A New Measure of Earnings Forecast Uncertainty

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Abstract:

Relying on the well-established theoretical result that uncertainty has a common and an idiosyncratic component, we propose a new measure of earnings forecast uncertainty as the sum of dispersion among analysts and the variance of mean forecast errors estimated by a GARCH model. The new measure is based on both common and private information available to analysts at the time they make their forecasts. Hence, it circumvents the limitations of other commonly used proxies for forecast uncertainty in the literature. Using analysts’ earnings forecasts, we find direct evidence of the new measure’s superior performance.

JEL Classifications: M41, C01

Keywords: Uncertainty, analyst dispersion, common information, private information, BKLS, GARCH

We thank Orie Barron, Sung Gon Chung, Steven Huddart, Yong Yu and workshop participants at EDHEC, Florida Atlantic University and HEC Paris for many helpful comments and suggestions. However, we alone are responsible for any remaining errors and shortcomings. We thank I/B/E/S for providing the forecast data.
1. Introduction

Analysts’ forecasts are widely used in the accounting and finance literature to study market participants’ expectations. Researchers and investors are especially interested in estimating uncertainty about future earnings, because it reveals important characteristics of the firm’s information environment prior to the release of accounting results. Since uncertainty is inherently unobservable, evaluating its estimates poses challenging methodological problems. As a result, researchers have experimented with alternative proxies for earnings forecast uncertainty.

Earnings forecast uncertainty in this paper is defined as the uncertainty that surrounds a typical analyst’s forecast of earnings. In predicting earnings, each analyst possesses two types of information – common, which is known by all analysts, and private, privy to individual analysts. As a result, the analyst’s forecast error is comprised of an error due to imprecise public information and an error due to imprecise private information. Consequently, earnings forecast uncertainty includes two components that correspond to the two types of analyst forecast errors. One component, common to all analysts, arises from the impact of unanticipated aggregate shocks that affect earnings from the time a forecast is made until the end of the fiscal period over which actual earnings are realized. The other component is individual-specific, arising from analysts’ information processing skills and different forecasting models. Thus, an appropriate measure of forecast uncertainty should reflect both components. Furthermore, uncertainty is essentially an ex ante concept attached to a forecast before the actual outcome is known, and good proxies for uncertainty should be based on information available to analysts at the time they make their forecasts.
One of the most commonly used measures of earnings forecast uncertainty is the dispersion among analysts (see, e.g. Baginski, Conrad and Hassell 1993; Diether, Malloy, and Scherbina 2002; Clement, Frankel and Miller 2003; Yeung 2009). Dispersion, as a proxy for uncertainty, has several advantages. It is easy to calculate and gives a measure of uncertainty around the time the forecast is made, i.e. in real time. However, Abarbanell, Lanen and Verrecchia (1995) and Johnson (2004), among others, point out that dispersion does not capture uncertainty fully. Indeed, dispersion represents only one element of uncertainty, namely uncertainty arising from analysts’ private information and diversity of forecasting models. In addition, Barron, Stanford and Yu (2009) show that the change in dispersion does not indicate a change in uncertainty but rather a change in information asymmetry. As a result, dispersion tends to be a noisy and unreliable proxy for earnings forecast uncertainty when the uncertainty shared by all analysts becomes dominant or when the change in uncertainty is the construct of interest.

Another popular proxy for uncertainty is the measure proposed by Barron, Kim, Lim and Stevens (1998). The authors suggest that uncertainty can be estimated as the sum of dispersion and the squared error in the mean forecast (BKLS measure hereafter). The BKLS measure correctly recognizes the fact that uncertainty is comprised of two components. However, there are important caveats when using the BKLS measure as a proxy for ex ante uncertainty. Since forecast errors are known to respondents only after the announcement of actual earnings, the BKLS measure provides an estimate of ex post uncertainty.1 As discussed in detail later in this paper, the BKLS measure is excessively affected by significant unanticipated events following the forecast, such as 9/11-type

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1 We should point out that the BKLS measure is only partially ex post because it includes contemporaneous dispersion.
disasters, bankruptcy and restructuring. In addition, it relies on the assumption that actual earnings are exogenous, which is unlikely to hold in practice, as there is an extensive stream of research showing that managers manipulate earnings to meet or beat analysts’ forecasts (see, e.g. Degeorge, Patel and Zeckhauser 1999; Abarbanell and Lehavy 2003). To the extent that the exogeneity assumption of actual earnings is violated, the squared error in the mean forecast will be understated and the resulting BKLS uncertainty will also be understated. Hence, the reliability of the BKLS measure as a proxy for ex ante uncertainty faced by analysts becomes an important empirical issue.

Based on the well-known BKLS model, we propose a new empirical measure of earnings forecast uncertainty. Since uncertainty is fundamentally an ex ante concept attached to a forecast before the actual earnings are known, it must be constructed using data available in real time. Accordingly, we estimate the variance of mean forecast errors using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, conditional on the information known to financial analysts when making their earnings forecasts. Specifically, this method provides an estimate of the volatility in analysts’ common forecast errors in the current period based on historical mean forecast errors. The new measure is then constructed as the sum of the projected variance of mean forecast errors, estimated by a GARCH model, and dispersion among financial analysts. Compared to other existing measures in the literature, the new uncertainty measure has the advantages that it is estimated using information known to analysts at the time they make forecasts, it captures both components of the theoretical construct and it is more stable and reliable in a variety of settings.
Next, we examine the performance of the new measure empirically using the I/B/E/S data set during 1984-2007. Our analysis shows that dispersion alone tends to understate uncertainty, especially at longer horizons. The BKLS measure, on the other hand, tends to become unduly volatile in periods of unanticipated significant events and understates uncertainty in other periods. In contrast, the new measure gives an appropriate measure of uncertainty faced by financial analysts under these circumstances.

For a further comparison, we test the hypothesis that analysts rely more on reported earnings to revise their forecasts when the \textit{ex ante} uncertainty in future earnings is relatively high. Since our uncertainty measure is expected to be superior to the other two especially at longer horizons, we predict that the positive relationship between forecast revisions and earnings surprises is stronger when uncertainty is measured by the new proxy. Our empirical results are consistent with this prediction and provide further evidence of the appropriateness and superiority of the new empirical proxy.

This paper makes an important contribution to the literature. We suggest a new measure of uncertainty as the sum of the observed dispersion among analysts and the projected variance of mean forecast errors estimated by a suitably specified GARCH model. The proposed measure is based on information available to analysts at the time they make their forecasts and does not depend on \textit{ex post} actual earnings, thus circumventing the limitations of the BKLS measure. In addition, the new measure captures the uncertainty arising from both analysts’ common and private information and therefore avoids the problems of using dispersion alone as a proxy for uncertainty.

The rest of the paper is organized as follows. Section 2 presents the theoretical construct of uncertainty. Section 3 discusses two commonly used proxies for uncertainty
and proposes a new measure. Section 4 describes the empirical experiment and presents the estimation results. Section 5 concludes. Additional details on the GARCH model estimation are provided in Appendix A.

2. The Theoretical Construct of Earnings Forecast Uncertainty

To obtain the theoretical construct of earnings forecast uncertainty, we adopt the well-known model of Barron et al. (1998). Let $A_t$ denote actual earnings. There are $N$ analysts who provide forecasts of earnings at time $t$ at horizon $h$ based on their available information. The common information is presented by: $y_{ih} = A_t + \eta_{ih}$, where $\eta_{ih} \sim N(0, a_{ih}^{-1})$ and $a_{ih}$ is the precision (inverse of the variance) of the common signal.\footnote{Similar to Barron et al. (1998), we assume that any information that is common between any two analysts is common to all analysts.}

The idiosyncratic information observed only by analyst $i$ is represented by $z_{ih} = A_t + \epsilon_{ih}$, where $\epsilon_{ih} \sim N(0, b_{ih}^{-1})$ and $b_{ih}$ is the precision of the private signal. It is assumed that $\eta_{ih}$ and $\epsilon_{ih}$ are independent of each other for any $t$ and $h$, and $\epsilon_{ih}$ is independent of $\epsilon_{jih}$ for any $i \neq j$. Let $F_{ih}$ be the $h$-quarter ahead earnings forecast made by analyst $i$, for target year $t$ and let $F_{ih}$ denote the mean forecast averaged over analysts. Then, the observed dispersion among analysts, $d_{ih}$, is expressed as the population variance of their point forecasts:

$$d_{ih} = \frac{1}{N} \sum_{i=1}^{N} (F_{ih} - F_{ih})^2. \quad (1)$$

Then the observed error in the mean forecast, $e_{ih}$ is:
\[ e_{th} = A_t - F_{th}. \]  

Barry and Jennings (1992) and Barron, et al. (1998) show that uncertainty at time \( t \) and horizon \( h \) is equal to the sum of the average covariance among analyst forecast errors and dispersion:

\[ U_{th} = C_{th} + D_{th}, \]  

where the average covariance among analyst beliefs, \( C_{th} \), may be interpreted as common uncertainty, i.e. the uncertainty shared by all analysts due to their exposure to common unpredictable shocks. \( D_{th} \) is the expected across-analyst dispersion and measures idiosyncratic uncertainty arising from analysts’ different information acquisition and processing skills. This result specifies the relationship between uncertainty and dispersion before observing any forecasts or actual earnings and hence, it cannot be applied in practice.

Barron et al. (1998) extend this result and suggest an empirical measure of earnings forecast uncertainty after observing forecasts at time \( t - h \). The authors show that uncertainty is equal to the sum of the expected squared error in the mean forecast and observed dispersion:

\[ U_{th} = E(A_t - F_{th})^2 + d_{th}. \]  

Equation (4) shows that earnings forecast uncertainty is comprised of two components – a common and an idiosyncratic element. One component is the variance of mean forecast errors,\(^3\) which is dominated by the volatility of unanticipated aggregate shocks (Lahiri and Sheng 2010). This common element can be interpreted as uncertainty arising from

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\(^3\) Under the assumption that forecasts are unbiased, the variance of mean forecast errors is the same as the expected squared error in the mean forecast.
future events that analysts can neither predict nor have private knowledge of. The other component captures uncertainty due to differences in analysts’ information sets or forecasting models and abilities. Combined, the variance of mean forecast errors and dispersion among analysts capture the two sources of earnings forecast uncertainty faced by financial analysts.

It should be noted that the theoretical construct of earnings forecast uncertainty expressed in equation (4) is inherently *ex ante* because it is based on information at time $t - h$. Therefore, it should be constructed using information known to analysts at the time they make their forecasts and should not be affected by future information, such as actual earnings. In practice, Barron et al. (1998) suggest using the *actual* squared error in the mean forecast as a proxy for the *expected* mean squared error. While this approach may be acceptable in some settings, it is inappropriate at longer forecast horizons or during volatile time periods, as we argue below.

3. **Empirical Measures of Earnings Forecast Uncertainty**

This section begins with a review of two popular measures of uncertainty used in the literature, namely, forecast dispersion and the BKLS measure. At the end of the section, we suggest a third measure based on the model described above.

3.1. **Forecast Dispersion**

Due to the ready availability of point forecasts, dispersion among analysts, as defined in equation (1), has been widely used in the accounting and finance literature as a proxy for uncertainty about future earnings (see, e.g. Imhoff and Lobo 1992; Barron and
The use of dispersion is attractive because it provides an *ex ante* measure of uncertainty. However, Abarbanell et al. (1995) and Johnson (2004), among others, point out that dispersion does not capture uncertainty fully. Therefore, it is questionable whether dispersion alone is a reliable measure of uncertainty in all settings.

To illustrate this point, we follow Zarnowitz and Lambros (1987) and plot different combinations of dispersion and uncertainty in Figure 1. The point forecasts reported by three individuals are viewed as the expected values of their respective probability distributions. For example, their point forecasts are equal to 8, 10 and 12, respectively in charts (a) and (b), and 6, 10 and 14 in charts (c) and (d). The dispersion among three analysts is said to be “low” when their point forecasts are clustered and “high” when they are widely dispersed. On the other hand, the degree of uncertainty is said to be “low” when the probability distributions are tight, and “high” when they are diffuse. As illustrated in charts (a) and (b) of the diagram, low dispersion may be associated with either low or high uncertainty. Similarly, high dispersion may be associated with either low or high uncertainty (panels (c) and (d)). Therefore, dispersion may not always be an appropriate proxy for uncertainty.

As shown in equations (3) and (4), dispersion is only one part of overall forecast uncertainty and their difference is the variance of mean forecast errors, which is dominated by the variance of unanticipated shocks that accumulate over horizons, i.e. the longer the period over which unexpected events may occur, the larger the difference on average. It also suggests that the robustness of the relationship between dispersion and uncertainty depends on the variability of aggregate shocks over time. In relatively stable
time periods where the variability of the aggregate shocks is low, dispersion will be a good proxy for unobservable uncertainty. In periods where the volatility of aggregate shocks is high, dispersion can become a tenuous proxy for uncertainty. Thus our analysis helps the understanding of the appropriateness of dispersion as a proxy for forecast uncertainty.

Prior studies, such as L’Her and Suret (1996), interpret changes in dispersion to imply changes in uncertainty. However, the recent research by Barron et al. (2009) reveals that levels of dispersion reflect levels of uncertainty and changes in dispersion measure changes in information asymmetry. Based on this argument, the authors are able to reconcile seemingly conflicting evidence in the accounting and finance literature. Therefore, researchers and investors should be especially cautious when using dispersion to measure changes in uncertainty.

3.2. BKLS Measure

An alternative measure of uncertainty has been proposed by Barron et al. (1998). Under a Bayesian learning framework, they connect the properties of analysts’ information environment to the properties of their forecasts. The authors suggest that one could use the actual squared error in the mean forecast as a proxy for the expected squared error. This measure has been extensively used to study analysts’ information environment revealed by their earnings forecasts (see, e.g. Barron, Byard, Kile and Riedl 2002; Liang 2003; Botosan and Stanford 2005; Doukas, Kim and Pantzalis 2006; Yeung 2009). Empirically, the authors estimate earnings forecast uncertainty using the following equation:
\[
\hat{U}_{th} = (A_i - F_{th})^2 + d_{th}.
\]  

(5)

Since forecast errors are known to analysts only after the announcement of actual earnings, equation (5) yields an \textit{ex post} measure of uncertainty. Hence, the reliability of the BKLS measure as a proxy for \textit{ex ante} uncertainty at the time the forecasts are made is questionable.

Using a unique data set in economics where professional forecasters provide density forecasts for output growth and inflation, Lahiri and Sheng (2010) compare the BKLS measure to a self-reported measure of uncertainty directly.\footnote{The data are taken from Survey of Professional Forecasters (SPF) that is provided by the Federal Reserve Bank of Philadelphia. Besides their point forecasts, forecasters are also asked to provide their probability distributions for output growth and inflation. See Lahiri and Sheng (2010) for the details of the data set.} They find that, compared to the survey measure of uncertainty, which is widely accepted to be the best available estimate of subjective uncertainty, \textit{ex post} uncertainty based on equation (5) is considerably more volatile. Furthermore, their regression analysis shows that adding the squared error in the mean forecast to dispersion makes the BKLS measure a somewhat worse proxy for uncertainty than dispersion alone. This is because the forecast error is an \textit{ex post} quantity, which, by definition, should not affect analysts’ uncertainty at the time they issue a forecast.

To further illustrate this point, consider AMR Corporation whose principal subsidiary is American Airlines. Following the 9/11 attack, American Airlines suffered a tremendous loss in revenues due to a two-day flying suspension, drop in the number of passengers and ticket prices and the loss of two planes with passengers and employees. This enormous drop in earnings in the last two quarters of the fiscal year results in a large error in the mean forecast, which, in turn, increases the BKLS measure of uncertainty.
tremendously. However, analysts unlikely predict the occurrence of such an extreme event and therefore their forecast uncertainty at three and four quarters ahead should not be affected by it. A look at the data for the year 2001 for AMR Corporation reveals that forecast uncertainty estimated by the BKLS measure at three-quarter ahead increased almost 350 times from the year before, while it increased less than five times based on dispersion or the new suggested measure, as discussed in the next section.5

Finally, the BKLS measure relies on an assumption that is unlikely to hold in practice. Namely, actual earnings are assumed to be exogenous and hence, unaffected by analysts’ forecasts. However, there is a large number of studies showing that managers manipulate earnings to meet or beat analysts’ forecasts (see, e.g. Degeorge et al. 1999; Abarbanell and Lehavy 2003). To the extent that earnings management exists, common uncertainty measured by the actual squared error in the mean forecast will be understated.

3.3. New Uncertainty Measure

Since uncertainty is essentially an *ex ante* concept attached to a forecast before the actual earnings are known, it must be constructed using data available to analysts at the time forecasts are made. The BKLS model suggests that earnings forecast uncertainty is comprised of dispersion, $d_{th}$, and the variance of mean forecast errors, which we denote by $\sigma_{th}^2$. The intuition behind this uncertainty measure is as follows. Uncertainty arises from two sources: the error components in common information and those in private information. The $\sigma_{th}^2$ captures primarily the imprecision of common information,

5 The uncertainty at three-quarter ahead is calculated using forecasts issued during the months of February, March and April and AMR Corporation has a December 31 fiscal year-end.
and $d_{th}$ reflects the imprecision in analysts’ idiosyncratic information and diversity in their forecasting models.\(^6\)

Estimating the variance of mean forecast errors empirically poses a problem because some periods are likely to be more volatile than others and volatile periods tend to cluster. To deal with these problems, Engle (1982) develops the celebrated Autoregressive Conditional Heteroskedasticity (ARCH) model, which is generalized by Bollerslev (1986) to form GARCH. These models can be used to estimate volatility conditional on historical data and are therefore suitable for our purpose. The technique is now a standard approach for modeling different types of uncertainty in economics and finance.\(^7\) In our setting, the GARCH model assumes that the volatility of mean forecast errors depends on past forecast errors and lagged earnings forecast uncertainty. Specifically, the method uses historical mean forecast errors to provide an estimate of the variance of mean forecast errors for the current period. We estimate a simple GARCH (1, 1) model and generate the conditional variance, $\hat{\sigma}_{th}^2$. Then our uncertainty measure is the sum of the projected variance of mean forecast errors and the observed dispersion:

$$U_{th} = \hat{\sigma}_{th}^2 + d_{th}.$$

This procedure provides a reliable and comprehensive estimate of overall uncertainty that can be used in settings where other measures cannot, such as when firms’ operations are affected by unanticipated events, bankruptcy and large restructuring charges and when the construct of interest is the change in uncertainty. The new measure

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\(^6\) As in Barron et al. (1998), $\sigma_{th}^2$ (SE in their model), captures common uncertainty and a fraction of idiosyncratic uncertainty. As the number of analysts following a given firm increases, idiosyncratic errors will be averaged out in the mean forecast and $\sigma_{th}^2$ will reflect only common uncertainty.

\(^7\) See Bollerslev, Chou and Kroner (1992) for a relatively early survey of its applications and Andersen, Bollerslev and Diebold (2010) for more recent advances.
is easy to implement, since many widely used statistical software packages, such as Stata, Eviews and SAS, contain pre-programmed routines for the estimation of GARCH models. In Appendix A, we provide theoretical and implementation details on the GARCH model estimation.

4. Empirical Analysis

To illustrate the performance of three alternative uncertainty measures, we test the hypothesis, assuming that the Bayesian model is descriptive, that analysts rely more on reported earnings to revise their forecasts when the \textit{ex ante} uncertainty in future earnings is relatively high. In a recent paper, Yeung (2009) gives a detailed discussion and conducts a regression test of this hypothesis. In this section, we extend Yeung’s analysis by examining the relation between forecast revisions and earnings surprises conditional on analysts’ uncertainty for different forecast horizons.

The initial sample includes all US firms in the I/B/E/S Detail tape for the 24-year period 1984-2007. Following Yeung (2009), we require that forecasts are made within 90 days before the earnings announcement and revised forecasts are issued no later than 30 days after the earnings announcement. If an analyst makes more than one forecast in the period before or after the announcement, we include only the forecasts that are closest to the earnings announcement date. To obtain a better measure of dispersion, we require that there are at least three forecasts for each firm/year in the 90 days before the earnings announcement.

We split the data based on the length of the forecast horizon. Figure 2 provides a general timeline of events related to our empirical analysis. The forecasts at Horizon 1
are issued from 90 days before the last quarter’s earnings announcement to 30 days after. Similarly, the forecasts at Horizon 2 and Horizon 3 are issued from 90 days before the earnings announcement that are made at two and three quarters before the end of the target year, respectively, to 30 days after. We examine analysts’ forecast revision behavior on a horizon-by-horizon basis, since uncertainty varies over horizons. As the forecast horizon becomes longer, the variance of mean forecast errors tends to become the dominant component of uncertainty, and by construction, the new measure is expected to provide a better estimate of uncertainty under this situation.

In our analysis we require that sample firms have no missing forecasts and actual values, have data available for all 24 years and are listed on Compustat during the sample period. This leaves us with 128 firms for Horizon 1, 107 for Horizon 2 and 108 for Horizon 3. Table 1 provides information about the industry distribution of our sample firms. There are a total of 166 unique firms for all three horizons, with Durable manufacturers accounting for 25 percent of the sample, followed by Utilities accounting for 10 percent.

We run the following regression to examine the relation between forecast revision and earnings surprise conditional on analysts’ uncertainty for different horizons:

\[
\text{Revision} = \beta_0 + \beta_1 \cdot \text{Surprise} + \beta_2 \cdot \text{Surprise} \cdot \text{Uncertainty} + \\
\beta_3 \cdot \text{Uncertainty} + \beta_4 \cdot \text{Surprise} \cdot \text{Neg} + \beta_5 \cdot \text{Neg} + \epsilon
\]  

\[\text{(7)}\]

where

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8 This requirement restricts the sample to large and heavily followed firms and hence, in our sample the variance of mean forecast errors is likely to approximate the variance of unanticipated aggregate shocks.

9 All variables and formulas are summarized in Appendix B. For convenience, firm, year, and horizon subscripts are omitted.
Revision is defined as the revised mean annual forecast minus the mean annual forecast prior to the earnings announcement;

Surprise is defined as I/B/E/S actual earnings for the current quarter minus the mean forecast for the current quarter;

Uncertainty represents the natural logarithm of one of the following three uncertainty measures:

Dispersion is the forecast dispersion defined in equation (1), measured before the current quarter’s earnings announcement;

BKLS is the uncertainty measure proposed by Barron et al. (1998), defined in equation (5) as the sum of the squared error in the mean forecast and dispersion, measured before the current quarter’s earnings announcement;

ST is the new uncertainty measure defined in equation (6), calculated before the current quarter’s earnings announcement; and

Neg is equal to 1 if the reported earnings are negative and zero otherwise.\(^{10}\)

We also include year and firm fixed effects in our regressions. Uncertainty variables are measured using forecasts issued in the 90 days before the respective earnings announcement. Table 2 presents descriptive statistics for the variables used in our analysis. Revision has a negative mean at Horizons 1 and 2 and a positive mean at Horizon 3, implying that analysts are more likely to revise their forecasts upwards at longer horizons and downwards as the end of the target year is approaching. When it comes to the uncertainty measures, several interesting observations emerge. First, Dispersion is always lower than the other two, suggesting that this proxy likely

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\(^{10}\) Yeung (2009) adds |Surprise| and AR1 as additional control variables for the noise in earnings surprises. Since our goal is to examine the performance of three alternative measures of uncertainty, we maintain a parsimonious regression model.
understates uncertainty, consistent with it capturing only one component of uncertainty. This is especially true at longer horizons. At Horizon 1, the mean of Dispersion is 6 times smaller than that of ST, and 11 and 19 times smaller at Horizons 2 and 3, respectively. The medians show the same trend. Second, ST has the highest median among the three measures for all horizons, while BKLS has the highest mean. This is not surprising considering the fact that one of the components of the BKLS measure is the error in the mean forecast, which may result in substantially overstated uncertainty estimate in periods when significant unanticipated events occur causing a large error in the mean forecast.

To further examine their performance, we plot the medians of the uncertainty measures over time and by horizon. The results are presented in Figure 3. Clearly, Dispersion is always lower than the other two in all years and horizons, providing additional evidence that it likely understates uncertainty especially at long horizons. Another interesting finding is the increase in uncertainty in year 2001. The moderate increase in Dispersion and ST may be attributed to an economy-wide recession that occurred from March to November 2001. However, while it rose only slightly at Horizon 1, BKLS jumped a lot at Horizons 2 and 3. For example, at Horizon 3 the uncertainty based on BKLS rose dramatically – an increase of almost 400 percent in year 2001 relative to year 2000. This is possibly due to an enormous drop in earnings for many firms in the last two quarters of the fiscal year, following the event of 9/11. This results in a large error in the mean forecast, which, in turn, increases the BKLS measure of uncertainty. As noted earlier, however, such an extreme event could not be predicted prior to its occurrence and therefore, should not affect analysts’ uncertainty at the time.
they issue a forecast at Horizon 3. The uncertainty based on the BKLS measure may give misleading inferences in periods when significant unanticipated events occur after the forecasts are made.\footnote{Similar results are obtained when we plot the medians of the log-transformed and scaled uncertainty measures by firm price at the beginning of the quarter.}

Another observation worth mentioning from Figure 3 is the substantial difference between \textit{ST} and \textit{BKLS}, especially at Horizons 2 and 3, for all years except 2001. Both \textit{ST} and \textit{BKLS} use mean forecast errors as inputs, which are likely to be biased towards zero due to earnings management. The \textit{BKLS} measure has the \textit{level} of the squared error in the mean forecast as one component and hence, it is unambiguously understated, if earnings management occurs. However, \textit{ST} may or may not be understated, since it is based on the \textit{variance} of mean forecast errors. For example, consider an increase in actual earnings to meet the mean forecast in the same amount for all years for a given firm. Then, the mean forecast errors will be understated by that amount in all years, but the variance will remain the same. This can partially explain why median \textit{ST} provides higher estimates of uncertainty than median \textit{BKLS}.

Since all uncertainty measures, especially \textit{BKLS}, display a much higher mean than median, they are positively skewed and may include outliers. To alleviate the impact of possible outliers and non-normality of the distribution of the uncertainty measures, we use the natural logarithm transformations of these variables in our regression analysis (Barron and Stuerke 1998). Table 3 presents the Spearman correlation coefficients among the transformed uncertainty variables. The three measures are highly correlated, with
correlation coefficients of 0.741 or higher for all horizons. This is not surprising, since both BKLS and ST have Dispersion as one of the components.\footnote{Similar results are also obtained when Pearson correlations are calculated.}

We run regressions for each horizon separately to test the hypothesis that analysts rely more on reported earnings to revise their forecasts when the \textit{ex ante} uncertainty in future earnings is relatively high. Since it is constructed to capture primarily the variance of aggregate shocks that accumulate over time, the new uncertainty measure should perform better than the other two measures at longer horizons. As a result, we expect that the coefficient on \textit{Surprise*Uncertainty} is positive and larger, when uncertainty is measured by \textit{ST} than by \textit{Dispersion} or BKLS, especially at longer horizons.

The main regression results are presented in Table 4. Panel A shows the coefficient estimates on \textit{Surprise*Uncertainty} and the corresponding standard errors from regressions of \textit{Revision} on \textit{Surprise}, \textit{Surprise*Uncertainty} and \textit{Uncertainty}. At Horizon 1, all three measures give the similar result that, conditional on analysts’ uncertainty, forecast revisions and earnings surprises are positively correlated. As the forecast horizon gets longer, \textit{ST} gives the highest coefficient estimates. This is especially pronounced at Horizon 3, where the new measure yields an estimate of 0.173, compared to 0.081 and 0.102 when using \textit{Dispersion} and BKLS, respectively. Panel B reports the estimated results from the full regression model as specified in equation (7). At Horizon 2, the coefficient on \textit{Surprise*ST} is estimated to be 0.172 versus 0.121 on \textit{Surprise*Dispersion} and 0.110 on \textit{Surprise*BKLS}. At Horizon 3, the estimates are 0.257 when using the new measure versus 0.092 and 0.166 when using \textit{Dispersion} and BKLS as proxies for forecast uncertainty, respectively. Taken together, the estimated results reported in Table 4 show that the relations between \textit{Revision} and \textit{Surprise}, conditional on analysts’ uncertainty, are
much stronger when forecast uncertainty is estimated by $ST$ than by $Dispersion$ and $BKLS$, especially when the forecast horizon lengthens.

While the results in Table 4 are supportive, they do not provide a statistical test of the superiority of the new measure over the other two. For this purpose, we run regressions on stacked data where every observation appears twice using two alternative measures of uncertainty. The results of this analysis are presented in Table 5. In one regression, uncertainty is measured by $Dispersion$ and $BKLS$ and in another, by $BKLS$ and $ST$. We define an indicator variable, $BetterMeasure$, equal to one if uncertainty is measured by $BKLS$ (Panel A) or $ST$ (Panel B) and zero, otherwise. The coefficient on $BetterMeasure*Surprise*Uncertainty$ provides the key information about the differences in coefficients between $BKLS$ and $Dispersion$ (Panel A), and between $ST$ and $BKLS$ (Panel B). In Panel A, $BKLS$ shows a modest improvement over $Dispersion$. In Panel B, the reported positive and highly significant coefficients imply that $ST$ provides stronger results than $BKLS$ in support of the hypothesis tested in this paper.

As an additional comparative analysis, we estimate regressions of the form:

$$Revision = \theta_0 + \theta_1*Surprise + \theta_2*Surprise*Uncertainty1 + \theta_3*Surprise*Uncertainty2 + \theta_4*Uncertainty1 + \theta_5*Uncertainty2 + \theta_6*Surprise*Neg + \theta_7*Neg + \varepsilon_3,$$

where $Uncertainty1$ and $Uncertainty2$ are two alternative measures of uncertainty. Our main interest is in whether $\theta_3$ is positive and statistically significant. That is, conditional on $Uncertainty1$, do analysts use more current information to revise their forecast of future earnings when $Uncertainty2$ is higher? The estimates in Table 6 indicate that $BKLS$ contains information not captured by $Dispersion$ at all horizons (Panel A) and $ST$

\[13\] The full regression models and additional details of this analysis are presented in Table 5.
provides incremental information to BKLS at Horizons 2 and 3 (Panel B), which is consistent with the results in Table 4 and Table 5.

Since the main advantage of the new measure over the BKLS measure comes from the way in which the expected squared error in the mean forecast is estimated, we break down total uncertainty into its two components. The results of this analysis are presented in Table 7. In a regression of Revision on the interactions between Surprise and the separate components of uncertainty, we find that the coefficients on the interaction terms are much higher at Horizons 2 and 3, when the expected squared errors in the mean forecasts are estimated by the GARCH model rather than by the ex post squared mean forecast errors as in Barron et al. (1998) (Panel B vs. Panel A). In particular, when Surprise is interacted with common uncertainty measured by GARCH, the coefficients on the interaction term are estimated to be 0.326 at Horizon 3 and 0.057 at Horizon 2, both highly significant, while they are 0.125 and 0.010 when common uncertainty is measured by the actual mean squared error. This provides additional evidence that our technique gives a better estimate of common uncertainty than the BKLS measure and common uncertainty has an incremental effect on Revision beyond idiosyncratic uncertainty measured by Dispersion.

Next, we examine the economic significance of the results obtained with the new uncertainty measure ST. Since we include the interaction term Surprise*Uncertainty, the marginal effects of the earnings surprise variable have to be interpreted conditionally on the interaction with earnings forecast uncertainty. In principle, there are two sensible ways to evaluate the marginal effects. Following Jaccard, Turrisi and Wan (1990, p. 27), we evaluate the marginal effects at the low as well as the high level of the interacted
variable, i.e. earnings forecast uncertainty. Using this method we are able to examine the influences of earnings surprise on forecast revision when earnings uncertainty is high and low. In addition, we also evaluate the marginal effects at the average level of earnings forecast uncertainty.

Table 8 reports the estimated marginal effects when forecast uncertainty is constructed according to the new measure. In Panel A, at the average level of earnings forecast uncertainty, an increase in the earnings surprise by one percent raises forecast revision by 0.548 percent at Horizon 1 and by about 0.330 percent at Horizons 2 and 3. Moreover, earnings surprise has the most significant effect on forecast revision when earnings uncertainty is high for all horizons. For example, at Horizon 1, a one percent increase in Surprise is associated with a 0.754 percent increase in Revision when earnings forecast uncertainty is high and a 0.342 percent increase when uncertainty is low. The similar marginal effects are also observed in Panel B with Neg as an additional variable to control for the noise in earnings surprises. By including different forecast horizons, the results reported in Table 8 confirm and extend earlier findings in Yeung (2009) that analysts rely more on reported earnings to revise their forecasts, when the ex ante uncertainty in future earnings is relatively high.

To check the robustness of our empirical results, we perform several additional analyses.\footnote{All robustness checks results are available upon request.} Prior research suggests that analysts issue optimistic forecasts for annual earnings (see, e.g. Francis and Philbrick 1993), although more recent studies suggest that individual forecast bias decreases over time (Matsumoto 2002), decreases over the forecast horizon (Richardson, Teoh and Wysocki 2004) and is more pronounced for firms reporting losses (Brown 2001). A systematic bias in analyst forecasts will inflate the
common error in forecasts and potentially inflate uncertainty. However, this problem can be avoided when estimating the variance of mean forecast errors, because in the GARCH model specification the bias will be taken into account by including a constant term, $\phi_0$, in equation (A1) in Appendix A. To the extent that the bias is diversified away in the estimate of dispersion, the new measure is less likely to be affected by the presence of an optimistic bias in analyst forecasts than the BKLS measure.

Nevertheless, to control for the potential bias in analysts’ forecasts, we obtain “debiased” forecasts by subtracting a measure of the average level of optimism from the original forecasts as in Barron, Byard and Kim (2002). We perform the same analysis as described above using the “debiased” forecasts. Our results and inferences do not change, although the differences in the coefficient estimates on \textit{Surprise*Uncertainty} between using \textit{ST} and the other two measures are somewhat smaller. In another experiment we scale all continuous regression variables by total assets at the beginning of the fiscal year and repeat our analysis. Our inferences remain the same. Finally, as described in more detail in Appendix A, we try different initial values for the variance of mean forecast errors in estimating the GARCH (1, 1) model and obtain qualitatively similar results.

It should be noted that our measure has some potential drawbacks. First, it assumes that the past is a good guide to the future. Although this assumption, in one form or another, underlies all statistical analyses, there is always a risk that structural changes to earnings may alter their inherent predictability, thereby reducing the relevance of past mean forecast errors for the prediction of future errors. One should be alert to evidence of structural change and other factors that may alter the predictability of earnings. Second, the GARCH estimation procedure requires a long time-series of data without missing
values, restricting its applicability to heavily followed firms. However, recent advances in the area of econometric research have proposed ways of dealing with missing data and we leave it to future research to apply our technique to the wider population of firms.

In summary, the empirical results reported in Tables 4-8, as well as various robustness checks, demonstrate that our proposed measure of uncertainty provides superior performance over other extensively used measures, such as Dispersion and BKLS, especially at long horizons. The good performance of the new uncertainty measure is due to three reasons. First, ST provides an estimate of \textit{ex ante} earnings forecast uncertainty because it uses information available to analysts at the time they make their forecasts and hence, it is better aligned with the theoretical construct it intends to measure. By contrast, BKLS is constructed by using actual earnings, which are unknown to analysts until a later time. As a result, the error in the mean forecast, which is a component of BKLS, may be greatly affected by events that occur after forecasts are made but theoretically, such events should not affect \textit{ex ante} forecast uncertainty. Second, the new measure captures both components of uncertainty arising from analysts’ private and common information. Dispersion, on the other hand, is a measure of uncertainty based on analysts’ idiosyncratic information only. Third, the new measure includes the variance of aggregate shocks that accumulate over forecast horizons and thus gives a better proxy for uncertainty especially at longer horizons. Other measures that do not take account of the variance of accumulated aggregate shocks would be tenuous proxies for uncertainty when the forecast horizon gets longer. For these reasons, we recommend the use of the new measure of earnings forecast uncertainty in practice.
5. Conclusion

Based on the theoretical finding that uncertainty includes a common and an idiosyncratic component, we propose a new measure of earnings forecast uncertainty as the sum of the projected variance of mean forecast errors from a suitably specified GARCH model and dispersion among analysts. Compared to the existing proxies for uncertainty in the literature, the proposed measure has some obvious advantages: (i) it provides a measure of uncertainty that is conditional on observing forecasts and hence, can be estimated in practice; (ii) it is based on information available to analysts at the time they make their forecasts and gives an *ex ante* measure of uncertainty, thus circumventing the limitations associated with the BKLS measure; and (iii) it captures the uncertainty arising from both analysts’ common and private information and therefore avoids the problems of using dispersion alone as a proxy for uncertainty.

To illustrate the performance of the new uncertainty measure, we test the hypothesis that analysts rely more on reported earnings to revise their forecasts when the *ex ante* uncertainty in future earnings is relatively high. Our estimation results show that the positive relationship between forecast revisions and earnings surprises becomes stronger at longer forecast horizons, when uncertainty is estimated by our proposed measure rather than by dispersion alone or the BKLS measure. The main advantage of our measure over the BKLS measure comes from the way in which the expected squared error in the mean forecast is estimated. Thus, besides its three merits mentioned above, the new measure has a fourth advantage. By construction, it captures the variance of aggregate shocks that accumulate over forecast horizons and thus gives a better proxy for uncertainty especially at longer horizons.
The new uncertainty measure is easy to implement by using standard statistical packages and allows for the study of hypotheses that have not been tested before. For example, one can use the measure proposed here to explore to what extent analysts’ uncertainty about future earnings reflects the uncertainty due to common information versus private information. Another worthwhile extension is to estimate the expected squared error in the mean forecast by using the technique suggested in this paper and develop empirical proxies for other theoretical constructs, such as consensus and precision of information in earnings forecasts.
Appendix A: Estimation of the conditional variance $\sigma^2_{th}$ by GARCH models

GARCH(1, 1) model specification:

The simple GARCH(1, 1) model specification at horizon $h$ is: \(^{15}\)

$$ e_i = \phi_0 + \phi_1 e_{i-1} + \ldots + \phi_{h-1} e_{i-(h-1)} + \varepsilon_i, \quad \varepsilon_i|\Psi_{i-1} \sim N(0, \sigma^2_i), \quad (A1) $$

$$ \sigma^2_i = \alpha_o + \alpha_1 \varepsilon^2_{i-1} + \alpha_2 \sigma^2_{i-1}. \quad (A2) $$

The mean equation in (A1) is written as a function of a constant, moving average terms, and an error term. Since $\sigma^2_i$ is the one-period ahead forecast variance based on past information set $\Psi_{i-1}$, it is called the conditional variance. The conditional variance equation specified in (A2) is a function of three terms: (i) a constant term, $\alpha_0$; (ii) news about volatility from the previous period, measured as the lag of the squared residual from the mean equation, $\varepsilon^2_{i-1}$ (the ARCH term); and (iii) the last period’s forecast variance, $\sigma^2_{i-1}$ (the GARCH term).

Steps in estimating the conditional variance:

1. For each firm, year and horizon, calculate the mean forecast error across analysts’ earnings forecasts, $e_{ih}$.

2. Remove the possible bias and autocorrelation in the mean forecast error, $e_{ih}$, by fitting moving average (MA) models of varying order as in equation (A1). Theoretically, optimal forecasts $h$ steps ahead have dependence of order $h-1$. Hence at Horizon 1 one should fit a MA(0), at Horizon 2 – a MA(1) and at Horizon 3 – a MA(2) model.

---

\(^{15}\) Firm and horizon subscripts are omitted.
(3) Estimate the GARCH(1, 1) model.

(4) Generate the conditional variance $\hat{\sigma}_{th}^2$ using estimated model parameters.

Some implementation details:

The pre-programmed routines for the estimation of GARCH models are contained in most software, including Stata, Eviews and SAS. Very often, equations (A1) and (A2) are estimated at the same time in the program such that steps 2 and 3 can be combined. For example, in Stata this is done by using the following command:

```
arch error, arch(1) garch(1) ma(h-1) [options],
```

where error is the mean forecast error, calculated in step 1.

Here we briefly discuss some implementation details involved in the model estimation.

1. Distributional assumptions: We estimate GARCH(1, 1) model by the method of maximum likelihood under the assumption that the errors are conditional normally distributed. Other distribution assumptions, such as $t$-distribution and the generalized error distribution, are also worth trying.

2. Number of ARCH and GARCH terms: We use one ARCH and one GARCH term, i.e. GARCH (1, 1) to maintain a parsimonious model that entails fewer coefficient restrictions. Since all coefficients in (A2) must be positive and all characteristic roots of (A2) must lie inside the unit circle to ensure that the conditional variance is finite, most empirical implementations of GARCH models adopt low orders for the lag lengths $p$ and $q$ (Bollerslev et al. 1992). Formally, one way to determine the order of $p$ and $q$ is to use model selection criteria, such as Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) (see, e.g. Enders 2010, chapter 3).
(3) **Initial variance** \( \sigma_0^2 \): In our analysis we set the initial variance \( \sigma_0^2 \) using the unconditional variance in the sample.\(^\text{16}\)

(4) **Iterative estimation control**: We use the iterative algorithm, Marquardt, in our estimation. As is well known, the likelihood functions of GARCH models are not always well-behaved so that convergence may not be achieved with the default setting in the particular software. One can select other iterative algorithm, such as BHHH, increase the maximum number of iterations or adjust the convergence criterion.

(5) **Data requirement**: GARCH model estimation requires a long time series of data without missing observations. If not, appropriate assumptions have to be made regarding the missing values.

\(^{16}\) As a robustness check, we also set \( \sigma_0^2 \) using the backcasting procedure. The estimation results are similar.
Appendix B: Variable definitions

*Revision* is defined as the revised mean annual forecast minus the mean annual forecast prior to the earnings announcement;

*Surprise* is defined as I/B/E/S actual earnings for the current quarter minus the mean forecast for the current quarter;

*Uncertainty* represents the natural logarithm of one of the following three uncertainty measures:

*Dispersion* is forecast dispersion, measured before the current quarter’s earnings announcement: $\frac{1}{N} \sum_{i=1}^{N} (F_{ih} - F_{ih})^2$, where $F_{ih}$ is the mean forecast prior to the earnings announcement;

*BKLS* is the uncertainty measure proposed by Barron et al. (1998), defined as the sum of the squared error in the mean forecast and dispersion, measured before the current quarter’s earnings announcement: $(A_t - F_{ih})^2 + d_{sh}$;

*ST* is the new uncertainty measure, defined as the sum of the variance of mean forecast errors and dispersion, calculated before the current quarter’s earnings announcement: $\hat{\sigma}_{ih}^2 + d_{sh}$, where $\hat{\sigma}_{ih}^2$ is the conditional variance estimated by a GARCH (1, 1) model; and

*Neg* is equal to 1 if the reported earnings are negative and zero otherwise.
References:


Table 1: Sample firms industry distribution

<table>
<thead>
<tr>
<th>Industry</th>
<th>Number</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining and construction</td>
<td>3</td>
<td>2%</td>
</tr>
<tr>
<td>Food</td>
<td>9</td>
<td>5%</td>
</tr>
<tr>
<td>Textiles and printing/publishing</td>
<td>14</td>
<td>8%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>12</td>
<td>7%</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>9</td>
<td>5%</td>
</tr>
<tr>
<td>Extractive industries</td>
<td>13</td>
<td>8%</td>
</tr>
<tr>
<td>Durable manufacturers</td>
<td>42</td>
<td>25%</td>
</tr>
<tr>
<td>Computers</td>
<td>11</td>
<td>7%</td>
</tr>
<tr>
<td>Transportation</td>
<td>14</td>
<td>8%</td>
</tr>
<tr>
<td>Utilities</td>
<td>16</td>
<td>10%</td>
</tr>
<tr>
<td>Retail</td>
<td>8</td>
<td>5%</td>
</tr>
<tr>
<td>Financial institutions</td>
<td>12</td>
<td>7%</td>
</tr>
<tr>
<td>Insurance and real estate</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Services</td>
<td>3</td>
<td>2%</td>
</tr>
<tr>
<td>Other industry</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>166</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

Notes:
Sample firms are taken from I/B/E/S Detail tapes, without missing forecasts and actual values for the 24-year period 1984-2007, when earnings announcement dates fall within 90 days following the quarter end. In our analysis, data are split based on the period when the forecasts are issued relative to the end of the target year. We refer to these time periods as Horizon 1, Horizon 2 and Horizon 3. The Horizon 1 forecasts are issued from 90 days before the last quarter’s earnings announcement to 30 days after. Horizon 2 and Horizon 3 forecasts are made around earnings announcements two and three quarters before the end of the target year, respectively. More details are provided in Figure 2. The final sample includes 128 firms at Horizon 1, 107 firms at Horizon 2 and 108 firms at Horizon 3. This table includes the unique sample of firms for all horizons.

The industry classification is as in Barth, Beaver, Hand and Landsman (1999): Mining and Construction SIC codes 1000-1999, excluding 1300-1399; Food 2000-2111; Textiles and printing/publishing 2200-2780; Chemicals 2800-2824, 2840-2899; Pharmaceuticals 2830-2836; Extractive industries 2900-2999, 1300-1399; Durable manufacturers 3000-3999, excluding 3570-3579 and 3670-3679; Computers 7370-7379, 3570-3579, 3670-3679; Transportation 4000-4899; Retail 5000-5999; Financial institutions 6000-6411; Insurance and real estate 6500-6999; Services 7000-8999, excluding 7370-7379; Other industry 700 (Agricultural services).
Table 2: Descriptive statistics

Panel A: Horizon 1

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean</th>
<th>Std.</th>
<th>Quartile1</th>
<th>Median</th>
<th>Quartile3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revision</td>
<td>3001</td>
<td>-0.015</td>
<td>0.195</td>
<td>-0.033</td>
<td>0.000</td>
<td>0.028</td>
</tr>
<tr>
<td>Surprise</td>
<td>2983</td>
<td>-0.004</td>
<td>0.166</td>
<td>-0.014</td>
<td>0.002</td>
<td>0.022</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispersion</td>
<td>3072</td>
<td>0.025</td>
<td>0.171</td>
<td>0.000</td>
<td>0.001</td>
<td>0.006</td>
</tr>
<tr>
<td>BKLS</td>
<td>3072</td>
<td>0.232</td>
<td>5.295</td>
<td>0.001</td>
<td>0.004</td>
<td>0.026</td>
</tr>
<tr>
<td>ST</td>
<td>3072</td>
<td>0.154</td>
<td>1.016</td>
<td>0.003</td>
<td>0.012</td>
<td>0.062</td>
</tr>
</tbody>
</table>

Panel B: Horizon 2

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean</th>
<th>Std.</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revision</td>
<td>2469</td>
<td>-0.008</td>
<td>0.279</td>
<td>-0.040</td>
<td>0.003</td>
<td>0.044</td>
</tr>
<tr>
<td>Surprise</td>
<td>2534</td>
<td>0.006</td>
<td>0.252</td>
<td>-0.011</td>
<td>0.005</td>
<td>0.028</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispersion</td>
<td>2568</td>
<td>0.071</td>
<td>0.826</td>
<td>0.000</td>
<td>0.003</td>
<td>0.014</td>
</tr>
<tr>
<td>BKLS</td>
<td>2568</td>
<td>0.864</td>
<td>13.185</td>
<td>0.002</td>
<td>0.014</td>
<td>0.089</td>
</tr>
<tr>
<td>ST</td>
<td>2568</td>
<td>0.764</td>
<td>14.487</td>
<td>0.007</td>
<td>0.036</td>
<td>0.193</td>
</tr>
</tbody>
</table>

Panel C: Horizon 3

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean</th>
<th>Std.</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revision</td>
<td>2436</td>
<td>0.007</td>
<td>0.263</td>
<td>-0.033</td>
<td>0.010</td>
<td>0.048</td>
</tr>
<tr>
<td>Surprise</td>
<td>2469</td>
<td>0.010</td>
<td>0.126</td>
<td>-0.009</td>
<td>0.005</td>
<td>0.030</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispersion</td>
<td>2592</td>
<td>0.056</td>
<td>0.449</td>
<td>0.001</td>
<td>0.003</td>
<td>0.014</td>
</tr>
<tr>
<td>BKLS</td>
<td>2592</td>
<td>1.226</td>
<td>24.146</td>
<td>0.003</td>
<td>0.020</td>
<td>0.117</td>
</tr>
<tr>
<td>ST</td>
<td>2592</td>
<td>0.960</td>
<td>6.115</td>
<td>0.010</td>
<td>0.053</td>
<td>0.204</td>
</tr>
</tbody>
</table>

Notes:
This table presents the descriptive statistics for variables used in the statistical analysis. Variables are defined in Appendix B except that the results for Uncertainty are based on the untransformed variables. Horizons 1, 2 and 3 are defined in Table 1 and Figure 2.

Sample is obtained as described in Table 1.
Table 3: Spearman correlations

Panel A: Horizon 1

<table>
<thead>
<tr>
<th></th>
<th>Dispersion</th>
<th>BKLS</th>
<th>ST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispersion</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BKLS</td>
<td>0.867</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>0.775</td>
<td>0.761</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Panel B: Horizon 2

<table>
<thead>
<tr>
<th></th>
<th>Dispersion</th>
<th>BKLS</th>
<th>ST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispersion</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BKLS</td>
<td>0.852</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>0.809</td>
<td>0.780</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Panel C: Horizon 3

<table>
<thead>
<tr>
<th></th>
<th>Dispersion</th>
<th>BKLS</th>
<th>ST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispersion</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BKLS</td>
<td>0.811</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>0.760</td>
<td>0.741</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Notes:
All correlations are statistically significant at the two-tailed 1 percent level.

Variables are defined in Appendix B.
Table 4: Regression results by horizon

Panel A

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surprise*Dispersion</td>
<td>0.094**</td>
<td>0.071**</td>
<td>0.081**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Surprise*BKLS</td>
<td>0.078**</td>
<td>0.080**</td>
<td>0.107**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Surprise*ST</td>
<td>0.090**</td>
<td>0.083**</td>
<td>0.173**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
<td>(0.014)</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surprise*Dispersion</td>
<td>0.088**</td>
<td>0.121**</td>
<td>0.092**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Surprise*BKLS</td>
<td>0.090**</td>
<td>0.110**</td>
<td>0.166**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Surprise*ST</td>
<td>0.086**</td>
<td>0.172**</td>
<td>0.257**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.019)</td>
</tr>
</tbody>
</table>

Notes:
Panel A presents the coefficient estimates and standard errors of $\alpha_2$ from the following regression (standard errors are in parentheses):

\[ \text{Revision} = \alpha_0 + \alpha_1*\text{Surprise} + \alpha_2*\text{Surprise*Uncertainty} + \alpha_3*\text{Uncertainty} + u. \]

Panel B presents the coefficient estimates and standard errors of $\beta_2$ from the regression:

\[ \text{Revision} = \beta_0 + \beta_1*\text{Surprise} + \beta_2*\text{Surprise*Uncertainty} + \beta_3*\text{Uncertainty} + \beta_4*\text{Surprise*Neg} + \beta_5*\text{Neg} + \varepsilon_1, \]

where Uncertainty is measured by Dispersion, BKLS and ST. All variables are defined in Appendix B.

Year and firm fixed effects are included in all regression models.\(^{17}\)

** denotes significance at the 1 percent level (two-tailed test).

\(^{17}\) Full regression results are available upon request.
Table 5: Test of statistical difference in coefficients from regressions on stacked data

Panel A

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BKLS vs. Dispersion</strong></td>
<td>0.006</td>
<td>-0.030**</td>
<td>0.032*</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.016)</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ST vs. BKLS</strong></td>
<td>0.019**</td>
<td>0.030**</td>
<td>0.078**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

Notes:
The Table 5 presents the coefficient estimates and standard errors of $\delta_3$ from the following regression (standard errors are in parentheses):

$$\text{Revision} = \delta_0 + \delta_1 \times \text{Surprise} + \delta_2 \times \text{Surprise} \times \text{Uncertainty} +$$
$$\delta_3 \times \text{BetterMeasure} \times \text{Surprise} \times \text{Uncertainty} +$$
$$\delta_4 \times \text{BetterMeasure} \times \text{Uncertainty} + \delta_5 \times \text{BetterMeasure} +$$
$$\delta_6 \times \text{Uncertainty} + \delta_7 \times \text{Surprise} \times \text{Neg} + \delta_8 \times \text{Neg} + \varepsilon_2,$$

where $\text{Uncertainty}$ is measured by $\text{Dispersion}$ or $\text{BKLS}$ (Panel A) and $\text{BKLS}$ or $\text{ST}$ (Panel B), and $\text{BetterMeasure}$ is an indicator variable equal to one if $\text{Uncertainty}$ is measured by $\text{BKLS}$ (Panel A) or $\text{ST}$ (Panel B) and zero, otherwise. All variables are defined in Appendix B.

Year and firm fixed effects are included in all regression models.18

* denotes significance at the 5 percent level (two-tailed test).

** denotes significance at the 1 percent level (two-tailed test).

---

18 Full regression results are available upon request.
Table 6: Test of statistical difference in coefficients from regressions with augmented measures of uncertainty

Panel A

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BKLS vs. Dispersion</strong></td>
<td>0.076**</td>
<td>0.039**</td>
<td>0.188**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.013)</td>
<td>(0.017)</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ST vs. BKLS</strong></td>
<td>-0.060**</td>
<td>0.085**</td>
<td>0.184**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.025)</td>
</tr>
</tbody>
</table>

Notes:
Table 6 presents the coefficient estimates and standard errors of $\theta_3$ from the following regression (standard errors are in parentheses):

$$
Revision = \theta_0 + \theta_1 * \text{Surprise} + \theta_2 * \text{Surprise} * \text{Uncertainty1} + \theta_3 * \text{Surprise} * \text{Uncertainty2} + \theta_4 * \text{Uncertainty1} + \theta_5 * \text{Uncertainty2} + \theta_6 * \text{Surprise} * \text{Neg} + \theta_7 * \text{Neg} + \epsilon_3,
$$

where $\text{Uncertainty1}$ is measured by $\text{Dispersion}$ (Panel A) or $\text{BKLS}$ (Panel B), and $\text{Uncertainty2}$ is measured by $\text{BKLS}$ (Panel A) or $\text{ST}$ (Panel B). All variables are defined in Appendix B.

Year and firm fixed effects are included in all regression models.19

** denotes significance at the 1 percent level (two-tailed test).

19 Full regression results are available upon request.
Table 7: Regression results with components of uncertainty

Panel A

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dispersion</strong></td>
<td>0.036**</td>
<td>0.112**</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.023)</td>
</tr>
<tr>
<td><strong>SqError</strong></td>
<td>0.070**</td>
<td>0.010</td>
<td>0.125**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.009)</td>
<td>(0.013)</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dispersion</strong></td>
<td>0.065**</td>
<td>0.097**</td>
<td>-0.100**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.023)</td>
</tr>
<tr>
<td><strong>GARCH</strong></td>
<td>0.046**</td>
<td>0.057**</td>
<td>0.326**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.015)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>

Notes:
Table 7 presents the coefficient estimates and standard errors of $\gamma_2$ and $\gamma_3$ from the following regression (standard errors are in parentheses):

$$\text{Revision} = \gamma_0 + \gamma_1 \cdot \text{Surprise} + \gamma_2 \cdot \text{Surprise} \cdot \text{Dispersion} + \gamma_3 \cdot \text{Surprise} \cdot \text{CommonUncertainty} + \gamma_4 \cdot \text{Dispersion} + \gamma_5 \cdot \text{CommonUncertainty} + \gamma_6 \cdot \text{Surprise} \cdot \text{Neg} + \gamma_7 \cdot \text{Neg} + \epsilon$$

where **CommonUncertainty** represents the natural logarithm of one of the following two common uncertainty measures:

- **SqError** is the actual squared error in the mean forecast, $(A_{f_{th}} - F_{th})^2$;
- **GARCH** is the estimated squared error in the mean forecast, $\hat{\sigma}_{th}^2$, by GARCH.

All other variables are defined in Appendix B.

Year and firm fixed effects are included in all regression models.

** denotes significance at the 1 percent level (two-tailed test).
Table 8: Marginal effects of earnings surprise at different levels of uncertainty

Panel A

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.342**</td>
<td>0.140*</td>
<td>-0.080</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.066)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Surprise*ST</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.548**</td>
<td>0.339**</td>
<td>0.328**</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.048)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>High</td>
<td>0.754**</td>
<td>0.539**</td>
<td>0.737**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.032)</td>
<td>(0.047)</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.339**</td>
<td>-0.190**</td>
<td>-0.365**</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.071)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Surprise*ST</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.536**</td>
<td>0.221**</td>
<td>0.241**</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.050)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>High</td>
<td>0.733**</td>
<td>0.633**</td>
<td>0.848**</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.035)</td>
<td>(0.053)</td>
</tr>
</tbody>
</table>

Notes:
Panel A is based on the following regression model:

\[ Revision = \alpha_0 + \alpha_1 \times \text{Surprise} + \alpha_2 \times \text{Surprise} \times \text{Uncertainty} + \alpha_3 \times \text{Uncertainty} + u. \]

Panel B is based on the following regression model:

\[ Revision = \beta_0 + \beta_1 \times \text{Surprise} + \beta_2 \times \text{Surprise} \times \text{Uncertainty} + \beta_3 \times \text{Uncertainty} + \beta_4 \times \text{Surprise} \times \text{Neg} + \beta_5 \times \text{Neg} + \varepsilon, \]

where \text{Uncertainty} is measured by \text{ST}. All variables are defined in Appendix B.

Standard errors are in parentheses.

Year and firm fixed effects are included in all regression models.

* denotes significance at the 5 percent level (two-tailed test).
** denotes significance at the 1 percent level (two-tailed test).
Figure 1: Combinations of dispersion and uncertainty

Notes:
This figure presents different combinations of dispersion and uncertainty as in Zarnowitz and Lambros (1987). The dispersion among analysts is said to be “low” when their point forecasts are clustered (charts (a) and (b)) and “high” when they are widely dispersed (charts (c) and (d)). The degree of uncertainty is said to be “low” when the probability distributions are tight (charts (a) and (c)) and “high” when they are diffuse (charts (b) and (d)).
Figure 2: Timeline

Notes:
This figure describes the timeline of events assumed in our empirical analysis. Uncertainty is measured using forecasts issued in the 90 days before the current quarter’s earnings announcement (EA). Revised forecasts are issued in the 30 days following the earnings announcement. Horizon 1 forecasts are issued from 90 days before the last quarter’s earnings announcement to 30 days after. Horizon 2 and Horizon 3 forecasts are made around earnings announcements two and three quarters before the end of the target year, respectively.
Figure 3: Evolution of earnings forecast uncertainty over time

Notes:
The figure plots the annual median uncertainty measured by untransformed $ST$, $BKLS$ and $Dispersion$. All variables are defined in Appendix B. The sample is the same as that used in our empirical analysis and is obtained as described in Table 1.

Note that different scales on the vertical axis are used at different horizons.