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Asymmetric impact of earnings news on investor uncertainty

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Keywords

asymmetric, uncertainty, investor, news, earnings, impact

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Abstract

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Key words: disclosure, earnings, implied volatility, investor uncertainty

1 Introduction

We study the impact of disclosure on investor uncertainty in a generalized Bayesian setting. We describe a model that caters for circumstances whereby new information, especially unfavourable information, can shake investor confidence and add to uncertainty about the firm's stochastic cash flow. Previous models, such as Lambert et al. (2007), carry the inherent limitation that any new information, regardless of whether it is favourable or unfavourable, must by the model's construction leave investors with reduced uncertainty.

To avoid that constraint on belief revision, while still using the same convenient Bayesian mathematics, we assume that the firm has two possible latent states (regimes) underlying its economic fundamentals, 'Normal' and 'Distress', where Distress is generally much less probable *a priori*. Investors then face two layers of uncertainty: (i) they do not know which state the firm is in (between-state uncertainty), and (ii) they do not know what the firm's cash flow will be even when they know which state it is in (within-state uncertainty).

The appeal of this model is that new information affects investors' beliefs in two ways, simultaneously. First, it gives an indication of which state the firm is in (unfavourable information points towards the bad state, but possibly not strongly). Second, it allows investors to revise the probability distribution of the firm's cash flow conditional on the firm being in one of the states. A concession to reality in this model is that bad news can raise significant doubts and leave investors very unclear about which state the firm is in. The firm's cash flow is then a draw from a mixture distribution of two conditional distributions, neither of which might have very high posterior probability (their posterior probabilities might be both 0.5), potentially leaving the cash flow much more uncertain than before the relevant information was received.[1] Given the arrival of sufficiently stronger information, investors will eventually become virtually certain about the firm's state and its cash flow. Certainty can thus be reached, but typically not monotonically.

The 'usual' Bayesian model, used throughout the accounting information literature, implies that (i) investors' uncertainty is affected by the precision of the information, but not by 'what is says', whether favourable or unfavourable, and (ii) uncertainty decreases monotonically with

[1] Our model falls into the Neururer et al. (2016, p.401) category of "*Bayesian Learning with Increased Posterior Uncertainty*" models , which the authors describe as being the most realistic.

any new information. That workhorse model is elegant and tractable for theoretical work, but is unrealistic empirically. If the market has broadly favourable prior expectations of the firm but learns that the firm's costs have increased and sales have decreased, such clearly relevant accounting information should not necessarily, if ever, leave investors more certain that the firm is in fact doing well. Johnstone (2018) provides a detailed critique of the usual Bayesian model in accounting research, including a technical explanation of why its assumptions imply that any new information must always decrease uncertainty.[2]

In contrast, our model describes the impact of news on uncertainty as the net effect from the change in the between-state uncertainty and the change in the within-state uncertainty. The model allows for a natural asymmetry in good news resolving more uncertainty than bad news, however it also allows for the possibility that disclosure can heighten uncertainty when investors' prior beliefs are sufficiently tight and the news is sufficiently bad. The upwards revision in uncertainty is attributed to the increase in between-state uncertainty, which offsets the resolution of the within-state uncertainty. These results lie in stark contrast to the usual Bayesian model.

Closest to our study, Dye and Hughes (2018) describe a voluntary disclosure model that also implies a possibility of an increase in uncertainty in response to new information. Specifically, they show that, when the manger's information endowment is uncertain, the perceived variance of the firm's cash flows must go up when the manager makes no voluntary disclosure. In their model, the absence of disclosure causes investors to guess whether the manager is genuinely uninformed or the manager is withholding unfavorable information, thus giving rise to a mixture distribution for investors' posterior beliefs. As a result, uncertainty increases when no disclosure is made even though investors can extract information from the absence of disclosure. This updating mechanism is in line with our model in the sense that ambiguity regarding the latent state that generates the observed information can increase investor uncertainty. While the uncertainty-increasing result in Dye and Hughes (2018) applies to a strategic disclosure setting in a risk-averse market, our model can explain information-driven uncertainty increases in a non-strategic setting regardless of investor preferences. In fact, Johnstone (2016) explains that the possibility of such uncertainty-increasing effects of information is more general because the

[2] Larson and Resutek (2017) draw a distinction between cash flow uncertainty and uncertainty about the quality of the firm's accounting information. We adopt the general Bayesian decision assumption that the market's uncertainty about the firm's cash flow is based on the set of all available information, which includes information about the quality of the accruals and other accounting signals that are included in that set.

resolution of uncertainty holds only on average but not necessarily in every case.[3] Our study extends Johnstone (2016) by systematically identifying a sufficient condition for the uncertainty increase to arise.

Our model describes a *causal* asymmetric effect of disclosure on uncertainty as a consequence of just Bayesian updating. This is a distinct effect to volatility feedback embraced in the asset pricing literature (e.g. Campbell and Hentschel 1992). For example, Veronesi (1999) proposes a dynamic regime-shift model that implies a negative association between stock returns and volatility through the discount rate, suggesting that bad news predicts higher volatility than good news. While this result appears similar to ours, models of this kind cannot speak to the causal effects of disclosure on volatility, because the information that causes the market reaction is unspecified.[4]

We test the model's predictions by examining the association between the revision of option-implied volatility around earnings announcements and earnings news. The first testable implication of our model is that the marginal effect of earnings news on uncertainty is asymmetric based on the sign of the news. If distress is on average a low probability state, then the between-state uncertainty will rise (decline) in response to bad (good) news. Therefore, a negative earnings surprise should resolve less uncertainty than an equal-sized positive surprise. Our regression results suggest that the change in implied volatility of various options around the earnings announcement decreases in the magnitude of the earnings surprise when the firm announces good news, and increases when the firm announces bad news, consistent with our prediction. The asymmetry of the marginal effect is economically large: one standard deviation of positive earnings surprise brings 10.2% more reduction in the 91-day option-implied volatility around earnings announcements, compared to an equal-sized negative surprise. In addition, we find that the level of uncertainty prior to the earnings announcement negatively predicts the revision in implied volatility measures, supporting our prediction that more uncertain investor priors foreshadow a greater extent of uncertainty resolution.

[3] Our model subsumes the classical understanding that disclosure always resolves uncertainty on average (e.g. Verrecchia 1983, Lambert et al. 2007), where between-state uncertainty is not considered and only within-state uncertainty takes effect. Specifically, the classical disclosure models suggest that uncertainty resolution increases in the precision of the disclosure irrespective of the content of the disclosure, and that information can never leave investors more uncertain.

[4] In volatility feedback models, the proxy for news (stock returns) and the proxy for uncertainty (volatility) are simultaneously co-determined. In fact, stock returns can change due to anticipated changes in future volatility. Hence, the causality between news and uncertainty is unclear.

Furthermore, our model suggests that given low prior uncertainty (i.e. tight beliefs that the firm is in a 'normal' state), sufficiently bad news can cause a *net* increase in uncertainty. It is important to emphasize that the the net effect on uncertainty is distinct from the marginal effect. While we show that a bad news announcement has a positive marginal effect on uncertainty, it is not evidence that uncertainty can increase after earnings announcements, because negative marginal effects can mean less reduction in uncertainty rather than an increase. To detect this net effect of earnings news on volatility, we use a nonparametric method that estimates the shape and confidence bands of the 'news impact curve' (i.e. the relation between the revision of implied volatility and earnings surprise), using a polynomial smoother. After conditioning the news impact curves on the level of prior uncertainty, we find that uncertainty increases overall when the firm announces sufficiently bad news that contradicts favorable investor priors.

We implement a battery of additional analyses to add credence to our findings. First, we show our results are inconsistent with the leverage effect suggested by Black (1976). Second, while we find moderate support for the volatility feedback effects around earnings announcements(Campbell and Hentschel 1992, Veronesi 1999), we show that this effect appears not to intervene with the Bayesian updating mechanism that we rely on. Finally, to ensure our results are not attributed to the 'jump' volatility induced by the earnings announcement, we exploit the term structure of option-implied volatility to extract a measure of 'long-run' volatility that is purged of the 'jump' component (Merton 1973, Barth and So 2014). All results remain similar when using this new measure.

Several empirical studies have documented evidence of disclosure-driven uncertainty revisions. In voluntary disclosure settings, Rogers et al. (2009) find that management earnings forecasts tend to increase uncertainty when the forecasts are sporadic or convey bad news. However, Billings et al. (2015) argue that these results are subject to sample selection bias because the managers' decision to issue unbundled forecasts is motivated by the anticipated uncertainty increase. While these studies examine the impacts of earnings information on uncertainty, their results are attributed to both the strategic considerations affecting managerial disclosure decisions as well as the information released itself. Our results based on the earnings announcement setting provides a cleaner connection between disclosure and uncertainty as a pure consequence of the Bayesian updating mechanism.

To our knowledge, Neururer et al. (2016) presents the first evidence on how uncertainty can increase in response to earnings announcements. Specifically, they detect a net increase in option-implied volatility after extreme absolute earnings surprises. However, their research design assumes a symmetric response of uncertainty to both good and bad news, because existing theories on Bayesian learning (e.g. Pastor and Veronesi 2009) do not incorporate the sign of the news. A critical insight from our two-state model is that the effect on uncertainty depends on the sign of the news. Our results complement Neururer et al. (2016) in this regard. We show that the increase in uncertainty in response to extreme surprises as reported by Neururer et al. (2016) is mostly attributed to bad news announcements.

He et al. (2019) are also inspired by Johnstone (2016), and find that negative earnings surprises following a series of prior positive earnings surprises tend to increase uncertainty, which they interpret as a contradiction to Bayesian learning. By using a more general model, we show that this effect is a natural consequence of Bayesian investors learning about the latent state of the firm, and accords with our model predictions. Specifically, as the stream of prior good news tightens investor beliefs, suggesting an even lower probability of distress, we show that the appearance of bad news would shake prior beliefs and increase the between-state uncertainty thus bringing an overall net increase in uncertainty.[5] Furthermore, He et al. (2019) do not say anything about whether uncertainty can experience a *net* increase in response to earnings news, which is a key result in Johnstone (2016) that we explicitly test in this study.

The remainder of the paper is organized as follows. Section 2 describes a theoretical model and derives testable implications. Section 3 specifies the empirical tests, and Section 4 describes our data. Empirical results are provided in Section 5. Section 6 reports several additional analyses and tests of alternative explanations. Section 7 concludes.

2 Model

Consider a firm with unknown future cash flow X. The firm discloses a signal x that is informative about cash flow X.

The distinctive feature of our model is that we introduce a kind of 'model risk' or 'regime risk' where investors believe that X is drawn randomly from one of two possible distributions,

[5] We thank an anonymous reviewer for bringing this paper to our attention.

depending on whether the firm is in 'Normal' (s = N) state or a state of 'Distress' (s = D). Distress can be of low prior probability (later we assume 5%), but always remains a possibility and is therefore incorporated in the market's prior beliefs.

Market prior beliefs hold that if the firm is in its Normal state, then $X \sim N(\theta, \sigma^2)$, where σ^2 is known and $\theta \sim N(\mu_1, \sigma_1^2)$ with specified values μ_1 and σ_1. If 'Normal' is the only admissible state, then the model reduces to the standard Bayesian model in accounting theory with an unknown mean, and has the well known characteristic that information is not only expected to reduce uncertainty about θ, it always does (e.g. Verrecchia 1983, Admati 1985, Lambert et al. 2007, Hughes et al. 2007, Gao 2010).

Allowing for the possibility that firm is in Distress, the firm's cash flow has the same prior distribution $X \sim N(\theta, \sigma^2)$ as above, except that $\theta \sim N(\mu_{D1}, \sigma_{D1}^2)$, where naturally $\mu_{D1} < \mu_1$. Taken as a whole, the market's prior beliefs are that cash flow X is drawn from a mixture distribution across the firm's two possible states, though one state might be highly improbable *ex ante* (i.e. prior to any observation). As a result, the investor faces two levels of uncertainty: (i) uncertainty regarding the state the firm is in (between-state uncertainty), and (ii) uncertainty regarding the realization of cash flow X under a specific state (within-state uncertainty).

Before arriving at posterior beliefs about the next cash flow X, the market observes a signal, x. The likelihood function of x given θ is:

$$p(x|\theta) = \sqrt{\frac{1}{2\pi\sigma^2}} \exp\left[-\frac{1}{2}\left(\frac{x-\theta}{\sigma}\right)^2\right] .$$

The posterior distribution of θ conditional on the firm being in Normal state is, by standard Bayesian results, $\theta \sim N(\mu_2, \sigma_2^2)$, where:

$$\frac{1}{\sigma_2^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma^2} \quad \text{and} \quad \mu_2 = \frac{\frac{1}{\sigma_1^2}\mu_1 + \frac{1}{\sigma^2}x}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma^2}} .$$

Similarly, the posterior distribution of θ conditional on the firm being in Distress is $\theta \sim N(\mu_{D2}, \sigma_{D2}^2)$, where:

$$\frac{1}{\sigma_{D2}^2} = \frac{1}{\sigma_{D1}^2} + \frac{1}{\sigma^2} \quad \text{and} \quad \mu_{D2} = \frac{\frac{1}{\sigma_{D1}^2}\mu_{D1} + \frac{1}{\sigma^2}x}{\frac{1}{\sigma_{D1}^2} + \frac{1}{\sigma^2}} \ .$$

If we know what state the firm is in, uncertainty is reduced by any new sample evidence, because both $\sigma_2^2 < \sigma_1^2$ and $\sigma_{D2}^2 < \sigma_{D1}^2$. It remains uncertain, however, even after observing x, whether the firm is in its Normal state or a state of Distress. That remaining uncertainty must be allowed for. As Dye and Hughes (2018) show, that can sometimes result in the next cash flow X becoming more uncertain after the evidence than it was prior to the evidence.

The observation x gives some indication of which state the firm is in, because lower values of x are relatively more probable under Distress. More specifically, the likelihood ratio $p(x|\mathrm{N})/p(x|\mathrm{D})$ generally decreases with (sufficiently) lower x. To find the likelihood ratio, we need to obtain:

$$p(x|\mathrm{N}) = \int_{-\infty}^{\infty} p(\theta|\mathrm{N})p(x|\theta)d\theta \ ,$$
$$p(x|\mathrm{D}) = \int_{-\infty}^{\infty} p(\theta|\mathrm{D})p(x|\theta)d\theta \ .$$

Note that the above expressions assume from the model that x is independent of s once given θ; i.e. $p(x|\theta, N) = p(x|\theta, D) = p(x|\theta)$. We know already that under state N, $\theta|x \sim N(\mu_2, \sigma_2^2)$, and under state D, $\theta|x \sim N(\mu_{D2}, \sigma_{D2}^2)$, so by the usual formula for the probability density of a normal distribution it holds:

$$p(\theta|x, \mathrm{N}) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left[-\frac{1}{2}\left(\frac{\theta - \mu_2}{\sigma_2}\right)^2\right] \ ,$$
$$p(\theta|x, \mathrm{D}) = \frac{1}{\sqrt{2\pi\sigma_{D2}^2}} \exp\left[-\frac{1}{2}\left(\frac{\theta - \mu_{D2}}{\sigma_{D2}}\right)^2\right] \ .$$

The predictive distribution for X given that the firm is in state N is therefore:

$$
\begin{aligned}
p(X|\text{N}) &= \int_{-\infty}^{\infty} p(\theta|x,\text{N})p(X|\theta)d\theta \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left[-\frac{1}{2}\left(\frac{\theta-\mu_2}{\sigma_2}\right)^2\right] \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2}\left(\frac{X-\theta}{\sigma}\right)^2\right] d\theta \\
&= \frac{1}{\sqrt{2\pi(\sigma_2^2+\sigma^2)}} \exp\left[-\frac{1}{2}\frac{(X-\mu_2)^2}{(\sigma_2^2+\sigma^2)}\right] \ ,
\end{aligned}
$$

which is a normal distribution with mean μ_2 and variance $\left(\sigma_2^2+\sigma^2\right)$.

An interesting aspect of this calculation is that we use the sample observation x to revise the probability distribution of θ, or more specifically the distribution of θ given N. Once we have that new distribution $p(\theta|x,\text{N})$ for θ, we use it to find the predictive (average) distribution of the next payoff X given N.

Similarly, the posterior predictive distribution of the next cash payoff X given D is:

$$
p(X|\text{D}) = \frac{1}{\sqrt{2\pi(\sigma_{D2}^2+\sigma^2)}} \exp\left[-\frac{1}{2}\frac{(X-\mu_{D2})^2}{(\sigma_{D2}^2+\sigma^2)}\right] \ ,
$$

which is a normal distribution with mean μ_{D2} and variance $\left(\sigma_{D2}^2+\sigma^2\right)$.

The unconditional predictive distribution of X is a probability-weighted mixture distribution of the two conditional predictive distributions of X. The mixture weights are the posterior probabilities of the two states, namely $p(N|x)$ and $p(D|x)$. Letting the prior probability of Normal be $p(\text{N}) \equiv 1-p(\text{D})$, the posterior probability of N is:

$$
p(\text{N}|x) = \frac{p(\text{N})p(x|\text{N})}{p(\text{N})p(x|\text{N})+p(\text{D})p(x|\text{D})} \ .
$$

We now have all the ingredients to find the unconditional posterior predictive distribution of the next cash flow X. The parameters of this mixture distribution are:

$$
\mu_{m|x}(X) = p(\text{N}|x)\mu_2 + p(\text{D}|x)\mu_{D2} \ ,
$$

and, by the law of total variance (Johnstone 2015, 2016, Dye and Hughes 2018), it holds that:

$$\sigma^2_{m|x}(X) = E[\mathrm{Var}(X|s)|x] + \mathrm{Var}(E[X|s]|x) \ , \tag{1}$$

where $E[\mathrm{Var}(X|s)|x]$ is the posterior average of the two predictive variances across the two states, that is:

$$\begin{aligned} E[\mathrm{Var}(X|s)|x] &= p(\mathrm{N}|x)\left(\sigma_2^2 + \sigma^2\right) + p(\mathrm{D}|x)\left(\sigma_{D2}^2 + \sigma^2\right) \\ &= \sigma^2 + \left(p(\mathrm{N}|x)\sigma_2^2 + p(\mathrm{D}|x)\sigma_{D2}^2\right) \ . \end{aligned}$$

and $\mathrm{Var}(E[\theta|s]|x)$ is the variance of the two posterior means, that is:

$$\mathrm{Var}(E[X|s]|x) = p(\mathrm{N}|x)\left(\mu_2 - \mu_{m|x}\right)^2 + p(\mathrm{D}|\overline{x})\left(\mu_{D2} - \mu_{m|x}\right)^2 \ .$$

The posterior predictive variance of θ, denoted by $\sigma^2_{m|x}(\theta)$, is:

$$\begin{aligned} \sigma^2_{m|x}(\theta) &= E[\mathrm{Var}(\theta|s)|x] + \mathrm{Var}(E[\theta|s]|x) \\ &= \left(p(\mathrm{N}|x)\sigma_2^2 + p(\mathrm{D}|x)\sigma_{D2}^2\right) + \left(p(\mathrm{N}|x)\left(\mu_2 - \mu_{m|x}\right)^2 + p(\mathrm{D}|\overline{x})(\mu_{D2} - \mu_{m|x})^2\right) \ , \end{aligned}$$

which allows us to rewrite equation (1) neatly as follows:

$$\sigma^2_{m|x}(X) = \sigma^2 + \sigma^2_{m|x}(\theta) \ . \tag{2}$$

Observe from equation (2) that there are two sources of uncertainty affecting our final uncertainty about cash flow X. First, even if we knew θ for certain, X still has known variance σ^2, because the model holds that $X \sim N(\theta, \sigma^2)$. Second, despite observing x we don't know θ. In fact, despite potentially narrowing down what state the firm is in, we don't know for certain the state or distribution from which θ is drawn. Rather, θ is drawn from a mixture distribution and its posterior predictive variance is $\sigma^2_{m|x}(\theta)$. Conveniently, the sum of these two uncertainties is captured correctly by the sum of the two variances, shown in equation (2).

Winkler (2003, p.181) further explains these two sources of variance and notes how the predictive variance of X "takes into account both uncertainty about θ and uncertainty about X given θ". Note that although the mixture distributions of θ and X are mixtures of normals and so are not normal, their predictive variances are found nonetheless by the law of total variance, which is a general law and distribution-free (see Gelman et al. 2014).

To understand the possible effects of information on investor certainty, we can now compare the posterior predictive variance of equation (2) with the prior predictive variance, as follows:

$$\sigma^2_m(X) = \sigma^2 + \sigma^2_m(\theta) \ , \tag{3}$$

which is found the same way as equation (1), but without the influence of the new observation x. Specifically, $\sigma^2_m(\theta)$ is the prior predictive variance of θ, which is the variance of the mixture distribution of θ across the two states, that is:

$$\sigma^2_m(\theta) = E[\mathrm{Var}(\theta|s)] + \mathrm{Var}([E[\theta|s]) \ ,$$

where:

$$E[\mathrm{Var}(\theta|s)] = p(\mathrm{N})\sigma^2_1 + p(\mathrm{D})\sigma^2_{D1} \ ,$$

and,

$$\mathrm{Var}(E[\theta|s]) = p(\mathrm{N})(\mu_1 - \mu_m)^2 + p(\mathrm{D})(\mu_{D1} - \mu_m)^2 \ ,$$

where:

$$\mu_m = p(\mathrm{N})\mu_1 + p(\mathrm{D})\mu_{D1} \ .$$

It is obvious that equations (2) and (3) have a common ingredient in σ^2. They differ therefore only to the extent that $\sigma^2_{m|x}(\theta)$ differs from $\sigma^2_m(\theta)$. Interestingly, it can occur that $\sigma^2_{m|x}(\theta) > \sigma^2_m(\theta)$ implying that the sample observation x can add to investor uncertainty about θ and the next cash flow X; i.e. $\sigma^2_{m|x}(X) > \sigma^2_m(X)$. That will occur if x adds sufficiently to uncertainty about which state, N or D, obtains.

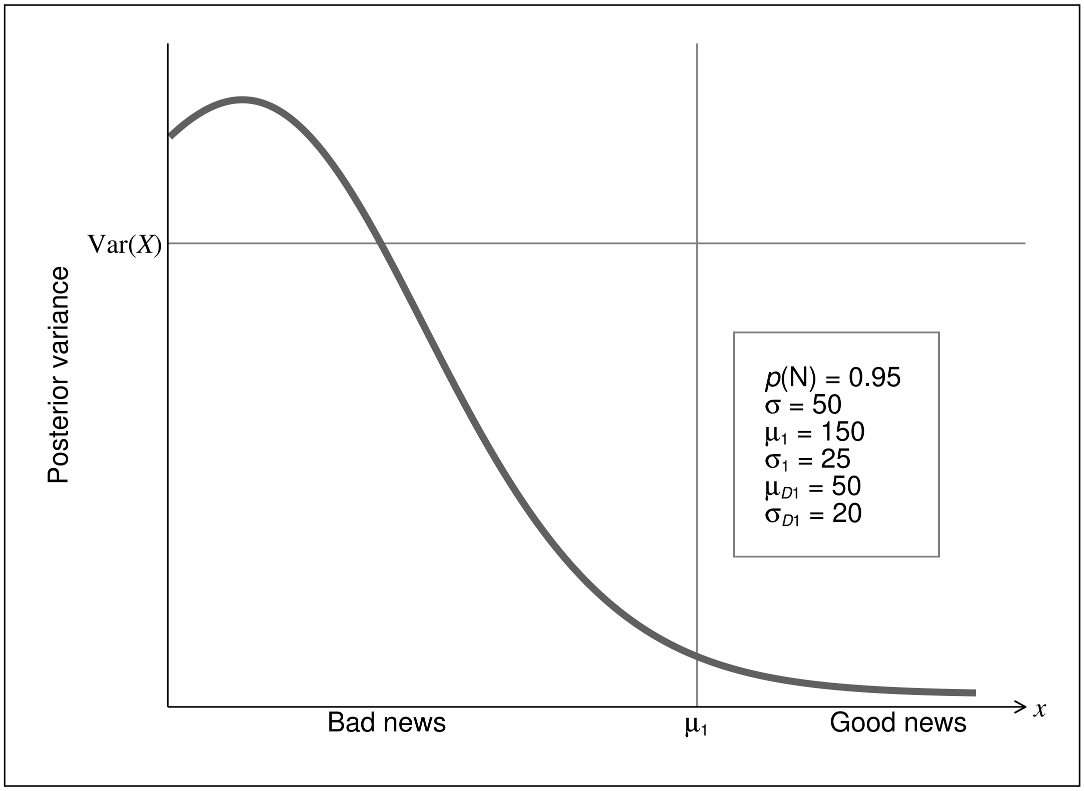
A clearer depiction of how information x affects investor uncertainty about cash flow X is obtained by looking at numerical examples. Figure 1 plots the posterior predictive variance for X, i.e. $\sigma^2_{m|x}(X)$, against the observation x. The horizontal line is the prior predictive variance, $\sigma^2_m(X)$. For the sake of illustration, we start with prior probability $p(D) = 0.05$, which is roughly in line with the empirical probability of US bankruptcies.[6] Uncertainty reacts to x in an rotated S-shape. There is a range of x for which uncertainty about X actually increases. That happens when the observed x is low, dragging the probability of Distress higher, up from 0.05, hence adding so much to uncertainty about which state the firm is in that the reduction in within-state variance is too little to make an overall reduction in the predictive variance of X.

3 Empirical design

To test our model predictions, we examine the association between earnings surprises (news) and the changes in implied volatility around earnings announcements (changes in uncertainty). Earnings announcements provide an appropriate setting because, unlike those of voluntary disclosures, earnings announcements are regular and well anticipated and therefore not subject to strategic choices (Bushee et al. 2010). Furthermore, to the extent that earnings surprises are not predictable, our proxy for news is not affected by the volatility feedback mechanism. This

[6] A firm in Distress need not end up bankrupt, and conversely a firm in Normal state can end up bankrupt. Bankruptcy would occur if the next cash flow X is sufficiently low. A negative signal raises the probability of Distress such that the investor can be left unsure of which regime the firm is in and hence highly unsure of its future cash flow. The firm's cash flow is drawn from one of two possible distributions and a negative signal can leave the market much less confident that the firm is in the Normal state and hence not believing strongly in either distribution/regime more than the other.

Figure 1: Posterior variance as a function of disclosure signal



Note: The figure shows the posterior predictive variance of cash flow X, $\mathrm{Var}(X|x) \equiv \sigma^2_{m|x}(X)$, as a function of the sample observation x. The prior probability that firm is in normal state is $p(N) = 0.95$, giving $p(D) = 0.05$. The firm's cash flow has unknown mean θ but known standard deviation $\sigma = 50$. If the firm is in Normal (Distress) state, θ has prior mean $\mu_1 = 150$ ($\mu_{1D} = 50$) and prior variance $\sigma_1 = 25$ ($\sigma_{D1} = 20$). The horizontal line shows the prior predictive variance of X, $\mathrm{Var}(X) \equiv \sigma^2_m(X)$. Note how for a range of x, uncertainty about X is increased.

feature helps us draw distinction from studies on the return-volatility asymmetry in the asset pricing literature (e.g. Veronesi 1999).

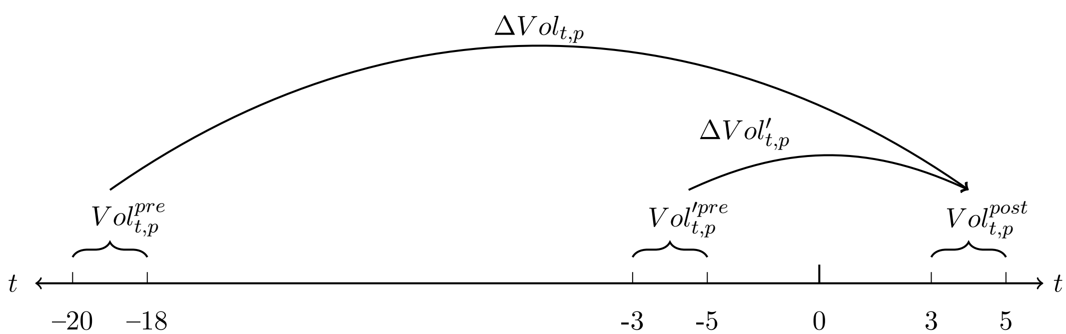
3.1 Measuring the change in uncertainty around earnings news

We measure investor uncertainty using option-implied volatility, which is an *ex ante* forward-looking indicator of investor uncertainty (e.g. Neururer et al. 2016, Rogers et al. 2009, Billings et al. 2015). This is an appealing feature especially by comparison to other proxies for uncertainty such as analyst forecast dispersion and *ex post* realized volatility. Also, option traders tend to be highly sophisticated, therefore inferences are less vulnerable to systematic behavioral biases (Jin et al. 2012).

Figure 2 describes our measurement windows of the change in implied volatility, $\Delta Vol_{t,p} =$

$Vol_{t,p}^{post} - Vol_{t,p}^{pre}$, using a timeline around the date of earnings announcement, at $t = 0$. The index $p = 30, 60, 91$ indicates the use of 30-day, 60-day or 91-day option durations. The time index t indicates sequential trading days, with $t < 0$ corresponding to pre-announcement days and $t > 0$ to post-announcement days. We measure the change in volatility using two windows, a wider window and a narrower window. The wider window measures the pre-announcement volatility, $Vol_{t,p}^{pre}$, as the average of the natural logarithms of daily implied volatility over the three-day interval of $t = -20, -19, -18$. The narrower window measures $Vol_{t,p}^{\prime pre}$ (note the use of prime $'$) as the average of the natural logarithms of daily implied volatility over the three-day interval of $t = -5, -4, -3$. The post-announcement volatility, $Vol_{t,p}^{post}$, is the same for both windows and is measured as the average of implied volatility over $t = 3, 4, 5$.[7]

Figure 2: Timeline of implied volatility measurement



Note: The timeline marks the trading days $t = -20, -19, \ldots, 20$ around the earnings announcement date at $t = 0$. $Vol_{t,p}^{pre}$ is the average of implied option volatility over the three-day interval $t = -20, -19, -18$, and $Vol_{t,p}^{\prime pre}$ is the average of implied option volatility over $t = -5, -4, -3$. Vol_t^{post} is the average volatility over $t = 3, 4, 5$. The change in volatility for the wider window is measured as $\Delta Vol_{t,p} = Vol_{t,p}^{post} - Vol_{t,p}^{pre}$, and for the narrower window as $\Delta Vol'_{t,p} = Vol_{t,p}^{\prime post} - Vol_{t,p}^{\prime pre}$. The index p indicates the use of 30-day, 60-day or 91-day options.

There are trade-offs between the two measurement windows. The narrower window is in accord to prior studies (Rogers et al. 2009, Neururer et al. 2016), whereby the pre-announcement volatility is less likely to be affected by confounding pre-announcement information but it is more likely to be contaminated by the volatility build-up in anticipation of the earnings announcement, e.g. Patell and Wolfson (1979, 1981) (see also the evidence presented in Figure 3). Therefore, the narrower window captures more of the resolution of the short-lived uncertainty (or 'jump' volatility) induced by the forthcoming earnings news rather than the revision of long-run uncertainty regarding the firm's future cash flows. Indeed, Billings and Jennings (2011) find that implied volatility immediately before the earnings announcement is a significant *ex ante*

[7]The averaging procedure over the three-day period mitigates potential measurement errors due to the large noise in the data.

indicator of the magnitude of the forthcoming earnings surprise. The short-lived uncertainty is bound to be fully resolved after the announcement, making it difficult for us to detect the uncertainty-increasing effects.

For this reason, our preferred choice is the use of the wider window, with $Vol_{t,p}^{pre}$ measured before most of the pre-announcement volatility build-up. This provides a more appropriate measure of the change in long-run investor uncertainty, because it is far less affected by the jump volatility induced by the forthcoming earnings announcement. Therefore, we focus our discussion of the results on the wider window, although the results based on the narrower window are qualitatively similar and are also reported to enable direct comparison with prior studies. We understand that taking a wider window design does not completely safeguard our measure against the 'jump' volatility. To further address this important aspect of the research design, in Section 6.2 we develop a new measure of the change in volatility that purges the anticipated 'jump' and separates out the long-run uncertainty from the implied volatility.

We also diversify the maturities of options in our research design. While short-maturity options are heavily traded around information events and thus more sensitive to earnings news (Billings and Jennings 2011), options of longer maturities embed more long-run volatility and thus are more consistent with our intention to capture investor uncertainty of long-run cash flows of the firm (Neururer et al. 2016). We consider standard options maturing in 30, 60 and 91 days. Notably, the use of 91-day options provides an additional safeguard against announcement-induced 'jump' volatility, because the option duration will cover exactly one earnings announcement both before and after the current announcement. Specifically, pre-announcement 91-day options will generally cover the current announcement but will expire before the next quarterly earnings announcement, and post-announcement 91-day options will expire after the next earnings announcement (Neururer et al. 2016).[8]

3.2 Testing the marginal effects of earnings news on uncertainty

To test the marginal effects of earnings surprises on uncertainty, we regress $\Delta Vol_{t,p}$ on key attributes of the earnings announcement and a range of control variables:

[8] We avoid using options expiring beyond 91 days because of the limited data. However, in untabulated analysis with much smaller samples, we find similar results using 182-day and 365-day option durations.

$$
\begin{aligned}
\Delta Vol_{t,p} = \alpha &+ \beta_1|ES_t| + \beta_2 BN_t + \beta_3 BN_t \times |ES_t| + \beta_4 Vol^{pre}_{t,p} + \beta_5|\overline{ES}|^{t-1}_{t-4} \\
&+ \gamma_1 MCap_t + \gamma_2 BM_{t-1} + \gamma_3 VIX_t + \gamma_4 \Delta VIX_t + \gamma_5 Lev_{t-1} \\
&+ \gamma_6 ES_t \times Lev_{t-1} + \gamma_7 Disp_t + \gamma_8 Follow_t + \epsilon_t
\end{aligned} \tag{4}
$$

The regression coefficients of inferential interest in equation (4) are denoted with β and the control variable coefficients are denoted with γ, and α is the model intercept and ϵ_t is the error term. ES_t is earnings surprise defined as the difference between realized earnings and the median of the latest prevailing analyst forecasts before the earnings announcement date. $|ES|_t$ is the magnitude of the earnings surprise measured as the absolute value of ES_t. Realized earnings are measured using IBES actual earnings.[9] If IBES actual earnings is missing, then we use income before extraordinary items from Compustat as a reasonable approximation for street earnings. BN_t (bad news) is a binary variable that takes the value of one if $ES_t < 0$, and it is a key variable of interest for identifying the asymmetry in the uncertainty effects of earnings news. The interaction term $BN_t \times |ES_t|$ captures the asymmetry in uncertainty effect and whether the asymmetry is amplified by the magnitude of earnings surprise.

A critical insight from our model described in Section 2 predicts an asymmetric effect of earnings news on uncertainty. If distress is on average a state that obtains with low unconditional probability, the revision of between-state uncertainty depends crucially on the sign of the earnings news. Specifically, a piece of good news further strengthens investors' belief that the firm is in the 'normal' state, because the likelihood of observing a positive signal given the state of 'distress' is very low. Therefore, good news further reduces uncertainty. By contrast, the arrival of bad news increases investors' posterior probability of the state of 'distress', though the the probability may still remain low. In this case, between-state uncertainty rises, offsetting the countervailing reduction in within-state uncertainty. Hence, bad news resolves less uncertainty than than good news. That is, we predict $\beta_1 < 0$, $\beta_2 > 0$ and $\beta_3 > 0$.

Our model also implies that the greater pre-announcement level of uncertainty is associated with greater reduction in volatility around the earnings announcement. $Vol^{pre}_{t,p}$ and $|\overline{ES}|^{t-1}_{t-4}$ are measures of investors' prior uncertainty. $Vol^{pre}_{t,p}$ is defined in Figure 2 and is a natural candidate

[9] GAAP earnings include transitory items, but analysts typically focus on the more persistent part of earnings (the 'street earnings'), and IBES actual earnings are usually adjusted for one-off items such as impairments and restructuring charges to be consistent with analysts' use of earnings (Gu and Chen 2004).

for prior uncertainty. $|\overline{ES}|_{t-4}^{t-1}$ is the average of absolute earnings surprises over the past four quarters. This measure follows from the rationale that if analysts appear recently surprised by the firm's earnings, then investors are likely to perceive high uncertainty pending for resolution in the forthcoming earnings announcement.[10] The use of information from the earnings surprise history adds focus to the measurement of uncertainty effect related to the earnings generating process. It also addresses the concern that $Vol_{t,p}^{pre}$ is algebraically related to the dependent variable. Typically, we expect higher variance in the prior belief distribution to lead to greater reduction in investor uncertainty with $\beta_4 < 0$ and $\beta_5 < 0$.

Control variables include $MCap_t$ defined as the natural logarithm of market capitalization at the end of the financial quarter t and is natural control for firm size. Larger firms have more communication channels, are subject to higher scrutiny, and disclose more information concurrently with their earnings announcements. Therefore, announcements released from larger firm are expected to resolve more uncertainty, with $\gamma_1 < 0$. BM_{t-1} is the lagged book-to-market ratio, computed as the book value of equity divided by the market value of equity at the end of quarter $t-1$. This is a control for growth opportunities, because growth firms tend to have much uncertainty pending for resolution through earnings announcements, thus the expectation that $\gamma_2 < 0$.[11]

VIX_t is the natural logarithm of the average CBOE VIX index over the same measurement window as that used for $Vol_{t,p}^{pre}$ (see Figure 2). The level of market volatility (as measured by the VIX) reflects the market-wide uncertainty. The higher the macro variance the less uncertainty resolution is expected at the firm level. Thus, we expect $\gamma_3 > 0$ (as per Neururer et al. 2016). ΔVIX_t is the change in the VIX index, using the same measurement window as that used for $\Delta Vol_{t,p}$. This is a control for market-wide sources of uncertainty changes. Since firm-specific volatility subsumes the effect of market volatility, we also expect that $\gamma_4 > 0$.

Lev_{t-1} is lagged leverage that is calculated as long-term debts over total assets, and $ES_t \times Lev_{t-1}$ is the interaction of leverage with the signed earnings surprise. Black (1976) and Christie (1982)

[10]We thank the anonymous reviewer for suggesting to consider the variance of ES_{t-4}^{t-1} as a measure of prior uncertainty, rather than $|\overline{ES}|_{t-4}^{t-1}$. Indeed, when earnings surprises have non-zero means, the variance provides a more appealing measure of uncertainty. Empirically, we confirm using either measures produce almost numerically identical results in all our regressions. However, the estimation of variance, a second-order moment relying on the estimation of the first-order moment, is less robust than the mean absolute value in small samples. Hence, we proceed with using $|\overline{ES}|_{t-4}^{t-1}$.

[11]We lag accounting-based variables by one quarter because the respective accounting numbers for the current quarter are not yet available before the earnings announcements.

suggest that bad news (proxied by stock returns) is associated with higher leverage, which in turn makes the stock value more volatile. If the leverage-based interpretation is at work in our context then we expect $\gamma_5 > 0$, implying bad news announcements increase uncertainty more for high-leverage firms. This prediction also acts as a simple test for the leverage effect, as discussed in Section 6.

$Disp_t$ is the dispersion of analyst forecasts and $Follow_t$ is the number of analyst following, and both capture the quality of the firm's information environment (e.g. Lang and Lundholm 1996, Barron et al. 1998). $Follow_t$ also indicates the number of forecasts included in the computation of the median analyst forecast. Although theory suggests that the greater the analyst following the more of the uncertainty is likely to be pre-empted by their forecasts, analysts may also be liable to self-selection such that they follow firms with high uncertainty in order to maximize the utility of their activities (Lee and So 2017).

3.3 Testing the net effect of earnings news on uncertainty

To test the net effect of earnings news on investor uncertainty, we consider a non-parametric test. Specifically, we investigate how well the empirical relation between earnings surprises and the change in implied volatility match with the our model's prediction as shown in Figure 1. Because the possibility of uncertainty increase in response to information is not owing to any particular specification of the underlying functional form or distributional assumptions (see Johnstone 2016), including those employed in Section 2, a non-parametric test is appropriate to help us assess the empirical appeal of our model.

The non-parametric approach estimates the *news impact curve* as the smoothed bivariate relation between the revision in uncertainty $\Delta Vol_{t,p}$ and the earnings surprise ES_t, using a kernel-weighted local polynomial smoother (Fan and Gijbels 1995). This method suits our data particularly well as implied volatilities are renowned to be very noisy. We apply the Epanechnikov kernel for a smoother depiction of the mean local density and estimate the third degree polynomial following the advice of Fan and Gijbels (1996), who explain that going from even to the next odd-degree polynomial reduces bias considerably without increasing the variability associated with adding this extra parameter. The local polynomial is estimated in 75 local bins of the data, ranging from the smallest to the largest value in ES_t.[12] Our model predicts that the revision in uncertainty can be positive when the earnings surprise is sufficiently negative, and the incidence of such net increase in volatility is expected to be more pronounced when prior uncertainty is low.

4 Data

Quarterly earnings announcements are identified using data from both Compustat and IBES. Following Barth and So (2014), we define the earnings announcement date as the earlier of Compustat reporting date or the IBES announcement date of actual earnings. If one of these sources is missing then we use the only date that is available. Stock price data is retrieved from the CRSP Daily Stock File. The implied volatility data for 30-day, 60-day and 91-day at-the-money call options are obtained from the OptionMetrics Standard Options database. The sample period begins from the first quarter of 1996 (the first year of coverage by OptionMetrics) to the fourth quarter of 2016. There are $117,821$ firm-quarter observations with data available from all data sources. Table 1 describes the sample selection procedure, the application of data management filters, and and the resulting final estimation sample $104,492$ observations covering $6,125$ firms. This is the sample used in the estimation of equation (4).

We present results by measuring investor uncertainty, using the 30-day, 60-day and 91-day option implied volatility around earnings announcements. We estimate Equation (4) using the iterative median regression that is robust to extreme values for which there is no need to manage outliers. However, to facilitate the comparison with prior studies, we also present OLS estimation results for equation (4), with univariate 99% winsorization on all continuous variables (as per Neururer et al. (2016)).

[12]The Epanechnikov kernel is the most efficient kernel-weight in minimizing the mean integrated squared error (Härdle 1990). We also round the rule-of-thumb (ROT) bandwidth to the nearest third decimal for an even smoother result. We test the sensitivity of our choices for non-parametric estimation using much more flexible but also more variable kernels, including the Parzen kernel which gives the most rugged detailed local depiction as well as a range of values for the bandwidth, and our conclusions remain robust. We also find that a larger number of bins creates a false impression of discontinuous areas and a smaller number of bins results in a more rugged curve.

Table 1: Sample selection

Steps	Obs.	Firms
Quarterly earnings announcement from Compustat, 1996-2016:[1]	466,301	15,441
with matched records from IBES and CRSP[2]	324,817	12,373
with 30-day, 60-day, 91-day options from OptionMetrics	117,821	6,535
Less observations with:[3]		
absolute surprises $> 2\%$ at $t = -20$	(5,227)	(85)
missing earnings surprises in 4 previous quarters	(1,807)	(97)
missing book-to-market ratios	(530)	0
missing lagged accounting leverage	(1164)	(53)
missing analyst forecast dispersion	(4,610)	(225)
Final estimation sample	104,492	6,125

Notes: [1]Net of observations with negative common equity. [2]Net of observations with stock prices lower than USD 5. [3]Sample selection qualifications that do not affect the useful sample are not shown. The Compustat and CRSP data are merged using the Compustat/CRSP Merged linking table provided by Wharton Research Data Services. The resulting combined data is then merged with IBES using the 6-digit CUSIP and company names as the firm identifiers. OptionMetrics data is then merged using the 6-digit CUSIP.

5 Empirical results

Table 2 provides the descriptive statistics of all variables in equation (4). The mean and median change in volatility $\Delta Vol_{t,p}$ is negative for all option maturities and for both measurement windows. However, the changes in all volatility measures turn positive at the 75^{th} percentile and above, suggesting that uncertainty increases are common empirical occurrences. Overall, our sample statistics are largely comparable to prior studies.

Table 3 provides a preliminary test of the asymmetry in the effects of earnings news on uncertainty. We partition the sample by the sign of earnings surprise and compare the mean revisions in implied volatility over both the wider and narrower windows. Consistent with our prediction, we find that the mean revision in volatility is always more negative in the good news sample, suggesting that good news reduces more uncertainty than bad news. The differences in mean volatility revisions, between good and bad news, are highly statistically significant for all option maturities and for both measurement windows. At the same time, the differences in the mean ΔVIX_t and $\Delta VIX'_t$ are not statistically significant, implying that the asymmetric effects are not not driven by the concern that bad news may cluster around times when the market-wide uncertainty increases.

Table 2: Descriptive statistics

Variables	Mean	St.Dev.	P_{10}	P_{25}	Median	P_{75}	P_{90}
Wider window: Change in average volatility from $t = -20, -19, -18$ to $t = 3, 4, 5$							
$\Delta Vol_{t,30}$	-0.0059	0.0597	-0.0694	-0.0367	-0.0085	0.0201	0.0601
$\Delta Vol_{t,60}$	-0.0042	0.0485	-0.0548	-0.0286	-0.0063	0.0161	0.0486
$\Delta Vol_{t,91}$	-0.0009	0.0409	-0.0418	-0.0202	-0.0032	0.0151	0.0427
$\Delta Vol_{t,LR}$	-0.0013	0.0577	-0.0604	-0.0292	-0.0040	0.0225	0.0611
ΔVIX_t	0.0029	0.1692	-0.1890	-0.1064	-0.0108	0.0947	0.2160
Narrower window: Change in average volatility from $t = -5, -4, -3$ to $t = 3, 4, 5$							
$\Delta Vol'_{t,30}$	-0.0135	0.0473	-0.0661	-0.0367	-0.0123	0.0082	0.0352
$\Delta Vol'_{t,60}$	-0.0062	0.0352	-0.0431	-0.0232	-0.0065	0.0085	0.0299
$\Delta Vol'_{t,91}$	-0.0032	0.0282	-0.0317	-0.0161	-0.0038	0.0078	0.0253
$\Delta Vol'_{t,LR}$	0.0019	0.0461	-0.042	-0.0176	0.0002	0.0196	0.0489
$\Delta VIX'_t$	0.0082	0.0994	-0.1065	-0.0525	-0.0014	0.0560	0.1343
Variables invariable to window specification							
ES_t	0.0005	0.0042	-0.0031	-0.0004	0.0003	0.0016	0.0044
$\lvert\overline{ES}\rvert_{t-4}^{t-1}$	0.312	0.566	0.0253	0.0527	0.117	0.2923	0.7682
$MCap_t$	7.4874	1.5258	5.6217	6.3799	7.3484	8.4369	9.6063
BM_{t-1}	0.4932	0.3432	0.1409	0.2481	0.4158	0.6533	0.9351
Lev_t	0.1862	0.1808	0.0000	0.0105	0.1487	0.3055	0.4476
$Disp_t$	0.0016	0.0029	0.0000	0.0003	0.0008	0.0017	0.0037
$Follow_t$	9.2494	6.6	2	4	8	13	18

Note: The sample contains 104,492 firm-quarter observations. Mean is arithmetic mean, St.Dev. is standard deviation, P_k is the k^{th} percentile. $\Delta Vol_{t,p}$ and $\Delta Vol'_{t,p}$ are the changes in option implied volatility, as defined in Figure 2. $m = 30, 60, 91$ indicates the maturity length of the options. LR indicates 'long-run' volatility as defined in Section 6.2. The following variables are defined in Section 3: $\Delta VIX1_t$ and $\Delta VIX'_t$ are the change in the CBOE VIX; ES_t is earnings surprise; $\lvert\overline{ES}\rvert_{t-4}^{t-1}$ is the average of absolute earnings surprises over the past four quarters; BM_{t-1} is the book-to-market ratio; Lev_{t-1} is the lagged ratio of the book value of liability over the book value of equity; $Disp_t$ is the standard deviation of analysts forecasts; Follow_t is the number of analysts following; $MCap_t$ is market capitalization.

The key observations reported in Table 3 are visualised in Figure 3, which graphs the movements of the standardized index of firm-specific implied volatility around the earnings announcement, for the Good News and the Bad News sub-samples. Each sample is partitioned into quartiles of magnitude of earnings surprises, $|ES_t|$, and each line tracks the medians of daily implied volatility index by quartile. The volatility index takes the value of 1 at $t = -20$. Note that Figure 3 uses the 30-day options, but a very similar graph applies also for 60-day and 91-day options. Consistent with the findings reported in Patell and Wolfson (1979, 1981), the implied volatility builds up in anticipation of the earnings announcement and drops sharply at

Table 3: Mean revision in implied volatility in good news and bad news

Variable	Good news mean	Bad news mean	Diff. in means	t-stat
Wider window: Change in average volatility from $t = -20, -19, -18$ to $t = 3, 4, 5$				
$\Delta Vol_{t,30}$	-0.0078	-0.0012	-0.0065	-15.77
$\Delta Vol_{t,60}$	-0.0062	0.0009	-0.0071	-21.22
$\Delta Vol_{t,91}$	-0.0025	0.0030	-0.0055	-19.32
$\Delta Vol_{t,LR}$	-0.0038	0.0046	-0.0084	-20.78
ΔVIX_t	0.0023	0.0043	-0.0020	-1.78
Narrower window: Change in average volatility from $t = -5, -4, -3$ to $t = 3, 4, 5$				
$\Delta Vol'_{t,30}$	-0.0158	-0.0079	-0.0078	-24.10
$\Delta Vol'_{t,60}$	-0.0080	-0.0020	-0.0060	-24.27
$\Delta Vol'_{t,91}$	-0.0047	0.0003	-0.0050	-25.39
$\Delta Vol'_{t,LR}$	0.0007	0.0047	-0.0039	-12.12
$\Delta VIX'_t$	0.0082	0.0081	0.0001	0.20

Note: Good news indicates the sample with $ES_t \geq 0$ and $74,736$ firm-quarter observations. Bad news indicates the sample with $ES_t < 0$ and $29,756$ firm-quarter observations. $\Delta Vol_{t,p}$ and $\Delta Vol'_{t,p}$ are the changes in option implied volatility, as defined in Figure 2. $m = 30, 60, 91$ indicates the maturity length of the options. LR indicates 'long-run' volatility as defined in Section 6.2. $\Delta VIX1_t$ and $\Delta VIX'_t$ are the change in the CBOE VIX index.

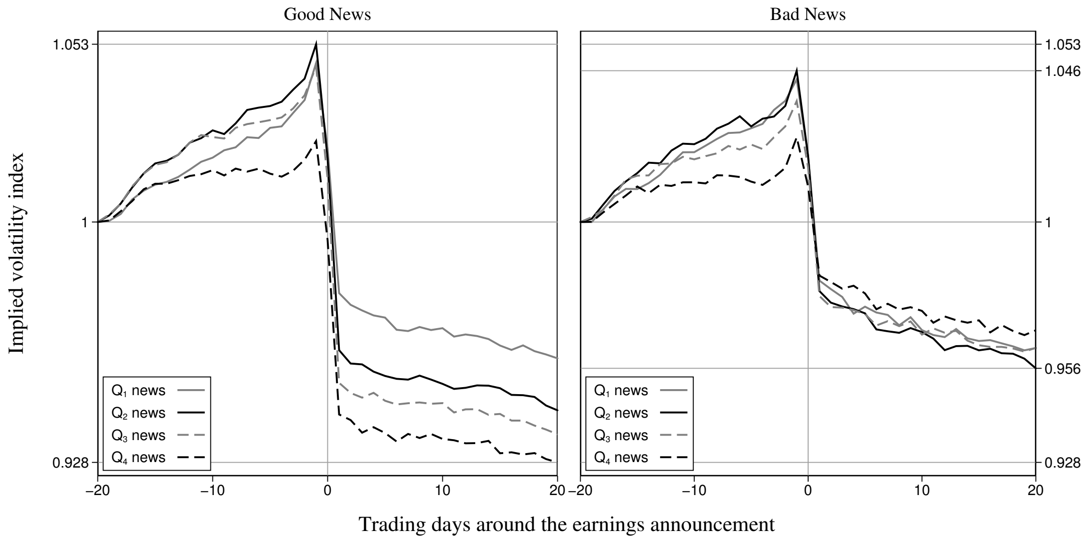
announcement date, $t = 0$. Notice how the median implied volatility in the post-announcement window lies below the value of 1, thus suggesting that earnings news typically reduces investor uncertainty.

However, there is an evident asymmetric effect on the revision of volatility, with uncertainty reduction being more pronounced following good news than bad news. Furthermore, the degree of uncertainty resolution becomes greater as the magnitude of the positive earnings surprise increases. This result is consistent with our model prediction but lies at odds with the attenuation effect described in Pastor and Veronesi (2009) and subsequently tested in Neururer et al. (2016). In contrast, in the bad news sample, larger surprises lead to weaker uncertainty resolution, again consistent with our model. It appears that the attenuation effect of the magnitude of earnings surprise is only observed when the surprise is negative.

5.1 Marginal effects

Table 4 reports the estimation results for equation (4) with $\Delta Vol_{t,p}$ as the dependent variable, measured over the wider window. Regardless of option maturity or whether we estimate the con-

Figure 3: Implied volatility index around earnings announcements, using 30-day options



Note: The x-axis gives the daily timeline around the earnings announcement which is denoted with $t = 0$. The y-axis gives the median option implied volatility by day over the four quartiles of magnitude of earnings surprises, $|ES_t|$, denoted as Q_1, Q_2, Q_3 ad Q_4. The left-hand side graph is qualified for the sample with $ES_t \geq 0$ (Good News), and the right-hand side graph is qualified for $ES_t < 0$ (Bad News). The median implied volatility is standardised with index equal to 1 at $t = -20$. The two graphs maintain common y-axis and x-axis scales.

ditional mean or median, the coefficients on BN_t and $BN_t \times |ES_t|$ are both highly significantly positive, whereas the coefficient on $|ES_t|$ is significantly negative. These estimates consistently suggest that positive surprises resolve significantly more uncertainty than equal-sized negative earnings surprises, rejecting the symmetric attenuation effect described in Pastor and Veronesi (2009) and tested in Neururer et al. (2016). The asymmetry of the marginal effect is also economically large. For instance, one standard deviation of positive earnings surprise brings 10.2% more reduction in the median 91-day option-implied volatility around earnings announcements, compared to an equal-sized negative surprise.[13] Therefore, the sign, in addition to magnitude, of the earnings surprise has a first-order effect on the revision of investor uncertainty.

We also find that our proxies for investors' prior uncertainty, $Vol_{t,p}^{pre}$ and $|\overline{ES}|_{t+4}^{t-1}$, both load significantly negatively on the change in implied volatility across all specifications, consistent with the theoretical prediction that wider investors' prior belief leaves more uncertainty for the disclosure to resolve.[14] The change in volatility is positively associated with analyst forecast dispersion and the level and the change in VIX, and negatively associated with book-to-market ratio, leverage, and firm size. These results are consistent with those reported in Neururer

[13] This is calculated as $0.0042 \times 0.991/0.0409 = 10.2\%$.

[14] The results are qualitatively the same if we include $|\overline{ES}|_{t+4}^{t-1}$ only in our regressions.

et al. (2016) and He et al. (2019). Overall, our results in Table 4 are highly consistent with the asymmetric pattern predicted by the model described in Section 2 and corroborate with our earlier observations from Table 3 and Figure 3.

To confirm that our results do not depart from prior studies simply because of the longer measurement window we use, we report in Table 5 the estimation results for equation (4) using the narrower window to measure $\Delta Vol'_{t,p}$. This measurement window is consistent with Rogers et al. (2009) and Neururer et al. (2016). All the coefficient estimates of our key inferential variables in Table 5 retain the signs of those in Table 4 and remain highly statistically significant, although the coefficients on $BN_t \times |ES|_t$ are about one third lower across the specifications.

Overall, the results reported in Table 4 and Table 5 paint a consistent picture indicating a strong asymmetric effect of earnings news on uncertainty, a key theoretical prediction of our model. In response to good news, both the within-state and between-state uncertainty decreases, reinforcing the uncertainty resolution effect. With the arrival of bad news, however, between-state uncertainty rises to offset the reduction in within-state uncertainty. These results complement the findings of Neururer et al. (2016) by showing a first-order effect of the sign of earnings news. This asymmetric pattern is not accommodated by existing investor learning theories, but it is a novel implication of our model with the presence of state uncertainty.

5.2 News impact curves

The above results show that both the sign and the magnitude of the earnings surprise are first-order determinants of the revision in investor uncertainty. However, the regression estimates focus only on the expected marginal effects (i.e. the response of uncertainty given an additional unit of good news or bad news), and they cannot describe the net effect on uncertainty. The 'news impact curves' reported in this section describe at which point exactly and under which conditions disclosure is expected to increase uncertainty. Our theory suggests that uncertainty is most likely to experience a net increase when the earnings news is sufficiently negative and the investor's prior is sufficiently tight.

Figure 4 presents the unconditional news impact curves for $\Delta Vol_{t,30}$, $\Delta Vol_{t,60}$ and $\Delta Vol_{t,91}$, with local 95%-level confidence bands as referenced by the shaded area around the curve. In contrast to the 'usual' disclosure models in accounting literature, the reduction in uncertainty

Table 4: Estimation of equation (4) by measuring $\Delta Vol_{t,p}$ using the wider window

	Median regressions			OLS regressions		
	$\Delta Vol_{t,30}$	$\Delta Vol_{t,60}$	$\Delta Vol_{t,91}$	$\Delta Vol_{t,30}$	$\Delta Vol_{t,60}$	$\Delta Vol_{t,91}$
Variables of inferential interest						
BN_t	0.001	0.002	0.002	0.002	0.003	0.003
	(3.23)	(6.65)	(8.54)	(3.97)	(7.53)	(7.42)
$\|ES\|_t$	-0.702	-0.544	-0.375	-0.542	-0.365	-0.297
	(-7.50)	(-8.13)	(-6.54)	(-5.29)	(-4.18)	(-5.00)
$BN_t \times \|ES\|_t$	1.568	1.294	0.991	1.628	1.327	1.085
	(10.16)	(10.55)	(9.79)	(9.39)	(9.08)	(11.33)
$Vol_{t,p}^{pre}$	-0.144	-0.100	-0.066	-0.159	-0.112	-0.076
	(-79.51)	(-71.09)	(-58.31)	(-70.27)	(-60.73)	(-65.18)
$\|\overline{ES}\|_{t-4}^{t-1}$	-0.006	-0.003	-0.002	-0.007	-0.004	-0.002
	(-16.96)	(-11.36)	(-9.59)	(-17.87)	(-12.65)	(-10.21)
Control variables						
BM_t	-0.012	-0.010	-0.008	-0.014	-0.011	-0.010
	(-22.85)	(-22.70)	(-24.49)	(-21.76)	(-20.69)	(-26.49)
Lev_t	-0.015	-0.009	-0.007	-0.016	-0.009	-0.007
	(-16.87)	(-12.83)	(-13.51)	(-15.00)	(-10.20)	(-10.45)
$Lev_t \times ES_t$	0.658	0.352	0.230	0.216	-0.041	-0.233
	(2.88)	(1.94)	(1.57)	(0.84)	(-0.19)	(-1.63)
$Disp_t$	0.826	0.690	0.332	0.907	0.716	0.412
	(7.91)	(9.14)	(5.46)	(10.02)	(9.14)	(8.24)
$Follow_t$	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(-1.69)	(-3.59)	(2.70)	(-2.88)	(-3.51)	(1.61)
VIX_t	0.039	0.028	0.020	0.045	0.033	0.025
	(67.73)	(62.00)	(53.09)	(63.32)	(55.33)	(61.15)
ΔVIX_t	0.084	0.069	0.053	0.099	0.087	0.070
	(55.10)	(58.85)	(54.33)	(51.86)	(54.56)	(56.74)
$MCap_t$	-0.007	-0.004	-0.003	-0.008	-0.006	-0.004
	(-45.66)	(-39.43)	(-30.62)	(-45.68)	(-39.76)	(-31.04)
Constant	-0.067	-0.052	-0.038	-0.069	-0.053	-0.044
	(-35.44)	(-35.14)	(-31.21)	(-29.70)	(-27.21)	(-31.15)
Pseudo/Adj R^2	0.0718	0.0624	0.0454	0.125	0.110	0.0841

Note: The sample contains 104,492 firm-quarter observations. The estimation of equation (4) is performed using $\Delta Vol_{t,p}$ as measured in the wider window (see Figure 2). $m = 30, 60, 91$ indicates the option maturity length. Median regressions indicates the estimation of the conditional median iterative quartile regression. OLS regressions indicate the estimation of the conditional mean. R^2 gives the pseudo-R^2 for the median regressions and the adjusted R^2 for the OLS regressions. The variable $MCap_t$ is re-scaled by the factor of 10^6 to produce estimates presentable within three decimal points. t-statistics are reported in the parentheses beneath each estimated coefficient. Standard error estimation is adjusted for cross-sectional and time-series correlations. The variable definitions are described in Section 3.

is expected only with good news and small bad news. A larger piece of good news appears to resolve more uncertainty. When the bad news is sufficiently large, the change in volatility

Table 5: Estimation of equation (4) by measuring $\Delta Vol'_{t,p}$ using the narrower window

	Median regressions			OLS regressions		
	$\Delta Vol'_{t,30}$	$\Delta Vol'_{t,60}$	$\Delta Vol'_{t,91}$	$\Delta Vol'_{t,30}$	$\Delta Vol'_{t,60}$	$\Delta Vol'_{t,91}$
Variables of inferential interest						
BN_t	0.003	0.002	0.002	0.003	0.003	0.003
	(8.57)	(9.16)	(12.44)	(8.37)	(9.54)	(11.14)
$\lvert ES\rvert_t$	-0.689	-0.486	-0.330	-0.552	-0.398	-0.281
	(-9.21)	(-9.48)	(-8.09)	(-6.73)	(-6.16)	(-5.32)
$BN_t \times \lvert ES\rvert_t$	1.184	0.889	0.606	1.301	0.905	0.715
	(10.31)	(9.97)	(9.46)	(9.74)	(8.49)	(8.20)
Vol_t^{pre}	-0.096	-0.052	-0.033	-0.116	-0.061	-0.039
	(-72.78)	(-54.73)	(-45.85)	(-65.80)	(-45.73)	(-35.73)
$\lvert\overline{ES}\rvert_{t-4}^{t-1}$	-0.004	-0.002	-0.001	-0.005	-0.003	-0.002
	(-20.81)	(-12.05)	(-7.09)	(-18.21)	(-13.73)	(-8.39)
Control variables						
BM_t	-0.005	-0.002	-0.002	-0.006	-0.002	-0.002
	(-11.56)	(-7.06)	(-8.67)	(-10.93)	(-5.69)	(-7.45)
Lev_t	-0.005	-0.002	-0.001	-0.006	-0.001	-0.001
	(-7.59)	(-3.54)	(-4.01)	(-7.48)	(-2.20)	(-1.49)
$Lev_t \times ES_t$	0.455	0.207	0.056	0.128	-0.031	-0.160
	(2.77)	(1.56)	(0.58)	(0.64)	(-0.19)	(-1.21)
$Disp_t$	0.824	0.323	0.179	0.897	0.380	0.194
	(12.87)	(6.38)	(5.28)	(12.98)	(6.77)	(4.14)
$Follow_t$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-14.14)	(-12.15)	(-8.79)	(-10.61)	(-10.11)	(-5.18)
VIX_t	0.025	0.015	0.009	0.031	0.017	0.010
	(64.30)	(48.90)	(38.85)	(56.12)	(39.93)	(30.29)
ΔVIX_t	0.087	0.075	0.060	0.096	0.087	0.072
	(79.01)	(93.80)	(96.89)	(62.86)	(74.48)	(75.76)
$MCap_t$	-0.004	-0.002	-0.001	-0.006	-0.003	-0.002
	(-37.40)	(-27.73)	(-20.96)	(-41.05)	(-29.63)	(-22.88)
Constant	-0.054	-0.033	-0.020	-0.057	-0.031	-0.019
	(-38.89)	(-32.67)	(-26.95)	(-32.29)	(-22.92)	(-17.03)
Pseudo/Adj R^2	0.0763	0.0696	0.0624	0.129	0.111	0.0981

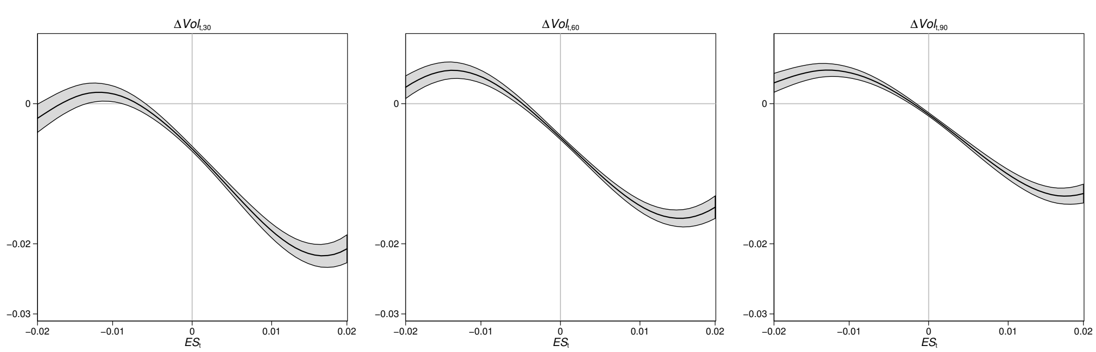
Note: The sample contains 104,492 firm-quarter observations. The estimation of equation (4) is performed using $\Delta Vol'_{t,p}$ as measured in the narrower window (see Figure 2). $m = 30, 60, 91$ indicates the option maturity length. Median regressions indicates the estimation of the conditional median iterative quartile regression. OLS regressions indicate the estimation of the conditional mean. R^2 gives the pseudo-R^2 for the median regressions and the adjusted R^2 for the OLS regressions. The variable $MCap_t$ is re-scaled by the factor of 10^6 to produce estimates presentable within three decimal points. t-statistics are reported in the parentheses beneath each estimated coefficient. Standard error estimation is adjusted for cross-sectional and time-series correlations. The variable definitions are described in Section 3.

becomes either insignificant or positive, consistent with the asymmetric marginal effects documented in our regression results above. We note an apparent upward shifting in the new impact curve as the option duration increases, thus lowering the threshold for detecting uncertainty increases. While the curve for 30-day options barely crosses zero, the left tails for 60-day and 91-day options reliably turn positive in the bad news region. The uncertainty increasing effect is the strongest for $\Delta Vol_{t,91}$, with its narrow confidence band lying well above zero at large bad news. These results suggest that large negative earnings surprise can lead to heightened investor uncertainty, and the increase is uncertainty is expected to be incrementally reflected in stock return volatilities over the longer horizon.

The shapes of the news impact curves are remarkably similar to our theoretical prediction demonstrated in Figure 1, appealing to an asymmetric impact of earnings news on uncertainty and corroborating the evidence on the marginal effects discussed above. We also note moderate reversals of the curves in the extreme news areas, which renders a rotated S-shape pattern.

Note that our model can be extended to accommodate the right-tail reversal as well by allowing for more than two states to be admitted the investors' prior belief, e.g. 'Distress' state, 'Normal' state, and 'Buoyant' state. One potential explanation for the right-tail reversal is that the attenuation effect suggested in Rogers et al. (2009) and Pastor and Veronesi (2009) takes effect in this region, as investors may infer lower precision of extreme earnings news. This result may also be consistent with the interpretation in Lu and Ray (2016) that extremely positive earnings news raises market scepticism. Regardless, the cause for this reversal is beyond the scope of this study.

Figure 4: Unconditional news impact curves



Note: The x-axis gives the earnings surprise, ES_t. The y-axis gives the smoothed $\Delta Vol_{t,p}$ using an Epanechnikov kernel-weighted local polynomial of the 3^{rd} degree as described in Section 5. The smoother is applied over the total estimation sample of 104,492 observations. The shaded area curve references the local confidence intervals for the 95% confidence level. The variable definitions are described in Section 3.

Figure 5 implements the stronger version of our test by conditioning the news impact curves by the level of prior uncertainty, as measured by the terciles of $|\overline{ES}|_{t-4}^{t-1}$.[15] The asymmetric shape is again evident in all terciles and for all option maturities, but it becomes steeper as prior uncertainty becomes lower. With high prior uncertainty (the rightmost column), the curve and the confidence band for $\Delta Vol_{t,30}$ stays below zero throughout, and those for 60-day and 91-day options do not rise reliably above zero even in the extreme bad news domain.

As prior uncertainty lowers, that is, when investors feel more confident that the firm is in the 'normal' state, the reaction to news becomes steeper and investors revise their uncertainty upwards more sharply and for even smaller bad news. The incidence of volatility increase becomes highly pronounced in the low prior uncertainty tercile (the leftmost column). Even for 30-day options, the curve rises significantly above zero for most of the bad news domain, and for 91-day options, any size of bad news is expected to cause an increase in volatility with a narrow confidence band.

These results are highly consistent with our model prediction that the disclosure of bad news under low prior uncertainty does not resolve but instead accentuates uncertainty. These findings also provide support for Johnstone (2016) by identifying the sufficient conditions for disclosure to increase uncertainty in the earnings announcement setting. Our results also extend the findings in Neururer et al. (2016) by showing that their uncertainty-increasing net effects of extreme earnings surprises are primarily driven by bad news announcements.

6 Sensitivity analysis

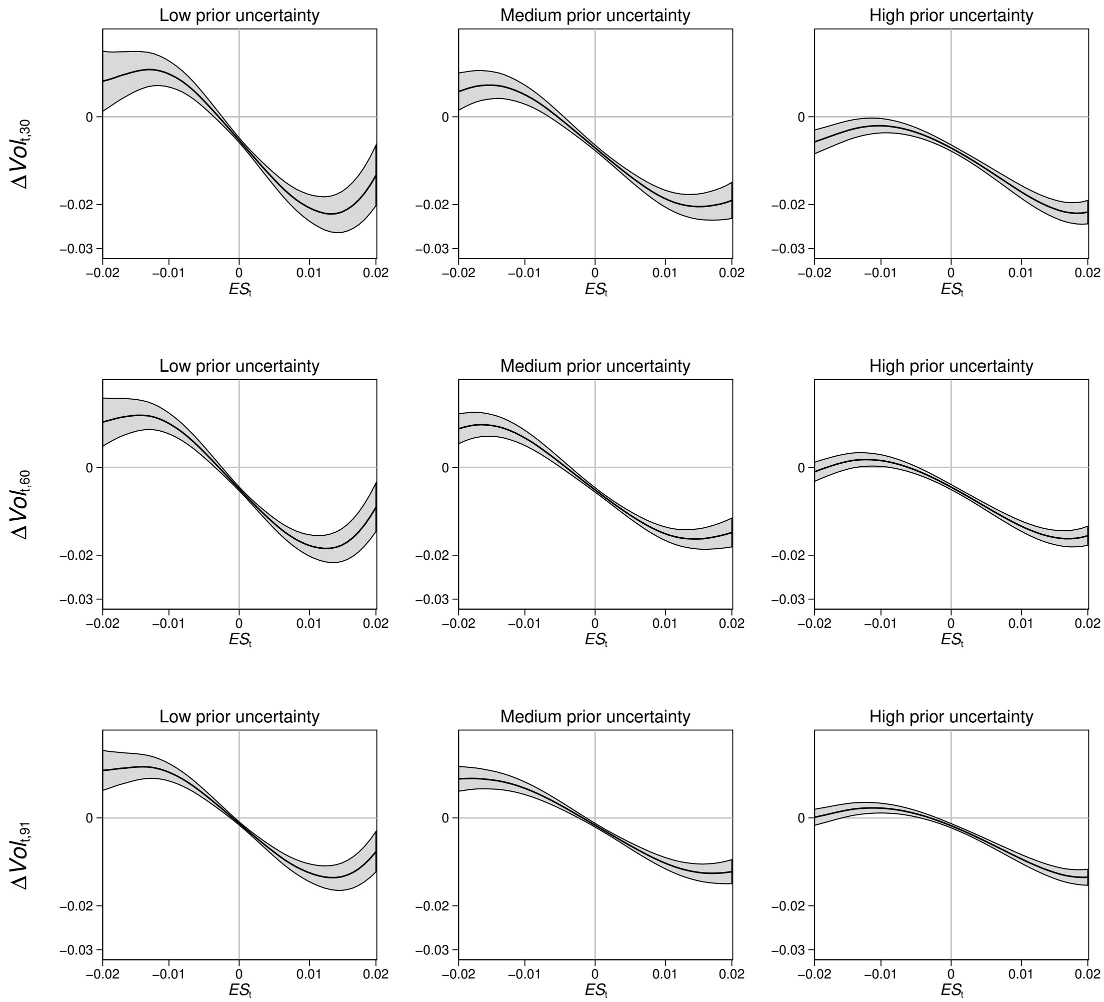
This section tests the robustness of our results to (i) two competing explanations, specifically the leverage effect and volatility feedback, and (ii) to an alternative measure of uncertainty purged of the jump volatility induced by the earnings announcement.

6.1 Competing explanations

We consider two competing explanations for our key results discussed just above. First, bad news is typically associated with higher leverage, which in turn can lead to increased stock

[15] We choose $|\overline{ES}|_{t-4}^{t-1}$, instead of $Vol_{t,p}^{pre}$, as the conditioning variable to avoid the mechanical relation between $Vol_{t,p}^{pre}$ and $\Delta Vol_{t,p}$, which would bias the results in favor of detecting uncertainty increases.

Figure 5: News impact curves conditional on the level of prior uncertainty



Note: The x-axis gives the earnings surprise, ES_t. The y-axis gives the smoothed $\Delta Vol_{t,p}$ using an Epanechnikov kernel-weighted local polynomial of the 3^{rd} degree as described in Section 5. Each smoother is applied over a third of the total estimation sample of 104,492 observations, by partitioning the sample into terciles of prior uncertainty as measured by $|\overline{ES}|_{t-4}^{t-1}$, denoted as Low, Medium and High prior uncertainty. The shaded area curve references the local confidence intervals for the 95% confidence level. All graphs maintain common y-axis and x-axis scales. The variable definitions are described in Section 3.

return volatility (e.g. Black 1976, Christie 1982). In anticipation of this effect, investors may revise upwards their volatility expectations which will then be reflected in the higher implied volatility. The regression model of equation (4) already examines this competing explanation by including the interaction term $ES_t \times Lev_{t-1}$. For the leverage-based interpretation to hold there must be a significantly positive coefficient for this interaction. However, the coefficient estimates in Table 4 and Table 5 fail to claim statistical significance consistently and flip signs across different specifications. These results do not support the leverage effect.

The second competing explanation is based on volatility feedback, which suggests that large surprises induce upward revisions in volatility, leading to increased discount rates. The positive discount rate news suppresses stocks prices, accentuates the effect of bad news and offsets the effect of good news. As a result, the stock price movement is stronger for bad news but weaker for good news. One way to examine this effect is check whether the asymmetric change in implied volatility induced by earnings news is subsumed by the contemporaneous discount rate news realized around the announcement.[16] Discount rate news may arise for two reasons, either because of changes in the market-wide risk factor premiums or the change in the firm-specific factor loadings (assuming constant interest rates around each announcement). Since firm-specific disclosure is unlikely to have a material impact on the factor premiums that pertain to market-wide conditions (see Table 3 results on ΔVIX_t), we proceed to consider the latter type of discount rate changes.

To perform the test, we partition our full sample into sixteen ordered portfolios on the basis on price-scaled earnings surprises ranging from -0.02 to 0.02. Then, we collect daily stock returns around the measurement windows as described in Figure 2 and the corresponding daily returns on the factor-mimicking portfolios of the Fama-French five factor model (Fama and French 2015). The cross-sectional factor loadings are estimated using the Ball and Kothari (1991) methodology for each day within the measurement window in each of the portfolios, and we measure the change in the factor loadings using the same windows as in $\Delta Vol_{t,p}$. Following Lyle and Wang (2015), we estimate the expected returns on the factor-mimicking portfolios using the lagged 60-month averages prior to the earnings announcement. The discount rate news, DRN_t, is equal to the sum of the products of the change in estimated factor loadings around the earnings announcement and their corresponding estimated factor premiums. Then, we repeat the estimation of equation (4) after including DRN_t and $BN_t \times DRN_t$ as additional controls. We acknowledge the possibility of measurement error in our proxy for discount rate news, but if volatility feedback fully explains our asymmetry results then we should observe at least weakened estimates for BN_t and $BN_t \times |ES_t|$ after the inclusion.

Table 6 reports the estimates. For the sake of brevity, we only report the estimated coefficients of interest and suppress the coefficients of the other control variables. The coefficient estimates on

[16] Bekaert and Wu (2000) propose a test of volatility feedback hypothesis based on the 'covariance asymmetry' of stock returns. However, while their test is useful to detect the existence of volatility feedback effects, it does not allow us to discriminate alternative explanations.

$BN_t \times DRN_t$ are consistent with the volatility feedback hypothesis, whereby discount rate news exacerbates the volatility in the presence of bad news (a positive coefficient on $BN_t \times DRN_t$). We do not find a consistent and significant effect for the discount rate news in the presence of good news. However, the inclusion of DRN_t and $BN_t \times DRN_t$ brings no material impact on the level and significance of coefficients on BN_t and $BN_t \times |ES_t|$. The asymmetric pattern remains highly pronounced across all specifications. Therefore, while we find weak support for volatility feedback, the way it affects uncertainty appears not to intervene with the effect of earnings surprises that we identify through our model. Hence, our results seem robust against the volatility feedback explanation.

Table 6: Volatility feedback test

	Median regressions			OLS regressions		
	$\Delta Vol_{t,30}$	$\Delta Vol_{t,60}$	$\Delta Vol_{t,91}$	$\Delta Vol_{t,30}$	$\Delta Vol_{t,60}$	$\Delta Vol_{t,91}$
BN_t	0.001	0.001	0.002	0.001	0.002	0.002
	(1.08)	(3.29)	(5.12)	(1.83)	(5.37)	(5.57)
$\|ES\|_t$	-0.912	-0.734	-0.517	-0.842	-0.591	-0.512
	(-10.47)	(-10.96)	(-9.70)	(-9.09)	(-7.79)	(-7.89)
$BN_t \times \|ES\|_t$	1.664	1.447	1.091	1.834	1.462	1.243
	(11.87)	(13.42)	(12.73)	(12.29)	(11.98)	(11.89)
Vol_t^{pre}	-0.094	-0.066	-0.043	-0.109	-0.077	-0.050
	(-62.23)	(-56.24)	(-46.77)	(-67.38)	(-58.20)	(-43.90)
$\|\overline{ES}\|_{t-4}^{t-1}$	-0.004	-0.002	-0.001	-0.005	-0.003	-0.002
	(-13.01)	(-9.22)	(-6.47)	(-14.41)	(-9.76)	(-6.41)
DRN_t	-0.000	0.000	0.000	0.000	0.000	0.001
	(-0.56)	(0.25)	(1.41)	(0.22)	(0.85)	(2.11)
$BN_t \times DRN_t$	0.003	0.002	0.002	0.004	0.003	0.003
	(3.98)	(3.28)	(3.30)	(4.89)	(4.48)	(4.17)
Pseudo/Adj. R^2	0.0769	0.0701	0.0664	0.131	0.120	0.0989

Note: The estimation sample is $N = 139,618$. The dependent variable is ΔVol_t. To enable direct comparison, 'Asy' indicates the asymmetric model estimates from equation (4) as also reported in Table 4. DRN_t is discount rate news as defined in Section 6. Estimation is repeated using median regression and OLS regression. t-statistics are reported in parentheses. R^2 gives the pseudo-R^2 for the median regressions and the adjusted R^2 for the OLS regressions. The control variables of equation (4) are included in estimation but are not reported for the sake of brevity. The unreported estimates are immaterially different from those reported in Table 4 and are available upon request. The remaining variable definitions are described in Section 3.

6.2 Purging jump volatility

Patell and Wolfson (1979, 1981) show that because earnings announcements are regular and well-anticipated events, there is a significant build-up of implied volatility prior to the announcement, as shown also in Figure 3. This anticipation induces a 'jump risk' in stock prices hence the additional volatility in option prices prior to the announcement, which is however a short-lived uncertainty that is directly associated with the earnings result of the forthcoming announcement. This portion of uncertainty should be fully resolved immediately post the announcement. This jump volatility is of no interest to us, given our focus on uncertainty revisions regarding long-run firm cash flows. This is why we avoid the region containing most of this jump and measure $\Delta Vol_{t,p}$ using a much wider window than usually applied in the literature (see Figure 2).

However, we acknowledge that the wider window may not completely remove the jump volatility. To further mitigate this concern, we develop a new measure of change in implied volatility that purges the pre-announcement volatility of the jump risk. Specifically, we adapt an approach proposed by Barth and So (2014) that exploits the differences in prices for options of different durations, using the Merton (1973) 'weighted average' property of implied volatility. That is, when there is an anticipated information event before the option expires, the total implied variance of the option with m days to expiration, σ_m^2, is a weighted average of the long-run (baseline) variance, σ_{LR}^2, and the extra jump risk variance, σ_{jump}^2, induced by the earnings announcement averaged over the remaining life of the option, as follows:[17]

$$\frac{\sigma_m^2}{252} = \frac{\sigma_{LR}^2}{252} + \frac{\sigma_{jump}^2}{m}, \tag{5}$$

where the division by 252 (the number of trading days in a year), follows from the fact that implied volatility data is quoted as annualised. Equation (5) explains that the average daily variance implied by the option price is equal to the sum of daily long-run variance plus the daily contribution of the jump variance. After the earnings announcement when the stock price reaction is complete, σ_{jump}^2 is almost fully resolved and only long-run variance remains in the right-hand-side of the equation. Therefore, we need to adjust only pre-announcement implied volatility for the implied jump risk.

Although σ_m^2 can be computed from observed option prices, neither σ_{LR}^2 nor σ_{jump}^2 is observable. Following Barth and So (2014), we estimate σ_{LR}^2 using the difference between options of 60-day and 30-day durations. Because both options are subject to the same jump risk prior to

[17] We reserve the term 'volatility' for the standard deviation (rather than variance) of returns only. In our implementation, we use standard options that originate on each day, so the remaining life of the option is equal to its total duration.

the announcement, we use the common jump component to uncover the long-run volatility. Applying equation (5) to $m = 30$ and $m = 60$, we obtain the estimated long-run volatility as a function of observed option implied volatilities:

$$\hat{\sigma}_{LR} = \sqrt{2\sigma_{60}^2 - \sigma_{30}^2}. \tag{6}$$

The pre-announcement volatility, $Vol_{t,LR}^{pre}$, is measured as the three-day average of $\hat{\sigma}_{LR}$ over the period of trading days $t = -5, -4, -3$. The post-announcement volatility, $Vol_{t,LR}^{post}$, is measured as the three-day average of implied volatility of 30-day options over $t = 3, 4, 5$. The adjustment as in equation (6) is no longer needed for calculating post-announcement volatility because $\sigma_p^2 = \sigma_{LR}^2$ post the announcement as neither the 30-day or 60-day option originating after the announcement anticipates another earnings announcement within its duration.

This measure of change in volatility is free of the jump risk and captures only the change in long-run uncertainty regarding firm fundamentals. Table 7 repeats the regression analysis using this measure of change in volatility and we find similar results to those reported in Section 3, although the OLS coefficients on $|ES|_t$ lose statistical significance. Overall, these results suggest that our results on the asymmetric effects on uncertainty are not driven by 'jump' volatility.

7 Conclusion

The study contributes to the understanding on how disclosure affects revisions in investor uncertainty, especially in the earnings announcement setting. We predict and find evidence of an asymmetric effect on uncertainty. Specifically, we find that good news resolves more uncertainty than bad news, and that the larger the positive news the larger the reduction in uncertainty. Larger negative news overall brings a smaller reduction in uncertainty, and sufficiently large negative news can cause a net increase in uncertainty when investors hold strong prior beliefs. In other words, uncertainty increases when investors feel confident before the news about the state of the firm and are then surprised by sufficiently bad news. The results are robust to competing explanations based on the leverage effect and volatility feedback as well as alternative measures of changes in investor uncertainty.

Table 7: Estimation of equation (4) with purging jump volatility

	Wider window $\Delta Vol_{t,LR}$		Narrower window $\Delta Vol'_{t,LR}$	
	Median	OLS	Median	OLS
Variables of inferential interest				
BN_t	0.003	0.004	0.001	0.002
	(9.28)	(8.93)	(5.66)	(5.23)
$\lvert ES\rvert_t$	-0.170	-0.040	-0.192	-0.055
	(-2.10)	(-0.38)	(-3.08)	(-0.65)
$BN_t \times \lvert ES\rvert_t$	0.997	1.017	0.514	0.469
	(7.58)	(5.73)	(5.09)	(3.37)
$Vol^{pre}_{t,LR}$	-0.072	-0.093	-0.015	-0.037
	(-44.48)	(-41.21)	(-13.73)	(-19.86)
$\lvert\overline{ES}\rvert^{t-1}_{t-4}$	-0.001	-0.002	-0.001	-0.002
	(-4.51)	(-6.40)	(-2.49)	(-5.76)
Control variables				
BM_t	-0.009	-0.008	-0.001	-0.003
	(-17.55)	(-12.48)	(-4.04)	(-5.72)
Lev_t	-0.003	-0.003	0.001	-0.001
	(-4.10)	(-2.44)	(1.37)	(-1.26)
$Lev_t \times ES_t$	0.205	-0.286	-0.073	-0.538
	(1.01)	(-1.08)	(-0.49)	(-2.59)
$Disp_t$	0.649	0.670	-0.050	0.093
	(7.24)	(7.08)	(-0.83)	(1.29)
$Follow_t$	-0.000	-0.000	0.000	0.000
	(-3.82)	(-2.42)	(0.35)	(4.99)
VIX_t	0.018	0.022	0.003	0.007
	(35.18)	(30.92)	(9.96)	(13.15)
ΔVIX_t	0.060	0.076	0.067	0.077
	(45.48)	(39.66)	(69.70)	(50.11)
$MCap_t$	-0.003	-0.005	-0.001	-0.002
	(-22.39)	(-27.67)	(-8.07)	(-15.49)
Constant	-0.033	-0.029	-0.005	-0.005
	(-19.86)	(-12.51)	(-4.42)	(-2.53)
Pseudo/Adj R^2	0.0266	0.0549	0.0237	0.0378

Note: The sample contains 104,492 firm-quarter observations. The estimation of equation (4) is performed using $\Delta Vol_{t,LR}$ as described in Section 6.2. Median regressions indicates the estimation of the conditional median iterative quartile regression. OLS regressions indicate the estimation of the conditional mean. R^2 gives the pseudo-R^2 for the median regressions and the adjusted R^2 for the OLS regressions. The variable $MCap_t$ is re-scaled by the factor of 10^6 to produce estimates presentable within three decimal points. t-statistics are reported in the parentheses beneath each estimated coefficient. Standard error estimation is adjusted for cross-sectional and time-series correlations. The control variable definitions are described in Section 3.

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