Tests of Investor Learning Models
Using Earnings Innovations and Implied Volatilities

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Abstract: This paper investigates alternative Bayesian models of learning to explain changes in uncertainty surrounding earnings innovations. We use model-free implied volatilities as our proxy for investor uncertainty; and quarterly unexpected earnings benchmarked to the consensus forecast as proxies for earnings innovations—that is, as signals of firm performance likely to drive investor perceptions of uncertainty. First, we document—consistent with simple Bayesian models of learning and prior research—that uncertainty declines on average after the release of quarterly earnings announcements. Second, we show that this decline is *attenuated* by the size of the signal—that is, by the magnitude of the earnings innovation. This latter result is inconsistent with simple models of Bayesian learning, and consistent with more sophisticated Bayesian learning models, which incorporate signal magnitude as a factor driving changes in uncertainty. Third and most important, we document that signals deviating sufficiently from expectations—that is, sufficiently large earnings innovations—lead to *net increases* in uncertainty. Critically, this latter result suggests that, for the subset of firms exhibiting large earnings innovations, learning models such as those incorporating regime shifts (Pastor and Veronesi 2009) are more descriptive of how investors incorporate the information in earnings to form expectations of future volatility.

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1. Introduction

This paper investigates alternative Bayesian models of learning to explain changes in uncertainty surrounding earnings announcements. Specifically, this paper attempts to distinguish between three broad classes of learning models as they relate to earnings releases. The first class of models suggest that additional signals of firm performance reduce investor expectations of posterior variances—that is, lead to declines in uncertainty (e.g., Lewellen and Shanken 2002). Collectively, we label these as "*Simple Bayesian Learning*" models. Under these models the magnitude of the signal does not play a role in the extent to which uncertainty is resolved. This is predicated on the notion of a firm having a fixed distribution of outcomes, and that the release of the signal helps to reveal what this distribution is (thus reduces uncertainty).

The second class of models we consider allow that uncertainty resolution surrounding a signal's release is also affected by the magnitude of the signal (e.g., Rogers et al. 2009). Collectively, we label these as "*Bayesian Learning Conditioned on Signal Size*." In such models, while the release of a signal helps to inform about the distribution of outcomes (and thus leads to reduced uncertainty), the signal's magnitude can attenuate this reduction.

The third set of models we consider allow for sufficiently large signals to cause a ***net increase*** in uncertainty, or a "regime shift" (Pastor and Veronesi 2009). Collectively, we label these as "*Bayesian Learning with Regime Shifts*." In these models, signals deviating sufficiently from expected values can lead to increases in uncertainty that are large enough to overwhelm the decline in uncertainty predicted from simple learning models due to the signal's release.

Prior research provides evidence consistent with the first class of models. Specifically, using earnings as a proxy for a signal likely to affect investor perceptions of a firm's future stock price volatility, it documents that uncertainty (measured with short-horizon volatilities) declines in the period surrounding the earnings release (Patell and Wolfson 1989, 1991; Skinner 1990). This is consistent with models such as Verrecchia (1983), in which any signals having informational content will reduce the posterior distribution variance about firm value. We add to this literature by further investigating whether the other two classes of models are descriptive of investor reactions to earnings announcements in their formation of expected volatility.

To proxy for uncertainty, we use model-free implied volatilities. This offers several advantages over more commonly-employed techniques, such as Black-Scholes implied volatilities. Most importantly for our setting, model-free volatilities take into account all option market prices in a given maturity, including out-of-the-money option prices; this provides a stronger measure of forecasted volatility, particularly for longer option maturities, which is the focus of our analysis. To proxy as a signal of firm performance expected to affect investor perceptions of future uncertainty, we use earnings innovations. These are defined as the absolute unexpected quarterly earnings, benchmarked to the consensus forecast. This proxy similarly offers advantages over other measures, as its mandated nature both provides generally well-known and recurring release dates, as well as minimizes potential self-selection issues that can affect voluntary disclosures such as management earnings forecasts.

Using a sample of US firms with financial, market, analyst, and options data spanning 1996–2011, we provide the following empirical insights. First, we document, consistent with prior research (e.g. Patell and Wolfson 1979, 1981) an on average decline in uncertainty surrounding the earnings release. However, consistent with our expectations, we then document that this decline is *attenuated* by the size of the earnings innovation. This result is found even after holding constant numerous firm and market level factors including leverage effects. We interpret this latter result as evidence inconsistent with models of "Simple Bayesian Learning" (in which the signal magnitude does not matter), and consistent with models of "Bayesian Learning Conditional on Signal Size." That is, we infer that models allowing for the incorporation of signal size—proxied in our setting by earnings innovations—are more descriptive of how investors use the information revealed in quarterly earnings releases to form expectations of future volatility.

Second, and more importantly, we then predict and find that sufficiently large earnings innovations lead to a *net increase* in uncertainty surrounding the earnings announcement. Specifically, we find that firms with the largest earnings innovations exhibit net increases in uncertainty; that is, the increased uncertainty for these firms is significantly larger than the average decline exhibited for firms lacking the largest earnings innovations. This net increase in uncertainty generally occurs for those firms within the top quartile of earnings innovations. As the Bayesian learning models to not establish empirical thresholds that should exhibit such net increases (e.g., Pastor and Veronesi 2009), we view this latter as descriptive evidence. Overall, we conclude that for the subset of observations exhibiting the largest earnings innovations, models of "Bayesian Learning with Regime Shifts" are more descriptive of how investors incorporate earnings information into their expectations of future volatility.

We conduct a number of sensitivity analyses to ensure the robustness of our results. These include: alternative definitions of the dependent variable of investor uncertainty, such as differing option maturities; alternative definitions for our experimental variable of earnings innovations, such as differing scalars and thresholds; and subsample analysis, such as partitioning our sample into observations falling within expansion versus recession years to better control for potentially differing levels of macro volatility.

This paper makes two central contributions. First, we build upon prior research examining the change in uncertainty surrounding earnings announcements. This research generally documents a decline in uncertainty (e.g., Patell and Wolfson 1989, 1991; Skinner 1990), consistent with simple Bayesian learning models, which predict that signals reduce uncertainty (e.g., Verrecchia 1983; Lewellen and Shanken 2002; Pastor and Veronesi 2003). We document that signal size mitigates these on average declines in uncertainty, consistent with Bayesian models incorporating the signal magnitude as a factor driving the change in uncertainty surrounding the earnings announcement. Second, we are the first to document that for a subset of firms—those exhibiting the most extreme earnings innovations—there is a *net increase* in uncertainty surrounding the earnings announcement. This suggests that for these firms, Bayesian learning models of regime shifts (e.g., Pastor and Veronesi 2009) are descriptive of the process by which investors incorporate earnings information into their perceived volatility.

Section 2 presents the hypothesis development. Section 3 presents the research design. Section 4 provides our sample and descriptive statistics, with Section 5 presenting the main empirical results. Section 6 provides sensitivity analyses, and Section 7 concludes.

2. Background and Hypothesis Development

This paper disentangles among existent Bayesian learning models to understand how signals affect investor updating of uncertainty. To proxy for a signal likely to affect investor uncertainty, we use quarterly earnings announcements, which have the following desirable properties. First, they are recurring, which allows investors to assess them relative to a history of previous signals; many learning models are predicated on a related notion of signals allowing users to formulate possible distributions of outcomes. Second, the timing of their release is generally known in advance. This avoids possible self-selection associated with other signals, such as management earnings forecasts (Rogers et al. 2009). Finally, earnings represent key performance indicators (Kothari 2001). Our empirical implementation benchmarks reported quarterly earnings to the consensus forecast; thus, our focus is on unexpected earnings, or earnings innovations, as signals of firm performance that can affect investor uncertainty.

Using quarterly earnings innovations as proxies for signals, we then disentangle their effects on investor uncertainty as predicted under alternative learning models. While the models we consider are all Bayesian in some form, the implications underlying each are quite different. The first set of models we consider, which we label as "*Simple Bayesian Learning*", assume investors learn about a set of valuation parameters (e.g., Lewellen and Shanken 2002; Pastor and Veronesi 2003, 2006). In these models, investors are assumed to have non-zero variance prior distributions on the valuation parameters of interest; as additional signals arrive, uncertainty about the valuation parameters is reduced. Because uncertainty about the valuation parameters is linked to the volatility of equity, this learning process reduces equity volatility as well. These latter learning models can be seen as extensions to those such as Verrecchia (1983), in which any signals having informational content reduce the posterior distribution variance about firm value. Thus, these models of investor learning predict that investor uncertainty will decrease with additional signals of firm performance. Empirical evidence supports this prediction: using short-term implied volatilities, Patell and Wolfson (1979, 1981) and Skinner (1990) document a decline in uncertainty following earnings announcements.

However, such simple Bayesian learning models do *not* suggest that the size of the realized signal affects the speed of learning. Following Pastor and Veronesi (2009), the variance of a posterior distribution for a parameter after receiving a signal with a known variance σ^2_{SIGNAL} and the prior distribution with a variance of σ^2_{PRIOR} is the following:[1]

$$\sigma^2_{POSTERIOR} = \left(\left[\sigma^2_{PRIOR}\right]^{-1} - \left[\sigma^2_{SIGNAL}\right]^{-1}\right)^{-1}$$

Restated, this model suggests that the actual size of the realized signal (in an absolute sense) will not affect the amount of uncertainty it resolves. That is, once the uncertainty prior to the signal realization and variance in the signal is ***held constant***, the actual realized signal does not matter in terms of how much investor uncertainty is reduced.

However, it is possible that the reduction in uncertainty around earnings announcements is also a function of the signal size; we label such models as "*Bayesian Learning Conditioned on Signal Size*." For example, the size of the earnings innovation can lead investors to update their views on the volatility of future firm growth and cash flows (e.g., Rogers et al. 2009). As shown by Timmerman (1993), stock return volatility is linked to dividend or earnings growth volatility; thus, a large earnings surprise can lead to an increased view of growth volatility, and should (in turn) produce an increase in implied volatilities, *ceteris paribus*. Even if the actual growth and cash flow volatility and performance of the firm does not change, the fact that future earnings announcements are expected to have higher volatility will cause investors to *attenuate* the drop in implied volatilities around earnings announcements, particularly for long-date implied volatilities. That is, implied volatilities incorporate the anticipated learning that investors will be able to do at later earnings announcement dates; if the market anticipates less uncertainty will be resolved at future signal releases, implied volatilities will drop less than they would otherwise.

Thus, we first examine which of these two learning models, "*Simple Bayesian Learning*" or "*Bayesian Learning Conditioned on Signal Size*," is more representative of quarterly earnings

[1] This setup assumes the signal and the prior have Gaussian distributions, as commonly used in theoretical models.

announcements' effects upon investor uncertainty. If signal size does affect learning, this leads to the following hypothesis (stated in alternative form):

H_1: The decrease in implied volatilities around earnings announcements is attenuated by the size of the earnings innovations.

Note that H_1 only suggests that the size of the earnings innovation will be positively related to movements of implied volatilities. It does not, however, imply that this increase in uncertainty will be sufficient to fully overcome the concurrent decrease in uncertainty predicted under simple Bayesian learnings models. That is, a traditional model of Bayesian learning will generally not predict a *net* increase in uncertainty with additional information. Empirically, this seems particularly true for the large and mature firms, which constitute the bulk for which options are available for trading. Indeed, in a traditional learning model, all uncertainty is eventually removed from the model if investors receive enough signals (Pastor and Veronesi, 2009). Additionally, even if the valuation model parameters do not evolve smoothly through time, the amount of uncertainty reduces to a fixed amount (e.g., Brennan and Xia 2001).

However, if the valuation parameters are viewed as subject to unobservable "regime shifts," then it is possible that large signals can actually lead to net increases in uncertainty (Pastor and Veronesi 2009). That is, regime shifts allow for non-degenerative uncertainty paths; we label such models as "*Bayesian Learning with Regime Shifts*." For example, consider a firm with growth or profitability of *n* regimes (e.g., high, medium and low growth), which switches by a Markov chain process. For this firm, a large positive or negative signal (e.g., a sufficiently large earnings innovation) can increase uncertainty as follows. If the firm has generated signals consistent with the medium growth state, leading investors to place a large posterior probability on that state, then a large signal can increase uncertainty by causing investors to readjust their probabilities of being in an alternative state (e.g., high or low growth).[2] The use of the regime shifting model helps to ensure that even with long signal histories, uncertainty levels do not fall to zero, or even to a fixed value, which appears to match the empirical proprieties of stock returns and analyst forecasts. Finally, mean-reversion in profitability can also be accommodated in the Markov switching framework. If the transition matrix places a high probability on switches from low or high profitability or growth states to more moderate states, then empirically we should observe mean-reversion or transitory profitability which, again, seems to match the empirical evidence (Freeman and Tse 1989). Thus, our second hypothesis (again in alternative form) is:

H_2: Implied volatilities around earnings announcements exhibit net increases in the presence of (sufficiently) large earnings innovations.

Thus, we view a rejection of H_2 as a rejection of "*Simple Bayesian Learning Models*," as well as rejection of "*Bayesian Learning Conditioned on Signal Size*," and consistent with "*Bayesian Learning with Regime Shifts*."

3. Research Design

To examine the impact of earnings innovations on investor learning, we proceed in two steps. First, we estimate a regression to assess whether investor uncertainty is unaffected by the magnitude of the earnings signal—as suggested by simple models of Bayesian learning (e.g., Lewellen and Shanken 2002), versus whether the expected decline in investor uncertainty is attenuated by the magnitude of that signal—as suggested by more sophisticated models of Bayesian learning (e.g., Rogers et al., 2009). Second, we estimate regressions to identify whether earnings signals that sufficiently deviate from expectations can *fully offset* the expected

[2] That is, the learning of the states can be modeled using the Wonham filter (see Wonham 1965 or David 1997). This is similar to the use of regime-shifting models in econometrics (see Ang and Timmermann 2012).

decrease in uncertainty that occurs when the signal is released, thus leading to *overall increased* uncertainty—as suggested by models incorporating regime shifts (Pastor and Veronesi 2009).

3.1 Re-assessing simple Bayesian learning: does the magnitude of the earnings signal increase investor uncertainty?

The simple Bayesian learning model suggests that signals—regardless of their magnitude—reduce uncertainty by a constant amount conditional on posterior and signal variances (*Simple Bayesian Learning*). More sophisticated models incorporate characteristics of the signal, such as its magnitude, as having additional effects on uncertainty (*Bayesian Learning Conditioned on Signal Size*). Accordingly, we first assess which learning models are more descriptive as applied to a common and recurring reporting signal: quarterly earnings announcements. We use the following regression:

$$\begin{aligned} IVOL\_365_{jt} = {} & \alpha_0 + \alpha_1 Abs\_SUE_{jt} + \alpha_2 LEV_{jt} + \alpha_3 LEV \times SUE_{jt} \\ & + \alpha_4 DISP_{jt} + \alpha_5 FIRM\_VOL_{jt} + \alpha_6 VIX_{jt} + \alpha_7 \Delta VIX_{jt} \\ & + \alpha_8 SIZE_t + \alpha_9 FOLLOW_t + \alpha_{10} BTM_{jt} + \varepsilon_{jt} \end{aligned} \tag{1}$$

where:

$IVOL\_365_{jt}$	the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*); data is from OptionMetrics, using option maturities of 365 days;
Abs_SUE_{jt}	the absolute value of firm *j*'s unexpected net income for quarter *t*, scaled alternatively by price per share and the absolute mean analyst forecast; unexpected net income is measured as the absolute reported earnings before special items per share less the consensus earnings forecast per share (both per IBES);
LEV_{jt}	firm *j*'s long-term debt divided by total assets, both reported as of the end of quarter *t-1*;

SUE_{jt} firm *j*'s unexpected net income per share for quarter *t*; unexpected net income is measured as the reported earnings before special items per share less the consensus earnings forecast per share (both per IBES);

$DISP_{jt}$ the standard deviation of analyst estimates comprising the consensus earnings forecast for firm *j* on day –3 preceding the quarter *t* earnings announcement, divided by price per share;

$FIRM\_VOL_{jt}$ the average of firm *j*'s 365-day model-free implied volatility, measured over days –5 to –3 preceding the earnings announcement for quarter *t*;

VIX_t the value of the CBOE Volatility Index, measured at day –4 preceding the earnings announcement of firm *j* for quarter *t*;

ΔVIX_t the change in natural logarithm of the ratio of the CBOE Volatility Index, measured on day –4 preceding firm *j*'s earnings announcement for quarter *t*, divided by that on day +4 after the earnings announcement for quarter *t*;[3]

$SIZE_{jt}$ natural logarithm of firm *j*'s total assets measured at the end of quarter *t-1*;

$FOLLOW_{jt}$ natural logarithm of firm *j*'s analyst following for quarter *t*, measured as the number of unique analysts comprising the consensus earnings forecast immediately preceding the earnings announcement; and

BTM_{jt} firm *j*'s book value of equity at the end of quarter *t-1* divided by market value of equity measured on day –3 before the earnings announcement.

Consistent with prior research (Patell and Wolfson 1979; Rogers et al. 2009), we proxy for investor uncertainty using implied volatilities derived from options markets. Thus, we measure the change in investor uncertainty using the change in implied volatilities. We compute the difference in average implied volatilities across the post-earnings and pre-earnings announcement periods using data compiled from OptionMetrics implied volatility surfaces. This allows us to create constant maturity implied volatilities on each trading date.[4] Thus, our

[3] *VIX* (measured at day –4) and Δ*VIX* (measured as the difference of day –4 and +4) may appear inconsistent with our calculation of *IVOL_365* (which is averaged across days –5 to –3, and days +3 to +5). As discussed below, we use averages for *IVOL_365* to minimize the effects of noise upon this firm-level construct. For the macro-level measures of volatility (*VIX* and Δ*VIX*), the effects of noise are likely much less severe: indeed, correlations for alternative measures of *VIX* using day –3, –4, –5, or the average across the three all exceed 95% (similar correlations occur for Δ*VIX*). Not surprisingly, results are unchanged to alternative definitions of *VIX* and Δ*VIX*.

[4] A constant implied volatility measures the next *n* days of volatility, and thus is not tied to any traded option maturity. Restated, a constant 30-day maturity volatility measured at time *t* measures the forecasted volatility

dependent variable is *IVOL_365*, measured as the natural log of implied volatility for the post-earnings announcement period divided by that for the pre-earnings announcement period, for options having 365-day maturities.

Three measurement attributes of our dependent variable warrant discussion. First, we measure volatility in the post-earnings (pre-earnings) announcement period using the average over trading days +3 to +5 (–5 to –3), where day 0 is the earnings announcement date for quarter *t*. To the extent measurement error in the implied volatility construct is random, using an average over several days will reduce this noise.

Second, we construct the implied volatilities by exploiting the full informational content of the options market using model-free estimation (see Appendix A). Prior accounting research typically uses the Black-Scholes (1973) at-the-money (ATM) volatility in an option month as a proxy for future volatility (e.g., Rogers et al., 2009). While computationally easier, ATM Black-Scholes implied volatilities may fail to fully capture the market's view of future stock volatilities. For example, two stocks may share an ATM volatility value but, due to differences in out-of-the-money option prices, the true forecasted volatility given by the options market will differ.[5] Critically, such differences become accentuated for longer option maturities (e.g. Demeterfi et al., 1999), which is the focus of our analysis. Thus, we use model-free implied volatilities as proxies of expected future equity volatility, which take into account all option

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from t to t+30, and at time t+1 the 30-day maturity volatility measures the forecasted volatility from $t+1$ to t+31. Thus, the length of maturity is held constant.

5 In the Heston (1993) option pricing model, the total variance of a stock is determined by (1) the current variance, (2) the long-term variance, and (3) the mean reversion rate. The shape of the implied volatility smile or smirk observed in the market, however, is determined by the "vol-of-vol" and correlation between stock and variance movements. Thus, two stocks may actually have different ATM volatilities but have the same expected variance if they have the same values for the first set of parameters but different values for the second set. If, for example, two stocks had the same value for the first three parameters then the stock with the higher vol-of-vol parameter would have a lower ATM implied volatility but higher OTM implied volatilities, in general.

market prices in a given maturity. While these volatilities are used in the finance literature (e.g., Jiang and Tian, 2005; Carr and Wu, 2009), their application in accounting is limited.[6]

Finally, options have differing maturities, which can be exploited. We use longer option maturities as the economic effects we wish to examine likely have longer term implications; that is, we wish to capture investor expectations of the future volatility of firm stock price over periods that encompass future earnings realizations. Accordingly, our analyses focus on longer window option maturities: first, a 365-day maturity; and then (as robustness) 273-day and 182-day maturities. In addition, the use of a 365-day maturity ensures that we hold constant the total number of quarterly earnings announcements in both the pre-announcement and post-announcement windows (see Figure 1). We do not use shorter window option maturities commonly employed in prior accounting research (e.g., 30-day maturities), as these windows do not provide insights into how current earnings innovations affect investor uncertainty of future performance (including future earnings realizations).

Our experimental variable is *Abs_SUE*, firm *i*'s absolute unexpected earnings for quarter *t*. As quarterly earnings are recurring and key performance metrics, we use firms' quarterly earnings announcements to proxy for a signal likely to impact investor uncertainty regarding future stock price changes. Simpler Bayesian learning models suggest that investor uncertainty will not incorporate the ***sign*** of the signal (Pastor and Veronesi 2009); accordingly, we use the unsigned (i.e., absolute) earnings innovation, defined as reported earnings benchmarked to the consensus analyst forecast. To focus our analysis on earnings signals more likely to have implications for future quarters, and to improve our benchmarking by aligning the reported amount with that forecasted by analysts (Gu and Chen 2004), our primary reported earnings and analyst expectation are both sourced from I/B/E/S (and generally exclude reported special items).

[6] One example is Sridharan (2012), which uses a limited sample of model-free volatilities as a robustness check.

We scale this absolute earnings innovation using two alternative measures: first, by share price (Das et al. 1998); second, by the mean absolute earnings forecast immediately preceding the earnings announcement (Bailey et al. 2006).[7] When scaling by the mean absolute earnings forecast, we remove observations with an absolute mean forecast less than a penny to mitigate the small denominator effect.[8]

If simple Bayesian learning models are representative of the average effect of quarterly earnings announcements upon investor uncertainty, then the magnitude of the earnings innovation will not affect our implied volatilities measures, consistent with *Simple Bayesian Learning*; that is, $\alpha_1 = 0$. However, if Bayesian models that incorporate the magnitude of the signal are more representative of this average effect, then we predict that the coefficient on *Abs_SUE* will be significantly positive. That is, we predict that uncertainty will increase in the magnitude of the earnings innovation, consistent with *Bayesian Learnings Conditioned on Signal Size*; hence, $\alpha_1 > 0$ is our primary test of H_1.

Equation (1) includes variables to control for firm and macro-economic performance that are expected to drive changes in implied volatility. These controls are based on recent accounting research examining the determinants of changes in implied volatilities (e.g., Rogers et al. 2009). We first include controls to capture the effects of leverage on uncertainty. This is critical, as prior research provides theoretical (Merton 1974; Black 1976) and empirical (e.g., Christie 1982; Schwert 1989) support that investor uncertainty is increasing in firm leverage. Accordingly, we include *LEV*, the firm's long-term debt divided by total assets, both measured at the end of quarter *t-1* (Rogers et al. 2009). As more leveraged firms are expected to have higher

[7] The correlation between the two experimental variables is 0.498, suggesting these capture similar but not completely overlapping, notions of earnings innovations.

[8] Specifically, we: (i) first identify the mean analyst forecasts; (ii) take the absolute value of these means; (iii) delete firm-quarters for which the absolute forecast is less than $0.01/share (to avoid large denominator effects); and (iv) then scale absolute unexpected earnings.

variance earnings, the predicted sign is positive. We also include the interaction of *LEV* x *SUE*, where *SUE* is defined as the signed unexpected earnings per share divided by stock price. This controls for the effect of the earnings announcement on leverage, and thus uncertainty. As firms with higher levels of leverage should see larger decreases in future uncertainty conditional on the magnitude of the earnings, the predicted sign is negative.[9]

Next, we include *DISP* as a proxy for disagreement among market participants, measured as the standard deviation in analyst earnings forecasts prior to the earnings announcement divided by stock price. Greater pre-earnings announcement dispersion (i.e., more disagreement) suggests the upcoming signal (earnings) has more variance and, following Bayesian updating, the amount of total uncertainty resolved by the signal should be lower. We thus predict a positive sign for *DISP*. Likewise, we include the firm-level 365-day implied volatility preceding the earnings announcement (*FIRM_VOL*). Again following the Bayesian model of learning, a signal should resolve more uncertainty if greater pre-announcement firm uncertainty exists; hence, we predict a negative coefficient.

We also include two control variables for the level (*VIX*) and change (*ΔVIX*) in market level volatility to proxy for overall changes in market uncertainty surrounding the earnings announcement. To measure market volatilities, we follow prior research and use the VIX index. *ΔVIX* controls for the change in market volatility coinciding with the pre- and post-earnings announcement periods; thus, the predicted sign on the coefficient is positive. In addition, we include the *level* of market volatility (*VIX*) as individual equity volatilities derive from both

[9] Note that the interaction of *LEV* x *SUE* includes the signed earnings announcement, while our experimental variable *Abs_SUE* is unsigned. This is intentional, and consistent with theory underlying the inclusion of the respective variables. Specifically, signed earnings has a direct effect on leverage, and thus is appropriate to use when assessing the effect of leverage on uncertainty. In contrast, the effect on uncertainty under Bayesian updating is not conditioned on the sign of the signal. Note that the Merton (1974) model of leverage suggests that a firm that has no leverage should not see a change in its volatility due to a change in its asset value. Further, we do not use the stock return as a proxy for the size of the surprise as uncertainty/volatility and stock prices are jointly determined.

systematic and idiosyncratic variance. While earnings announcements resolve idiosyncratic uncertainty, they should have relatively little effect on the macro sources. Thus, higher macro variance will result in less total firm uncertainty being resolved, leading to a predicted positive coefficient on *VIX*.

Finally, we include three variables to capture other economic attributes of the firm (Rogers et al. 2009). We include *SIZE*, measured as the natural logarithm of the firm's total assets for quarter *t-1*.[10] Larger firms are expected to have more stable economic performance (e.g., due to larger customer bases) and richer information environments; both suggest a lower surprise in reported earnings, and hence a predicted positive sign (i.e., a smaller change in implied volatilities across the pre- and post-earnings announcement periods). However, larger firms are also more likely to have dispersed ownership (e.g., Demsetz and Lehn, 1985), leading investors to obtain extra protection in the options market prior to earnings announcements. This suggests a predicted negative sign (i.e., a larger decrease in implied volatilities over the announcement period). Accordingly, we do not predict the sign of the coefficient on *SIZE*.

We also include *FOLLOW* as a more direct proxy for the firm's information environment (Lang and Lundholm, 1996), measured as the number of analysts following the firm just before the earnings announcement. To the extent analysts seek to identify firms having more uncertainty as contexts in which their analysis can add the greatest marginal value (holding all else constant), the predicted coefficient is negative. Lastly, we include *BTM* to proxy for differences in value (high BTM) versus glamour (low BTM) stocks, measured as the firm's book value of equity divided by the market value of equity. As the association with implied volatility is unclear, we do not predict the sign.

[10] Results are robust to alternative definitions of size, including the natural log of equity market capitalization.

To facilitate inferences, we follow prior accounting research (e.g., Chen et al. 2012; Liang and Riedl 2014) by demeaning and standardizing all control variables using the sample-wide means and standard deviations calculated across all observations (Greene 1993). Demeaning allows for direct interpretations of the experimental indicator variables, whose coefficients relate to a relevant area (the grand mean) of the control variables instead of zero. Note that standardizing the variables does *not* change the interpretations of the control variables, nor the regression power/degrees of freedom (Greene 1993; Echambadi and Hess 2007); it simply facilitates inferences. All regressions also use firm-clustered standard errors to address correlations across observations due to the inclusion of multiple quarterly observations per firm.

3.2 Do earnings signals reveal regime shifts?

As our second step, we examine whether earnings signals, which deviate sufficiently from expectations, lead to "regime shifts"—that is, net increases in uncertainty—as predicted by more recent models of Bayesian learning (Pastor and Veronesi 2009). We use two analyses to identify this effect. First, we use the following regression:

$$\begin{aligned} IVOL\_365_{jt} = \; & \beta_0 + \beta_1 TopX\%\_Abs\_SUE_{jt} + \beta_2 LEV_{jt} + \beta_3 LEV \times SUE_{jt} \\ & + \beta_4 DISP_{jt} + \beta_5 FIRM\_VOL_{jt} + \beta_6 VIX_{jt} + \beta_7 \Delta VIX_{jt} \\ & + \beta_8 SIZE_t + \beta_9 FOLLOW_t + \beta_{10} BTM_{jt} + \rho_{jt} \end{aligned} \tag{2}$$

The dependent variable (*IVOL_365*) and the control variables are as defined in Equation (1). The only change is the replacement of the previous experimental variable of *Abs_SUE* with the variable *TopX%_Abs_SUE*. This variable is defined as an indicator variable equal to 1 for those observations exhibiting the largest X% absolute earnings innovations, and 0 otherwise. We determine the largest absolute earnings innovations as the firm ranking above a particular percentage threshold within a given calendar quarter based on the earnings report date. Four alternative thresholds are used: *Top5%*, *Top10%*, *Top25%,* and *Top50%,* defined as firms in the top 5%, 10%, 25%, and 50% of a given calendar quarter's earnings innovations, respectively.

Our definition of this experimental variable follows from the regime shift theories of Bayesian learning: signals, which deviate *sufficiently* from some expectation, lead to an *overall increase* (as opposed to attenuating the expected decrease) in uncertainty by adding a new potential distribution of outcomes not previously considered. However, such theories do not specify the magnitude of the signal necessary for a regime shift to occur. Accordingly, we employ empirical analysis to ascertain the pattern consistent with this theory.

Specifically, we assess whether a "regime shift" has occurred by examining whether there is a net increase in uncertainty for those firms exhibiting the largest earnings innovations. This net increase is assessed by comparing (i) the expected increase in uncertainty for firms with the largest earnings innovations with (ii) the expected decrease in uncertainty for the average firm. The latter is captured by the intercept: that is, since we demean all continuous variables, the intercept reflects the change in uncertainty across quarterly earnings announcements for firms assessed to have average sample-wide values for each of the control variable. Based on prior research documenting declines in uncertainty following earnings announcements, we expect that the intercept will be significantly negative. However, our primary test of H_2 lies in comparing the coefficient for *TopX%_Abs_SUE* to the intercept: that is, we examine whether $\beta_1 > \beta_0$. Under H_2, we predict that sufficiently large earnings innovations will lead to net increases in uncertainty, and that these will be large enough to overcome the average decrease predicted by typical Bayesian learning models (i.e., consistent with *Bayesian Learning with Regime Shifts*). Further, because regime shift models are predicated are sufficiently extreme signals, we descriptively expect that β_1 will decline as we broaden the inclusion of observations designated to be "large" earnings innovations.

As a second analysis, we use the following regression:

$$\begin{aligned} IVOL\_365_{jt} = \; & \delta_1 Abs\_SUE\_0\%\text{-}5\%_{jt} + \delta_2 Abs\_SUE\_5\%\text{-}10\%_{jt} \\ & + \delta_3 Abs\_SUE\_10\%\text{-}25\%_{jt} + \delta_4 Abs\_SUE\_25\%\text{-}50\%_{jt} \\ & + \delta_5 Abs\_SUE\_50\%\text{-}75\%_{jt} + \delta_6 Abs\_SUE\_75\%\text{-}100\%_{jt} \\ & + \delta_7 LEV_{jt} + \delta_8 LEV \times SUE_{jt} \\ & + \delta_9 DISP_{jt} + \delta_{10} FIRM\_VOL_{jt} + \delta_{11} VIX_{jt} + \delta_{12} \Delta VIX_{jt} \\ & + \delta_{13} SIZE_t + \delta_{14} FOLLOW_t + \delta_{15} BTM_{jt} + \tau_{jt} \end{aligned} \tag{3}$$

The dependent variable (*IVOL_365*) and the control variables again remain as defined in Equation (1). The experimental variables are now *Abs_SUE_0%-5%* through *Abs_SUE_75%-100%*; these are indicator variables equaling 1 for firm quarters falling within the respective percentage ranges of absolute unexpected earnings for a given calendar quarter, and 0 otherwise. Thus, *Abs_SUE_0%-5%* captures the mean shift in uncertainty across the earnings announcements for those observations having absolute unexpected earnings in the top 5% within that calendar quarter (i.e., the <u>*largest*</u> earnings innovations), and so on. Because we include indicator variables capturing the full array of observations (i.e., from the largest to the smallest earnings innovations), we exclude an intercept term from this regression. Further, as previously, all control variables have been demeaned. Thus, we alternatively test H_2 by examining whether $\delta_1 > 0, \ldots \delta_6 > 0$. That is, we successively examine δ_1 through δ_6 to ascertain the magnitude of earnings innovation necessary to lead to increased uncertainty (i.e., a regime shift).

4. Sample Selection and Descriptive Statistics

Panel A of Table 1 presents our sample selection. Financial, market, analyst, and options data are sourced from Compustat, CRSP, IBES, and OptionMetrics, respectively. The primary sample includes IBES quarterly earnings announcement data from 1996Q1 through 2011Q4, for which valid model-free volatility estimates using the OptionMetrics database are available. We choose 1996 as the starting point, and 2011 as the ending point, to correspond with the availability of options data. We eliminate firms lacking necessary data, and those having non-positive assets and book equity; we also exclude financial firms because their leverage ratios are not comparable to other firms. Our sample selection leads to 92,358 observations, representing 4,537 unique firms. Panel B shows the observations per year. Consistent with option coverage over time, we observe a general increase in observations over the sample period, as well as a decline around 2000 coinciding with the Internet bubble.

Table 2 presents the descriptive statistics. We first note that all values of our dependent variables (*IVOL_365*, *IVOL_273*, and *IVOL_182*) are negative as expected: this is consistent with the decrease in implied volatilities surrounding earnings announcement documented in prior literature (e.g., Patell and Wolfson, 1981). To assess how the requirement for option data affects the sample selection, the table also includes a comparison of sample observations to the full set having available Compustat/IBES/CRSP data. Relative to all Compustat firms, our sample firms are larger (*SIZE*), more leveraged (*LEV*), have higher analyst following (*FOLLOW*), and have lower book-to-market ratios (*BTM*). These differences are consistent with prior research using options data, and suggest that firms for which options are available tend to be larger, have more stable cash flows (allowing greater use of debt in the financing structure), and are higher growth.

5. Empirical Results

5.1 Re-assessing simple Bayesian learning: does the magnitude of the earnings signal increase investor uncertainty?

Table 3 presents the results of our analysis examining if the earnings signal magnitude increases investor uncertainty. We first discuss Column (1), where the experimental variable (*Abs_SUE*) is scaled by price. Coefficients on the control variables are consistent with expectations. Specifically, we find that more levered firms experience more attenuated decreases in uncertainty (coefficient on *LEV* = 0.206, *t*-stat = 4.21), and a significant leverage effect as predicted by structural credit models (coefficient on *LEV* x *SUE* = –0.386, *t*-stat = 7.33). We further find that the reduction in uncertainty is smaller for firms having higher pre-announcement disagreement among analysts (coefficient on *DISP* = 0.563, *t*-stat = 9.18), and enhanced for firms having larger pre-announcement volatility (coefficient on *FIRM_VOL* = –3.290, *t*-stat = 43.69). We also document that both the market level of volatility preceding the earnings announcement (*VIX* = 1.708, *t*-stat = 35.21) and the change in macro volatility surround the earnings announcement (Δ*VIX* = 2.382, *t*-stat = 54.53) are positively associated with the change in uncertainty. Finally, we find that the change in uncertainty is decreasing in firm size (*SIZE* = –1.611, *t*-stat = 23.71), and increasing in the firm's book-to-market ratio (*BTM* = 0.287, *t*-stat = 5.34). The coefficient on *FOLLOW* is insignificant, though it takes the predicted negative sign.

We further find that the intercept is significantly negative (–0.448, *t*-stat = 10.82). Recall that we demean all control variables; this allows a particular interpretation of the intercept. Specifically, for firms having an average value of each control variable, the significantly negative intercept is consistent with a decrease in uncertainty surrounding the quarterly earnings announcements; this follows from prior empirical findings of decreases in uncertainty following earnings announcements (e.g., Patell and Wolfson 1979).

Turning to our experimental variable, we find that the coefficient on *Abs_SUE* is significantly positive (0.309, *t*-stat = 4.90). This suggests that while there is a decrease in uncertainty overall (reflected in the significantly negative intercept), this decrease is attenuated the larger the absolute earnings innovation. That is, we document consistent with H_1 that the magnitude of the earnings signal does affect uncertainty.

Similar results obtain in Column (2), in which *Abs_SUE* is now scaled by the mean absolute forecast. Specifically, we again find a significantly negative intercept (–0.451, *t*-stat = 9.80) and significantly positive coefficient on *Abs_SUE* (0.161, *t*-stat = 3.18). This again suggests that the magnitude of the signal—that is, the magnitude of the earnings innovation—increases uncertainty. Results on the control variables are unchanged, except that the coefficient on *FOLLOW* is now marginally significantly negative as predicted.

Overall, these results support H_1, that the size of the earnings signal does affect investor uncertainty. This evidence is consistent with *Bayesian Learning Conditioned on Signal Size,* and appears inconsistent *Simple Bayesian Learning*, in which the size of the signal does not play a role in investors' formation of uncertainty.

5.2 Do earnings signals reveal regime shifts?

Table 4 presents results examining whether sufficiently large earnings innovations lead to regime shifts—that is, *net increases* in uncertainty surrounding earnings announcements. We focus on Panel A, which presents results in which the experimental variable is scaled by price before deriving the respective percentile rankings. As above in Table 3, the control variables attain the predicted signs and are all highly significant, with the exception of *FOLLOW.* Turning to our experimental variables, we find in Column (1) that *Top5%_Abs_SUE* is significantly positive (1.276, *t*-stat = 5.29) as predicted. This indicates that firms having absolute unexpected earnings in the top 5% of a given calendar quarter set of observations experience attenuated decreases in uncertainty surrounding the quarterly earnings announcement, consistent with our previous Table 3 finding that the magnitude of the signal attenuates the decline in uncertainty. Critically, we also document a ***net increase*** in uncertainty: that is, we find that the sum of *Top5%_Abs_SUE* plus the average decrease in uncertainty experienced for the average firm (represented in the intercept) is significantly positive; specifically, we find that 1.276 + –0.512 = 0.764 (*F*-test *p*-value = 0.001). This is consistent with H_2, and suggests that firms with sufficiently large earnings innovations (in the top 5%) experience net increases in uncertainty surrounding quarterly earnings announcements, consistent with models of regime shifts.

Column (2) provides similar evidence redefining the experimental variable to be *Top10%_Abs_SUE*: that is, firms with absolute unexpected earnings in the top 10% of a given calendar quarter. Specifically, we again find the coefficient to be significantly positive (1.267, *t*-stat = 7.30), and that the sum of this plus the average decline in uncertainty is significantly positive (1.267 + –0.575 = 0.692; *F*-test *p*-value = 0.001). The latter result again supports H_2, and is consistent with the regime shift hypothesis also applying for firms with earnings innovations in the top 10%.

In Columns (3) and (4), we redefine the experimental variable to be *Top25%_Abs_SUE* and *Top50%_Abs_SUE*, respectively; that is, we successively expand the range of firms included as having the largest earnings innovations. We find, as expected, that the coefficients for both are significantly positive (*Top25%_Abs_SUE* is 0.947, *t*-stat = 8.68; *Top50%_Abs_SUE* is 0.519, *t*-stat = 6.38). However, only observations in the top 25% of earnings innovations experience net increases in uncertainty consistent with a regime shift: (0.947 + –0.685 = 0.262; *F*-test *p*-value = 0.003). We fail to find such evidence using the top 50% of earnings innovations, as the coefficient on *Top50%_Abs_SUE* appears lower than the average decline represented in the intercept in Column (4). Finally, we note that the coefficients on *TopX%_Abs_SUE* monotonically decline as the threshold for "large" earnings innovations is expanded. Combined, this evidence is consistent with regime shifts (that is, net increases in uncertainty surrounding earnings announcements) occurring for earnings innovations in the top quartile of a given calendar quarter.

Panel B reveals similar results alternatively scaling the experimental variable by the mean absolute forecast; the coefficients on the control variables are again unchanged. In Column (1) using *Top5%_Abs_SUE*, we again find that the coefficient is significantly positive (0.991, *t*-stat = 4.64), and that it is significantly larger than the average decline in uncertainty represented by the intercept (0.991 + –0.501 = 0.490; *F*-test *p*-value = 0.009). Similarly, we find that the net effect is significantly positive using *Top10%_Abs_SUE* in Column (2) (0.946 + –0.546 = 0.400; *F*-test *p*-value = 0.004). However, the net effect is directionally consistent though insignificant using *Top25%_Abs_SUE* in Column (3) (0.752 + –0.639 = 0.113; *F*-test *p*-value = 0.105); and again is not positive using *Top50%_Abs_SUE* in Column (4). We again note the monotonic decline in coefficient value for *TopX%_Abs_SUE* as we broaden the inclusion of observations across the four columns. Thus, the results in Panel B suggest that earnings innovations in the top 10% lead to net increases in uncertainty surrounding quarterly earnings announcements.

Table 5 presents an alternative test examining whether sufficiently large earnings innovations lead to regime shifts; the control variable coefficients are again unchanged. Recalling our previous research design discussion, our inclusion of indicator variables capturing the full range of earning innovations (i.e., *Abs_SUE_0%-5%* through *Abs_SUE_75%-100%*) provides an alternative specification to identify which ranges of earnings lead to increased uncertainty. Focusing on Column (1), in which our experimental variables are scaled by price before defining the respective percentile ranges, we document that *Abs_SUE_0%-5%* is significantly positive (1.033, *t*-stat = 4.38). This is consistent with a net increase in uncertainty, conditional on other factors, for those firms in the top 5% of absolute earnings innovations in a given calendar quarter. Similarly, we find that *Abs_SUE_5%-10%* is significantly positive (0.621, *t*-stat = 3.04); this suggests that firms with absolute earnings innovations in the top 5%-10% also experience net increases in uncertainty. For the remaining ranges, we find either insignificant (*Abs_SUE_10%-25%* = –0.001, *t*-stat = 0.01) or significantly negative (*Abs_SUE_25%-50%* = –0.579, *t*-stat = 7.34; *Abs_SUE_50%-75%* = –0.764, *t*-stat = 10.21; *Abs_SUE_75%-100%* = –0.782, *t*-stat = 9.64) coefficients. These latter results are consistent with the on average decline in uncertainty surrounding earnings announcements. Finally, we again note the monotonic decline in coefficients across the range of *Abs_SUE*. Results are similar in Column (2), where we alternatively scale the experimental variables by price the mean absolute forecast.

Overall, the results of Tables 4 and 5 provide evidence consistent with *Bayesian Learning with Regime Shifts*. Specifically, we document that firms exhibiting the largest absolute earnings innovations do exhibit net increases in uncertainty across quarterly earnings announcements, providing support for H_2. Descriptively, we note that these net increases appear concentrated in the top 10% to 25% of absolute earnings innovations.

6. Sensitivity Analyses

6.1 Alternative measures of the dependent variable

To confirm the robustness of our results, we re-estimate Table 4 using alternative definitions of the dependent variable. Specifically, we examine (a) model-free implied volatilities using 273-day option maturities, which incorporate three future earnings releases; (b) model-free implied volatilities using 182-day option maturities, which incorporate two future earnings releases; and (c) Black-Scholes option maturities, consistent with prior accounting research (Rogers et al. 2009).

Results are presented in Table 6. For expositional convenience, we do not tabulate the control variables, which mirror those from Equation (1); their coefficients and significance levels are unchanged from Table 4, except that *FOLLOW* is now significantly negative in all specifications. Panel A presents results using model-free implied volatilities with 273-day maturities. Two findings stand out. First, the coefficients on all *TopX%_Abs_SUE* variables are significantly positive (e.g., *Top5%_Abs_SUE* = 1.059, *t*-stat = 4.38), consistent with the size of the earnings innovation attenuating the decline in uncertainty. Second, we find a significant ***net increase*** in uncertainty for firms in the top 5% of absolute unexpected earnings (*F*-test = 0.015), in the top 10% (*F*-test = 0.003), and in the top 25% (*F*-test = 0.073). We fail to find that firms in the top 50% experience such a net increase. This pattern parallels that documented in Table 4.

Panel B then presents results using model-free implied volatilities with 182-day maturities. While exhibiting lower power, we again find (i) that the coefficients on all *TopX%_Abs_SUE* variables are significantly positive, and (ii) significant net increases in uncertainty for firms in the top 5% (*F*-test = 0.097), top 10% (*F*-test = 0.086), and top 25% (*F*-test = 0.094). Overall, these panels suggest that our previous results are robust to alternative option maturity lengths.[11]

Finally, Panel C presents results using Black-Scholes implied volatilities. We find that the coefficients on all *TopX%_Abs_SUE* are again significantly positive. However, we fail to

[11] We also note that untabulated results replicating Table 5 are unchanged to using the alternative option maturities of 273- and 182-days.

find that these are large enough to lead to net increases in uncertainty surrounding the earnings announcements. We view this as unsurprising. Specifically, as previously discussed, model-free volatilities have the advantage of (i) placing fewer restrictions on how volatilities are modeled and (ii) taking into accounting all option market prices (i.e., ATM and out-of-the-money options), which becomes more important for longer option maturities (e.g. Demeterfi et al., 1999). Thus, we believe it likely that the use of Black-Scholes implied volatilities ignores the changes in the market's view of extreme future movements that are impounded in out-of-the money options.

6.2 Expansionary versus recessionary periods

We next partition the sample years into those that are expansionary versus those that are recessionary. This partition is intuitive, owing to potential systematic differences in market volatility that can vary by macro factors; such differences were reflected (for example) in the increased volatility coinciding with the 2008–2009 global financial crisis. Accordingly, we partition our sample into years that are expansionary, defined as 1996–2000, 2003–2007, and 2010–2012; and those that are recessionary, defined as 2001–2002 and 2008–2009.[12]

Panel A of Table 7 presents the results for the expansionary years. Consistent with our previous findings, we again document significantly positive coefficients on *TopX%_Abs_SUE* for all measures, consistent with the size of the earnings innovation attenuating the decline the uncertainty surrounding the earnings release. Further, we find a net increase in uncertainty for observations in the top 5% (*F*-test = < 0.001), top 10% (*F*-test = < 0.001), and top 25% (*F*-test = < 0.001). As previously, we fail to find such results for observations in the top 50%.

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[12] While the NBER does not technically define 2002 to be a recessionary year, we do so as it was characterized by substantial negative total market returns (e.g., a decline of 22% for the S&P 500).

Panel B then presents results for the recessionary years. We again find significantly positive coefficients for all *TopX%_Abs_SUE* measures. However, we fail to find any evidence of regime shifts, as in no case is the coefficient on top X% significantly larger than the intercept. These latter results can reflect either (a) a lack of power due to the lower number of observations relative to the expansionary years subsample, and/or (b) the recessionary years exhibiting larger declines in uncertainty (as reflected in the more negative intercepts).[13] Overall, these analyses suggest the results are (in)consistent with years designated as expansionary (recessionary).

6.3 Alternative measures of leverage

Because of the prominence of leverage in driving uncertainty, and thus our need to provide adequate empirical specifications to control for the effects of leverage (Welch 2011), we replicate our results using alternative measures of leverage. Specifically, we first redefine leverage to be total liabilities divided by total assets, and then to be total book liabilities divided by total book liabilities plus market value of equity (all defined at quarter *t-1*). Untabulated results replicating Tables 4 and 5 continue to provide evidence that (a) the decrease in uncertainty is attenuated by the size of the earnings innovation; and (b) that for sufficiently large earnings innovations (generally in the top 25% of calendar quarter observations), there is ***net increase*** in uncertainty surrounding earnings announcements.

7. Conclusion

This paper investigates three alternative classes of Bayesian models of learning to explain changes in uncertainty surrounding earnings innovations. The three classes of models are:

[13] Again, untabulated results replicating Table 5 for the expansionary and recessionary years are similar to those discussed above.

Simple Bayesian Learning, in which signals are predicted to uniformly reduce uncertainty; *Bayesian Learning Conditional on Signal Size*, in which the size of the signal is predicted to attenuate the reduction in uncertainty upon the signal's release; and *Bayesian Learning with Regime Shifts*, in which signals that deviate sufficiently from expectations are predicted to cause net increases in uncertainty upon the signal's release.

To empirically assess these three models of investor uncertainty, we use a sample of US quarterly firm observations spanning 1996 to 2011. As a proxy for investor uncertainty, we use model-free implied volatilities; as a proxy for a signal expected to affect investor expectations of the volatility of the firm's future stock price, we use quarterly earnings innovations—that is, unexpected quarterly earnings benchmarked to the consensus analyst forecast.

Our empirical analyses provide three primary findings. First, consistent with simple Bayesian models of learning and prior research, we document that uncertainty declines on average surrounding the release of quarterly earnings announcements. Second, we then show that this decline is *attenuated* by the magnitude of the earnings innovation; this suggests that the process by which investors use earnings releases to update their priors of future uncertainty is better captured in more sophisticated Bayesian learning models that incorporate signal magnitude as a factor driving changes in uncertainty. Third and most important, we provide evidence that large earnings innovations—that is, signals which deviate sufficiently from expectations—lead to *net increases* in uncertainty. This result is consistent with learning models that incorporate regime shifts (Pastor and Veronesi 2009); that is, it suggests that for the subset of firms exhibiting the largest earnings innovations, there is actually a net increase in uncertainty surrounding the release of the earnings.

Appendix A

Model-Free Volatility Estimates

This appendix details our derivation of implied volatilities, which are calculated using model-free volatility estimates based on OptionMetrics data. While most option pricing models theoretically reflect underlying volatility, a critical empirical choice is modeling the dynamics of volatility. The simplest case is the Black and Scholes (1973) model, which assumes volatility is constant and known by investors: here, solving for implied volatility using a quoted option price leads to the correct market implied forecast of volatility. Further, if the Black-Scholes model is correct, for every option in a quoted month the implied volatilities should be the same.

However, it is commonly known that the Black-Scholes model does not fit actual market prices correctly; that is, if one backs out the implied volatilities from quoted option prices, then the actual volatilities will generate a curve (called a "smile") instead of a flat straight line. Thus, the use of at-the-money volatilities provides an approximation to forecasted volatility; however, more precise estimation techniques (1) do not rely on a specific option pricing model, and (2) incorporate all the quoted option prices to form an estimate.

Accordingly, an alternative to using an option pricing model to back out implied volatilities is to use model-free volatilities. Relying on a set of relatively weak assumptions (the primary of which is that stock prices do not jump), it can be shown that the total variance of the underlying asset can be approximated by the following formula (Carr and Madan, 1998; Demeterfi et al., 1999; Britten-Jones and Neuberger, 2000):

$$E^{Q}[VAR_t] = \frac{2e^{rt}}{t}\left[\int_{0}^{F_t}\frac{P(t,K)}{K^2}dK + \int_{F_t}^{\infty}\frac{C(t,K)}{K^2}dK\right] \tag{A.1}$$

The left-hand side is the expected risk-neutral variance of the underlying over the period, K is the strike price, F_t is the forward price of the asset, t is the time to maturity, r is the risk-free interest rate, *C(t, K)* is the price of a European call for the given maturity and strike price, and *P(t, K)* is the price of a European put for the given maturity and strike price. Of note, this formula does *not* assume a particular option pricing formula; further, it uses a continuum of option prices, instead of simply using the at-the-money option.[14] Thus, model-free variance and volatility may change *even if* the price of the at-money-option does not change.

To create the model-free variance and volatility estimates for each asset/date/option maturity, we begin with the OptionMetrics surface database. This contains implied volatilities for standardized maturities and deltas.[15] Along with each delta is a calculated strike price for the hypothetical option. For each asset/date/option maturity, we apply the following procedure:

1) The forward price is given by OptionMetrics for the stock on the date for the particular expiration date. If a forward price is not found for that particular asset for the date for the correct expiration date, we use a simple linear regression to interpolate or extrapolate the forward price from the other available forward prices for the asset on that date. If there are insufficient data points for a proper fitting of the regression line the following calculations were skipped (these represent approximately 1.8% of firm-day pairings).

2) The implied volatility data in a month for each asset for each day was fit using the following representation:

$$\text{var}(k; a, b, \sigma, \rho, m) = a + b\left[\rho\left(k - m\right) + \sqrt{(k-m)^2 + \sigma^2}\right]$$

   Here, *var* is the implied variance, *k* is the natural log of the strike price divided by forward price and *a*, *b*, *σ*, *ρ*, and *m* are the parameters to be fit. This representation comes from Gatheral (2004) and Gatheral and Jacquier (2011). This particular formulization

[14] This procedure is quite close to that used by the CBOE (2009) to calculate the VIX. In addition, Zhang et al. (2012) shows that for the parameter estimates of Duffie et al. (2000) the model-free volatility estimates are much closer to the true values than at-the-money volatilities.

[15] The delta of an option is the partial derivative of the option's price to the underlying's price.

has some useful theoretical properties, which include being linear as $|k| \to \infty$ which Lee (2004) shows is necessary.

3) We use the Nelder-Mead (1965) algorithm to fit the model, with the following restrictions on the parameters as given by Gatheral and Jacquier (2012):

   $a \in \mathbb{R}$, $b \geq 0$, $|\rho| < 1$, $m \in \mathbb{R}$ and $\sigma > 0$

4) The optimization was done by minimizing the squared percentage error between the implied variances as given by OptionMetrics and the model fit. The fitting algorithm was allowed to run for 10,000 loops. If the algorithm did not terminate with a solution before the last iteration the best fit for the previous 10,000 loops was used as the solution. In addition, as is commonly done in industry, only out-of-the money and at-the-money implied volatilities were used in the optimization.[16] In other words, implied volatilities were used only if the absolute delta of the option was less than or equal to 50.
5) The risk-free interest rate information comes from the OptionMetrics database as well.
6) Finally, using the implied volatility curve fit for each maturity, equation (A.1) is approximated using at least 200 steps for the integral evaluation. The fit from the previous steps is used to price the European options needed in the formula. In addition, the maximum and minimum strike prices are chosen to give sufficient coverage of the strike space. The algorithm uses a function of the time-to-maturity and at-the-money volatility to determine the integral starting and ending points.

[16] There is also some precedence for using only at-the-money and out-of-the-money options in academic studies. Carr and Wu (2010) state: "Since out-of-the money options are more actively traded than in-the-money options, the quotes on out-of-the-money options are usually more reliable."

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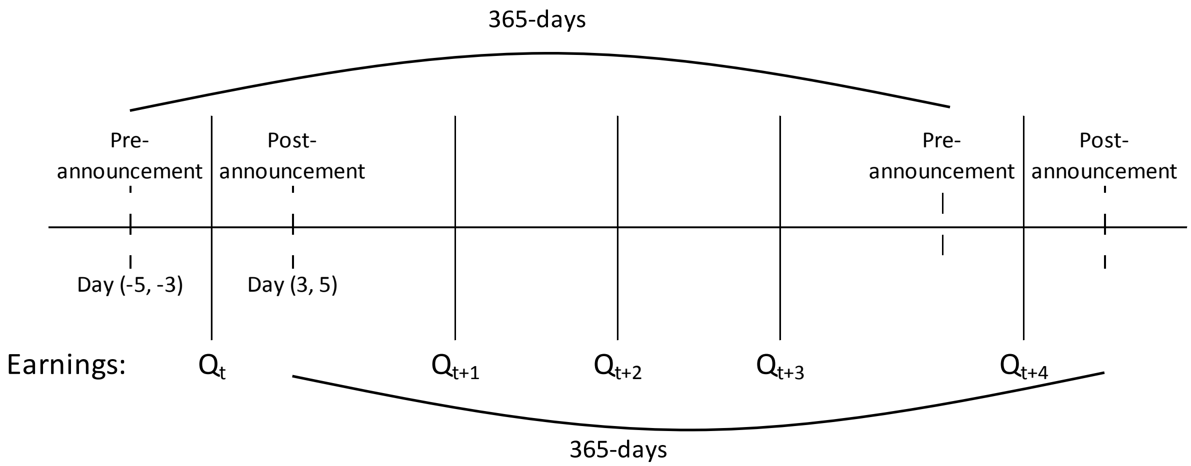
Figure 1

Measurement of the dependent variable, *IVOL_365*.



This figure presents the measurement of the dependent variable, *IVOL_365*. *IVOL_365* is defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*), using option maturities of 365 days.

The figure shows that the 365-day maturity holds constant the number of quarterly earnings announcements in both the pre-announcement and post-announcement windows. Specifically, the pre-announcement window includes the quarterly earnings announcements of *t*, *t+1*, *t+2*, and *t+3* (a total of four); and the post-announcement window includes the quarterly earnings announcements of *t+1*, *t+2*, *t+3*, and *t+4* (also a total of four).

Table 1
Sample selection and yearly distribution.

Panel A: Sample selection

	Observations	**Unique Firms**
Total quarterly on Compustat during 1996Q1–2011Q4	502,279	18,526
Less:		
- Negative assets or negative book equity	(51,645)	(617)
- Missing IBES analyst data	(247,133)	(8,001)
- Missing CRSP market data	(9,007)	(419)
- Missing OptionMetrics option data	(87,839)	(4,140)
- Financial firms	(14,297)	(812)
Final sample	**92,358**	**4,537**

Panel B: Annual distribution (N = 92,358)

Year	**Observations**	**Year**	**Observations**
1996	3,671	2004	5,515
1997	4,547	2005	6,147
1998	5,184	2006	6,526
1999	5,322	2007	7,161
2000	4,433	2008	6,963
2001	4,508	2009	6,783
2002	4,946	2010	7,668
2003	4,940	2011	8,044

Notes: This table presents the sample selection process. Panel A begins with all Quarterly Compustat observations for the period 1996Q1–2011Q4. Panel B provides the annual distribution, with years defined by the quarterly earnings release dates.

Table 2
Descriptive statistics.

	Sample (*N* = 92,358)		Compustat-IBES-CRSP Population (*N* = 157,894)	
Variable	**Mean**	**Median**	**Mean**	**Median**
	(1)	(2)	(3)	(4)
Dependent Variables:				
IVOL_365	–0.004 †	–0.007 †	n/a	n/a
IVOL_273	–0.005 †	–0.008 †	n/a	n/a
IVOL_182	–0.006 †	–0.010 †	n/a	n/a
Experimental Variables:				
Abs_SUE/Price	0.004	0.001	0.011 ***	0.002 ^^^
Abs_SUE/MeanAbsAF‡	0.378	0.107	0.542 ***	0.136 ^^^
Control Variables:				
LEV	0.177	0.147	0.170 ***	0.125 ^^^
SUE	0.007	0.044	–0.230 ***	0.041 ^^^
DISP	0.177	0.078	0.257 ***	0.073 ^^^
FIRM_VOL	0.506	0.456	n/a	n/a
VIX	0.221	0.206	0.227 ***	0.214 ^^^
Δ*VIX*	0.020	0.005	0.017 ***	0.002 ^^^
SIZE	7.099	6.986	6.266 ***	6.124 ^^^
FOLL	1.932	1.946	1.467 ***	1.609 ^^^
BTM	0.555	0.417	0.691 ***	0.471 ^^^

Notes: This table presents the descriptive statistics; for the control variables, values are presented prior to their demeaning and standardizing, as used within our regression analyses. Columns (1) and (2) present means and medians for our final sample (*N* = 92,358), which includes all quarterly observations over 1996Q1 through 2011Q4 with available financial data from Compustat, market data from CRSP, analyst data from IBES, and options data from OptionMetrics. Columns (3) and (4) present means and medians for the total population for the same period with available data from Compustat/IBES/CRSP (*N* = 157,894) (i.e., not imposing the requirement for OptionMetrics data). Both samples exclude financial firms.

The dependent and experimental variables are winsorized at the top and bottom 0.5%. † represents values that are significantly different from zero at the 1% level, using two-tailed tests. ***, **, * in Column (3) (^^^, ^^, ^ in Column (4)) denote significant differences in means (medians) at the 1%, 5%, and 10% levels, respectively, based on two-tailed tests from a non-parametric bootstrap using 2,500 samples. ‡ represents variables that are calculated only when the absolute mean forecast is greater than or equal to 0.01.

The dependent variable is *IVOL*, defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*). The suffixes of *_365*, *_273*, and *_182* denote option maturities of 365-, 273-, and 182-days, respectively.

The experimental variable is *Abs_SUE*, the absolute value of firm *j*'s unexpected net income for quarter *t*, scaled alternatively by price per share ("*/Price*") and the mean absolute analyst forecast ("*/MeanAbsAF*"). Unexpected net income is measured as reported earnings before special items per share less the consensus earnings forecast per share (both per IBES).

The control variables are defined as follows. LEV_{jt} is firm *j*'s long-term debt divided by total assets, both reported as of the end of quarter *t-1*. SUE_{jt} is firm *j*'s unexpected net income per share for quarter *t*, scaled by price; unexpected net income is measured as the reported earnings before special items per share less the consensus earnings forecast per share (both per IBES). $DISP_{jt}$ is the standard deviation of analyst estimates comprising the consensus earnings forecast for firm *j* on day –3 preceding the quarter *t* earnings announcement, divided by price per share. $FIRM\_VOL_{jt}$ is the average of firm *j*'s 365-day model-free implied volatility, measured over days –5 to –3 preceding the earnings announcement for quarter *t*. VIX_t is the value of the CBOE Volatility Index, measured at day –4 preceding the earnings announcement of firm *j* for quarter *t*. ΔVIX_t is the change in natural logarithm of the ratio of the CBOE Volatility Index, measured on day –4 preceding firm *j*'s earnings announcement for quarter *t*, divided by that on day +4 after the earnings announcement for quarter *t*. $SIZE_{jt}$ is the natural logarithm of firm *j*'s total assets measured at the end of quarter *t-1*. $FOLLOW_{jt}$ is the natural logarithm of firm *j*'s analyst following for quarter *t*, measured as the number of unique analysts comprising the consensus earnings forecast immediately preceding the earnings announcement. BTM_{jt} is firm *j*'s book value of equity at the end of quarter *t-1* divided by market value of equity measured on day –3 before the earnings announcement.

Table 3
Re-assessing simple Bayesian learning: does signal magnitude increase investor uncertainty?

Variable	Predicted Sign	Scaling *Abs_SUE* by Price		Scaling *Abs_SUE* by Absolute Forecast	
		(1)		(2)	
Intercept	–	–0.448	(10.82 ***)	–0.451	(9.80 ***)
***Abs_SUE* (H$_1$)**	**+**	**0.309**	**(4.90 ***)**	**0.161**	**(3.18 ***)**
LEV	+	0.206	(4.21 ***)	0.204	(4.15 ***)
LEV x *SUE*	–	–0.386	(7.33 ***)	–0.431	(8.31 ***)
DISP	+	0.563	(9.18 ***)	0.665	(11.74 ***)
FIRM_VOL	–	–3.290	(43.69 ***)	–3.229	(43.04 ***)
VIX	+	1.708	(35.21 ***)	1.696	(34.81 ***)
Δ*VIX*	+	2.382	(54.53 ***)	2.377	(54.46 ***)
SIZE	+ / –	–1.611	(23.71 ***)	–1.575	(23.23 ***)
FOLLOW	–	–0.068	(1.20)	–0.094	(1.65 *)
BTM	+ / –	0.287	(5.34 ***)	0.303	(5.69 ***)
Adj-R^2		9.0%		9.0%	
N		92,358		91,416	

Notes: This table presents empirical results examining if the magnitude of the signal, proxied via unexpected quarterly earnings, attenuates observed decreases in uncertainty.

The dependent variable is *IVOL_365*, defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*), using option maturities of 365 days.

The experimental variable (highlighted in bold) is *Abs_SUE*, the absolute value of firm *j*'s unexpected net income for quarter *t*; unexpected net income is measured as reported earnings before special items per share less the consensus earnings forecast per share (both per IBES). The variable is scaled alternatively by price per share in Column (1) and the mean absolute analyst forecast in Column (2). We test H$_1$ by examining whether the coefficient on *Abs_SUE* is significantly positive.

All control variables are defined in Table 2, and have been demeaned and standardized to facilitate inferences. Standard errors are clustered by firm. ***, **, * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests, respectively.

Table 4
Do earnings signals reveal regime shifts?

Panel A: Scaling Abs_SUE by Price

Variable	Predicted Sign	(1)		(2)		(3)		(4)	
Intercept	–	–0.512	(10.70 ***)	–0.575	(11.72 ***)	–0.685	(12.79 ***)	–0.707	(11.62 ***)
Top5%_Abs_SUE	+	**1.276**	**(5.29 ***)**						
Top10%_Abs_SUE	+			**1.267**	**(7.30 ***)**				
Top25%_Abs_SUE	+					**0.947**	**(8.68 ***)**		
Top50%_Abs_SUE	+							**0.519**	**(6.38 ***)**
LEV	+	0.208	(4.24 ***)	0.201	(4.11 ***)	0.190	(3.88 ***)	0.195	(3.99 ***)
LEV x *SUE*	–	–0.409	(7.87 ***)	–0.422	(8.18 ***)	–0.456	(8.82 ***)	–0.465	(8.96 ***)
DISP	+	0.600	(10.27 ***)	0.563	(9.57 ***)	0.567	(9.70 ***)	0.633	(11.14 ***)
FIRM_VOL	–	–3.273	(43.75 ***)	–3.293	(43.92 ***)	–3.305	(44.15 ***)	–3.280	(43.79 ***)
VIX	+	1.725	(35.44 ***)	1.736	(35.68 ***)	1.740	(35.79 ***)	1.724	(35.50 ***)
Δ*VIX*	+	2.384	(54.59 ***)	2.386	(54.62 ***)	2.384	(54.63 ***)	2.382	(54.55 ***)
SIZE	+ / –	–1.604	(23.62 ***)	–1.605	(23.71 ***)	–1.600	(23.69 ***)	–1.594	(23.57 ***)
FOLLOW	–	–0.081	(1.42)	–0.056	(0.98)	–0.037	(0.66)	–0.066	(1.17)
BTM	+ / –	0.297	(5.55 ***)	0.290	(5.41 ***)	0.280	(5.26 ***)	0.290	(5.41 ***)
***F*-Test (H_2):**									
TopX%_Abs_SUE* > *Intercept		**< 0.001 *****		**< 0.001 *****		**0.003 *****		**n/a**	
Adj-R^2		9.0%		9.1%		9.1%		9.0%	
N		92,358		92,358		92,358		92,358	

Panel B: Scaling Abs_SUE by Mean Absolute Forecast

Variable	**Predicted Sign**	**(1)**		**(2)**		**(3)**		**(4)**	
Intercept	–	–0.501	(10.57 ***)	–0.546	(11.29 ***)	–0.639	(12.21 ***)	–0.749	(12.44 ***)
Top5%_Abs_SUE	+	**0.991**	**(4.64 ***)**						
Top10%_Abs_SUE	+			**0.946**	**(6.09 ***)**				
Top25%_Abs_SUE	+					**0.752**	**(7.30 ***)**		
Top50%_Abs_SUE	+							**0.596**	**(7.53 ***)**
LEV	+	0.203	(4.14 ***)	0.201	(4.11 ***)	0.199	(4.06 ***)	0.197	(4.03 ***)
LEV x *SUE*	–	–0.431	(8.35 ***)	–0.426	(8.24 ***)	–0.438	(8.50 ***)	–0.455	(8.81 ***)
DISP	+	0.668	(11.89 ***)	0.654	(11.61 ***)	0.638	(11.28 ***)	0.647	(11.47 ***)
FIRM_VOL	–	–3.231	(43.10 ***)	–3.245	(43.34 ***)	–3.262	(43.40 ***)	–3.258	(43.37 ***)
VIX	+	1.699	(34.86 ***)	1.706	(35.04 ***)	1.715	(35.17 ***)	1.712	(35.07 ***)
Δ*VIX*	+	2.378	(54.47 ***)	2.377	(54.48 ***)	2.377	(54.52 ***)	2.377	(54.48 ***)
SIZE	+ / –	–1.571	(23.20 ***)	–1.567	(23.18 ***)	–1.559	(23.11 ***)	–1.556	(23.07 ***)
FOLLOW	–	–0.093	(1.63 *)	–0.082	(1.44 *)	–0.066	(1.16)	–0.072	(1.26)
BTM	+ / –	0.303	(5.68 ***)	0.298	(5.58 ***)	0.293	(5.51 ***)	0.295	(5.54 ***)
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**0.009 *****		**0.004 *****		**0.105**		**n/a**	
Adj-R^2		9.0%		9.0%		9.0%		9.0%	
N		91,416		91,416		91,416		91,416	

Notes: This table presents results from examining whether earnings signals, which sufficiently deviate from expectations, lead to "regime shifts"—that is, net increases in investor uncertainty.

The dependent variable is *IVOL_365*, defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*), using option maturities of 365 days.

The experimental variables (highlighted in bold) are *TopX%_Abs_SUE*, defined as an indicator variable equal to 1 if firm *j* exhibits an absolute earnings innovation in the top X% ranked by reporting quarter, and 0 otherwise. We examine four alternative thresholds: *Top5%*, *Top10%*, *Top25%*, and *Top50%*, defined as firms in the top 5%, 10%, 25%, and 50% of absolute earnings innovations, respectively. In Panel A, *TopX%_Abs_SUE* is scaled by price per share (prior to defining the indicator variable); in Panel B, *TopX%_Abs_SUE* is scaled by the mean absolute analyst forecast (again, prior to defining the indicator variable). We test H_2 by examining whether the sum of (*TopX%_Abs_SUE* + *Intercept*) is significantly positive; the *F*-tests values are presented with one-sided *p*-values, and calculated using clustered covariance matrices.

All control variables are defined in Table 2, and have been demeaned and standardized to facilitate inferences. Standard errors are clustered by firm.***, **, * represent significance at the 1%, 5%, and 10% levels for the two-tailed tests, respectively.

Table 5
Do earnings signals reveal regime shifts? An alternative test

Variable	**Predicted Sign**	**Scaling *Abs_SUE* by Price**		**Scaling *Abs_SUE* by Absolute Forecast**	
		(1)		(2)	
Abs_SUE_0%-5%	**+ / –**	**1.033**	**(4.38 ***)**	**0.579**	**(2.78 ***)**
Abs_SUE_5%-10%	**+ / –**	**0.621**	**(3.04 ***)**	**0.331**	**(1.66 *)**
Abs_SUE_10%-25%	**+ / –**	**–0.001**	**(0.01)**	**–0.079**	**(0.73)**
Abs_SUE_25%-50%	**+ / –**	**–0.579**	**(7.34 ***)**	**–0.410**	**(5.31 ***)**
Abs_SUE_50%-75%	**+ / –**	**–0.764**	**(10.21 ***)**	**–0.818**	**(10.87 ***)**
Abs_SUE_75%-100%	**+ / –**	**–0.782**	**(9.64 ***)**	**–0.714**	**(9.03 ***)**
LEV	+	0.186	(3.82 ***)	0.195	(3.99 ***)
LEV x *SUE*	–	–0.428	(8.20 ***)	–0.431	(8.32 ***)
DISP	+	0.503	(8.33 ***)	0.623	(10.99 ***)
FIRM_VOL	–	–3.329	(44.21 ***)	–3.281	(43.58 ***)
VIX	+	1.757	(36.05 ***)	1.723	(35.32 ***)
Δ*VIX*	+	2.387	(54.68 ***)	2.377	(54.52 ***)
SIZE	+ / –	–1.606	(23.81 ***)	–1.555	(23.10 ***)
FOLLOW	–	–0.009	(0.16)	–0.052	(0.91)
BTM	+ / –	0.270	(5.07 ***)	0.287	(5.40 ***)
Adj-R^2		9.3%		9.2%	
N		92,358		91,416	

Notes: This table presents results from examining whether earnings signals, which sufficiently deviate from expectations, lead to "regime shifts"—that is, net increases in investor uncertainty.

The dependent variable is *IVOL_365*, defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*), using option maturities of 365 days.

The experimental variables (highlighted in bold) are *Abs_SUE_X%-X%*, an indicator variable equal to 1 if the absolute value of firm *j*'s scaled unexpected net income for quarter *t* falls within the indicated percentage range for observations as ranked by reporting quarter; unexpected net income is measured as reported earnings before special items per share less the consensus earnings forecast per share (both per IBES).. Scaling is done alternatively by price per share in

Column (1), and by the mean absolute analyst forecast in Column (2). We define six mutually exclusive ranges of scaled absolute unexpected earnings: 0%-5% (the top 5%); 5%-10%; 10%-25%; 25%-50%; 50%-75%; and 75%-100%. We test H_2 by examining whether the coefficient on *Abs_SUE_X%-X%* is significantly positive.

All control variables are defined in Table 2, and have been demeaned and standardized to facilitate inferences. Standard errors are clustered by firm. ***, **, * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests, respectively.

Table 6
Sensitivity analysis: alternative definitions of the dependent variable of implied volatility

Variable	Predicted Sign	(1)		(2)		(3)		(4)	
Panel A: Dependent Variable = IVOL_273 (N = 92,358)									
Intercept	–	–0.555	(12.28 ***)	–0.608	(13.15 ***)	–0.714	(14.19 ***)	–0.720	(12.41 ***)
Top5%_Abs_SUE	+	**1.059**	**(4.38 ***)**						
Top10%_Abs_SUE	+			**1.064**	**(6.10 ***)**				
Top25%_Abs_SUE	+					**0.847**	**(7.91 ***)**		
Top50%_Abs_SUE	+							**0.438**	**(5.52 ***)**
Control variables		Included		Included		Included		Included	
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**0.015 ****		**0.003 *****		**0.073 ***		**n/a**	
Adj-R^2		8.4%		8.5%		8.5%		8.4%	
Panel B: Dependent Variable = IVOL_182 (N = 92,358)									
Intercept	–	–0.682	(16.00 ***)	–0.728	(16.66 ***)	–0.807	(16.91 ***)	–0.828	(15.04 ***)
Top5%_Abs_SUE	+	**0.966**	**(4.26 ***)**						
Top10%_Abs_SUE	+			**0.939**	**(5.69 ***)**				
Top25%_Abs_SUE	+					**0.692**	**(6.80 ***)**		
Top50%_Abs_SUE	+							**0.389**	**(5.07 ***)**
Control variables		Included		Included		Included		Included	
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**0.097 ***		**0.086 ***		**0.094 ***		**n/a**	
Adj-R^2		8.6%		8.6%		8.6%		8.6%	

Panel C: Dependent Variable = IVOL_BS (N = 92,358)

Intercept	–	–0.264	(18.34 ***)	–0.280	(18.89 ***)	–0.299	(18.53 ***)	–0.272	(14.39 ***)
Top5%_Abs_SUE	+	**0.286**	**(4.04 ***)**						
Top10%_Abs_SUE	+			**0.302**	**(5.89 ***)**				
Top25%_Abs_SUE	+					**0.196**	**(4.92 ***)**		
Top50%_Abs_SUE	+							**0.045**	**(1.70 *)**
Control variables		Included		Included		Included		Included	
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**0.375**		**0.325**		**n/a**		**n/a**	
Adj-R^2		10.4%		10.4%		10.4%		10.4%	

Notes: This table presents results from sensitivity analyses examining whether earnings signals, which sufficiently deviate from expectations, lead to "regime shifts"—that is, net increases in investor uncertainty.

The dependent variables across all panels are defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*). In Panel A, *IVOL_273* uses option maturities of 273 days. In Panel B, *IVOL_182* uses option maturities of 182 days. In Panel C, *IVOL_BS* calculates volatilities using the Black-Scholes at-the-money (versus model-free) implied volatilities.

The experimental variables (highlighted in bold) are *TopX%_Abs_SUE*, defined as an indicator variable equal to 1 if firm *j* exhibits an absolute earnings innovation in the top X% ranked by reporting quarter, and 0 otherwise. We examine four alternative thresholds: *Top5%*, *Top10%*, *Top25%*, and *Top50%*, defined as firms in the top 5%, 10%, 25%, and 50% of absolute earnings innovations, respectively. We test H_2 by examining whether the sum of (*TopX%_Abs_SUE* + *Intercept*) is significantly positive; the *F*-tests values are presented with one-sided *p*-values, and calculated using clustered covariance matrices.

The untabulated control variables include all variables in Table 3; these have been demeaned and standardized to facilitate inferences. Standard errors are clustered by firm. ***, **, * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests, respectively.

Table 7
Sensitivity analysis: expansionary versus recessionary years

Variable	Predicted Sign	(1)		(2)		(3)		(4)	
Panel A: Expansionary Years (N = 69,158)									
Intercept	–	–0.219	(4.14 ***)	–0.278	(5.10 ***)	–0.370	(6.19 ***)	–0.394	(5.78 ***)
Top5%_Abs_SUE	+	**1.143**	**(3.85 ***)**						
Top10%_Abs_SUE	+			**1.165**	**(5.64 ***)**				
Top25%_Abs_SUE	+					**0.834**	**(6.50 ***)**		
Top50%_Abs_SUE	+							**0.465**	**(4.92 ***)**
Control variables		Included		Included		Included		Included	
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**< 0.001 *** **		**< 0.001 *** **		**< 0.001 *** **		**n/a**	
Adj-R^2		9.2%		9.3%		9.3%		9.2%	
Panel B: Recessionary Years (N = 23,200)									
Intercept	–	–1.375	(17.21 ***)	–1.440	(17.50 ***)	–1.598	(17.99 ***)	–1.621	(15.06 ***)
Top5%_Abs_SUE	+	**1.485**	**(3.47 ***)**						
Top10%_Abs_SUE	+			**1.392**	**(4.43 ***)**				
Top25%_Abs_SUE	+					**1.191**	**(6.06 ***)**		
Top50%_Abs_SUE	+							**0.641**	**(4.16 ***)**
Control variables		Included		Included		Included		Included	
***F*-Test (H_2):**									
TopX%_Abs_SUE > Intercept		**0.395**		**0.436**		**n/a**		**n/a**	
Adj-R^2		8.6%		8.6%		8.7%		8.6%	

Notes: This table presents results from sensitivity analyses examining whether earnings signals, which sufficiently deviate from expectations, lead to "regime shifts"—that is, net increases in investor uncertainty. Panel A presents results using years defined as expansionary (N = 69,158), which include: 1996–2000, 2003–2007, and 2010–2012. Panel B presents results using years defined as recessionary (N = 23,200), which include: 2001–2002 and 2008–2009.

The dependent variable is *IVOL_365*, defined as the natural logarithm of the ratio of firm *j*'s post-earnings announcement implied volatility (measured as the average over the trading days +3 to +5 after the earnings announcement for quarter *t*) divided by the pre-earnings announcement implied volatility (measured as the average over the trading days –5 to –3 before the earnings announcement for quarter *t*), using option maturities of 365 days.

The experimental variables (highlighted in bold) are *TopX%_Abs_SUE*, defined as an indicator variable equal to 1 if firm *j* exhibits an absolute earnings innovation in the top X% ranked by reporting quarter, and 0 otherwise. We examine four alternative thresholds: *Top5%*, *Top10%*, *Top25%*, and *Top50%*, defined as firms in the top 5%, 10%, 25%, and 50% of absolute earnings innovations, respectively. We test H_2 by examining whether the sum of (*TopX%_Abs_SUE* + *Intercept*) is significantly positive; the *F*-tests values are presented with one-sided *p*-values, and calculated using clustered covariance matrices.

The untabulated control variables include all variables in Table 3; these have been demeaned and standardized to facilitate inferences. Standard errors are clustered by firm. ***, **, * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests, respectively.