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Quantifying differential interpretation of public information using financial analysts' earnings forecasts

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ABSTRACT

Based on a standard Bayesian learning model, we propose a new measure of differential interpretation of public information, which is applicable to firms with analyst following. We validate our measure in the context of earnings announcements and provide evidence of its greater applicability, relative to a number of previously used proxies, such as the change in dispersion, Kandel and Pearson's (1995) metric, abnormal volume and the bid–ask spread. We find that the new measure of differential interpretation is related positively to other commonly used proxies, namely trading volume, disclosure informativeness, and the cost of capital, and is related negatively to disclosure readability and management guidance precision. This more precise measure of opinion divergence will enable researchers to pursue studies that were previously difficult to conduct.

1. Introduction

For decades, researchers, practitioners and regulators have taken great interest in the effect of disclosure on the behavior of market participants. Public disclosures, such as earnings announcements, are particularly intriguing, because they are perceived to play a role in leveling out the information playing field (Levitt, 1998), but often spur very different responses from the various market participants. Researchers have provided a variety of potential explanations for this phenomenon, one of which is differential interpretation of the public disclosure (Cao & Ou-Yang, 2009; Harris & Raviv, 1993; Kandel & Pearson, 1995). Unfortunately, differential interpretation is unobservable, and obtaining an adequate measure of this construct has been a challenge in the literature.[1]

To infer opinion divergence, researchers have used proxies such as dispersion, abnormal volume or the bid–ask spread. However, all of these measures capture more than differential interpretation. Dispersion also reflects uncertainty about earnings (Doukas, Kim, & Pantzalis, 2006) or idiosyncratic risk (Johnson, 2004). Abnormal volume may be driven by differences in prior beliefs (Banerjee & Kremer, 2010). The bid–ask spread contains inventory holding and order processing costs (George, Kaul, & Nimalendran, 1991). Motivated by this issue, Garfinkel (2009) conducts a systematic comparison of alternative proxies to a "true" measure of opinion divergence, based on proprietary data of investors' orders in NYSE stocks. We build upon Garfinkel's research by providing further comparative evidence on the adequacy of various proxies of opinion

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[1] The terms differential interpretation and opinion divergence are used interchangeably throughout the paper.

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divergence. More importantly, we advance a new alternative, which is well aligned with theory and obtainable for a large sample of firms.

The proposed measure of differential interpretation originates from the Bayesian learning model developed by Kandel and Pearson (1995). In this context, we show that the dispersion of analysts' expectations following public disclosure comes from two sources: differences in prior beliefs and differences in the interpretation of the public signal. This decomposition allows us to remove the effect of differences in priors from differential interpretation, which provides an empirical estimate of opinion divergence based only on analyst forecasts. The new empirical proxy is a function of pre- and post-disclosure dispersion and the weight analysts place on prior beliefs.

To assess our measure, we examine its ability to capture variation in opinion divergence using several analyses. The results provide convincing evidence that our proposed measure is as good as or superior to previously used proxies, such as the change in dispersion, Kandel and Pearson's (1995) measure, several estimates of abnormal volume, and the bid–ask spread. Specifically, we find that the new measure is related positively to several common proxies for opinion divergence, namely trading volume, the informativeness of the earnings announcement and the cost of capital, while it is related negatively to disclosure readability and management guidance precision. Furthermore, only the proposed measure provides consistent, statistically significant evidence in all empirical applications. In summary, the analyses indicate that the proposed measure captures the unobserved differential interpretation reliably in a variety of settings.

One potential limitation of the proposed metric is its dependence on a heavy analyst following to reliably estimate the weight analysts put on their prior belief. In our last set of analyses, we relax the data requirements and perform the validity tests using three alternative estimates of the new measure. For example, one approach requires only three forecasts before and after an earnings announcement, which is a common data requirement in studies that consider dispersion as a variable of interest. The results are similar to those of the main analyses, and suggest that our method can be applied to a wider sample of firms with analyst followings.

This paper contributes to the literature by separating the two possible explanations for investor disagreement following public disclosure: differences in prior beliefs and differences in the interpretation of the public signal. Prior studies have found this task difficult (Bamber, Barron, & Stober, 1999). More importantly, we employ this decomposition to develop an improved measure of differential interpretation. The proposed metric is preferable to previously used proxies because of its strong alignment with the theoretical construct and its ease of implementation with any statistical software that is capable of regressions. The wide applicability of our proposed measure opens the door to a myriad of new research questions and untested hypotheses. Prior proxies for differential interpretation provide measures that do not capture the construct fully (Kandel & Pearson, 1995) or rely on largely unavailable data (Garfinkel, 2009). Finally, in addition to validating the new measure using empirical applications that already exist in the literature, we also show a link between differential interpretation and other constructs of interest. Specifically, we find that opinion divergence decreases as earnings press releases become more transparent and as management provides more precise guidance, while differential interpretation is associated with increases in the firm cost of capital.

The rest of the paper is organized as follows. Section 2 proposes the new measure and summarizes alternative proxies for differential interpretation. Section 3 discusses the validation tests and presents the results of our empirical analyses. Finally, Section 4 concludes.

2. Empirical estimates of differential interpretation

2.1. A new measure of differential interpretation

The proposed empirical measure of differential interpretation stems from a Bayesian learning model, which is most closely related to the seminal work of Kandel and Pearson (1995). Recently, similar learning models have been applied and extended by a number of authors, such as Clements (2014), Kandel and Zilberfarb (1999), Lahiri and Sheng (2008, 2010), and Manzan (2011). The key elements and implications of our model are discussed next.

Before observing any public signals, analysts hold prior beliefs about firm *j*'s earnings. We assume that analyst *i*'s initial prior belief about firm *j*'s earnings for the year t, $\tilde{F}_{it}$, is represented by $\tilde{F}_{it} \sim N(BF_{it}, a_t^{-1})$ for $i = 1, \ldots, N$, $t = 1, \ldots, T$, where BF_{it} and a_t are the mean and precision of analyst *i*'s initial prior belief, respectively. In our model specification, analysts are endowed with divergent prior beliefs. For simplicity, the firm and horizon subscripts are omitted.

With the arrival of new public information, analysts modify their initial beliefs. We assume that all analysts receive a common signal, L_t, about future earnings, but they may not interpret it identically. In particular, analyst *i*'s estimate, Y_{it}, of earnings, conditional only on the new public signal observed at time t, can be written as $Y_{it} \sim N(L_t - \mu_{it}, b_t^{-1})$. This implies that analysts form expectations about earnings based on the public signal plus a random error. They may disagree about the mean of the error, which is captured by μ_{it}. With respect to an earnings announcement, this is akin to all analysts observing the same disclosure, but having heterogeneous assessments of its implications for future earnings. To ensure the tractability of our model, we follow Banerjee and Kremer (2010) by assuming that analysts agree on the precision of the public signal, b_t, which may vary over time and across firms. In our Bayesian learning model, differential interpretations are modeled by endowing analysts with different likelihood functions, which corresponds to analysts using different models to interpret public signals. Alternatively, investors may use the public signal to develop new private information, which will also cause differential interpretation following the earnings announcement. However, as Kim and Verrecchia (1997, p. 399) state, it is not possible to distinguish between differences in likelihood functions