extraordinary items, scaled by assets, using the data from 8 quarters prior to the announcement. % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date.Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, and FRIDAY. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	On Time Revisions (ONTIME)			
Variables	(1)	(2)	(3)	(4)
EVOLRANK	0.007***		0.006***	
	(0.001)		(0.001)	
% UNCERTAIN		0.153***		0.037***
		(0.006)		(0.005)
Constant	0.681***	0.541***		
	(0.006)	(0.010)		
Observations	144,728	123,124	140,213	119,156
Adjusted R-squared	0.002	0.020	0.217	0.208
Controls	No	No	Yes	Yes
Industry and Quarter FE	No	No	Yes	Yes

A Internet Appendix

A.1 Model

I study how a representative investor allocates attention among different firms.[17] She holds the net supply of risky assets. Each period, she receives dividends from the risky asset holdings. She can either consume the dividends in the same period they are received, or shift some of the consumption between periods t and $t+1$ by borrowing or lending at the risk-free asset rate r_f.

Dividends at $t+1$ are unknown to the investor at time t. She only knows the distribution from which the dividends are drawn. At t she can receive a noisy signal about $t+1$ dividends by processing information that is released at time t. The information can be considered as an earnings release. By allocating attention to a firm's news release, she can receive a signal about the future dividends of the firm. By allocating more attention she can increase the precision of the signal. After observing the signal, she uses Bayes rule to arrive at posterior distribution of dividends at $t+1$. However, the investor's available attention capacity is limited. Therefore, allocating more attention to one firm reduces the available capacity for processing information about other firms.

The investor's problem is two fold. First, she has to decide how much attention to allocate to different firms to receive signals about $t+1$ dividends. Second, after observing signals, she then solves the utility maximization problem and makes efficient intertemporal consumption decision.

[17]This model is a simplified version of Peng and Xiong (2006) where a representative investor allocates attention between market, sector, and firm-specific news.

The paper talks about earnings uncertainty while the model looks at uncertainty in dividends. The results still hold in the absence of large variation in payout ratios in adjacent periods.

A.1.1 Assets

The risk-free rate r_f is known to the investor. The investor holds a portfolio of N risky assets. Let d_{it} denote the dividend paid by asset i at time t. Dividend at time $t+1$, d_{it+1} is unknown to the investor at time t. Dividends are assumed to be cross-sectionally independent but not identically distributed. [18] Dividends for a firm i are independent across time.

$$d_{it} \sim N(\mu_i, \sigma_i^2), i = 1, ..., N \tag{1}$$

A.1.2 Utility

The investor has CARA exponential utility over consumption.

$$u(c) = -\frac{1}{\rho} exp(-\rho c), \tag{2}$$

where ρ is the absolute risk aversion coefficient. She derives utility over current and future values of consumption.

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t[u(c_{t+1})], \tag{3}$$

where c_t is the level of consumption in time t, $\beta \in (0, 1)$ is the time preference parameter. The decision problem is how much to consume current period. As the representative investor holds the net supply of risky assets, she can either consume the dividends from risky assets

[18] Peng and Xiong (2006) model a factor structure in dividends. The dividends are affected by market and sector factors. Further, for simplicity, they assume that the part of dividends that is firm-specific is independently and identically distributed among firms within the same sector. Their model predicts that investors allocate more attention to market as compared to firm-specific information.

For simplicity, I assume that there is no factor structure in dividends. Further, the dividends for different firms are not identically distributed. This helps me study the difference in attention allocation to firms having different uncertainty in dividends.

or shift consumption to next period by purchasing δ of risk-free assets.

$$c_t = \sum_i d_{it} - \delta \tag{4}$$

Then, consumption at t+1 is then given by

$$c_{t+1} = \sum_i d_{it+1} + \delta(1 + r_f) \tag{5}$$

A.1.3 Signal

At t, she can observe a signal s_{it} about next period dividend d_{it+1} by allocating attention to information about firm i. The signal is unbiased but noisy and is drawn from a normal distribution.

$$s_{it} = d_{it+1} + \epsilon_{si}, \tag{6}$$

where

$$\epsilon_{si} \sim N(0, \sigma_{si}^2), i = 1, ..., N \tag{7}$$

The signals are assumed to be independent. After observing the signal, she arrives at the posterior distribution of d_{it+1} using Bayes rule.

$$E[d_{it+1}|s_{it}] = \hat{\mu_i} = \left(\frac{1}{\sigma_i^2} + \frac{1}{\sigma_{si}^2}\right)^{-1}\left(\frac{1}{\sigma_i^2}\mu_i + \frac{1}{\sigma_{si}^2}s_{it}\right) \tag{8}$$

$$Var[d_{it+1}|s_{it}] = \hat{\sigma}_i^2 = \left(\frac{1}{\sigma_i^2} + \frac{1}{\sigma_{si}^2}\right)^{-1} \tag{9}$$

Given the assumptions about the unconditional distribution of dividends and the distribution of signals, the posterior distribution of dividends is distributed normally,

$$\hat{d}_{it+1} \sim N(\hat{\mu}_i, \hat{\sigma}_i^2), i = 1, ..., N \tag{10}$$

A.1.4 Attention resources

The total amount of attention available to an investor is assumed to be K.[19] The fraction of the attention allocated to an asset is given by $\lambda_i \in [0, 1]$. The attention constraint is given by

$$\sum_{1}^{N} \lambda_i \leq 1 \tag{11}$$

As the fraction of attention given to a specific asset λ_i increases, the precision of signal s_{it} increases, and therefore the posterior variance $\hat{\sigma}_i^2$ decreases. [20]

A.1.5 Learning Process

Investors learning process involves collecting and processing the signals about assets. Following Peng and Xiong (2006), I use entropy as the measure of information contained about asset payoff in signal s. Entropy of a random variable is a measure of its uncertainty. The entropy H of an asset i's dividend (with normal distribution) is given by

$$H(d_{it+1}) = \frac{1}{2}\ log\ \sigma_i^2 + 0.5\ log\ (2\pi e) \tag{12}$$

[19]This model does not allow for any factor structure in the dividends. The attention resources available to the representative investor (K) can be thought as a subset of investor's total available attention resources (L) after we account for the attention being allocated to market and sector related information (L-K) in Peng and Xiong (2006).

[20]Given the assumptions about the distribution of dividends and signals, any choice of signal precision corresponds to unique posterior variance $\hat{\sigma}_i^2$ from the equation (9). Therefore, I economize on notation and directly model the choice of posterior variance.

The investor observes signal s_{it} about the dividends d_{it+1}. The amount of information in signal s_{it} about d_{it+1}, $I(d_{it+1}; s_{it})$ is the reduction in entropy $H(d_{it+1})$

$$I(d_{it+1}; s_{it}) = H(d_{it+1}) - H(d_{it+1}|s_{it}) = \frac{1}{2}\ log\ \frac{\sigma_i^2}{\hat{\sigma}_i^2} \tag{13}$$

As the information in a signal is related to the attention paid to the asset, the relationship between both is assumed to be linear, following Peng and Xiong (2006).

$$I(d_{it+1}; s_{it}) = \frac{1}{2} K\lambda_i \tag{14}$$

From (13) and (14)

$$\hat{\sigma_i^2} = \sigma_i^2\ e^{-K\lambda_i} \tag{15}$$

As λ_i increases, the posterior variance of dividends $\hat{\sigma}_i^2$ decreases. The investor therefore can increase the precision of beliefs about firm i by increasing the attention allocated to it.

A.1.6 Decision Problem

Investor's optimization problem is given by

$$\max_{\lambda} E\{\max_{\delta} u(c_t) + \beta E_t[u(c_{t+1})]\}, \tag{16}$$

The investor has to make two decisions. First, the investor decides optimum allocation of attention to processing signals of each assets subject to constraint (11). Next, based on the signals the investor needs to choose current consumption subject to constraints (4) and (5).

A.1.7 Solution

I solve the investor's optimization problem by first deriving optimum investor's consumption given information about next period asset fundamentals. Then, I use the optimum consumption to solve the attention allocation problem.

The first order condition for the maximization problem

$$\max_{\delta} u(c_t) + \beta E_t[u(c_{t+1})] \tag{17}$$

with respect to constraints (4) and (5) is

$$u'(c_t) = \beta E_t[u'(c_{t+1})(1 + r_f)] \tag{18}$$

$$exp(-\rho c_t) = \beta(1 + r_f)E_t[exp(-\rho c_{t+1})] \tag{19}$$

$$exp(-\rho c_t) = \beta(1 + r_f)E_t[exp(-\rho\{\sum_i d_{it+1} + \delta(1 + r_f)\})] \tag{20}$$

Using the expectation of log-normal variable to reduce this we get

$$exp(-\rho c_t) = \beta(1 + r_f)exp\Big\{E_t[-\rho \sum_i d_{it+1}] + \frac{\rho^2}{2}Var_t[\sum_i d_{it+1}] - \rho\delta(1 + r_f)\Big\} \tag{21}$$

Now the consumption at time t can be written as

$$c_t = -\frac{ln(\beta(1 + r_f))}{\rho} - \frac{1}{\rho}\Big\{E_t[-\rho \sum_i d_{it+1}] + \frac{\rho^2}{2}Var_t[\sum_i d_{it+1}] - \rho\delta(1 + r_f)\Big\} \tag{22}$$

$$c_t = -\frac{ln(\beta(1 + r_f))}{\rho} - \frac{1}{\rho}\Big\{ - \rho \sum_i \hat{\mu}_i + \frac{\rho^2}{2} \sum_i \hat{\sigma}_i^2 - \rho\delta(1 + r_f)\Big\} \tag{23}$$

Utility of this consumption is

$$u(c_t) = -\frac{1}{\rho}exp\Big[-\rho\Big(-\frac{ln(\beta(1+r_f))}{\rho} - \frac{1}{\rho}\Big\{-\rho\sum_i \hat{\mu}_i + \frac{\rho^2}{2}\sum_i \hat{\sigma}_i^2 - \rho\delta(1+r_f)\Big\}\Big)\Big] \quad (24)$$

$$u(c_t) = -\frac{\beta(1+r_f)}{\rho} - \frac{1}{\rho}exp\Big\{-\rho\sum_i \hat{\mu}_i + \frac{\rho^2}{2}\sum_i \hat{\sigma}_i^2 - \rho\delta(1+r_f)\Big\} \quad (25)$$

Similarly, expected utility of consumption at time $t+1$ can be reduced to

$$\beta E_t[u(c_{t+1})] = -\frac{\beta}{\rho}exp\Big\{-\rho\sum_i \hat{\mu}_i + \frac{\rho^2}{2}\sum_i \hat{\sigma}_i^2 - \rho\delta(1+r_f)\Big\} \quad (26)$$

Substituting (25) and (26) in (16) gives

$$\max_\lambda E\Big[-\frac{\beta(1+r_f)}{\rho} - \frac{1+\beta}{\rho}exp\Big\{-\rho\sum_i \hat{\mu}_i + \frac{\rho^2}{2}\sum_i \hat{\sigma}_i^2 - \rho\delta(1+r_f)\Big\}\Big] \quad (27)$$

The decision to allocate attention happens before observing signals. The expectation in (27) is unconditional as the optimization problem is solved before observing signals. The only term that is affected by the optimization problem is the term with $\hat{\sigma}_i^2$. Therefore the problem (27) is equivalent to

$$\min_\lambda \sum_i \hat{\sigma}_i^2 \quad (28)$$

subject to

$$\sum_1^N \lambda_i \leq 1 \quad (29)$$

$$\lambda_i \geq 0, i = 1, ..., N \quad (30)$$

The last two constraints are with respect to attention constraints. The first of which states the fraction of attention allocated to different assets cannot sum over 1. The second one is to ensure attention to any asset cannot be negative. T The lagrangian is given by,

$$L = \sum_i \hat{\sigma}_i^2 - \psi(1 - \sum_1^N \lambda_i) - \sum_1^N \theta_i \lambda_i \tag{31}$$

where ψ and θ_i are lagrangian multipliers. Applying (15) to (31) gives

$$L = \sum_i \sigma_i^2 \; e^{-K\lambda_i} - \psi(1 - \sum_1^N \lambda_i) - \sum_1^N \theta_i \lambda_i \tag{32}$$

Whenever investor allocates positive attention to an asset i, $\lambda_i > 0$, the first order condition becomes

$$\psi e^{K\lambda_i} = K\sigma_i^2 \;\; if \;\; \lambda_i > 0 \tag{33}$$

ψ is the opportunity cost of allocating an unit of attention. A firm i receives positive attention, $\lambda_i > 0$, only when there is a marginal benefit to paying more attention. For the assets where $\lambda_i > 0$, the amount of attention allocated increases with the prior variance of dividends σ_i^2.

A.1.8 Discussion

In Peng and Xiong (2006) there is a market component and an industry component to dividends. In their model, investors allocate more attention to market information as compared to firm-specific information. In that regard, the total attention resources available to the investor in the model here can be thought of as the attentions resources available after deducting the market and industry attention resources. Furthermore, in Peng and Xiong (2006) the firm-specific dividends are independently and identically distributed. In this paper, the dividends are independent but not identically distributed, which helps me solve for the relationship between attention and prior uncertainty in dividends. [21]

Van Nieuwerburgh and Veldkamp (2010) solve attention allocation for a problem of an investor. They derive conditions under which the solution is either generalized learning which leads to diversified holdings of assets or specialized learning where investors are under-diversified. In this paper, the assumption that the investors hold net supply of risk assets precludes the possibility of under-diversification.

[21] In related work,Peng (2005) solves an attention model in continuous time where an investor allocates attention to fundamental factors affecting dividends. By normalizing all parameters, but making the supply of shares different, that model predicts that that large stocks get more attention.

Table IA.1: Google Search Activity Around Earnings Release

The table reports the results of regressing the abnormal search volume index (ASVI) during the week of earnings release on document tone measures from 10-K or 10-Q filings in the quarter before the announcement date. % UNCERTAIN represents the fraction of uncertain words, % WEAKMODAL represents the fraction of weak modal words, % NEGATIVE is the percentage of negative words, and % POSITIVE is the fraction of positive words. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, and FRIDAY. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Abnormal Search Volume Index (ASVI)			
Variables	(1)	(2)	(3)	(4)
% UNCERTAIN	0.048***			
	(0.016)			
% WEAKMODAL		0.095***		
		(0.025)		
% NEGATIVE			0.023**	
			(0.011)	
% POSITIVE				-0.016
				(0.028)
Observations	83,326	83,326	83,326	83,326
Adjusted R-squared	0.009	0.009	0.008	0.008
Controls	Yes	Yes	Yes	Yes
Industry and Quarter FE	Yes	Yes	Yes	Yes

Table IA.2: Attention and Continuous Historical Earnings Volatility

The table reports the results of regressing attention measures on log of historical earnings volatility. Abnormal search volume index (ASVI) is the difference between natural logarithm of SVI during the earnings week and the natural logarithm of median SVI in the previous 8 weeks. Abnormal institutional attention (AIA) is a dummy variable that takes value 1 if the Bloomberg readership on any day during the week of earnings was above 94 percentile of the readership in the stock in prior 30 days. Abnormal volume (AVOL[0,1]) is the average daily dollar trading volume during the earnings release period divided by the average trading volume in the 7 to 46 days before the earnings release. LEVOL is the natural logarithm of earnings volatility (EVOL). ASRANK is the decile ranking of absolute surprises. Controls included are decile rankings of size (RSIZE), book-to-market (RBM), and number of simultaneous announcements (NRANK). Other controls include the turnover (TURNOVER), number of analyst estimates (NUMEST), the lag in days between quarter end and earnings announcement (REPORTLAG), stock volatility in the month before earnings announcement (STOCKVOL), and Friday Dummy (FRIDAY). Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	ASVI		AIA		AVOL([0,1])	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ASRANK					0.040***	0.054***
					(0.003)	(0.003)
LEVOL	0.012***	0.002	0.005	0.012***	0.049***	0.001
	(0.003)	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)
Constant	0.274***		0.543***		2.743***	
	(0.018)		(0.028)		(0.062)	
Observations	93,228	89,257	23,012	21,466	278,755	269,015
Adjusted R-squared	0.000	0.008	0.116	0.147	0.007	0.022
Controls	No	Yes	No	Yes	No	Yes
Industry and Quarter FE	No	Yes	No	Yes	No	Yes

Table IA.3: Earnings Volatility And PEAD At Different Horizons

The table reports the results of regressing delayed response at different horizons (30,45,60, and 75 days) on surprise rank (SRANK), earnings volatility decline rank (EVOLRANK), and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into deciles (SRANK) on the earnings announcement surprise. EVOLRANK is the decile ranking of earnings volatility. Earnings volatility is the standard deviation of income before extra-ordinary items, scaled by total assets, computed using the previous 8 quarters of data. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Delayed Price Response			
	CAR[2,30]	CAR[2,45]	CAR[2,60]	CAR[2,75]
Variables	(1)	(2)	(3)	(4)
SRANK	0.557***	0.718***	1.061***	1.209***
	(0.059)	(0.071)	(0.086)	(0.103)
EVOLRANK	-0.000	-0.036	-0.018	-0.081*
	(0.027)	(0.033)	(0.038)	(0.047)
SRANK x EVOLRANK	-0.022***	-0.025***	-0.028***	-0.028***
	(0.005)	(0.006)	(0.007)	(0.008)
Observations	269,095	269,095	269,095	268,129
Adjusted R-squared	0.035	0.039	0.047	0.044
Controls	Yes	Yes	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	Yes	Yes	Yes	Yes

Table IA.4: Uncertain Language And PEAD At Different Horizons

The table reports the results of regressing delayed response at different horizons (30,45,60, and 75 days) on surprise rank (SRANK), measure of uncertain language in filings (% UNCERTAIN), and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into deciles (SRANK) on the earnings announcement surprise. % UNCERTAIN is the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the earnings date. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Delayed Price Response			
	CAR[2,30]	CAR[2,45]	CAR[2,60]	CAR[2,75]
Variables	(1)	(2)	(3)	(4)
SRANK	0.499***	0.710***	1.105***	1.292***
	(0.074)	(0.093)	(0.111)	(0.129)
% UNCERTAIN	0.346*	0.375*	0.520*	0.713**
	(0.189)	(0.226)	(0.272)	(0.322)
SRANK x % UNCERTAIN	-0.093***	-0.147***	-0.199***	-0.257***
	(0.032)	(0.040)	(0.048)	(0.056)
Observations	224,241	224,241	224,241	223,727
Adjusted R-squared	0.036	0.040	0.048	0.043
Controls	Yes	Yes	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	Yes	Yes	Yes	Yes

Table IA.5: Post Earnings Announcement Drift By Firm Complexity

The table reports the results of regressing the delayed price response (CAR[2,60]) on surprise rank (SRANK), measures of earnings uncertainty, and their interaction. EVOLRANK is the decile ranking of earnings volatility (EVOL). % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Low (High) complexity firms have the natural logarithm of SEC filing size below (above) the median in the quarter. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Delayed Price Response (CAR[2,60])			
	Low	High	Low	High
Variables	(1)	(2)	(3)	(4)
SRANK	1.075***	1.005***	1.152***	1.052***
	(0.132)	(0.150)	(0.155)	(0.160)
EVOLRANK	0.035	0.007		
	(0.054)	(0.057)		
SRANK x EVOLRANK	-0.034***	-0.029***		
	(0.010)	(0.010)		
% UNCERTAIN			0.730*	0.245
			(0.375)	(0.373)
SRANK x % UNCERTAIN			-0.221***	-0.184***
			(0.069)	(0.066)
Observations	112,223	112,012	112,226	112,015
Adjusted R-squared	0.057	0.042	0.056	0.042
Controls	Yes	Yes	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	Yes	Yes	Yes	Yes

Table IA.6: Post Earnings Announcement Drift By Firm Size

The table reports the results of regressing the delayed price response (CAR[2,60]) on surprise rank (SRANK), earnings uncertainty measures, and their interaction. EVOLRANK is the decile ranking of earnings volatility (EVOL). % UNCERTAIN represents the fraction of uncertain words in the 10-K or 10-Q filing in the quarter before the announcement date. Small (Large) firms have market capitalization below (above) the median in the quarter. Controls included are RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, and their interactions with SRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Delayed Price Response (CAR[2,60])			
	Small	Large	Small	Large
Variables	(1)	(2)	(3)	(4)
SRANK	1.207***	0.706***	1.285***	0.697***
	(0.118)	(0.157)	(0.149)	(0.191)
EVOLRANK	-0.015	-0.073		
	(0.053)	(0.047)		
SRANK x EVOLRANK	-0.037***	-0.004		
	(0.009)	(0.009)		
% UNCERTAIN			0.921**	-0.251
			(0.373)	(0.357)
SRANK x % UNCERTAIN			-0.278***	-0.046
			(0.063)	(0.067)
Observations	130,508	138,587	107,871	116,370
Adjusted R-squared	0.071	0.030	0.072	0.029
Controls	Yes	Yes	Yes	Yes
Controls x SRANK	No	No	Yes	Yes
Industry and Quarter FE	Yes	Yes	Yes	Yes

Table IA.7: Delayed Price Response, Earnings Volatility, and Abnormal Volume

The table reports the results of regressing the post-earnings announcement drift (CAR[2,60]) on surprise rank (SRANK), abnormal volume (AVOL), measures of earnings uncertainty, and their interactions. EVOLRANK is the decile ranking of earnings volatility (EVOL). Controls included are AVOL, RSIZE, RBM, NRANK,TURNOVER,NUMEST, REPORTLAG, STOCKVOL, FRIDAY, their interactions with SRANK, and AVOL x EVOLRANK. Also included are the industry and quarter fixed effects. Sample period is from 1995 to 2018. Standard errors clustered both by firm and the reporting date are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	CAR[2,60]	
Variables	(1)	(2)
SRANK	0.357***	0.947***
	(0.037)	(0.089)
EVOLRANK	-0.152***	-0.085
	(0.051)	(0.052)
SRANK x EVOLRANK	-0.005	-0.012
	(0.007)	(0.008)
SRANK x EVOLRANK x AVOL	-0.007***	-0.008***
	(0.002)	(0.003)
Constant	-0.823***	
	(0.228)	
Observations	278,755	269,015
Adjusted R-squared	0.003	0.047
Controls	No	Yes
Controls x SRANK	No	Yes
Industry and Quarter FE	No	Yes