News impact on investor uncertainty: The asymmetric effects of earnings announcements on implied volatility

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Abstract

This study examines the effect of earnings announcements on investor uncertainty. We show that the typical change in investor uncertainty is increasing in the magnitude of earnings surprise when the surprise is negative but is decreasing in the magnitude of surprise when the surprise is positive. Moderate good news is most effective in reducing investor uncertainty, but extreme news (good or bad) typically increases uncertainty or attenuates uncertainty resolution. Finally, we document evidence that investors typically experience an increase in uncertainty around announcements conveying large negative earnings surprises when the pre-announcement uncertainty is low.

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1 Introduction

This study examines the effect of disclosure on investor uncertainty, and we particularly focus on the differential implications of good and bad news. Investors face uncertainty in the parameters of the probability distributions of firm values/stock returns, and they rely on information disclosure to resolve that uncertainty. Therefore, the uncertainty effects of disclosure is a naturally important phenomenon to study. In this paper, we use the earnings announcement as our setting for disclosure and option implied volatility as proxy for investor uncertainty to test the determinants of the response of investor uncertainty to earnings announcements.

Static Bayesian models have largely predicted that information arrivals indeed resolve investor uncertainty (Lewellen and Shanken 2002; Lambert et al. 2007; Verrecchia 2001). Rational investors should update their knowledge by weighing the new information against their priors and optimally choose their posteriors. Given that ignoring the new information is always a feasible alternative, the optimality of investors' posteriors can be of no greater uncertainty than their priors.[1] This intuition suggests that disclosures reduce investor uncertainty as long as the information conveyed is relevant for assessing firm value. Numerous empirical studies have found and interpreted their results consistent with this prediction (Barron et al. 2002; Billings et al. 2015; Patell and Wolfson 1981, 1979). Johnstone (2015), however, argues that this intuition is only available if some restrictive assumptions are made and that the possibility of uncertainty increase in response to information cannot be ruled out in general.

Furthermore, the models identify that the extent of uncertainty reduction is increasing in the variance in the investor's prior and decreasing in the variance in the information, which has a special bearing on the policy implications regarding the quality of accounting

[1] In these models, ignoring the new information is optimal if and only if the the information is irrelevant or entirely unreliable. More details are discussed in Section 2.

disclosure.[2] Subramanyam (1996) adds a new assumption that investors perceive higher variance in information for disclosure conveying larger surprises in that investors view more confirmatory news as more precise. Indeed, Rogers et al. (2009) and Neururer et al. (2016) find that the magnitude of surprise attenuates uncertainty reduction around the disclosure. Interpreted in the context of static Bayesian models, their findings seem to validate the added assumption of the model.

The Subramanyam (1996) model, however, has assumed a symmetric uncertainty effect of disclosure. That is, the sign of the news has no role to play and larger surprises in the positive and negative domains of surprises have similar impacts on investor uncertainty. In contrast, our study features the sign of the news as an important conditioning variable, and we find that investor uncertainty responds to good news and bad news asymmetrically. Our focus on the role of the sign is motivated by several finance studies highlighting how good news and bad news (indicated by the sign of stock returns) have differential implications on return volatility: volatility increases more strongly in response to negative stock returns (Black 1976; French et al. 1987; Campbell and Hentschel 1992; Chen and Ghysels 2011; Patton and Sheppard 2015). Black (1976) attributes this result to the rise in leverage in face of negative price movements heightening market sensitivity to future information, but Campbell and Hentschel (1992) interpret this result through the "feedback" effects of news-induced volatility on discount rates.[3]

While our study is not intended to discriminate the two competing explanations, it is distinguished from these studies in several ways. First, we examine the firm-level effects, whereas the studies above focus on the aggregate-level results. To the extent that firm-level news can be diversified away, there is no guarantee that the aggregate-level phenomenon

[2]One commonly shared view on this issue is highlighted by a former member of the Financial Accounting Standards Board that more precise financial reporting (that is of lower perceived variance) reduces investor uncertainty and thus the cost of capital (Foster 2003).

[3]To the extent that volatility is persistent, larger surprises tend to be follow by further large surprises, leading to rises in future volatility. Anticipating this, stock prices will be "discounted" in response to such changes in anticipated volatility by building in a higher required return. Therefore, the price response to good news is dampened by the volatility discount, and the response to bad news is "doubly bad". Therefore, Campbell and Hentschel (1992) interpretation implies that volatility drives returns, which reverses the causality of Black (1976) interpretation.

also holds at the firm level. Second, we measure news in terms of earnings surprise (i.e. the difference between reported earnings and *ex ante* consensus analyst forecast) conveyed by the earnings announcement, instead of returns as in these studies. To the extent that analyst earnings forecast is a reasonable proxy for market expectation, the earnings surprise captures cash flow news only. In contrast, stock returns embed uncertainty changes in addition to cash flow news and are therefore is endogenously related to volatility (see footnote 3). Finally, we focus on implied volatility rather than realized volatility to uncover forward-looking volatility to emphasize on investor learning.

Our findings show that there is indeed a strong asymmetric pattern in the relation between the earnings surprise and investor uncertainty. First we show that the typical change in investor uncertainty is increasing in the magnitude of earnings surprise when the surprise is negative but is decreasing in the magnitude of surprise when the surprise is positive. This appears to be inconsistent the prediction that follows from Subramanyam (1996) model, where investor uncertainty should be reduced by a lesser amount as the earnings surprise gets larger in both directions. This result also suggests that the attenuation effect of the magnitude of earnings surprise reported in Neururer et al. (2016) is likely to be driven by the observations with bad news announcements.

Next, we conduct a non-parametric estimation of the "news impact curve" describing the relation between changes in investor uncertainty and earnings surprises. Wee deem the non-parametric approach particularly useful in our study, for it allows us to discover regularities outside the descriptions of static Bayesian models.[4] Strikingly, our results reveal that the news impact curve exhibits a U-shape bottoming up at a moderate level of *positive* earnings surprise (instead of zero). Specifically, as the magnitude of earnings surprise increase form zero to the negative direction, the change in implied volatility increases monotonically; as the magnitude of earnings surprise increase form zero to the positive direction, the change in volatility first declines through a moderate level of surprise and rises afterwards, though the

[4]There are many specialized models that depart from the structure of static Bayesian models, but these models typically do not supply empirically tractable closed-form solutions that can motivate a well-specified parametric test.

rise is flatter than that in the negative region. This finding suggests that investors appear to feel more confident about good news compared to bad news, but their posterior uncertainty is relatively larger when the news is "extreme". This pattern also helps us interpret the opposite uncertainty effects of positive and negative earnings surprises: moderate good news accounts for more density in our sample, so the attenuation effect that is only apparent over the relatively extreme region, is muted in the good news sample. We next partion our sample into three equal-sized subsamples based on the levels of pre-announcement uncertainty (measured with the average of absolute values of earnings surprises of earnings announcements of the previous four quarters) and find that the reversal of news impact curve in the positive region is only present in the low pre-announcement uncertainty subsample. Otherwise, the curve is almost monotonically doward sloping across the spectrum of earnings surprise—better news leads to more (less) uncertainty resolution (increase).

Furthermore, we document evidence that investors typically experience an increase in uncertainty around announcements conveying large negative earnings surprises when the pre-announcement uncertainty is low. This result highlights a limitation of the static Bayesian model that does not accommodate the possibility of news-induced uncertainty increase, consistent with the conjecture in Johnstone (2015) that uncertainty can rise when investors receive information that severely challenges their firm priors. The result also suggests that large bad news challenges investors' priors more severely than good news. Ours is not the only study that systematically identifies the cases for uncertainty increase after the earnings announcement. Neururer et al. (2016) show that extremely large earnings surprises cause increases in implied volatility. Nevertheless, we further identify that the sign and pre-announcement uncertainty are important conditioning variables for identifying uncertainty increases as the evidence for uncertainty increases is not significant where the earnings surprise is extreme in the positive direction and where the pre-announcement uncertainty is not sufficiently low.[5] These new set of regularities suggest that the static Bayesian models are perhaps oversimplified for studying the uncertainty effect of disclosure[6], models that al-

[5]We acknowledge that our measurement and research design is likely to understate the instance of uncertainty increase. See more details in Section 3

[6]They might be well suited for other research purposes though.

low for plausible uncertainty increases such as those in Schwert (1989), Kim and Verrecchia (1994), Veronesi (1999) and David and Veronesi (2013) are likely to be more useful.

Our study can also be compared to papers in the growing empirical literature studying information contents of earnings announcements using option markets data. The majority of such studies focus on the *ex post* effects of earnings announcements on investors' anticipation of future stock price movements. For instance, Patell and Wolfson (1979, 1981), Billings and Jennings (2011) and Barth and So (2014) examine the *ex ante* anticipation of the disequilibrium jump volatility induced by earnings announcements. Our study is more in line with the spirit of Neururer et al. (2016) in that we examine the *ex post* effects of earnings announcement on the equilibrium levels of investor uncertainty.

The remainder of the paper is organized as follows. We first develop our hypotheses in the contexts of the related literature in Section 2. Section 3 describes our data sources and empirical sample, and in Section 4 we discuss our findings. Section 5 concludes the paper.

2 Related literature and hypothesis development

We directly test the asymmetric uncertainty effects of information on investor uncertainty and disclosure in the setting of earnings announcements. This choice of focusing on earnings announcements helps us distinguish ours from prior studies of the news-induced asymmetric uncertainty effects in the finance literature (Black 1976; French et al. 1987; Campbell and Hentschel 1992; Chen and Ghysels 2011; Patton and Sheppard 2015). These studies measure information by returns on broad-based stock market indexes, but stock returns are not exogenous to uncertainty (proxied by volatility) because revisions in investor uncertainty feed back to discount rates and thus affect stock returns. This endogenous relation clouds the inference that can be drawn from relation between news and volatility. In contrast, earnings surprises conveyed by earnings announcements as our news proxy are unlikely to be driven by the feedback effect from investor uncertainty and thus allow us to be clear about the direction of causality.

Investors generally face two sources of uncertainty before the earnings announcement:(1) the short-term uncertainty about the forthcoming earnings realizations and (2) the long-term uncertainty about the the parameters of the probability distribution governing the firm's earnings generation process. Since the earnings announcement almost always fully resolves the former source of uncertainty, we are particularly interested in resolution of uncertainty from the second source. Static Bayesian models such as those described in Verrecchia (1983), Lewellen and Shanken (2002) and Lambert et al. (2007) argue that more information available to investors increases the precision of their beliefs regarding the parameters of the probability distribution of future cash flows.[7] This intuition is most commonly shown via a normal-normal Bayesian learning model. Specifically, if an investor has a prior belief about a parameter X that can be represented as a normal distribution with variance $Var(X) = \sigma^2_{prior}$ and he/she receives a signal Y drawn from a normal distribution describing the true parameter with variance σ^2_{info}, then the variance of the distribution describing his rational posterior belief can be expressed as

$$Var(X|Y) = Var(X) - Var(E[X|Y]) = \frac{\sigma^2_{info}}{\sigma^2_{prior} + \sigma^2_{info}} \sigma^2_{prior} \tag{1}$$

Equation 1 shows that, if investor uncertainty is represented by the variance of the probability distribution describing his subjective beliefs, information arrivals *always* reduces his uncertainty. This is guaranteed because $\frac{\sigma^2_{info}}{\sigma^2_{prior}+\sigma^2_{info}} < 1$ as long as the investor does not have perfect foresight before the announcement($\sigma^2_{prior} > 0$) and the information is infinitely unreliable ($\sigma^2_{info} < \infty$).

Existing studies seem to have largely confirmed that earnings announcements and other types of disclosures indeed resolve investor uncertainty. Barron et al. (2002) find that the dispersion of analyst forecasts decreases on average around earnings announcements, sug-

[7] In Bayesian models, the precision is defined as the reciprocal of variance.

gesting earnings announcements resolving analysts' uncertainty about future earnings.[8] In addition, Patell and Wolfson (1981, 1979) document a general decline in option implied volatility (a proxy for investor uncertainty, see (Veronesi 1999)) around earnings announcements. Furthermore, Rogers et al. (2009) and Billings et al. (2015) show that earnings guidance typically leads to reduction in implied volatility, consistent with more disclosure resolving more uncertainty.

Beyond the *direction* of the change in investor uncertainty, the model represented by equation 1 identifies two determinants of the *degree* of uncertainty resolution. First, the degree of uncertainty resolution is increasing the perceived precision of the earnings information. That is, when σ^2_{info} is lower, the earnings information can only be generated by a narrower set of states of nature and is thus more informative about the parameters of the underlying probability distribution governing the earnings generation process. Second, uncertainty resolution is decreasing in the precision of the investor's prior beliefs. Intuitively, when the investor is already certain about the parameters of the earnings process (i.e. σ^2_{prior} is already low), he/she has less to gain from observing additional information to resolve uncertainty. In summary, under the normal-normal model, uncertainty resolution is only affected the variances in the prior and the information.

Whereas the variance in the prior may be empirically proxied with reasonably transparent motivation (more details in Section 3), the precision of the earnings information is hard to quantify as it is somewhat elusive. Subramanyam (1996) describes a model where investors infer information precision from the magnitude of the information surprise. That is, information with larger surprise magnitude is interpreted by investors to be of lower precision relative to more confirmatory disclosure. While he does not examine uncertainty resolution, his model would predict that large earnings surprises lead to less reduction in investor uncertainty. The intuition appears to be plausible: Large earnings surprises have been found to be associated with more transitory items and/or earnings management, adding to investors'

[8] Some researchers argue that the dispersion of analyst forecasts is a proxy for information asymmetry, but not uncertainty. Barron et al. (1998) show that the dispersion in analyst forecasts is indeed tautologically related to both uncertainty and information asymmetry. In this study we follow Barron et al. (1998) to view information asymmetry to be a component of total uncertainty.

information processing frictions and hence resolving less uncertainty. Indeed, Rogers et al. (2009) and Neururer et al. (2016) show that large surprises in earnings announcements and earnings guidance attenuate reductions in implied volatility.

However, the framework implies a symmetric relation between earnings surprises and changes in investor uncertainty. It seems plausible that positive and negative earnings surprises may induce differential uncertainty changes. Black (1976), for example, argues that bad news that causes negative stock returns also leads to increases in leverage, making future market performance more sensitive to future information flows and hence heightening investor uncertainty. In addition, prior accounting studies have also found that large negative earnings surprises, especially accompanied with losses, are associated with less persistent and less predictable earnings (Li and Mohanram 2014; Hayn 1995). Such lower predictability may translate to greater investor uncertainty. This effect may be explained by the fact that bad news tends to make firms' liquition options and/or restructuring options more attractive, which in trun makes current performance less indicative of future performance.

Numerous studies in the finance literature have documented the asymmetric response of *ex post* future return volatility to news reflected in the stock returns. The result holds for monthly, daily, and intra-daily data (Campbell and Hentschel 1992; Chen and Ghysels 2011). Besides that we use earnings surprises instead of stock returns to measure news, our study is futher distinguished from these studies in two ways. First, we measure investor uncertainty using forward-looking implied volatility instead of realized volatility to emphasize on how investors anticipate future return behavior. Second, our investigation pertains to the firm level, whereas these studies focus on aggregate-level effects.

Motivated by the discussions above, we form our first hypothesis as follows.

H1: *The change in implied volatility around the earnings announcement is*

1) increasing in the magnitude of earnings surprise;

2) decreasing in the level of pre-announcement uncertianty; and

3) higher when the announcement reports a negative earnings surprise.

Although the static Bayesian model is an elegant and intuitive description of how investor uncertainty responds to information arrivals, it is based on two restrictive assumptions: (1) the probability distributions describing investor beliefs and information draws are normal and (2) the "true" parameters of investors' concern are non-stochastic (i.e. subject to no stochastic variance itself) (Johnstone 2015). This model does not allow for uncertainty increases. Johnstone (2015) points out that if (1) and (2) are relaxed, uncertainty reduction is true *on average* only, but not in all specific cases. Formally, the general formula for uncertainty response to information is:

$$E[Var(X|Y)] = Var(X) - Var(E[X|Y]) \tag{2}$$

Note that equation 2 says that the mean conditional variance $E[Var(X|Y)]$, not the conditional variance $Var(X|Y)$ as in equation 1, goes down after information arrival. Therefore, uncertainty increases is a possibility in general. Nevertheless, unlike equation 1, equation 2 is too general to provide any clue on the determinants of uncertainty changes around information arrivals. Ad hoc imposition of alternative assumptions on the probability distributions usually do not lead to closed-form solutions that facilitate clear empirical predictions. In principle, it is possible to make specific distributional assumptions that accommodate uncertainty increases, but such assumptions are difficult to motivate and defend.[9] One dynamical model that allows for uncertainty increases in response to disclosure is the Veronesi (1999) regime-shift model (see also David and Veronesi (2013) and Patton and Sheppard (2015)), in which investors face uncertainty about the true regime underlying observable signals as well as uncertainty due to the randomness of signal realizations within each regime. Information arrivals may raise uncertainty when large surprises indicate potential regime shifts and shake investors' prior regarding the underlying regime.

While we are unable to analytically derive the cases for uncertainty increases, we can use the intuitions offered by the regime-shift model to identify a testable special case. We view large

[9] A static normal-gamma model is one of few examples that yields an analytic solution, but it does not reflect the asymmetric uncertainty effects we wish to uncover.

negative earnings surprise as an indicator of a potential regime shift. As is discussed in our motivation for H1, firms reporting large negative surprises are facing unanticipated adverse events and are likely to take radical measures to adapt to the new conditions, leading to shifts in its strategy, operations, and potentially disclosure practice and thus higher uncertainty about the firms' future prospects. If investors formerly hold a firm belief about the underlying regime prior to the arrival of the surprise and they can correctly anticipate higher probability regime shifts associated with large negative surprise, we expect investor uncertainty to rise in response to the earnings announcement reporting a large negative surprise. We restate this intuition as our second hypothesis.

H2: *Implied volatility increases around earnings announcements if*

1) the earnings surprise is large negative; and

2) the pre-announcement volatility is low.

3 Data and measurement

3.1 Sample

We identify quarterly earnings announcements from the intersection between Compustat and IBES. Following Barth and So (2014), we define earnings announcement dates as the earlier of Compustat reporting dates and IBES announcement dates of actual earnings. If one of these sources has missing earnings announcement date, we use the only date available. Stock price data are retrieved from CRSP Daily Sotck File. We obtain implied volatility data of 30-day at-the-money call options from OptionMetrics Standard Options file. We choose 30-day options because of their highest coverage on the daily basis compared to longer-maturity options.[10] Since the coverage of OptionMetrics starts from 1996, we restrict our sample period from the first quarter of 1996 to the third quarter of 2015. Within this period,

[10]We replicate our analyses with 60-day options and find qualitatively similar results. The results related to H2 is even stronger.

Table 1: Descriptions of sample selection and distribution

Panel A: Sample selection procedures

Sampling procedure	Observations	Firms
Quarterly earnings announcements from Compustat (1996-2015) [1]	470,963	14,620
out of which:		
mathed records from IBES and CRSP[2]	312,151	12,414
with 30-day options coverd by OpetionMetrics	157,157	6,672
Sample restrictions applied[3]:		
Observations with extreme earnings surprises[3]	(7,656)	(71)
missing earnings surprises for the 4 previous quarters	(81)	(3)
missing book-to-market ratios	(1,299)	(7)
missing lagged accounting leverage	(1,269)	(9)
missing analyst forecast dispersion	(6,605)	(204)
Final sample	140,276	6,348

[1] We eliminate observations with negative common equity in this step.
[2] We eliminate observations with stock prices lower than USD 5 in this step.
[3] Restrictions that do not affect the sample are not shown.
[4] Suprirse surprises are defined as extreme when their absolute values exceed 2% of their stock prices 20 days before the earnings announcements.

we obtain 157,157 firm-quarter observations with data available from all four sources, out of which we identify 137,713 observations with magnitudes of earnings surprises within two percent of stock prices, positive common equity values, stock prices above \$5, and non-missing values for other control variables we use for our empirical tests. Table 1 Panel A outlines the details of the effects of our sample selection procedures.

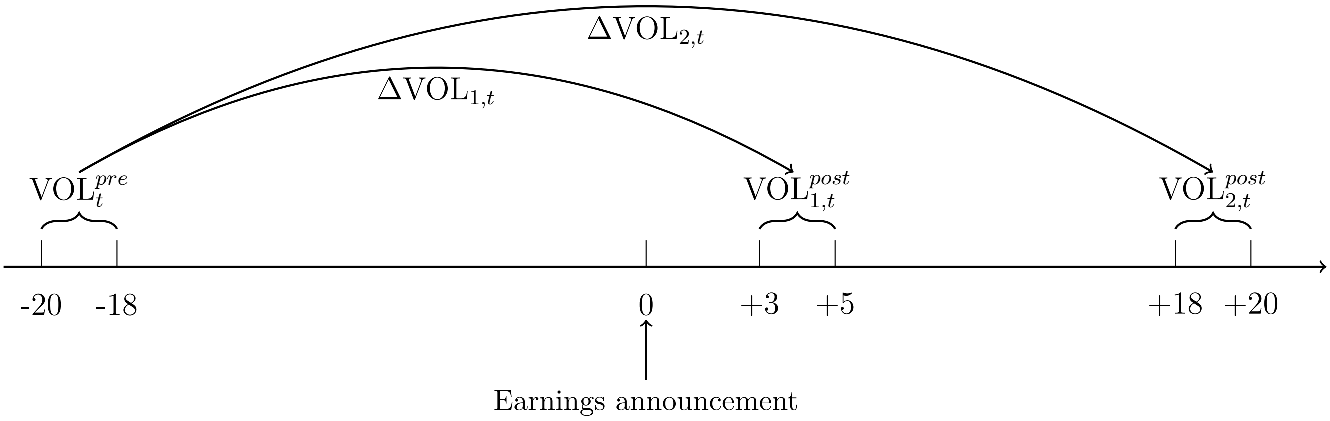
Table 1 Panel B provides our sample distibution by calendar year. It is apparent that both the number of earnings announcements and the number of unique firms increase though time except for the drops due to the 2000-2001 bust of the technology bubble and the 2008-2009 financial crisis, consistent with a increasing number of firms having actively traded stock options over time.

Panel B: Sample distribution

Calendar year	Observations	Firms	Pecentage
1996	4,092	1,296	2.92
1997	5,216	1,596	3.72
1998	6,029	1,829	4.30
1999	6,259	1,923	4.46
2000	5,447	1,762	3.88
2001	5,183	1,600	3.69
2002	5,694	1,693	4.06
2003	5,675	1,622	4.05
2004	6,133	1,765	4.37
2005	6,717	1,915	4.79
2006	7,066	2,044	5.04
2007	7,655	2,227	5.46
2008	7,432	2,201	5.30
2009	7,219	2,171	5.15
2010	8,194	2,323	5.84
2011	8,775	2,544	6.26
2012	8,891	2,603	6.34
2013	9,711	2,746	6.92
2014	10,406	2,942	7.42
2015[1]	8,482	2,950	6.05
Total	140,276		100.00

[1] The year 2015 include the first three quarters.

Figure 1: Time line for implied volatility measurement



3.2 Measurement of investor uncertainty change

We measure investor uncertainty using 30-day option implied volatility around earnings announcements. We choose 30-day options to minimize constraints imposed by data availability, but our results remain qualitatively similar, and even stronger in some cases, when we replicate our analyses using 60-day options. For our purpose, the implied volatility has the merit of being forward-looking and available on daily frequency. Also, option traders tend to be highly sophisticated (Jin et al. 2012), so the inferences are less vulnerable to alternative explanations based on systematic misjudgments.

Figure 1 describes our measurement. Specifically, we measure implied volatility at three points in time around each firm-quarter earnings announcement. Let index day 0 denote the earnings announcement date, and let negative (positive) index days denote the days in the pre(post)-announcement period. In the pre-announcement period, we define VOL_t^{pre} as the average of the natural logarithms of daily implied volatility over the interval $[-20, -18]$. In the post-announcement period, we measure $\text{VOL}_{1,t}^{post}$ and $\text{VOL}_{2,t}^{post}$ as the averages of the natural logarithms of daily implied volatility over the intervals $[+3, +5]$ and $[+18, +20]$. We adopt the averaging procedure across three trading days to mitigate potential measurement errors due to large noises in the data. This is a standard practice in the literature (Rogers et al. 2009; Neururer et al. 2016).

We employ two alternative proxies of uncertainty change around earnings announcements. The first proxy $\Delta\text{VOL}_{1,t} = \text{VOL}_{1,t}^{post} - \text{VOL}_t^{pre}$ captures the change in implied volatility from the interval $[-20, -18]$ up to the interval $[+3, +5]$. This design distinguishes our study from many previous studies, where the measurement windows are typically shorter. For example, Neururer et al. (2016) measure the change in investor uncertianty using the difference in average volatility between intervals $[-5, -3]$ and $[+3, +5]$. We argue that our choice of proxy is more consistent with our focus on the changes in investor uncertainty regarding the underlying earnings generating process (the second source of uncertainty)[11]. It is well deocumented that the implied volatility rises significantly from day -20 to the announcement date in anticipation of the uncertain realization of the current earnings and drops sharply and levels off quickly after the announcement (Patell and Wolfson 1979, 1981). Therefore, the change in implied volatility from shortly before the announcement to shortly after the announcement is dominated by the resolution of the uncertainty regarding the current earnings (the first source of uncertainty), which is almost fully resolved. In contrast, since VOL_t^{pre} is measured before substantial pre-announcement build-up in volatility has taken place, our measure is relatively more reflective of the change in the second source of uncertainty. Admittedly, since 30-day options initiated within the interval $[-20, -18]$ expire after the earnings announcement, our measure is not immune to the volatility build-up. However, this effect appears not to affect our results significantly.[12] While it is feasable to measure implied volatility 30 trading days before the announcement, but such choice would incur the cost of including the effects more potential confounding events.

Alternatively, we use $\Delta\text{VOL}_{2,t} = \text{VOL}_{2,t}^{post} - \text{VOL}_t^{pre}$ to proxy for uncertainty change. This measure accommodates the possibility that the volatility adjustments around earnings announcements may experience delays or reversals due to either market frictions or post-announcement information dissemination that we cannot identify. Our analysis discussed later suggests at least some weak evidence of such a pattern (see Figure 2). We employ this measure to ensure that our results are not driven by these factors. Note that

[11]Note that we do not argue that our measure is "superior".

[12]To mitigate this concern, we repeat our analyses using the window $[-33, 31]$ instead of $[-20, -18]$ for robustness check and we spot no significantly change in our results.

if $\text{VOL}^{post}_{2,t} = \text{VOL}^{post}_{1,t}$ is indeed zero as expected, then the two proxies are equivalent.

4 Empirical results

4.1 The asymmetric uncertainty effects

H1 identifies the sign of earnings surprise, in addition to the magnitude of surprise and pre-announcement uncertainty, as an important determinant of the uncertainty effect of the earnings announcement. Earnings surprise (denoted as UE_t for unexpected earnings) is defined as the difference between the realized earnings and the median of the latest prevailing analyst forecasts before the earnings announcement date. In measuring the realized earnings, we use the IBES actual earnings records to ensure that the measure of realized earnings is consistent with analysts' treatment of earnings information. Particularly, accounting earnings (GAAP net income) include transitory items, but analysts focus on more persistent components of earnings (”street earnings”). IBES actual earnings records are usually adjusted for one-off items such as impairments and restructuring charges, consistent with analysts' use of earnings (Gu and Chen 2004). If IBES actual earnings is missing, we use income before extraordinary items from Compustat as a reasonable approximation for street earnings. We create a binary variable BN_t (for ”bad news”) to indicate firm-quarters with negative surprises, and we define Abs_UE_t as the absolute value of earnings surprise.

To capture the effect of pre-announcement uncertainty, we introduce two experimental variables. First, we consider the average implied volatility within $[-20, -18]$ (VOL^{pre}_t) as an apparent natural candidate to proxy for pre-announcement uncertainty. The second variable we consider is the mean of absolute values of earnings surprises of past four quarters. If analysts have been recently surprised by the firm's earnings, investors are likely to perceive high uncertainty pending for resolution in the forthcoming earnings announcement. We include this variable to complement VOL^{pre}_t for two reasons. Most importantly, while our first measure is consistent with our measures of uncertainty change under the framework in Equation 1, it appears mechanically negatively related to pre-announcement implied volatility because the latter is subtracted from the former by construction.[13]. Second, measuring prior uncertainty from earnings surprise history adds focus because this measure specifically concerns the uncertainty related to earnings, which is what the earnings announcement is surely expected to affect.

Having defined the experimental variables, we specify the following regression model to jointly test H1:

$$\begin{aligned}\Delta\mathrm{VOL}_{1(2),t} = \alpha &+ \beta_1|\mathrm{UE}_t| + \beta_2\mathrm{BN}_t + \beta_3\mathrm{BN}_t \times |\mathrm{UE}_t| + \beta_4\mathrm{VOL}_t^{pre} + \beta_5|\overline{\mathrm{UE}}|_{t-4}^{t-1} \\ &+ \gamma_1\mathrm{Mcap}_t + \gamma_2\mathrm{BM}_{t-1} + \gamma_3\Delta\mathrm{VIX}_{1,t} + \gamma_4\mathrm{Lev}_{t-1} + \gamma_5\mathrm{BN}_t \times \mathrm{Lev}_{t-1} \\ &+ \gamma_6\mathrm{Disp}_t + \gamma_7\mathrm{Follow}_t + \epsilon_t\end{aligned} \tag{3}$$

Note that the dependent variable can be either $\Delta\mathrm{VOL}_{1,t}$ or $\Delta\mathrm{VOL}_{2,t}$, our two alternative measures of uncertainty change. To mitigate the effects of extreme values, we use iterative median regression to estimate equation 3. Unlike ordinary least squares (OLS) estimation, which models the mean of the dependent variable, median regression models the median of the dependent variables, which is robust to the presence of outliers. To facilitate comparison with prior studies, we also estimate OLS regression after winsorizing all variables.

The β coefficients in the first line of equation 3 supply direct tests of H1. Specifically, H1 predicts that the change in investor uncertainty is increasing in the magnitude of earnings surprise ($\beta_1 > 0$) and higher for bad news announcements ($\beta_2 > 0$). We include the interaction term $|\overline{\mathrm{UE}}|_{t-4}^{t-1}$ to test if the asymmetry of uncertainty effects hold across different levels of surprise magnitudes ($\beta_3 > 0$)). H1 also suggest that $\beta_4 < 0$ and $\beta_5 < 0$L: higher pre-announcement uncertainty leads to greater reduction in investor uncertainty.

[13]We recognize this concern does not necessarily threaten the validity of our inferences, because as a mathematical fact, the difference does not necessarily correlate with the level. Introducing the second proxy is to address the *appearance* mechanical relation

We include the natural logarithm of market capitalization of the firm Mcap_t measured at the end of the financial quarter t to control for firm size. How firm size affects uncertainty resolution is not *a priori* clear. On one hand, larger firms are associated with more alternative sources of information, pre-empting the informativeness of earnings announcement and thus attenuating uncertainty resolution. On the other hand, Barth and So (2014) show that earnings announcements of large firms are more macro-significant and thus impose higher announcement risk to investors, creating more hedging demand for options of larger firms prior to the announcement. To the extent that the hedging needs affects the option prices as early as twenty trading days before the announcement, the drop in volatility following the announcement is also expected to be greater. Thus we cannot predict the sign of γ_1.

We also control for the book-to-market ratio, computed as the book value of equity divided by the market value of equity at the end of quarter $t-1$, to control for growth opportunities or financial distress. Since both high expected growth and financial distress can lead to high anticipated uncertainty, we again cannot predict the sign of γ_2.

The variable $\Delta\text{VIX}_{1(2),t}$ is the contemporaneous change in the natural logarithm of CBOE VIX index over the same measurement window as that used to measure the dependent variable. We include it to control for market-wide movements in uncertainty. Since firm-specific volatility assumes the effect of market volatility, we predict γ_3 to be positive.

The lagged leverage ratio Lev_{t-1} is calculated as long-term debts over total assets of quarter $t-1$. If the interpretation of Black (1976) is at work in our context, γ_5 is expected to be positive, implying bad news announcements increase uncertainty for high-leverage firms.

We use the dispersion of analyst forecasts (Disp_t) and the number of analyst following (Follow_t) to capture the quality of the firm's information environment Lang and Lundholm (1996); Barron et al. (1998). While more analysts following the firm means more of the uncertainty are likely to be pre-empted by analysts' forecasting and recommendations, analysts may self-select themselves to follow firms with high uncertainty to maximize the utility of their activities. Therefore, the effects of these variables are ambiguous.

Table 2: Descriptive statistics

Variables	Mean	Std Dev	P_{25}	Median	P_{75}	N
$\Delta\mathrm{VOL}_{1,t}$	-.0493999	.199516	-.1661979	-.0516847	.0568205	157,157
$\Delta\mathrm{VOL}_{2,t}$	-.051476	.2259015	-.186634	-.0580403	.0674533	157,157
UE_t	-.0001848	.0092505	-.0005448	.0003097	.0017123	156,899
$\lvert\mathrm{UE}_t\rvert$	.0040878	.0083003	.000369	.00125	.0037037	156,899
VOL_t^{pre}	-.8528664	.477249	-1.183989	-.8595655	-.5253785	157,157
$\lvert\overline{\mathrm{UE}}\rvert_{t-4}^{t-1}$	.0768047	.1236078	.0175	.0375	.0825	157,064
BM_{t-1}	.5679143	.5940929	.2454833	.4309488	.6991279	155,754
Lev_{t-1}	.1998656	.2183487	.0106278	.1514945	.3145806	155,308
Disp_t	.0021696	.0042959	.0003481	.0008254	.0020151	149,058
Follow_t	9.0482	6.501965	4	7	12	157,157
$\Delta\mathrm{VIX}_{1,t}$	.0080573	.1952201	-.1124311	-.0074388	.1052793	157,157
$\Delta\mathrm{VIX}_{2,t}$	.0173131	.2489061	-.1394872	-.0148963	.1308683	157,157
Mcap_t	14.25024	1.521786	13.14511	14.12583	15.21314	157,120

Columns (1) to (4)

Table 2 provides some descriptive statistics for variables in regression equations 3. The two alternative measures of uncertainty changes around earnings announcements exhibit negative means (medians) of $-.04940$ and $-.0515$ ($-.0517$ and $-.0675$), consistent with earnings announcements typically reducing investor uncertainty. However, the 75-percentiles of these two variables are .05168 and .06745, respectively, suggesting that the frequency of uncertainty increase is not trivial in our sample. In addition, the opposite signs and small magnitudes of the means and medians of the changes in the VIX index around earnings announcements are consistent with firm-specific information events lacking impacts on market-wide uncertainty. The key statistics of the remaining variables also appear to be consistent with those reported in prior studies.

Table 3 provides the correlation matrix of the regression variables. All correlations reported in the table are significant at the 95% level. The correlation coefficient between the two alternative measures of uncertainty change around the earnings announcement is .7030, indicating that these two proxies capture similar, but still distinct, uncertainty effects of earnings announcements. Out of all the tabulated variables, measures of the contemporaneous change in the market-wide uncertainty ($\Delta\mathrm{VIX}_{1(2),t}$) show the strongest univariate correlations with the change in the change in firm-specific uncertainty measures (ranging from .2686 to .4290). Turning to our experimental variables, note that $\Delta\mathrm{VOL}_t$ measures show positive correlations with BN_t, implying that earnings announcements that report bad news tend to inrease uncertainty or lessen the degree of uncertainty resolution, consistent with the predictions of H1. The magnitude of eanrings surprise $|\mathrm{UE}_t|$, however, has correlation coefficients of opposite signs with our two uncertainty change proxies, which cannot be interpreted unambiguously by the arguments of H1. Uncertainty change measures are also negatively associated with the pre-announcement volatility level and average historical surprise magnitude, consistent with the prediction of H1 that uncertainty resolution is stronger when pre-announcement uncertainty is high. Besides, the positive yet relatively weak correlation between $|\overline{\mathrm{UE}}|_{t-4}^{t-1}$ and VOL_t^{pre} confirms that these two variables are complementary measures of prior uncertainty and alleviate the concern that any potential effect of surprise history on uncertainty resolution is inherited from the mechanical relation between $\mathrm{VOL}_{1,t}^{pre}$ and ΔVOL_t measures.

Table 3: Correlation matrix

	$\Delta\text{VOL}_{1,t}$	$\Delta\text{VOL}_{2,t}$	$\lvert\text{UE}_t\rvert$	VOL_t^{pre}	$\lvert\overline{\text{UE}}\rvert_{t-4}^{t-1}$	BM_{t-1}	Lev_{t-1}	Disp_t	Follow_t	$\Delta\text{VIX}_{1,t}$	$\Delta\text{VIX}_{2,t}$	Mcap_t
$\Delta\text{VOL}_{1,t}$	1											
$\Delta\text{VOL}_{2,t}$	.7030	1										
$\lvert\text{UE}_t\rvert$	-.0035	.0020	1									
VOL_t^{pre}	-.1533	-.1884	.2347	1								
$\lvert\overline{\text{UE}}\rvert_{t-4}^{t-1}$	-.0382	-.0244	.3045	.0044	1							
BM_{t-1}	.0121	.0159	.1859	-.0064	.1364	1						
Lev_{t-1}	.0129	.0261	.0717	-.1082	.0872	-.0695	1					
Disp_t	.0106	.0119	.4591	.2666	.3212	.1918	.1137	1				
Follow_t	-.1164	-.0964	-.1737	-.1982	-.0631	-.1223	-.0172	-.1334	1			
$\Delta\text{VIX}_{1,t}$	.3495	.3160	-.0174	-.0732	-.0057	-.0091	-.0072	-.0178	-.0175	1		
$\Delta\text{VIX}_{2,t}$	.2686	.4290	-.0136	-.0932	.0040	-.0120	-.0054	-.0128	-.0139	.7364	1	
Mcap_t	-.0728	-.0490	-.2648	-.5223	.0215	-.1751	.0873	-.2548	.6228	-.0075	.0020	1

Before presenting our formal regression tests, we provide some exploratory analyses to enhance intuitions. Figure 2 tracks how implied volatility changes around earnings announcements. Panel A of Figure 2 presents evidence in terms of a time index of firm-specific implied volatility. Specifically, we use the implied volatility measured 20 trading days prior to each earnings announcement to standardize median implied volatility up to 20 days subsequent to the earnings announcement. That is, the implied volatilities of day -20 are standardized to 1, and those of subsequent days are calculated as the median of the ratios relative the levels on day -20. We examine the behavior of this index by the signs of earnings surprises and four equal-size portfolios formed based on the magnitude of earnings surprises given the signs of surprises. The vertical axes represent this implied volatility index, and the horizontal axes the number of days relative to the earnings announcement, indicated by day 0. Consistent with the findings in Patell and Wolfson (1979, 1981), the implied volatility tends to build up prior to the earnings announcement and drop sharply immediately after the announcement, suggesting that investors anticipate earnings announcements to induce price reactions and hence excess volatility. Overall, the implied volatility in the post-announcement window typically lies below 1, consistent with earnings announcements reducing investor uncertainty on average. However, there is an asymmetric uncertainty effect around earnings announcements: bad news reduces uncertainty to a much lesser extent, as is evidenced by the flatter slope around day 0 in the negative-surprise subsample. This appears consistent with H1.

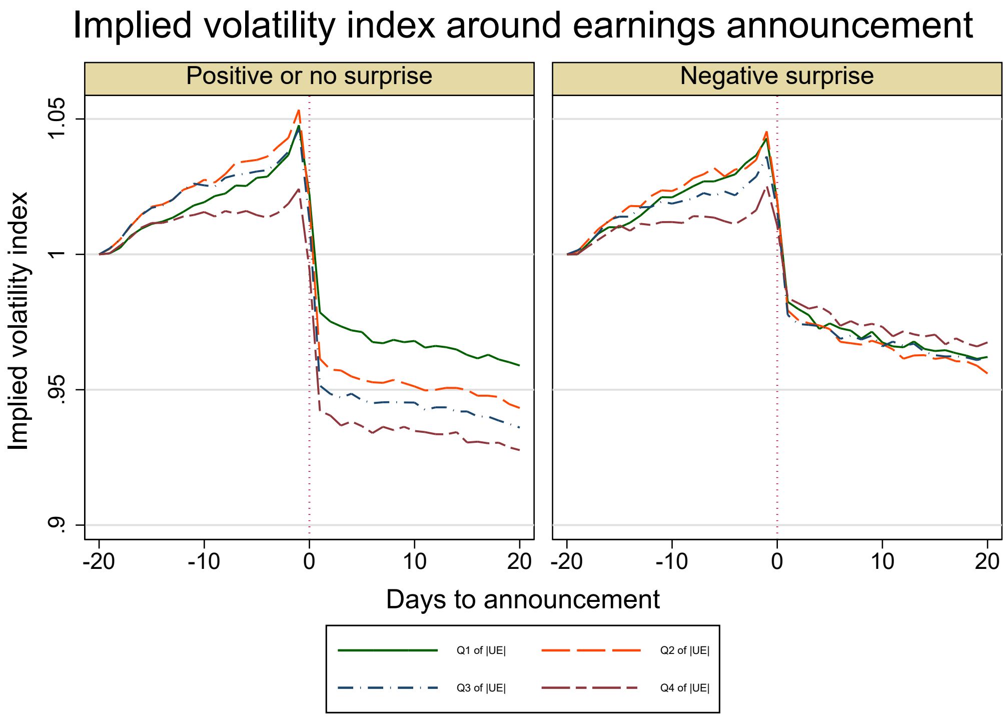
Furthermore, a surprising pattern emerges from Panel A. In the subsample with positive or zero earnings surprises, the degree of uncertainty resolution appears typically stronger where the magnitude of earnings surprise is larger. This seems to be inconsistent with the prediction of H1 and the findings of Neururer et al. (2016) that larger surprises lead to weaker uncertainty resolution. In contrast, in the bad-news subsample, this pattern is almost reversed–larger surprises are associated with less uncertainty resolution, although the relation is not quite monotonic. Besides, another interesting observation is that the implied volatility index continues to decline in the post-announcement period, regardless of sign and magnitude of the realized earnings surprise. This indicates that investor uncertainty is resolved gradually over time, although most of the resolution take place immediately after the announcement.

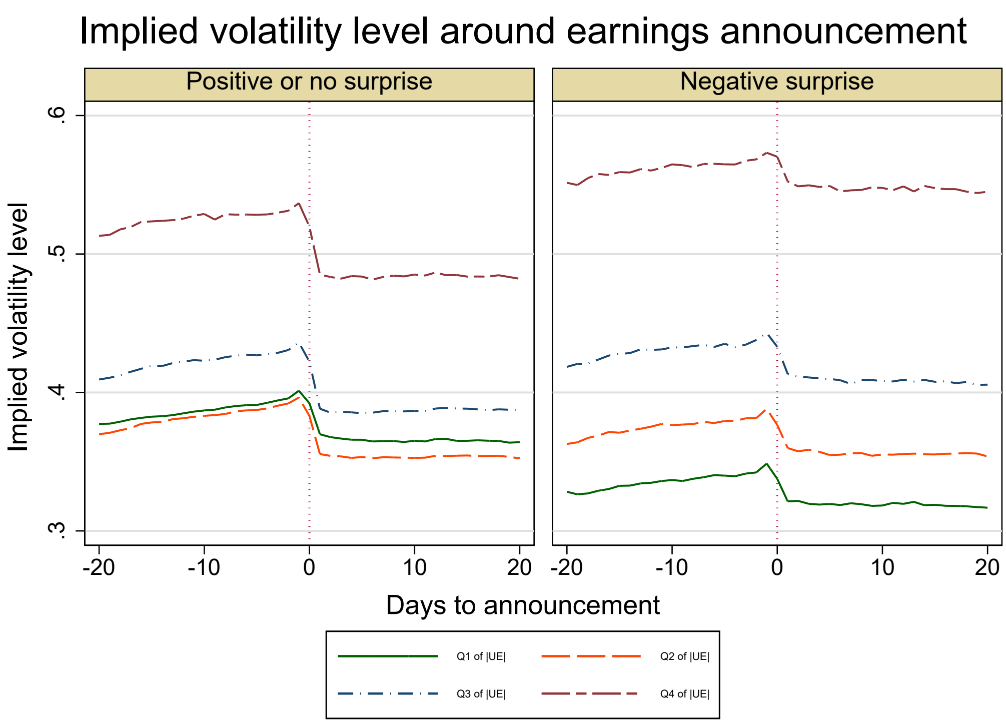
Panel B of Figure 2 is constructed in the same way except that the vertical axes measure the *absolute level* instead of the index of implied volatility. We make two additional observations from tracking the levels. First, it is evident that larger magnitudes of earnings surprises, regardless of their signs, are associated with higher overall levels of implied volatility. The only exception is that the overall volatility levels of firms in first surprise magnitude quartile of the non-negative sample is slightly higher than those in the second quartile. This is consistent with that investors are able to anticipate the magnitude of new information to be conveyed by earnings announcements (Billings and Jennings 2011) and/or that firms who tend to surprise the market are likely to be in relatively uncertain states. Second, except for the first quartile of earnings surprise magnitude, firms who report bad news tend to exhibit higher overall volatility level, consistent with bad-news firms are in relatively uncertain states.

Table 4 reports our estimation results for the regression in euation 3. Penal A pertains the model with our first proxy for uncertainty change as the dependent variable. Column (1) reports the median regression estimates when the bad news indicator variable (BN_t) is excluded from our experimental variables (though we keep its interaction term with leverage for controls). This model specifies a symmetric uncertainty effect. Strikingly, we obtain a statistically significiant negative coefficient on the magnitude of earnings surprise (-0.451), suggesting that larger surprises lead to greater reduction or smaller increase in investor uncertainty. This appears to contrast the prediction of H1 and the results in Neururer et al. (2016), but it is consistent with our earlier observation from Figure 2 and Table 3. Column (5), on the other hand, shows a positive yet insignificant OLS coefficient estimate for the magnitude of earnings surprise.

Column (2) estimates the full specification of equation 3, which accommodates the potential asymmetry in the uncertainty effects. The coefficients on the bad news indicator varaible

Figure 2: Implied volatility around earnings announcement





and its interaction with the magnitude of earnings surprise are both significantly posiitve (0.013 and 4.100 respectively), consistent with the sign of the news being a critical determinant of uncertainty effects of earnings announcements. It is also important to note that the sign of news affects investor uncertainty mainly through the magnitude of eanrings surprise, which can guaged by comparing the coefficients on BN_t alone and on the interaction term $\mathrm{BN}_t \times |\mathrm{UE}_t|$. Furthermore, the coefficient on the magnitude of earnings surprise remain significantly nagtive, and the magtinude and significance of the coefficient are enhanced compared to Column (1). This highlights a key finding of our study: *The change in investor uncertainty is decreasing in the magnitude of earnings surprise for postive susprises, but it is increasing in the magnitude of earnings surprise for negative susprises.* This result is also confirmed by OLS regeression results in Column (6).

To enhance visualization, Columns (3) and (4) estimate separate median regressions for negative susprise (observations with $\mathrm{BN}_t = 1$) and non-negative susprise (observations with $\mathrm{BN}_t = 0$) samples respectively. In principle, running separate regressions for two exclusive samples also does not resctrict the coefficients on other variables to be equal across the two samples. Again, the results confirm that the coefficient on the magnitude of eanring surprise is positive for bad news but negative for good news. Columns (7) and (8) replicate the separate regressions using OLS estimation and produce very similar results.

In addition to the earnigns surprise, pre-announcement uncertainty is found to be negatively associated with the change in investor uncertainty, consistent with the prediction of H1. Specifically, the coeffecent estimates for our first measure of prior uncertainty VOL_t^{pre} range from -0.129 to -0.0865 across the eight columns of Panel A, and those for our second measure $|\overline{\mathrm{UE}}|_{t-4}^{t-1}$ take values close to -0.10 across the columns. Therefore, we find both pre-announcemnet measures incrementally important to explain the change in investor uncertainty.

Table 4: Regression tests for asymmetric uncertainty effects of eanrings announcements

	Median regressions (1)-(4)				OLS regressions (5)-(8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	symmetric	asymmetric	$BN_t = 1$	$BN_t = 0$	symmetric	asymmetric	$BN_t = 1$	$BN_t = 0$
Panel A: Regressions with dependent variable $\Delta VOL_{1,t}$								
$\|UE_t\|$	-0.451**	-2.312***	2.546***	-2.800***	0.0700	-1.878***	3.319***	-2.480***
	(-2.71)	(-11.22)	(9.20)	(-13.30)	(0.42)	(-9.20)	(12.03)	(-11.80)
BN_t		0.0130***				0.0125***		
		(7.76)				(7.53)		
$BN_t \times \|UE_t\|$		4.100***				4.201***		
		(14.00)				(14.48)		
VOL_t^{pre}	-0.0715***	-0.0711***	-0.0804***	-0.0672***	-0.0967***	-0.0963***	-0.109***	-0.0908***
	(-55.64)	(-55.07)	(-32.92)	(-44.74)	(-75.54)	(-75.31)	(-44.76)	(-60.52)
$\|\overline{UE}\|_{t-4}^{t-1}$	-0.103***	-0.101***	-0.0998***	-0.102***	-0.104***	-0.0999***	-0.107***	-0.0957***
	(-19.45)	(-18.99)	(-11.05)	(-15.53)	(-19.64)	(-18.92)	(-11.91)	(-14.60)
BM_{t-1}	-0.00906***	-0.00840***	-0.00882***	-0.00803***	-0.00851***	-0.00855***	-0.00857***	-0.00847***
	(-9.25)	(-8.54)	(-5.06)	(-6.78)	(-8.71)	(-8.77)	(-4.94)	(-7.16)
Lev_{t-1}	-0.0157***	0.00167	-0.0137**	-0.000185	-0.0165***	0.000923	-0.00990*	-0.000216
	(-6.02)	(0.60)	(-3.09)	(-0.07)	(-6.35)	(0.33)	(-2.23)	(-0.08)
$BN_t \times Lev_{t-1}$	0.0438***	-0.0170***			0.0452***	-0.0123*		

Table 4 – continued

	Median regressions (1)-(4)				OLS regressions (5)-(8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	symmetric	asymmetric	$\text{BN}_t = 1$	$\text{BN}_t = 0$	symmetric	asymmetric	$\text{BN}_t = 1$	$\text{BN}_t = 0$
	(12.11)	(-3.42)			(12.56)	(-2.50)		
Disp_t	2.981***	2.686***	1.102***	3.967***	3.427***	3.223***	1.544***	4.550***
	(15.24)	(13.67)	(3.47)	(15.82)	(17.59)	(16.55)	(4.88)	(18.18)
Follow_t	-0.00249***	-0.00239***	-0.00168***	-0.00265***	-0.00217***	-0.00212***	-0.00138***	-0.00238***
	(-25.18)	(-24.06)	(-8.33)	(-23.50)	(-22.10)	(-21.53)	(-6.86)	(-21.22)
$\Delta\text{VIX}_{1,t}$	0.342***	0.342***	0.330***	0.346***	0.336***	0.336***	0.329***	0.339***
	(137.62)	(136.86)	(69.42)	(119.36)	(135.65)	(135.77)	(69.42)	(117.16)
Mcap_t	-0.0140***	-0.0141***	-0.0172***	-0.0126***	-0.0177***	-0.0177***	-0.0210***	-0.0160***
	(-27.66)	(-27.78)	(-17.72)	(-21.51)	(-35.14)	(-35.23)	(-21.65)	(-27.39)
Constant	0.111***	0.109***	0.154***	0.0942***	0.141***	0.138***	0.181***	0.121***
	(17.50)	(17.10)	(12.54)	(12.74)	(22.22)	(21.78)	(14.78)	(16.44)
N	140,276	140,276	40,276	100,000	140,276	140,276	40,276	100,000
R^2/Pseudo R^2	0.0969	0.0987	0.0897	0.1009	.18011	.17981	.18945	.17565

Table 4 – continued

	Median regressions (1)-(4)				OLS regressions (5)-(8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	symmetric	asymmetric	$\mathrm{BN}_t = 1$	$\mathrm{BN}_t = 0$	symmetric	asymmetric	$\mathrm{BN}_t = 1$	$\mathrm{BN}_t = 0$
Panel B: Regressions with dependent variable $\Delta\mathbf{VOL}_{2,t}$								
$\|\mathrm{UE}_t\|$	0.241	-1.342***	2.865***	-1.577***	0.756***	-0.955***	3.447***	-1.351***
	(1.30)	(-5.85)	(9.32)	(-6.67)	(4.19)	(-4.28)	(11.37)	(-5.90)
BN_t		0.00616**				0.00697***		
		(3.29)				(3.84)		
$\mathrm{BN}_t \times \|\mathrm{UE}_t\|$		3.675***				3.776***		
		(11.26)				(11.92)		
VOL_t^{pre}	-0.0903***	-0.0901***	-0.0995***	-0.0865***	-0.118***	-0.118***	-0.129***	-0.113***
	(-62.94)	(-62.59)	(-36.64)	(-51.16)	(-84.51)	(-84.36)	(-48.14)	(-69.13)
$\|\overline{\mathrm{UE}}\|_{t-4}^{t-1}$	-0.103***	-0.0986***	-0.103***	-0.0967***	-0.102***	-0.0981***	-0.106***	-0.0933***
	(-17.44)	(-16.60)	(-10.31)	(-13.12)	(-17.63)	(-17.02)	(-10.72)	(-13.05)
BM_{t-1}	-0.00659***	-0.00653***	-0.00629**	-0.00664***	-0.00691***	-0.00688***	-0.00554**	-0.00751***
	(-6.03)	(-5.96)	(-3.25)	(-4.99)	(-6.48)	(-6.46)	(-2.91)	(-5.83)
Lev_{t-1}	-0.00366	0.00747*	0.00541	0.00636*	-0.00186	0.0109***	0.00381	0.00983***
	(-1.26)	(2.40)	(1.10)	(2.07)	(-0.66)	(3.61)	(0.78)	(3.30)
$\mathrm{BN}_t \times \mathrm{Lev}_{t-1}$	0.0374***	-0.00354			0.0329***	-0.00913		

Table 4 – continued

	Median regressions (1)-(4)				OLS regressions (5)-(8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	symmetric	asymmetric	$\mathrm{BN}_t = 1$	$\mathrm{BN}_t = 0$	symmetric	asymmetric	$\mathrm{BN}_t = 1$	$\mathrm{BN}_t = 0$
	(9.29)	(-0.64)			(8.36)	(-1.70)		
Disp_t	3.233***	3.103***	2.237***	3.737***	3.897***	3.735***	2.547***	4.669***
	(14.82)	(14.17)	(6.34)	(13.28)	(18.32)	(17.56)	(7.32)	(17.12)
Follow_t	-0.00215***	-0.00209***	-0.00157***	-0.00226***	-0.00186***	-0.00182***	-0.00124***	-0.00204***
	(-19.48)	(-18.90)	(-7.02)	(-17.93)	(-17.32)	(-16.97)	(-5.64)	(-16.68)
$\Delta\mathrm{VIX}_{2,t}$	0.380***	0.379***	0.367***	0.384***	0.367***	0.367***	0.354***	0.372***
	(174.50)	(173.45)	(87.94)	(150.70)	(172.91)	(173.00)	(86.08)	(150.93)
Mcap_t	-0.0150***	-0.0152***	-0.0184***	-0.0139***	-0.0196***	-0.0197***	-0.0233***	-0.0180***
	(-26.76)	(-27.02)	(-17.07)	(-21.11)	(-35.82)	(-35.89)	(-21.90)	(-28.19)
constant	0.0957***	0.0971***	0.136***	0.0826***	0.136***	0.134***	0.179***	0.116***
	(13.52)	(13.63)	(9.97)	(9.96)	(19.64)	(19.42)	(13.31)	(14.48)
N	140,276	140,276	40,276	100,000	140,276	140,276	40,276	100,000
R^2/Pseudo R^2	0.1323	0.1331	0.1217	0.1371	.19657	.1964	.20811	.19141

The table presents regression estimates from the model in equation 3. Panel A and Panel B report estimates using $\Delta\mathrm{VOL}_{1,t}$ and $\Delta\mathrm{VOL}_{2,t}$ as dependent variables respectively. Results in Columns (1) to (4) in each panel are obtained from median regression, and those in Columns (5) to (8) are obtained from OLS regressions after winsorizing all variables.

Panel B of Table 4 replicates Panel A results after replacing $\Delta \text{VOL}_{1,t}$ with $\Delta \text{VOL}_{2,t}$ as the dependent varaible and $\Delta \text{VIX}_{1,t}$ with $\Delta \text{VIX}_{2,t}$ as the control variable for contemporaneous change in market-wide volatility. Although we notice that our second proxy for uncertanty change behaves differently from the first, the results pertaining to our key findings discussed above are unaffected.

We also note that our design of the tests above builds in a robustness check against interpretations based on volatility feedback and leverage. First, as we discussed in previous sections, using the earnings surprise instead of returns to measure news breaks the endogenous link between news and volatility through discount rate changes. Therefore, the volatility feedback interpretation is unlikely to explain the asymmetric pattern we identify in Table 3. Second, our regression results do not show a consistently significant effect for leverage. For example, Panel A Column (2) reports a marginally significant cofficient on leverage and an insignificantly negative coefficient on its interaction with the bad news indicator, whereas the leverage-based interpretation suggests that there should be a significantly positive coefficient on the interaction term. Interestingly, we find that the cofficients on the interaction term are significantly positive only if we specify a symmetric model for uncertainty effects (i.e. columns (1) and (5) for each panel), and the leverage effect is muted once we incorporate asymmetry.

Collectively, our results in this subsection are partly consistent with H1 in that we find significant negative association between the change in uncertainty and pre-announcement uncertianty measures. Strikingly, we document a strong evidence of asymmetric effects of earnings surpises on investor uncertainty such that the change in investor uncertainty is decreasing in the magnitude of earnings surprise for postive susprises, but it is increasing in the magnitude of earnings surprise for negative susprises. This effect is robust against alterative explanations based on volatility feedback and leverage. The role played by the sign of earnings surprise cannot accommodated by existing versions of static Bayesian models.

4.2 News impact curve

The previous subsection shows that both the sign and magnitude of the earnings surprise are important determinants of investor ucnertainty change around eanrings announcements through a parameterized model, suggesting that static Bayesian models are unlikely to be sufficient descriptions and that it may be fruitful to examine the uncertainty effects throughout the spectrum of eanrings surprises. This will not only aid interpretations of results above but also supply a way to identify potential cases of uncertainty increases for testing H2.

We consider a non-parametric test. The non-parametric approach is suitable in this case, where limited theoretical guidance and prior evidence is available, so that we can allow the data to "speak" with minimal risk of misspecification. Our non-parametric estimation is based on the Kernel-weighted local polynomial smoothing described in Fan and Gijbels (1995, 1996). Specifically, for any data point $(x_0, y_0 = G(x_0))$ in the scatter plot with earnings surprise and uncertainty change representing the x- and y-axes, we identify its "neighborhood" observations $\{(x_i, y_i)\}, i = 1, 2, \ldots, M$ based on their deviations from (x_0, y_0) on the x-axis $(x_i - x_0)$. The "neighborhood" is defined relative to a statistically optimized constant bandwidth surrounding x_0. Then we approximate the y-coordinates of these neighborhood observations using the following degree-3 polynomials of $(x_i - x_0)$

$$y_i = a + b_1(x_i - x_0) + b_2(x_i - x_0)^2 + b_3(x_i - x_0)^3 + u_i, i = 1, 2, \ldots, M$$

which is optimized by weighted least squares with the weights specified by the Epanechnikov kernel. Then the intercept estimate $\hat{a}$ is our non-parametric estimate for $G(x_0)$. This procedure is then repeated for all observed points across the x-axis.

We note two related features of this estimation procedure pertinent to our study. First, for any two observations with earnings surprises sufficiently close to each other, their "neighborhoods" contain many same observations. This means that the estimates for these two observations should also be close to each other, giving rise the smoothing effect. This is a valuable feature for examining our question as the options data around earnings announcements are coupled with very large noises. Second, the choice of using the third-degree polynomials is based on the trade-off between flexibility and the smoothing effect. Indeed, higher-order polynomials are better able to capture local changes in the function curve and thus may help reduce bias. Nonetheless, the flip side of flexibility entails greater variation so that the estimates are potentially "too sensitive" to noises in the data, compromising the benefit of the smoothing effect. Furthermore, it is a standard suggestion to favor odd-order polynomials over even-order ones (Fan and Gijbels 1996).

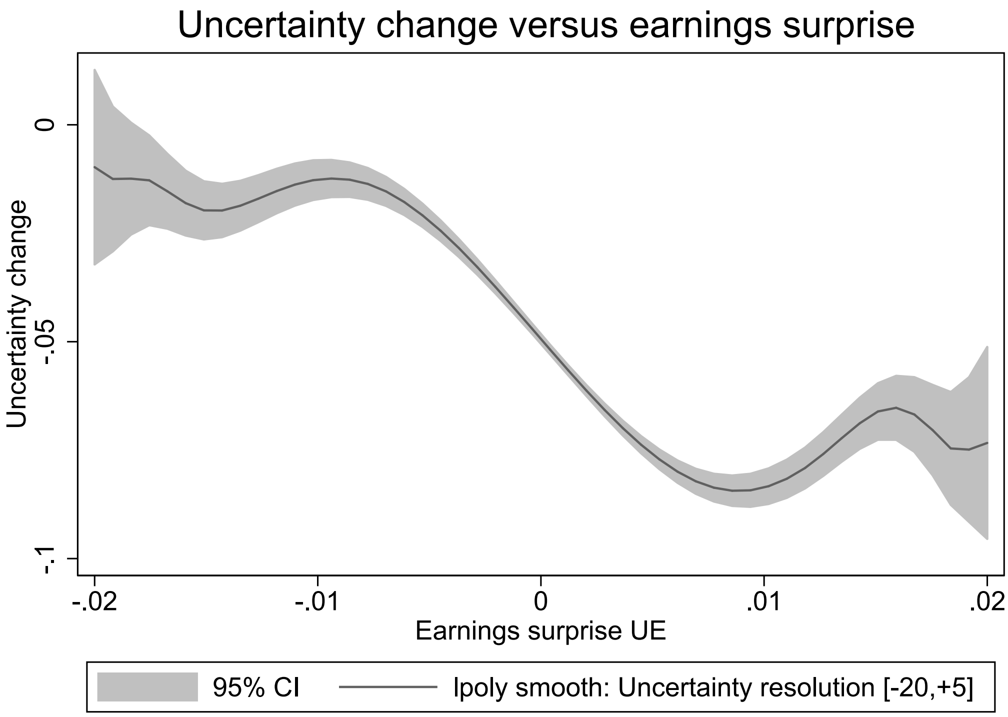
As is the case in general for most non-parametric tests, our results are most efficiently reported graphically, as in Figure 3. The figure shows the change in investor uncertainty around earnings announcements (measured by $\Delta\mathrm{VOL}_{1,t}$) on the vertical axis and earnings surprise on the horizontal axis.[14] The solid curve (which we label as the "news impact curve") tracks the non-parametric estimates across the spectrum of UE_t, and the shaded area plots the 95% confidence bands.[15]

In Figure 3, we note that the uncertainty change is reliably negative with the estimated news impact curve and confidence bands lying below 0 across the spectrum of earnings surprises, except for the region with extreme negative surprise. This is consistent with earnings announcements resolving uncertainty on average. as the magnitude of earnings surprise increase form zero to the negative direction, the change in implied volatility increases monotonically; as the magnitude of earnings surprise increase form zero to the positive direction, the change in volatility first declines through a moderate level of surprise and rises afterwards, though the rise is flatter than that in the negative region. This finding suggests that investors appear to feel more confident about good news compared to bad news, but their posterior uncertainty is relatively larger when the news is "extreme". This pattern also helps us interpret the opposite uncertainty effects of positive and negative earnings surprises: moderate good news accounts for more density in our sample, so the

[14]The figure based on $\Delta\mathrm{VOL}_{2,t}$ (unreported) is very similar.

[15]The confidence bands are calculated based on statistically optimized bandwidth using ROT method.

Figure 3: The news impact curve



attenuation effect that is only apparent over the relatively extreme region, is muted in the good news sample.

4.3 Identifying uncertainty increase

Figure 3 suggests that conditioning on earnings surprises is not sufficient to identify cases for uncertainty increases, but H2 identifies the pre-announcement uncertainty as an additional conditioning variable. Therefore, we test H2 by estimating the news impact curve over different levels of pre-announcement uncertainty measures.

Two caveats for our tests for H2 are worth noting. First, The results of our non-parametric test are most effectively conveyed through graphical presentation but are difficult to summarize through one or a handful of formal test statistic. This is of particular concern if the density of observations varies across the spectrum of our independent variables. This is true for our case: most observations have earnings surprises that are very close to zero, but the observations with extremely large earnings surprises are sparse.[16] This will result in wider confidence intervals as the earnings surprise moves away from zero. Because we expect better chance of observing uncertainty intensification when surprise magnitudes are larger, it is more difficult to detect significant uncertainty increase based on non-parametric tests. In addition, using implied volatility of short-maturity options to capture investor uncertainty, by design, may induce difficulty to detect increases in uncertainty around earnings announcements. As the announcement fully resolves the uncertainty in the current earnings realization, the total uncertainty is expected to decrease unless a sufficiently large increase in the uncertainty regarding the earnings generating process. Therefore, our tests may understate the instances of uncertainty intensification.[17]

The planes of Figure 4 plot the news impact curve for three equal-sized subsamples with low, medium and high pre-announcement uncertainty respectively from left to right. Pre-announcement uncertainty is proxied by $|\overline{\mathrm{UE}}|_{t-4}^{t-1}$ in this figure to avoid potential concerns over the appearance of mechanical relation.[18]

When pre-announcement uncertainty is high, as is shown in the rightmost plane of Figure 4, we cannot identify systematic uncertainty increase: The curve and confidence bands are reliably below zero throughout. In addition, the reversal to the right of the moderate good news region is only mild. The middle plane shows a similar pattern: while the estimates reach above zero where the earnings surprise is large negative, the lower bound of the confidence band never reaches above zero.

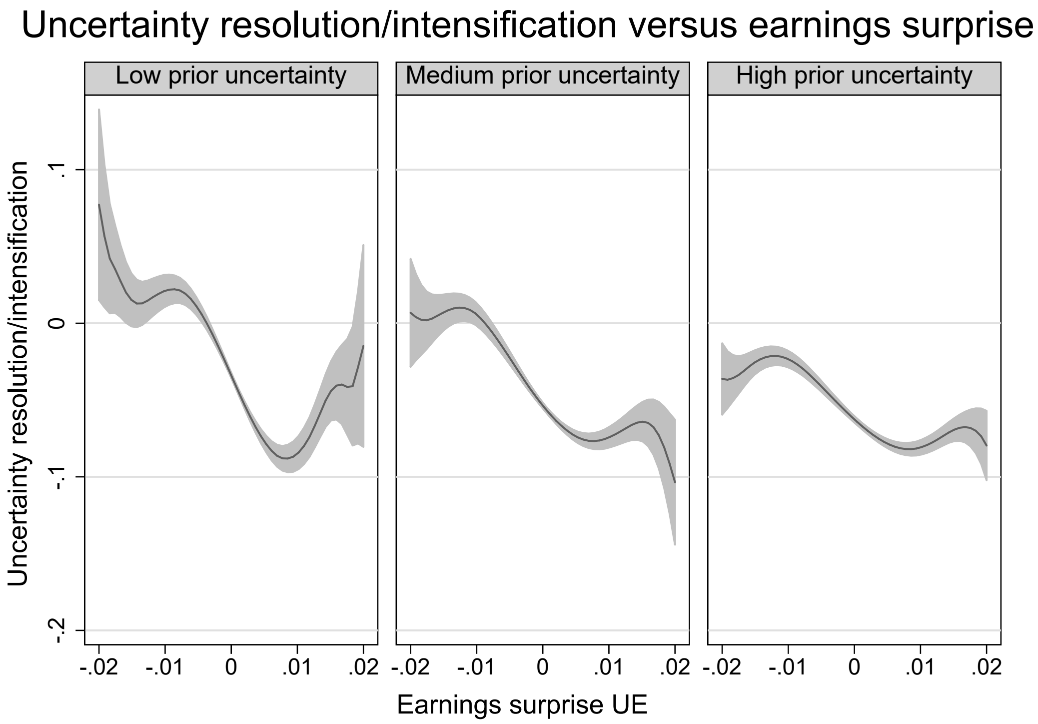
Now focusing on the subsample with low prior uncertainty depicted in the left plane, we note that the estimated curve far surpasses zero in the domain of large negative surprises and the lower bound the confidence band lies above zero for most of this domain. This suggests that large negative surprises induce uncertainty increases if the pre-announcement uncertainty is low, consistent with the prediction of H2. The intuition is simple, given that

[16]For instance, earnings announcements with surprise magnitudes larger than 0.02 account for less than 5% of observations in our sample.

[17]Neururer et al. (2016) use 365-day options and find uncertainty increases can be detected by conditioning on the level of earnings surprises only.

[18]Using VOL_t^{pre} (unreported) produces even stronger results.

Figure 4: Uncertainty change around earnings announcements



the firm has reported only small surprises in the near past, investors may perceive the firm's earnings to be relatively predictable and conceive relatively low-uncertainty state for the firm. Then investors may experience a shake-down in their beliefs and perceive a higher uncertainty in the wake of a large unanticipated surprise. In other words, large negative surprise may cause a perceived regime shift in this case and lead to uncertainty increase. Hence, our test results are consistent with the predictions of H2.

The left plane also exhibits a strong reversal in the extreme good news region, much more pronounced than those in the other two planes. This seems to indicate that investor uncertainty is more sensitive to large positive surprises when they feel more confident about their priors, which is also at odds with the implications of the static Bayesian models.

5 Conclusion

Our study sheds light on the asymmetric effects of earnings announcements on investor uncertainty. We show that the change in investor uncertainty is decreasing in the magnitude of earnings surprise for good news, but it is increasing in the magnitude of earnings surprise for bad news. The former effect is driven by the U-shaped relation between earnings surprises and uncertainty changes when the surprise is positive. In other words, moderate good news is most effective in resolving investor uncertainty. We also show that investors experience hightened uncertainty when they hold a firm prior but receive a large piece of bad news. These findings are unlikely to be explained by volatility feedback and leverage effects. Collectively, our results suggests that good news and bad news cannot be treated symmetrically when evaluating their effects on investor learning.

References

Orie E Barron, Oliver Kim, Steve C Lim, and Douglas E Stevens. Using analysts' forecasts to measure properties of analysts' information environment. *Accounting Review*, pages 421–433, 1998.

Orie E Barron, Donal Byard, and Oliver Kim. Changes in analysts' information around earnings announcements. *The Accounting Review*, 77(4):821–846, 2002.

Mary E Barth and Eric C So. Non-diversifiable volatility risk and risk premiums at earnings announcements. *The Accounting Review*, 89(5):1579–1607, 2014.

Mary Brooke Billings and Robert Jennings. The option markets anticipation of information content in earnings announcements. *Review of Accounting Studies*, 16(3):587–619, 2011.

Mary Brooke Billings, Robert Jennings, and Baruch Lev. On guidance and volatility. *Journal of Accounting and Economics*, 60(2):161–180, 2015.

Fischer Black. {Stuedies of stock price volatility changes}. 1976.

John Y Campbell and Ludger Hentschel. No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of financial Economics*, 31(3):281–318, 1992.

Xilong Chen and Eric Ghysels. Newsgood or badand its impact on volatility predictions over multiple horizons. *Review of Financial Studies*, 24(1):46–81, 2011.

Alexander David and Pietro Veronesi. What ties return volatilities to price valuations and fundamentals? *Journal of Political Economy*, 121(4):682–746, 2013.

Jianqing Fan and Irene Gijbels. Data-driven bandwidth selection in local polynomial fitting: variable bandwidth and spatial adaptation. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 371–394, 1995.

Jianqing Fan and Irene Gijbels. *Local polynomial modelling and its applications: monographs on statistics and applied probability 66*, volume 66. CRC Press, 1996.

Noreen Foster. The fasb and the capital markets. *The FASB Report (June 2003)*, 2003.

Kenneth R. French, G.William Schwert, and Robert F. Stambaugh. Expected stock returns and volatility. *Journal of Financial Economics*, 19(1):3 – 29, 1987.

Zhaoyang Gu and Ting Chen. Analysts treatment of nonrecurring items in street earnings. *Journal of Accounting and Economics*, 38:129–170, 2004.

Carla Hayn. The information content of losses. *Journal of accounting and economics*, 20 (2):125–153, 1995.

Wen Jin, Joshua Livnat, and Yuan Zhang. Option prices leading equity prices: Do option traders have an information advantage? *Journal of Accounting Research*, 50(2):401–432, 2012.

David Johnstone. The effect of information on uncertainty and the cost of capital. *Contemporary Accounting Research*, 2015.

Oliver Kim and Robert E Verrecchia. Market liquidity and volume around earnings announcements. *Journal of accounting and economics*, 17(1-2):41–67, 1994.

Richard Lambert, Christian Leuz, and Robert E Verrecchia. Accounting information, disclosure, and the cost of capital. *Journal of accounting research*, 45(2):385–420, 2007.

Mark H Lang and Russell J Lundholm. Corporate disclosure policy and analyst behavior. *Accounting review*, pages 467–492, 1996.

Jonathan Lewellen and Jay Shanken. Learning, asset-pricing tests, and market efficiency. *The Journal of Finance*, 57(3):1113–1145, 2002.

Kevin K Li and Partha Mohanram. Evaluating cross-sectional forecasting models for implied cost of capital. *Review of Accounting Studies*, 19(3):1152–1185, 2014.

Thaddeus Neururer, George Papadakis, and Edward J Riedl. Tests of investor learning models using earnings innovations and implied volatilities. *Review of Accounting Studies*, 21(2):400–437, 2016.

James M Patell and Mark A Wolfson. Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics*, 1(2):117–140, 1979.

James M Patell and Mark A Wolfson. The ex ante and ex post price effects of quarterly earnings announcements reflected in option and stock prices. *Journal of Accounting Research*, pages 434–458, 1981.

Andrew J Patton and Kevin Sheppard. Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, 97(3):683–697, 2015.

Jonathan L Rogers, Douglas J Skinner, and Andrew Van Buskirk. Earnings guidance and market uncertainty. *Journal of Accounting and Economics*, 48(1):90–109, 2009.

G William Schwert. Why does stock market volatility change over time? *The journal of finance*, 44(5):1115–1153, 1989.

KR Subramanyam. Uncertain precision and price reactions to information. *Accounting Review*, pages 207–219, 1996.

Pietro Veronesi. Stock market overreactions to bad news in good times: a rational expectations equilibrium model. *Review of Financial Studies*, 12(5):975–1007, 1999.

Robert E Verrecchia. Discretionary disclosure. *Journal of accounting and economics*, 5: 179–194, 1983.

Robert E Verrecchia. Essays on disclosure. *Journal of accounting and economics*, 32(1): 97–180, 2001.