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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 alleviates some of 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.

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.

One of the most commonly used measures of earnings forecast uncertainty is the dispersion among analysts (see, e.g. Baginski et al., 1993; Diether et al., 2002; Clement et al., 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 et al. (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 et al. (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

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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 et al. (1998). The authors suggest that uncertainty be estimated as the sum of dispersion and the squared error in the mean forecast (BKLS Uncertainty hereafter). BKLS Uncertainty correctly recognizes the fact that uncertainty is comprised of two components. However, there are important caveats when using BKLS Uncertainty as a proxy for *ex ante* uncertainty. Since forecast errors are known to respondents only after the announcement of actual earnings, BKLS Uncertainty provides an estimate of *ex post* uncertainty.[1] As discussed in detail later in this paper, BKLS Uncertainty is excessively affected by significant unanticipated events following the forecast, such as 9/11-type 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 et al., 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 BKLS Uncertainty as a proxy for *ex ante* uncertainty faced by analysts becomes an important empirical issue.

In this paper we propose a new empirical measure of earnings forecast uncertainty. Since uncertainty is fundamentally an *ex ante* concept attached to a forecast before 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 and it captures both components of the theoretical construct.

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. BKLS Uncertainty, 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 *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 relation 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.

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

2. Empirical measures of earnings forecast uncertainty

Before discussing the possible empirical proxies for uncertainty, one must understand the theoretical construct. We adopt the well-known model of Barron et al. (1998). Let μ_{ith} be the h-quarter ahead earnings forecast made by analyst i, for target year t, where $i=1,\ldots,N$, $t=1,\ldots,T$ and $h=1,\ldots,H$, and μ_{th} be the mean forecast averaged over N analysts. Then the observed dispersion among analysts, d_{th}, is expressed as the population variance of their point forecasts[2]

$$d_{th}=\frac{1}{N}\sum_{i=1}^{N}(\mu_{ith}-\mu_{th})^2. \tag{1}$$

Let y_t denote actual earnings. The observed error in the mean forecast, e_{th}, is defined as

$$e_{th}=y_t-\mu_{th}. \tag{2}$$

Barron et al. (1998) find that after observing forecasts at time $t-h$, overall uncertainty is equal to the sum of the expected squared error in the mean forecast and observed dispersion:

$$V_{th}=E(e_{th}^2)+d_{th}. \tag{3}$$

Eq. (3) shows that overall earnings forecast uncertainty is comprised of two elements—a common and an idiosyncratic. 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 future events that

[1] We should point out that BKLS Uncertainty is only partially *ex post* because it includes contemporaneous dispersion.

[2] Barron et al. (1998) define dispersion as the sample variance of forecasts rather than the population variance and note that all of their formulas can be obtained using either definition of dispersion.

[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.