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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 $i = 1, \dots, N$, $t = 1, \dots, T$, 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 and differential interpretations of an earnings announcement from event-period information. Hence, the two types of models are analogous.

Under the normality assumption, the Bayes rule implies that analyst i's posterior mean, AF_{it}, is the weighted average of his prior mean and his estimate of earnings, conditional on the new public signal:

$$AF_{it} = \lambda_t BF_{it} + (1 - \lambda_t)(L_t - \mu_{it}), \tag{1}$$

where $\lambda_t = a_t/(a_t + b_t)$ is the weight analysts put on the prior belief. Since we expect the prior mean, BF_{it}, and the interpretation bias, μ_{it}, to be mutually independent, from Eq. (1) we can derive the following relationship for disagreement before and after observing public signals:[2]

$$AD_t = \lambda_t^2 BD_t + (1 - \lambda_t)^2 DI_t, \tag{2}$$

where AD_t is the dispersion after the earnings announcement (cross-analyst variance of AF_{it}), BD_t is the dispersion before the earnings announcement (cross-analyst variance of BF_{it}), and DI_t is the differential interpretation of public information (cross-analyst variance of μ_{it}) for each firm/year. In Eq. (2), forecast disagreement is postulated to have two components, due to cross-analyst differences in (i) prior beliefs, BD_t, and (ii) the interpretation of public signals, DI_t.[3] This decomposition of forecast dispersion is aligned with a large body of theoretical and empirical research that explains the way in which disagreement arises from agents' possession of private pre-disclosure information (e.g. Abarbanell, Lanen, & Verrecchia, 1995; Kim & Verrecchia, 1991), or becoming differentially informed following a commonly-observed signal (e.g. Harris & Raviv, 1993; Kandel & Pearson, 1995). Past empirical results have lent support to both sets of theories (e.g. Bamber et al., 1999; Barron, Harris, & Stanford, 2005).

The decomposition of post-disclosure dispersion allows us to distinguish between differential interpretation and differences in priors and to obtain an empirical estimate of opinion divergence across analysts as follows:

$$DI_t = \frac{AD_t - \hat{\lambda}_t^2 BD_t}{(1 - \hat{\lambda}_t)^2}. \tag{3}$$

In Eq. (3), $\hat{\lambda}_t$ is obtained in each firm-quarter from the cross-analyst demeaned regression of Eq. (1). Specifically, we run the following regression:

$$(AF_{it} - AF_t) = \alpha_t + \lambda_t (BF_{it} - BF_t) + e_{it}, \tag{4}$$

where AF_t (BF_t) is the average forecast across analysts after (before) the earnings announcement. We perform the cross-analyst demeaned estimation for each firm-quarter in Eq. (4) to control for possible correlations across analysts, since their forecasts are affected by the same public information. Also, note that the error term in Eq. (4) might exhibit heteroskedasticity of an unknown form. However, an OLS estimation still yields consistent estimates of λ_t.

The proposed DI_t measure is better at identifying opinion divergence, due to the way in which DI_t captures the "unexpected dispersion" from the differential interpretation of new information. As was pointed out by Barron, Stanford, and Yu (2009), changes in dispersion capture information asymmetry. However, it is important to note that information asymmetry and differential interpretation are two distinct concepts. On the one hand, information asymmetry may arise due to differential interpretation if some market participants become better informed than others. However, Bloomfield and Fischer (2011) suggest that divergence of opinion may occur without an increased information asymmetry. A higher estimate of DI_t suggests that analysts have more heterogeneous assessments of the implications of currently reported earnings for future earnings. The strengths of this differential interpretation measure are its strong basis in theory and its ease of implementation using any statistical software package that is capable of regressions.

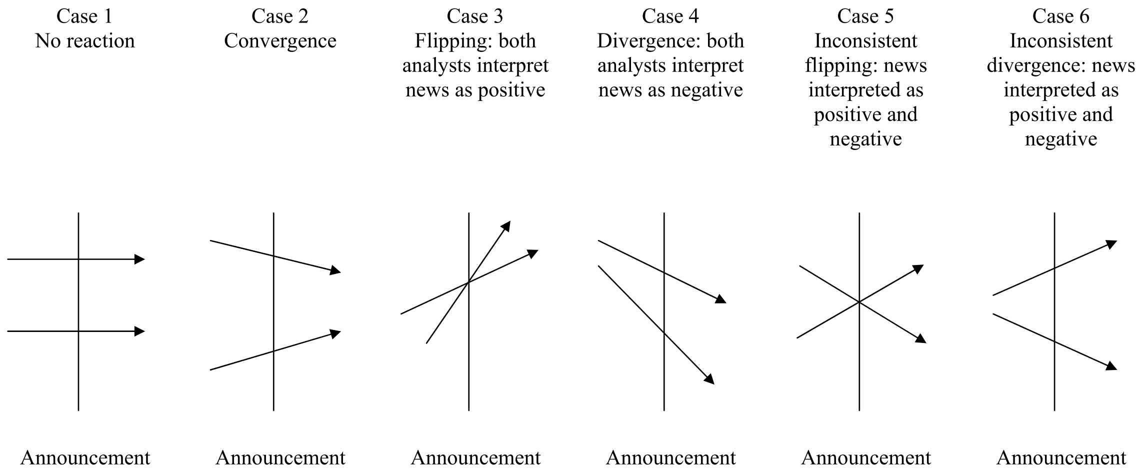
2.2. Other measures of differential interpretation

There are several measures of differential interpretation that have been used in the literature. One commonly-used such measure is the forecast dispersion or change in dispersion around some disclosure event, such as an earnings announcement (Ajinkya, Atiase, & Gift, 1991; Berkman, Dimitrov, Jain, Koch, & Tice, 2009; Diether, Malloy, & Scherbina, 2002; Rees & Thomas, 2010). The problem with this metric is that dispersion captures other unobservable constructs, such as uncertainty about earnings or idiosyncratic risk (Ramnath, Rock, & Shane, 2008; Sheng & Thevenot, 2012).

Another popular proxy for opinion divergence is Kandel and Pearson's (1995) measure. Fig. 1, adapted from Bamber et al. (1999, p. 372), illustrates six possible types of analysts' revisions of annual earnings, following a quarterly earnings announcement. Case 1 demonstrates the no-revision situation, which occurs if the announcement has no information content and analysts continue to rely on their priors. Case 2 shows convergence of opinions, which occurs when analysts' degree of consensus increases following the announcement. Cases 3–6 illustrate instances where analysts revise differentially. However, Kandel and Pearson's (1995) divergence of opinions measure is defined only as the percentage of analyst pairs that revise their expectations in opposite directions, as in Cases 5 and 6 in Fig. 1. Revising in opposite directions happens only if opinions about the signals diverge (even if pre-disclosure information also differs). Kandel and Pearson's approach underestimates differential interpretation because it classifies Cases 3 and 4, where analysts revise in the same direction, as homogeneous. These cases may occur due to

[2] Interested readers can refer to Lahiri and Sheng (2008) for the additional assumptions and detailed derivation of Eq. (2) from Eq. (1).

[3] In the general case, where analysts assign different weights to new information depending on their prior beliefs, forecast disagreement also arises from a third source: the cross-analyst differences in the weights attached to public information. However, in this case we cannot estimate separately the cross-analyst differences in (i) interpreting the public information and (ii) the weights attached to the new information for each horizon and each time period. By pooling the observations over time, Lahiri and Sheng (2008) find that the cross-analyst differences in the weights, that is, the third channel, have barely any effect on forecast disagreement on average, implying that analysts place very similar weights on their updated prior beliefs.



Notes

The figure, adapted from Bamber, et al. (1999, p. 372), illustrates six possible types of analysts' revisions of annual earnings following a quarterly earnings announcement. Case 1 is the no-revision situation, which occurs if the announcement has no information content and analysts continue to rely on their priors. Case 2 shows a convergence of opinions, which occurs when analysts' degree of consensus increases following the announcement. Cases 3 and 4 illustrate instances where analysts revise differentially due to differences in their pre-disclosure information, a differential interpretation, or both, but differential interpretation need not exist. Cases 5 and 6 occur only if opinions about the signals diverge (even if the pre-disclosure information differs).

Fig. 1. Alternative possible reactions to public news.

either differences in pre-disclosure information or differential interpretation.[4] In the latter case, Kandel and Pearson's metric does not capture the underlying construct fully, and may not provide enough power in statistical tests. In addition, this measure is designed primarily to capture differential interpretation in cases where the disclosure does not have an information content, which is only a small subset of all disclosures.[5]

The next set of proxies includes different measures of unexplained trading volume. These measures derive their justification from research that finds either abnormal amounts of volume that should not exist without divergence of opinions (Kandel & Pearson, 1995) or a positive relationship between volume and proxies for differential interpretation (Banerjee, 2011). Recent research by Garfinkel (2009) concludes that such proxies are most consistently and strongly correlated with the author's newly constructed measure based on proprietary data of investors' orders in NYSE stocks. However, abnormal volume measures are not without shortcomings when used as proxies for differential interpretation. Firm-specific volume may also be correlated with liquidity (Petersen & Fialkowski, 1994), market volume (Tkac, 1999) and other information-based variables (Atiase, Ajinkya, Dontoh, & Gift, 2011). Moreover, Banerjee and Kremer (2010) show that the volume around an earnings announcement consists of two components: volume due to the resolution of previous disagreement that leads to convergence and volume due to differential interpretation. These dual trading incentives imply that the abnormal volume by itself may not be a reliable measure of opinion divergence in the market.

Finally, researchers have used the bid–ask spread as a proxy for differential interpretation (Handa, Schwartz, & Tiwari, 2003). As is well known, bid–ask spreads represent three components: holding inventory cost, cost of processing orders and risk of trading with more informed investors. To the extent that divergence of opinion makes some investors become more informed than others, the information asymmetry component of the bid–ask spread is correlated with differential interpretation. However, the presence of the other two components adds noise to this measure. Furthermore, George et al. (1991) show that the order processing cost dominates the information asymmetry component in bid–ask spread measures. Even if the information asymmetry aspect could be isolated, Bloomfield and Fischer (2011) argue that information asymmetry and differential interpretation are two distinct constructs and should not be substituted for one another.

Overall, the accounting and finance literature provides various measures of opinion divergence, but all have significant shortcomings. We address these problems with our new measure of differential interpretation. Next, we examine the discussed proxies and compare their performances in several validation tests.

3. Empirical analysis

3.1. Precedents

Convincingly demonstrating that a proxy for an unobservable variable is adequate is difficult, because a comparison to a true measure of the construct may not be possible.

[4] Bamber et al. (1999) provide an example for Case 3 as follows. If an analyst has more pre-disclosure optimism and also more precise pre-disclosure information, then this analyst will weigh the news less heavily and the revision will be smaller than that of the less informed analyst.

[5] Bamber et al. (1999, p.379) discuss in detail the limitations and lack of power of Kandel and Pearson's measure.

Garfinkel (2009) provides a notable exception by using the limit orders in the New York Stock Exchange to obtain a direct measure of opinion divergence. This allows the author to draw conclusions about which proxies are better than others, based on correlations with the direct measure. Since we are unable to perform such an analysis, the validation of our proposed measure is not as straightforward. However, we present results from several tests, suggested by theory, prior research and intuition, and presume that a good measure should perform well in all of those settings.

To illustrate the performances of the new and alternative differential interpretation measures, we consider the following empirical assessments. First, we examine the relationship between the new measure of opinion divergence and other commonly used proxies. If the proposed metric and the other candidates capture the same underlying construct, then they should be positively correlated. Second, we examine the theoretical implications of the findings of Banerjee and Kremer (2010) and Kandel and Pearson (1995), and test whether the firm volume increases with differential interpretation. Since this result has been documented by Bamber et al. (1999) and others, we use this relationship to assess the new measure. Third, we examine the potential determinants of differential interpretation and explore whether the measure is related positively to the informativeness of the disclosure, as was suggested by Holthausen and Verrecchia (1990). In addition, we also test whether opinion divergence is related positively to the lack of readability of the earnings press releases and negatively to the precision of management earnings guidance. The reason for these predictions is as follows. If the disclosure is more difficult to understand and includes dubious language, i.e., is less transparent, then analysts are more likely to disagree about the implications of the disclosure for future earnings, and hence, the degree of differential interpretation will be higher. Similarly, if management provides voluntary disclosure along with the earnings announcement, and such disclosure is of high precision, such as a point forecast, then differential interpretation of this information should decrease. Prior research by Lehavy, Li, and Merkley (2011) has found that a lack of 10-K readability is associated with a greater analyst forecast dispersion, lower accuracy, and greater uncertainty. We build upon this study by examining the effect of 8-K readability on another feature of the information environment—opinion divergence. In addition, we also consider an important type of voluntary disclosure that provides a nice setting for a direct investigation of the relationship between the precision of disclosed information and opinion divergence.

Finally, we explore the link between differential interpretation and the cost of capital. Some theory has suggested a positive relationship (Varian, 1985), but direct empirical evidence on the link between opinion divergence and the cost of capital is overwhelmingly scarce. In a recent review of the literature on trading volume around earnings announcements, Bamber, Barron, and Stevens (2011, p. 433) state:

"There is a growing belief that the cost of capital increases in opinion divergence, if this divergence results from some investors being at information disadvantage that causes them to require a price lower than intrinsic value to enter the market".

This implies an information asymmetry effect on the cost of capital, which has been well documented (Easley & O'Hara, 2004), but also an understudied differential interpretation effect. It is important to note that these constructs are distinct. On the one hand, information asymmetry may arise due to differential interpretation, as was implied by Bamber et al. (2011). On the other, Bloomfield and Fischer (2011) suggest that a divergence of opinion may occur without an increased information asymmetry. Therefore, the link between differential interpretation and the cost of capital should be studied directly. In addition, prior research suggests that a higher cost of capital results when either the amount of public information is low or the precision of private information is high (Barron, Sheng, & Thevenot, 2014). All of these elements may be linked to investors having diverse opinions about the firm, which translates into a positive relationship with the cost of capital. Although these constructs are related, they have significant theoretical differences, and the link between differential interpretation and the cost of capital has not been examined carefully in the literature to date.

In summary, we investigate the relationships between the new measure of differential interpretation and (i) other commonly used proxies, (ii) firm trading volume around the announcement, (iii) the information content of disclosure, (iv) the readability of the earnings press release, (v) the precision of management guidance, and (vi) the cost of capital. Our ex ante expectation is that the proposed measure will be related positively to firm volume and disclosure informativeness, but these links will not necessarily be stronger than the other divergence of opinion proxies. Simply by construction, the volume-based measures will have the strongest association with volume. However, we expect that the proposed measure will outperform all other proxies in the readability, guidance and cost of capital tests, due to the its close ties to theory.

3.2. Data and descriptive statistics

The initial sample that is used to calculate the measure of differential interpretation proposed in this study is taken from the Institutional Brokers' Estimate System (I/B/E/S) Detail tape, which includes US firms with available annual forecasts and actual earnings data during the time period 1984–2012. We require that quarterly earnings announcement dates be within 90 days of the fiscal quarter end and be available on I/B/E/S. In order to estimate the weight that analysts put on the prior belief for each firm-quarter, we require that at least ten analysts provide a forecast prior to the announcement of quarterly earnings, then revise their forecasts following the announcement in each firm-quarter. To be included in the sample, an analyst must make a forecast no more than 90 days before the earnings announcement and revise it no later than 45 days after the announcement. If an analyst makes multiple forecasts in either of these windows, we keep the forecasts

Table 1
Descriptive statistics.

	N	Mean	Std Dev	Q1	Median	Q3
DI	16,837	0.629	3.690	0.001	0.008	0.058
Lambda	16,837	0.431	0.247	0.234	0.414	0.609
AD	16,837	0.062	0.281	0.001	0.004	0.019
BD	16,837	0.090	0.368	0.001	0.007	0.032
ChangeD	16,837	−0.027	0.147	−0.009	−0.001	0.000
RatioD	16,837	0.858	2.482	0.339	0.600	0.968
KP	16,837	11.041	12.293	0.000	7.500	19.853
MATO	16,837	0.023	0.037	−0.003	0.010	0.038
DTO	16,837	0.017	0.024	0.002	0.010	0.027
SUV	16,837	3.144	4.595	0.133	2.244	5.070
BAspread	16,837	0.007	0.013	0.001	0.001	0.008
Vol	16,837	0.066	0.077	0.020	0.043	0.085
Mktvol	16,837	0.027	0.013	0.017	0.024	0.036
AbCAR	16,837	0.055	0.061	0.017	0.038	0.073
Follow	16,837	14.473	4.570	11.000	13.000	17.000
GuidePrec	16,837	0.828	1.378	0.000	0.000	3.000
Mktvalue	16,610	16,038	35,291	1913	4975	14,056
BM	16,609	0.494	0.445	0.250	0.409	0.640
Growth	16,810	0.683	3.476	0.106	0.183	0.380
Beta	16,180	1.312	0.778	0.797	1.166	1.639
COC	15,350	0.126	0.085	0.084	0.103	0.140
Fog	6,521	17.001	2.485	15.383	16.822	18.491

Notes
The table is based on available firm-quarter observations from 1984–2011. We require that at least ten analysts produce forecasts of annual earnings in the 90 days before the earnings announcement of the first, second and third quarters' earnings, and then these same analysts revise their forecasts in the 45 days following the quarterly earnings announcement. The variables are defined in Appendix.
ChangeD and *DI* are winzorized at the 1% and 99% levels.

that are closest to the earnings announcement.[6] We include data from three horizons and measure differential interpretation around the first three quarters' earnings announcements using analyst forecasts for the current year's earnings.

To obtain the proposed differential interpretation measure, we first run the regression in Eq. (4) in each firm-quarter, to estimate the weight attached to the prior belief, λ, with the requirement that a firm must have an analyst following of at least ten analysts. In the additional analyses reported later in the paper, we relax the data requirement of ten analysts. Since the weight, λ, is bounded by 0 and 1, we set it to 0.01 if the estimated $\hat{\lambda}$ is less than or equal to zero, and to 0.99 if $\hat{\lambda}$ is greater than or equal to one. Using the estimated $\hat{\lambda}$ and the dispersion after/before the earnings announcement as the input for Eq. (3) yields the estimated differential interpretation measure, *DI*, in each firm-quarter.

As has been discussed, we consider several alternative measures of differential interpretation in addition to *DI*. First, our model shows that differential interpretation is a function of dispersion pre- and post-disclosure. Therefore, we consider the change in dispersion (*ChangeD*) as one candidate metric. Second, we take Kandel and Pearson's (1995) measure (*KP*), defined as the percentage of pairs of analysts who revise their forecasts as in Cases 5 and 6 of Fig. 1. For consistency, we estimate *ChangeD* and *KP* using the same I/B/E/S forecast data that we use to estimate *DI*. Since *DI* and *ChangeD* produce some large outlying observations, we winsorize these variables at the top and bottom 1%.[7] The volume-based measures are taken from Garfinkel (2009). We calculate three measures of the unexplained volume using daily CRSP data over a three-day window, centered on the day of the earnings announcement: *MATO* (market-adjusted turnover), *DTO* (*MATO* adjusted for liquidity trading) and *SUV* (the standardized prediction error from a regression of trading volume on the absolute value of returns). Our last measure is the average percentage bid–ask spread over the three-day window, centered on the day of the earnings announcement, *BAspread*.[8] For the purpose of comparing the alternative measures of differential interpretation, we keep only observations with valid values for all proxies. The definitions of all variables are summarized in the Appendix.

Table 1 provides descriptive statistics for the differential interpretation proxies, the components of the proposed metric, and the variables used in our regression analyses. The dispersion following the disclosure (*AD*) is lower than the preceding dispersion (*BD*), suggesting that,

6 While the 90-day threshold for forecasts prior to the earnings announcement may cause some stale forecasts to be included in the sample and the length of the after-EA window of 45 days may include forecast revisions that are not related to the earnings announcement, we choose these windows in order to avoid the loss of too many observations. However, we also employ a second sample that requires forecasts made at most 45 days before and 30 days after the earnings announcement. Since the results from the two samples are qualitatively similar and the inferences are identical, we only present the results of the long window sample here.

7 All of our results remain qualitatively the same if we do not winsorize these variables.

8 We also use five-day versions of the volume and bid–ask spread measures, centered on the day of the earnings announcement. Since the results for the alternative windows are very similar, we present the results for the three-day window only.

Table 2
Spearman (below the diagonal) and Pearson (above the diagonal) correlation coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LDI (1)	1	**0.288**	**0.148**	**0.077**	**0.030**	**0.042**	**0.032**	**0.029**	**0.108**	0.000	**0.064**	0.009	**0.250**	**0.067**	**0.043**	**0.330**
ChangeLD (2)	**0.466**	1	0.001	0.011	0.010	**0.030**	**0.022**	**0.027**	0.005	0.002	**0.038**	**0.040**	0.002	0.013	**0.060**	0.002
LKP (3)	**0.209**	**0.051**	1	**0.035**	**0.090**	**0.115**	**0.034**	**0.040**	**0.068**	**0.101**	**0.073**	**0.064**	**0.087**	**0.016**	**0.018**	**0.060**
MATO (4)	**0.035**	**0.021**	**0.057**	1	**0.761**	**0.359**	**0.155**	**0.788**	**0.229**	**0.405**	**0.128**	**0.219**	**0.052**	**0.066**	**0.382**	**0.158**
DTO (5)	0.002	**0.016**	**0.107**	**0.711**	1	**0.506**	**0.184**	**0.655**	**0.289**	**0.416**	**0.075**	**0.150**	**0.060**	**0.034**	**0.247**	**0.047**
SUV (6)	**0.061**	**0.024**	**0.135**	**0.451**	**0.587**	1	**0.096**	**0.397**	**0.171**	**0.257**	**0.055**	**0.056**	**0.102**	0.014	**0.061**	**0.079**
BAspread (7)	0.015	0.015	**0.024**	**0.184**	**0.288**	**0.221**	1	**0.330**	**0.497**	0.006	**0.088**	**0.141**	**0.130**	**0.017**	**0.051**	**0.135**
LVol (8)	**0.019**	**0.033**	**0.045**	**0.868**	**0.720**	**0.462**	**0.404**	1	**0.528**	**0.431**	**0.144**	**0.243**	**0.140**	**0.043**	**0.399**	**0.097**
LMktvol (9)	**0.152**	0.010	**0.081**	**0.174**	**0.315**	**0.205**	**0.617**	**0.508**	1	**0.154**	**0.073**	**0.043**	0.012	0.003	**0.040**	0.004
AbCAR (10)	**0.023**	0.006	**0.095**	**0.399**	**0.418**	**0.258**	0.008	**0.441**	**0.157**	1	0.002	**0.196**	**0.028**	**0.030**	**0.227**	**0.111**
LFollow (11)	**0.063**	**0.031**	**0.022**	**0.150**	**0.088**	**0.078**	**0.162**	**0.134**	**0.059**	**0.019**	1	**0.326**	**0.067**	**0.019**	**0.055**	**0.031**
LMktvalue (12)	0.012	**0.043**	**0.047**	**0.252**	**0.147**	**0.052**	**0.264**	**0.261**	**0.026**	**0.188**	**0.320**	1	**0.253**	**0.084**	**0.237**	**0.289**
LBM (13)	**0.305**	**0.021**	**0.096**	**0.075**	**0.091**	**0.132**	**0.164**	**0.141**	0.013	**0.056**	**0.073**	**0.241**	1	**0.070**	**0.026**	**0.330**
Growth (14)	**0.024**	**0.046**	0.013	**0.175**	**0.078**	0.001	**0.127**	**0.144**	**0.089**	**0.116**	**0.018**	**0.254**	0.005	1	**0.056**	**0.220**
Beta (15)	**0.044**	**0.069**	**0.043**	**0.400**	**0.242**	**0.102**	0.001	**0.397**	**0.020**	**0.222**	**0.067**	**0.231**	**0.018**	**0.256**	1	**0.142**
COC (16)	**0.291**	**0.035**	**0.095**	**0.140**	0.003	**0.089**	**0.241**	**0.067**	**0.066**	**0.060**	**0.029**	**0.329**	**0.366**	**0.762**	**0.198**	1

Notes
All variables are defined in the Appendix.
Correlation coefficients presented in bold are significant at the 5% level.

on average, earnings announcements resolve disagreements. The mean (median) weight on the prior belief (*Lambda*) is 0.431 (0.414), suggesting that, on average, analysts rely more on new information than on their priors in their earnings forecasts. The distributions of the measures based on analyst forecasts are skewed, with large standard deviations. Hence, we take logarithm transformations of *DI* and *KP* to mitigate skewness in the distributions (denoted by "L" in front of the variable's name). For the dispersion measure, we take the difference in the logarithm transformations of dispersion after and before the earnings announcement (*ChangeLD*), as per Barron et al. (2009).[9] We include this metric in Table 1 as *RatioD*, because it can be interpreted as the logarithm transformation of the ratio of dispersion after to dispersion before the earnings announcement. While this specification does not capture the change in dispersion *per se*, it behaves very similarly to the change in dispersion, and mitigates distributional problems.[10]

To examine our research question in relation to guidance, we obtain management forecasts made in the five-day window centered on the earnings announcement from Thomson's First Call database. We code point forecasts as 4, range forecasts as 3, open-ended (min, max) as 2, other guidance, such as descriptive forecasts, as 1, and no guidance as zero. The untabulated results are consistent with prior research, and suggest that the majority of such guidance comes in the form of ranges (83%), followed by point forecasts (13%). The mean (median) market value of equity (*Mktvalue*) is approximately $16,038 ($4,975) million, indicating that our sample consists primarily of large firms, which is not surprising, given our data requirement for a sufficient analyst following. The mean (median) book-to-market ratio (*BM*) is 0.494 (0.409), implying that our sample firms trade at a large premium above book value. We follow prior research by taking the natural logarithm transformations of *Mktvalue* and *BM* in our subsequent analyses. The mean (median) cost of capital estimate based on Easton's (2004) PEG (price/earnings to growth) ratio is 12.6% (10.3%). The average Fog index (*Fog*), or the number of years of education required to comprehend our sample firms' earnings press releases, is about 17.[11] The sample of firms with an available readability score, *Fog*, is substantially smaller, because of its restriction to firm/quarters after the year 2004 — the initial year earnings press releases were required to be furnished to the SEC.

Table 2 presents Pearson and Spearman correlation coefficients among certain variables of interest. The proposed measure, *LDI*, is correlated positively with most other differential interpretation measures, except for *SUV*, with which it is correlated negatively. The Spearman correlation coefficients of *LDI* with *DTO* and *BAspread* are statistically insignificant. *BAspread* is correlated insignificantly or negatively with all proxies, except for the Pearson's correlation with *LDI* and *ChangeLD*. This result is not surprising, based on the evidence in the finance literature that heavily traded stocks experience narrower spreads (e.g. Petersen & Fialkowski, 1994). However, this incompatibility raises the concern that either the bid–ask spread or abnormal volume is an inappropriate measure of differential interpretation, since both proxies may capture other constructs in addition to opinion divergence. Interestingly, *LKP* is correlated negatively with all measures but *LDI* and *ChangeLD*. The three volume-based measures are correlated positively with each other. Furthermore, the proposed measure is related positively to firm and market volume, analyst following, book-to-market ratio, growth

9 Our results are similar if we use the raw change in dispersion and the ranked change in dispersion as per Rees and Thomas (2010).

10 The Spearman correlation coefficient between our specification of the variable and the change in dispersion is 0.722, and is highly statistically significant.

11 Similarly to prior research on the readability of a given document (see e.g. Lehavy et al., 2011), we measure readability using the Fog Index. Lehavy et al. (2011) describe the metric as follows: "This index, developed in the computational linguistics literature, captures the written complexity of a document as a function of the number of syllables per word and the number of words per sentence. …The index is interpreted as the number of years of formal education required for a person of average intelligence to read the document once and understand it".

Table 3
The new measure and other common proxies for differential interpretation.

	LDI	LDI	LDI	LDI	LDI	LDI	LDI
Intercept	4.756***	5.100***	5.138***	5.108***	5.102***	5.263***	4.950***
	(−18.786)	(−18.860)	(−18.983)	(−18.876)	(−18.855)	(−19.286)	(−19.388)
ChangeLD	0.397***						0.399***
	(46.222)						(46.394)
LKP		0.012***					0.015***
		(3.844)					(5.249)
MATO			1.901***				3.059***
			(3.607)				(4.378)
DTO				1.150*			−1.389
				(1.712)			(−1.497)
SUV					0.002		−0.006*
					(0.760)		(−1.791)
BAspread						6.629***	5.992***
						(4.438)	(4.285)
N	16,837	16,837	16,837	16,837	16,837	16,837	16,837
R^2	0.61	0.56	0.56	0.56	0.56	0.56	0.62

Notes
This table presents the results of regressions of the new measure on alternative proxies for differential interpretation. Each column represents a separate regression. All regressions include year and firm fixed effects. All variables are defined in the Appendix. *t*-statistics are presented in parentheses below the coefficient estimates.
* Indicates significance of the coefficient at the 10% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

and the cost of capital, but negatively to market beta. However, its relationship to the absolute abnormal return around the announcement (*AbCAR*) is ambiguous, which is why we need to examine these relationships in a multivariate setting.

3.3. Assessment of opinion divergence measures

Our initial analysis examines the relationships between the proposed measure and other commonly used proxies for opinion divergence, while controlling for year and firm fixed effects. The results are presented in Table 3. When the new measure is regressed on each of the alternatives individually, the coefficients are all positive. Apart from the insignificant coefficient on *SUV* and the marginally significant coefficient on *DTO* at the 10% level, all other coefficients are statistically significant. When *LDI* is regressed on all proxies together, the coefficient on *DTO* becomes insignificant and the coefficient on *SUV* becomes negative and marginally significant. The most noteworthy point here is the fact that the proposed measure is significantly positively related to *ChangeLD*, *LKP*, *MATO* and *BAspread* in all specifications. However, these proxies, together with the year and firm fixed effects, explain a maximum of 62% of the total variation in *LDI*, suggesting that the proposed measure includes a significant amount of variation which is not captured by any of the other proxies.

Our second validation test examines the way in which trading volume may be affected by the degree of opinion divergence. Both theoretical (e.g. Banerjee & Kremer, 2010; Kandel & Pearson, 1995) and empirical (e.g. Ajinkya et al., 1991; Bamber et al., 1999) research has established that divergence of opinions increases the trading volume. Therefore, we expect a positive and statistically significant coefficient on *LDI* in regressions of volume on differential interpretation and other controlling factors, such as the informativeness of the earnings announcement, the market value of equity and market volume. We use the total firm share turnover in the three-day window centered on the earnings announcement, *LVol*, as the dependent variable, and control for the total market turnover in the same time period, *LMktvol*. First, *LVol* is regressed only on *LDI* and the results are presented in the first column of Table 4. The coefficient on *LDI* is 0.009, with a *t*-value of 3.427. When control variables are included, *LDI* continues to be positive and statistically significant, and the coefficient is now 0.006, with a *t*-value of 2.490. All control variables are highly statistically significant in the expected direction. This analysis provides additional convincing evidence that the proposed measure captures differential interpretation.

When we perform this analysis using all other measures of opinion divergence, *ChangeLD* is statistically insignificant, while *LKP* and *BAspread* are related negatively to *LVol*. The negative coefficient on *LKP* disagrees with the results of Bamber et al. (1999), who find an insignificant relationship to volume in their full sample but a positive relationship in a sub-sample of firms where the information content of the earnings announcement is very low. The negative relationship between *BAspread* and *LVol* is consistent with prior research (e.g. Petersen & Fialkowski, 1994), but suggests that *BAspread* captures other constructs that may not be related to opinion divergence. All volume-based measures are strongly positively associated with volume, as the high R^2 also reflects. However, these results should not be used to evaluate the adequacy of these volume-based measures, because a strong relationship follows by construction.

Our third validation test examines whether the degree of differential interpretation increases with the information content of the public announcement, measured by the absolute abnormal return around the announcement, *AbCAR*. We expand this analysis by exploring whether the differential interpretation metrics are related to certain firm characteristics, such as size, book-to-market ratio and analyst following. In this continued analysis, we regress each

Table 4
Differential interpretation measures and trading volume.

Full sample	Dependent variable = LVol LDI	LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	−4.291***	−1.748***	−1.782***	−1.763***	−1.850***	−1.427***	−2.071***	−1.715***
	(−47.817)	(−10.481)	(−10.728)	(−10.618)	(−17.125)	(−9.952)	(−13.881)	(−10.101)
DiffInt	0.009***	0.006**	0.003	−0.004***	15.610***	13.187***	0.050***	−0.947**
	(3.427)	(2.490)	(1.120)	(−4.760)	(141.724)	(71.141)	(59.421)	(−2.052)
AbCAR		3.776***	3.780***	3.751***	1.081***	2.011***	2.767***	3.793***
		(50.417)	(50.487)	(49.961)	(20.682)	(29.056)	(39.895)	(50.555)
LMktvalue		−0.053***	−0.052***	−0.052***	−0.020***	−0.047***	−0.088***	−0.052***
		(−6.903)	(−6.772)	(−6.839)	(−4.064)	(−7.229)	(−12.843)	(−6.859)
LMktvol		0.448***	0.449***	0.452***	0.535***	0.537***	0.341***	0.457***
		(17.044)	(17.065)	(17.200)	(31.272)	(23.646)	(14.403)	(17.177)
N	16,837	16,610	16,610	16,610	16,610	16,610	16,610	16,610
R^2	0.771	0.811	0.811	0.811	0.920	0.859	0.848	0.811

Notes
The table presents the results of regressions of the firm trading volume on alternative proxies for differential interpretation, indicated at the top of each column, and control variables. Each column represents a separate regression. All regressions include year and firm fixed effects. All variables are defined in the Appendix. *t*-statistics are presented in parentheses below the coefficient estimates.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

Table 5
Differential interpretation measures and the information content of the earnings announcement.

	LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	−9.335***	−2.053***	0.672	0.036***	0.009**	−4.282***	0.030***
	(−25.213)	(−6.086)	(0.659)	(6.717)	(2.190)	(−4.394)	(15.082)
AbCAR	1.008***	0.612***	−6.691***	0.170***	0.131***	20.527***	0.014***
	(4.034)	(2.687)	(−9.727)	(47.287)	(46.087)	(31.214)	(9.951)
LMktvalue	0.300***	0.057**	0.232***	−0.006***	−0.002***	0.559***	−0.001***
	(9.894)	(2.077)	(2.784)	(−13.023)	(−5.362)	(7.015)	(−3.686)
LBM	0.293***	−0.042	0.784***	−0.007***	−0.003***	−0.324***	0.001***
	(8.725)	(−1.386)	(8.471)	(−15.402)	(−8.704)	(−3.658)	(6.873)
LFollow	0.774***	0.284***	−0.878***	0.011***	0.004***	0.199	−0.000
	(12.113)	(4.879)	(−4.992)	(11.588)	(5.596)	(1.186)	(−0.712)
N	16,362	16,362	16,362	16,362	16,362	16,362	16,362
R^2	0.57	0.12	0.24	0.66	0.50	0.25	0.62

Notes
Each column represents a separate regression, with the dependent variable indicated at the top of each column. All regressions include year and firm fixed effects. All variables are defined in the Appendix. *t*-statistics are presented in parentheses below the coefficient estimates.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

of the alternative opinion divergence measures on *AbCAR*, *LMktvalue*, *LBM* and *LFollow* and year and firm fixed effects. The results are presented in Table 5.

The proposed measure is strongly positively related to the absolute value of the abnormal earnings announcement return; the coefficient is 1.008 and is highly statistically significant, with a *t*-value of 4.034. In addition, the evidence suggests that larger firms, firms with higher book-to-market ratios, and firms with higher analyst followings have more opinion divergence following an earnings announcement. All other measures are also strongly positively related to the information content of the announcement, except *LKP*, which is negative and significant. This result casts doubt once again on the ability of *LKP* to capture investors' differential interpretation of information. The three volume-based measures are especially strongly positively related to *AbCAR*, which is not surprising, given the well-documented and robust relationship between earnings announcement information content and volume (see, e.g. Bamber et al., 1999; Kim & Verrecchia, 1991). Overall, only *LKP* fails to show a positive relationship with the informativeness of the earnings announcement, providing evidence that the other measures all capture differential interpretation.[12]

Our fourth validation test investigates the relationship between differential interpretation and the readability of earnings press releases. We expect that investors will differ more in their interpretations of the earnings release when the disclosure is less readable. This prediction follows from the work of Li (2008), who shows that annual reports that are more difficult to read are associated with lower earnings, and Bozanic and Thevenot (2014), who find that the readability of earnings press releases is associated with

12 In addition, we examine the question of whether higher levels of differential interpretation are related to lower returns around the earnings announcement, as was documented by Berkman et al. (2009). We find that all opinion divergence proxies are related negatively to the three-day abnormal return centered on the earnings announcement, although the results are statistically insignificant for *MATO* and *DTO*, statistically significant at the 5% level for *LKP* and *ChangeLD*, and statistically significant at the 1% level for *LDI*, *SUV* and *BAspread*.

Table 6
Differential interpretation measures and disclosure readability.

	LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	−6.236***	−1.476**	−0.566	0.173***	0.085***	−1.335	0.008***
	(−5.738)	(−2.249)	(−0.244)	(11.648)	(6.974)	(−0.580)	(9.501)
Fog	0.056***	0.014	0.076*	−0.000	−0.000	−0.003	0.000
	(3.066)	(1.292)	(1.929)	(−0.889)	(−1.398)	(−0.073)	(0.302)
LMktvalue	−0.122	−0.031	0.031	−0.017***	−0.008***	0.705***	−0.001***
	(−1.289)	(−0.537)	(0.152)	(−13.027)	(−7.277)	(3.517)	(−10.740)
LBM	0.149*	−0.092*	0.632***	−0.007***	−0.003***	−0.107	0.000
	(1.652)	(−1.684)	(3.280)	(−5.767)	(−3.021)	(−0.561)	(0.369)
LFollow	0.787***	0.172*	−0.501	0.015***	0.007***	0.208	0.000
	(5.218)	(1.886)	(−1.551)	(7.451)	(4.074)	(0.651)	(0.584)
Observations	6427	6427	6427	6427	6427	6427	6427
R^2	0.53	0.17	0.30	0.65	0.44	0.30	0.38

Notes
Each column represents a separate regression, with the dependent variable indicated at the top of each column. All regressions include year and firm fixed effects. All variables are defined in the Appendix. t-statistics are presented in parentheses below the coefficient estimates.
* Indicates significance of the coefficient at the 10% level, a two-tailed test.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

changes in several characteristics of analysts' information environment. Since a higher *Fog* implies a less readable document, we predict a positive coefficient on *Fog*. The results in Table 6 show that *LDI* is significantly positively related to *Fog*, with a t-value of 3.066. The only other differential interpretation proxy that is positively related to the lack of readability is *LKP*, but it is only marginally significant at the 10% level. None of the other metrics exhibit a significant relationship with *Fog*. In summary, this empirical application shows evidence of the superiority of the proposed measure over other commonly used proxies for opinion divergence.

To provide additional insights into the link between disclosure characteristics and differential interpretation, we also examine management guidance. Management guidance is a form of voluntary disclosure, and is sometimes provided along with an earnings announcement. We are interested in examining the variation in opinion divergence as a result of guidance because the quality, or precision, of this information is observable directly, in the form of the forecasts provided by management. For example, if management provides a point forecast, there should not be much variation in the way in which analysts interpret this information. In contrast, range or min-max forecasts could potentially trigger differential interpretations among analysts. Therefore, we expect a negative relationship between differential interpretation and management guidance precision (*GuidePrec*). We examine this relationship using both our full sample and the sub-sample of firms that provide guidance around the earnings announcement. The results from this analysis are presented in Table 7. The coefficient on *GuidePrec* is negative and highly statistically significant in both samples (Panels A and B), with t-values of −10.729 and −2.035, respectively, when differential interpretation is measured using the proposed metric. The alternative metrics, with the exception of *ChangeLD*, do not provide consistent results in the two samples.

Finally, we test for a positive relationship between differential interpretation and the cost of capital. We use two different analyses to examine this relationship, in order to avoid making erroneous inferences caused by inaccurate cost of capital measures. Our first analysis relies on firm-specific cost of capital estimates, based on Easton (2004), as follows:

$$COC_{it} = \sqrt{(eps_{i(t+2)} - eps_{i(t+1)})/p_{it}}, \tag{5}$$

where *COC* is the cost of capital estimate obtained in the month following the earnings announcement, $eps_{i(t+1)}$ ($eps_{i(t+2)}$) is the firm's one-year-ahead (two-year-ahead) mean forecast of earnings, and p_{it} is the current price from the I/B/E/S summary files.

We choose this method because it provides some of the most reliable and well-behaved estimates of the cost of capital (Botosan & Plumlee, 2005). Following prior research on the cost of capital, we include control variables for risk, size and growth in all of our empirical analyses. We examine the relationship between divergence of opinions and the cost of capital under the expectation that good proxies of differential interpretation will be related positively to the cost of capital, after controlling for market beta, size, growth, and year and firm fixed effects. The result of this analysis is presented in Table 8, Panel A. Direct empirical evidence on the relationship between opinion divergence and the cost of capital is overwhelmingly scarce, but this paper explores this connection.[13]

The coefficient on *LDI* is 0.007, which is highly statistically significant, with a t-value of 21.904, suggesting that differential interpretation of the earnings announcement increases the firm cost of capital. This is important, because one purpose of public disclosures is to level out the information playing field. However, if the common signal is interpreted differentially, then public disclosure has a detrimental effect on the firm, as indicated by the higher

13 One exception is Rees and Thomas (2010), whose primary research question deals with the relationship between changes in dispersion and contemporaneous stock returns. As a sensitivity check, the authors examine the relationship between changes in dispersion and changes in the cost of capital around earnings announcements. However, the authors do not investigate the effect of opinion divergence on the cost of capital, per se.

Table 7
Differential interpretation measures and management guidance.

Panel A: Full sample							
	LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	−9.429***	−2.052***	−0.064	0.047***	0.019***	−2.693***	0.032***
	(−25.565)	(−6.085)	(−0.063)	(8.274)	(4.269)	(−2.677)	(15.544)
GuidePrec	−0.160***	−0.042***	−0.218***	−0.001***	0.000	0.041	0.000
	(−10.729)	(−3.080)	(−5.276)	(−5.216)	(0.836)	(1.013)	(0.108)
LMktvalue	0.313***	0.057**	0.329***	−0.007***	−0.003***	0.353***	−0.001***
	(10.380)	(2.083)	(3.943)	(−15.324)	(−8.548)	(4.283)	(−4.485)
LBM	0.302***	−0.040	0.794***	−0.007***	−0.003***	−0.319***	0.001***
	(9.021)	(−1.305)	(8.553)	(−14.112)	(−8.042)	(−3.490)	(6.869)
LFollow	0.733***	0.277***	−1.012***	0.012***	0.005***	0.414**	0.000
	(11.493)	(4.745)	(−5.732)	(12.081)	(6.930)	(2.381)	(−0.319)
N	16,362	16,362	16,362	16,362	16,362	16,362	16,362
R^2	0.57	0.12	0.24	0.61	0.43	0.20	0.61
Panel B: Management guidance sample							
Intercept	−8.631***	−1.972	−1.113	0.046	0.024	−10.358*	0.007
	(−4.583)	(−0.980)	(−0.205)	(1.542)	(1.004)	(−1.799)	(1.400)
GuidePrec	−0.143**	−0.161**	0.081	0.002	0.002**	−0.200	−0.000**
	(−2.035)	(−2.143)	(0.399)	(1.427)	(2.231)	(−0.932)	(−2.226)
LMktvalue	0.245***	−0.001	0.873***	−0.006***	−0.003***	0.620**	−0.001***
	(2.961)	(−0.014)	(3.666)	(−4.649)	(−3.157)	(2.451)	(−3.225)
LBM	0.168**	−0.163*	1.290***	−0.008***	−0.004***	−0.411	0.001***
	(2.013)	(−1.828)	(5.380)	(−6.219)	(−3.876)	(−1.613)	(2.788)
LFollow	0.679***	0.206	−1.535***	0.011***	0.006***	0.383	0.000
	(5.410)	(1.539)	(−4.250)	(5.632)	(4.026)	(0.998)	(0.941)
N	4532	4532	4532	4532	4532	4532	4532
R-squared	0.46	0.16	0.26	0.65	0.48	0.21	0.46

Notes
Panel A provides results using the full sample, where *GuidePrec* is set to zero if no guidance was provided. Panel B provides results using the sub-sample of firms that provided guidance. Each column represents a separate regression, with the dependent variable indicated at the top of each column. All regressions include year and firm fixed effects. All variables are defined in the Appendix. *t*-statistics are presented in parentheses below the coefficient estimates.
* Indicates significance of the coefficient at the 10% level, a two-tailed test.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

cost of equity capital. This evidence is consistent with the predictions of Varian (1985) and the findings of Garfinkel and Sokobin (2006).

Most other measures do not yield convincing evidence of a positive link to the cost of capital. The measure capturing the change in dispersion, *ChangeLD*, has a coefficient of 0.001 and is only marginally significant, which is consistent with it measuring differential interpretation with noise. Kandel and Pearson's measure is not statistically significant, casting doubt once again on its ability to capture variation in differential interpretation. The volume-based measures provide mixed results. *MATO* has a positive and statistically significant coefficient, *DTO* is insignificant, and *SUV* is negative and statistically, but not economically, significant. Another metric that exhibits a strong relationship with the cost of capital is *LBAspread*. However, this positive relationship may be driven by information asymmetry rather than differential interpretation, since the bid–ask spread has been used widely as a proxy for information asymmetry (see e.g. Armstrong, Core, Taylor, & Verrecchia, 2011).[14]

So far, our cost of capital analysis has tested the joint hypothesis that there is a positive relationship between divergence of opinions and the cost of capital, and that Easton's (2004) method provides an appropriate measure of the cost of capital. However, there is a great debate in the literature about the most appropriate measure of the cost of capital, and therefore the second assumption may not hold. Therefore, we check the robustness of our results by performing a portfolio-based analysis that does not require firm-specific estimates of the cost of capital, as suggested by Easton, Taylor, Shroff, and Sougiannis (2002) and described by Easton (2009). The method regresses the

[14] We also perform several additional analyses in order to examine the robustness of the positive relationship between our new measure and the cost of capital. First, we run a regression of the cost of capital on all differential interpretation metrics together, the control variables, and firm and year fixed effects, and find that the new measure is positive and highly statistically significant, suggesting that it includes variation which is not captured fully by the other metrics. Second, we include controls for other information environment variables, such as uncertainty and information asymmetry, and find that *LDI* continues to be positive and highly statistically significant, implying that the new measure does not capture previously documented uncertainty and asymmetry effects. Third, we include *AbCAR* as an additional control so as to alleviate the concern that the differential interpretation variable captures the magnitude of news, which may affect the cost of capital. The inclusion of the additional control does not affect the magnitude or statistical significance of *LDI*. Finally, since prior research suggests that analysts issue optimistic forecasts of annual earnings (see e.g. Francis & Philbrick, 1993), we obtain "debiased" forecasts by subtracting a measure of the average optimism from the original forecasts, and repeat the analysis. Our results and inferences do not change.

Table 8
Differential interpretation measures and the cost of capital.

Panel A. The PEG ratio as a measure of the cost of capital

	Dependent variable = COC						
	LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	0.413***	0.358***	0.358***	0.350***	0.358***	0.357***	0.345***
	(29.364)	(25.436)	(25.427)	(24.824)	(25.359)	(25.360)	(24.349)
DiffInter	0.007***	0.001*	0.000	0.152***	0.021	−0.000**	0.390***
	(21.904)	(1.714)	(1.641)	(6.962)	(0.749)	(−2.084)	(6.703)
Beta	0.005***	0.005***	0.005***	0.003***	0.005***	0.005***	0.005***
	(4.639)	(3.912)	(3.841)	(2.714)	(3.826)	(3.894)	(3.966)
LMktvalue	−0.026***	−0.024***	−0.024***	−0.023***	−0.024***	−0.024***	−0.024***
	(−22.366)	(−19.927)	(−19.961)	(−19.181)	(−19.869)	(−19.825)	(−19.692)
LBM	0.011***	0.014***	0.014***	0.015***	0.014***	0.014***	0.013***
	(8.425)	(10.224)	(10.082)	(10.861)	(10.224)	(10.158)	(9.828)
Growth	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(17.954)	(18.366)	(18.350)	(17.991)	(18.312)	(18.357)	(18.412)
N	14,333	14,333	14,333	14,333	14,333	14,333	14,333
R^2	0.561	0.544	0.544	0.546	0.544	0.544	0.545

Panel B. Portfolio-based approach

	Dependent variable = Y							
		LDI	ChangeLD	LKP	MATO	DTO	SUV	BAspread
Intercept	0.058***	0.053***	0.057***	0.058***	0.058***	0.057***	0.058***	0.056***
	(7.711)	(7.626)	(7.324)	(7.269)	(7.626)	(7.785)	(7.921)	(6.105)
X	0.030***	0.032***	0.032***	0.030***	0.030***	0.030***	0.030***	0.030***
	(8.205)	(9.744)	(8.117)	(7.486)	(8.065)	(8.504)	(8.506)	(7.763)
DDiffInt		0.014***	0.001	−0.001	0.000	0.001	−0.000	0.002
		(3.158)	(0.236)	(−0.494)	(0.072)	(0.395)	(−0.054)	(0.342)
X*DDiffInt		−0.003*	−0.003**	0.001	0.001	−0.000	0.001	0.001
		(−1.835)	(−2.322)	(0.685)	(0.570)	(−0.091)	(0.524)	(0.601)
AdjBeta	−0.002	−0.001	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(−0.548)	(−0.425)	(−0.644)	(−0.555)	(−0.497)	(−0.585)	(−0.546)	(−0.597)
X*AdjBeta	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***
	(−6.383)	(−6.463)	(−6.380)	(−6.383)	(−5.884)	(−6.040)	(−6.339)	(−6.302)
AdjMktvalue	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(4.862)	(4.871)	(4.930)	(4.864)	(4.852)	(4.827)	(4.896)	(4.938)
X*AdjMktvalue	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.487)	(0.520)	(0.475)	(0.485)	(0.548)	(0.470)	(0.471)	(0.535)
AdjBM	−0.034***	−0.037***	−0.034***	−0.034***	−0.034***	−0.034***	−0.034***	−0.035***
	(−9.384)	(−9.717)	(−9.410)	(−9.421)	(−9.215)	(−9.276)	(−9.342)	(−9.498)
X*AdjBM	0.008***	0.009***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(3.864)	(4.443)	(3.867)	(3.909)	(3.853)	(3.826)	(3.827)	(3.811)
Observations	14,849	14,849	14,849	14,849	14,849	14,849	14,849	14,849
R^2	0.477	0.478	0.478	0.477	0.477	0.477	0.477	0.477
Estimated growth rate	0.058	0.053	0.057	0.058	0.058	0.057	0.058	0.056
Estimated COC	0.088	0.085	0.089	0.088	0.088	0.087	0.088	0.086
Effect of DiffInt on growth		0.014***	0.001	−0.001	0.000	0.001	−0.000	0.002
Effect of DiffInt on COC		0.011***	−0.002	0.000	0.001	0.001	0.001	0.003
p-value		0.000	0.236	0.752	0.663	0.586	0.791	0.519

Notes
Panel A presents results of regressions of the cost of capital on alternative proxies for differential interpretation, indicated at the top of each column, and control variables. All regressions include year and firm fixed effects. All variables are defined in the Appendix. Panel B presents results of the portfolio-based approach to estimation of the effect of differential interpretation on the cost of capital, described by Easton (2009), based on Easton et al. (2002). The variables used in this analysis are as follows. Y is the median consensus forecast of one-year-ahead earnings, scaled by book value per share. X is price per share, scaled by book value per share. Following Easton et al. (2002), observations for Y and X in the top and bottom 2% are trimmed. *DDiffInt* is a dummy variable, and is equal to one if the value of the given differential interpretation measure is above the median, and zero otherwise. *AdjBeta* is *Beta* less the mean of *Beta*. *AdjMktvalue* is *Mktvalue* less the mean of *Mktvalue*. *AdjBM* is *BM* less the mean of *BM*. Each column represents a separate regression. t-statistics are calculated using standard errors clustered by firm, and are presented in parentheses below the coefficient estimates.
The "Effect of DiffInt on COC" represents the effect of differential interpretation, measured by the given proxy, on the cost of capital for the average-beta, size and book-to-market firm. The "p-value" presents the p-values of F-tests of whether the given effect on the cost of capital is equal to zero, i.e. a test of $DDiffInt + X^*DDiffInt = 0$.
* Indicates significance of the coefficient at the 10% level, a two-tailed test.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

median one-year-ahead earnings forecast, scaled by book value, which we define as Y, on price, scaled by book value, defined as X. The intercept captures the estimated average growth rate, and the sum of the intercept and the regression coefficient on X captures the estimated average cost of capital. The effect of a variable of interest, such as differential interpretation, on the cost of capital is then examined using a dummy-variable approach. We define a variable *DDiffInt*, which is equal to 1 if the value of the given differential interpretation measure is above the median, and zero otherwise. We then include *DDiffInt* and an interaction term between *DDiffInt* and X in the regression model discussed above. The coefficient on *DDiffInt* captures the effect of differential interpretation on growth and the sum of the coefficients on *DDiffInt*, and the interaction term captures the effect of opinion divergence on the cost of capital. In addition, we also include control variables for beta, size, and the book-to-market ratio, as was suggested by Easton (2009), where these variables are mean-centered and interactions between X and the mean-centered control variables are also included. The result of this analysis is presented in Panel B of Table 8.

The first column provides the result of the benchmark regression, where Y is regressed on X and the control variables. The estimated growth rate is 5.8% and the estimated cost of capital is 8.8% for a firm with an average beta, size and book-to-market ratio. This estimate of the cost of capital is lower than that presented in Table 1, which is consistent with the tendency of the PEG ratio to provide an inflated estimate of the cost of capital (Easton & Sommers, 2007). The subsequent columns provide results for the effect of differential interpretation on the cost of capital, using the alternative proxies. Based on the new measure, higher levels of differential interpretation are associated with higher levels of growth and the cost of capital, and both effects are statistically and economically significant. For example, having a level of opinion divergence that is above the sample median is associated with a 1.4% higher growth and 1.1% higher cost of capital for a firm with an average beta, size and book-to-market ratio. None of the other variables provide significant growth or cost of capital effects. Therefore, our earlier results are not driven by a potentially noisy or biased estimate of the cost of capital based on PEG ratios.

Overall, the proposed measure of opinion divergence gives results with a high explanatory power that are consistent with both theory and prior research. No other proxy seems to capture differential interpretation as precisely or predictably as the proposed measure. The superiority of the new measure is consistent with its close alignment to and direct relationship with the theoretical construct. Furthermore, our proposed metric is easy to estimate using only analyst forecast data. However, one disadvantage in the specification of the proposed measure so far is that it requires ten or more analysts around an earnings announcement. Next, we relax this requirement and examine whether the proposed measure can be obtained reliably with fewer analysts.

3.4. Alternative estimates of DI

To relax the data requirement in the estimation of the proposed measure, we compute three alternative estimates of differential interpretation, requiring: (i) five analysts revising around a given quarterly earnings announcement (rather than 10, as in previous analyses), defined as *DI5hor*; (ii) three analysts revising around a given earnings announcement, defined as *DI3hor*; and (iii) 10 analysts revising around any quarterly earnings announcement in a given year, defined as *DI10yr*. Then, we repeat all previous analyses, and present the evidence in Table 9.

In the most general case, a minimum of only three analysts are needed around a given earnings announcement. This improves the applicability of the new method dramatically, provided that the generalization does not come at the cost of reliability. The empirical results from our analyses are very promising. All three alternative estimates provide highly statistically significant results in the correct direction for all analyses. Although some analyst following remains a requirement, the proposed method can measure opinion divergence for a large number of firms.

4. Conclusion

Using a standard Bayesian learning model, we quantify opinion divergence by decomposing the dispersion following information disclosure into two separate components: heterogeneous prior beliefs and differential interpretation of the new disclosure. We validate our differential interpretation measure by showing a positive relationship with other commonly used proxies for opinion divergence, the trading volume around the announcement, the information content of the earnings announcement, the lack of readability in the earnings press release, and the cost of capital; and a negative relationship with management guidance precision. In these assessment categories, our measure provides the most consistent results, and often outperforms other previously used proxies, such as the change in dispersion, Kandel and Pearson's (1995) metric, several measures of abnormal volume, and the bid–ask spread. As such, we extend the work of Garfinkel (2009) by providing comparative evidence on the adequacy of different opinion divergence proxies and introducing a superior alternative. Furthermore, our new empirical evidence of a direct positive relationship between differential interpretation of public information and the firm cost of capital has significant economic and policy implications for managers, regulators and academics.

Admittedly, our proposed measure of opinion divergence has some limitations. First, following the literature on financial analysts, we presume that divergence in analysts' opinions reflects differences in opinions among investors. Second, our approach requires an analyst following both before and after an earnings announcement, thus limiting its applicability for all firms. Our main results are based on at least ten analysts providing a forecast prior to an earnings announcement and then revising the forecast afterward, which restricts our sample to large firms, hence reducing the generalizability of the results. However, the robustness analyses show that our approach can also be applied to firms with smaller analyst followings. Nevertheless, we caution the reader of these limitations and urge further research on the applicability of the metric to the wider population of firms and to additional empirical applications.

This study provides a better, more widely applicable tool for extending our understanding of the effects of public disclosure on investor behavior. One perceived benefit

Table 9
Alternative estimation of *DI*.

Panel A. Volume analysis			
	Dependent variable = LVol		
	LDI5hor	LDI3hor	LDI10yr
Intercept	−0.742	−1.243	−3.000***
	(−1.296)	(−1.408)	(−8.688)
DiffInt	0.005***	0.009***	0.003**
	(3.642)	(9.204)	(2.363)
AbCAR	4.343***	4.537***	4.383***
	(91.179)	(109.322)	(106.618)
LMktvalue	0.059***	0.137***	0.086***
	(12.033)	(32.829)	(20.228)
LMktvol	0.396***	0.396***	0.389***
	(22.680)	(25.610)	(25.938)
N	49,522	75,841	68,521
R^2	0.76	0.74	0.75

Panel B. Information content analysis			
	LDI5hor	LDI3hor	LDI10yr
Intercept	−11.454***	−14.382***	−11.807***
	(−5.489)	(−4.440)	(−12.566)
AbCAR	1.444***	1.384***	0.948***
	(8.071)	(8.893)	(8.119)
LMktvalue	0.466***	0.421***	0.512***
	(21.342)	(22.422)	(35.930)
LBM	0.487***	0.432***	0.611***
	(20.478)	(21.029)	(39.104)
LFollow	0.983***	1.329***	0.465***
	(30.091)	(57.429)	(27.754)
N	48,567	74,278	67,130
R^2	0.56	0.53	0.68

Panel C. Readability analysis			
	LDI5hor	LDI3hor	LDI10yr
Intercept	−10.459***	−7.144***	−8.274***
	(−16.297)	(−7.017)	(−18.775)
Fog	0.044***	0.042***	0.027***
	(3.992)	(4.238)	(3.800)
LMktvalue	−0.153***	−0.206***	−0.004
	(−3.190)	(−4.981)	(−0.127)
LBM	0.167***	0.157***	0.269***
	(3.798)	(4.084)	(9.458)
LFollow	0.991***	1.337***	0.378***
	(16.463)	(31.221)	(12.706)
N	19,167	27,846	25,161
R^2	0.57	0.55	0.71

Panel D: Management guidance analysis			
	LDI5hor	LDI3hor	LDI10yr
Intercept	−14.216***	−15.113***	−3.301***
	(−6.781)	(−5.869)	(−2.841)
GuidePrec	−0.184***	−0.184***	−0.149***
	(−17.181)	(−19.763)	(−20.658)
LMktvalue	0.467***	0.420***	0.521***
	(23.450)	(25.455)	(39.619)
LBM	0.491***	0.438***	0.635***
	(22.674)	(24.177)	(43.918)
LFollow	1.012***	1.342***	0.513***
	(32.833)	(63.292)	(32.222)
N	55,386	89,579	76,067
R^2	0.56	0.53	0.67

(continued in next column)

Table 9 (*continued*)

Panel E. Cost of capital analysis			
	Dependent variable = COC		
	LDI5hor	LDI3hor	LDI10yr
Intercept	0.356***	0.340***	0.387***
	(5.096)	(4.212)	(9.643)
DiffInter	0.006***	0.005***	0.010***
	(37.280)	(43.687)	(55.023)
Beta	0.007***	0.008***	0.008***
	(9.395)	(13.490)	(12.954)
LMktvalue	−0.039***	−0.041***	−0.042***
	(−52.161)	(−69.230)	(−66.251)
LBM	0.010***	0.012***	0.007***
	(11.495)	(17.658)	(9.274)
Growth	0.002***	0.002***	0.002***
	(20.544)	(24.375)	(22.542)
N	45,766	72,131	62,642
R^2	0.50	0.50	0.51

Notes
The table presents results with alternative estimates of *DI*. Each column represents a separate regression. In panel A, *LVol* is the dependent variable. In panels B, C and D, *DI* is the dependent variable. In panel E, COC is the dependent variable. *LDI5hor* requires that at least five analysts make a forecast in the 90 days prior to a given earnings announcement and then the same analysts revise in the 45 days following the earnings announcement. *LDI3hor* requires that at least three analysts make a forecast in the 90 days prior to a given earnings announcement and then the same analysts revise in the 45 days following the earnings announcement. *LDI10yr* requires that at least ten analysts make a forecast in the 90 days prior to the announcement of the first, second or third quarter's earnings in a given year, and then the same analysts revise in the 45 days following the earnings announcement. Then, *LDI5hor*, *LDI3hor* and *LDI10yr* are estimated similarly to *DI* using the analyst forecasts specified above. All regressions include year and firm fixed effects. All other variables are defined in the Appendix. *t*-statistics are presented in parentheses below the coefficient estimates.
** Indicates significance of the coefficient at the 5% level, a two-tailed test.
*** Indicates significance of the coefficient at the 1% level, a two-tailed test.

of earnings announcements providing information to everyone simultaneously is that it levels out the information playing field and decreases information asymmetry in the market. However, our research shows that less transparent information may increase the degree of differential interpretation. Future research is necessary to establish whether the increased opinion divergence represents a benefit or a cost. Further study is also warranted to reexamine the disagreement-return and disagreement-volume relationships by using the proposed opinion divergence measure. For example, using the abnormal trading volume as a proxy for investors' opinion divergence, Garfinkel and Sokobin (2006) find that differential interpretation is related *positively* to post-earnings-announcement returns. However, Diether et al. (2002), Boehme, Danielsen, and Sorescu (2006) and Barinov (2013) find a *negative* relationship between analyst dispersion, their proxy for differential interpretation, and future returns, and Berkman et al. (2009) document a *negative* relationship between several measures of opinion divergence and returns around earnings announcements. Having an improved measure of opinion divergence may prove useful in reconciling these seemingly contradicting results. Thus, the proposed measure opens the door to a myriad of new research questions and hypotheses.

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Table A.1
Variable measurement.

DI = $\frac{AD-\hat{\lambda}^2 BD}{\left(1-\hat{\lambda}\right)^2}$, where $\hat{\lambda}$ is the coefficient estimate obtained by regressing each analyst's deviation from the mean forecast after an earnings announcement on each analyst's deviation from the mean forecast prior to the earnings announcement, and *AD* (*BD*) is dispersion after (before) an earnings announcement. *LDI* is the logarithm transformation of *DI*.
ChangeD = change in dispersion, *AD* − *BD*. *ChangeLD* indicates the change in logarithm transformations of *AD* and *BD*.
RatioD = ratio of *AD* to *BD*.
KP = percentage of pairs of analysts whose forecasts flip or diverge around an earnings announcement, as in cases 5 and 6 in Fig. 1. *LKP* indicates the logarithm transformation of *KP*.
MATO = percentage of outstanding shares traded in the three-day window centered on the earnings announcement, less the percentage of all shares traded in the same window of all NYSE/AMEX stocks. *LMATO* indicates the logarithm transformation of *MATO*.
DTO = MATO less the median market-adjusted turnover, averaged over the 180-day period prior to the measurement of MATO. *LDTO* indicates the logarithm transformation of *DTO*.
SUV = standardized prediction error from a regression of the trading volume on the absolute value of returns, as per Garfinkel (2009). *LSUV* indicates the logarithm transformation of *SUV*.
BAspread = average percentage bid–ask spread over the three-day window centered on the earnings announcement. *LBAspread* indicates the logarithm transformation of *BAspread*.
AbCAR = absolute value of the three-day abnormal return centered on the earnings announcement (using the standard market-model methodology).
Vol = percentage of outstanding shares traded in the three-day window centered on the earnings announcement. *LVol* indicates the logarithm transformation of *Vol*.
Mktvol = percentage of all shares traded in the market in the three-day window centered on the earnings announcement. *LMktvol* indicates the logarithm transformation of *Mktvol*.
Follow = number of analysts revising their forecasts around an earnings announcement. *LFollow* indicates the logarithm transformation of *Follow*.
GuidePrec = the precision of management guidance that occurred in the five-day window centered on the earnings announcement, where point forecasts are coded as 4, range forecasts as 3, open-ended as 2, descriptive as 1 and no guidance as 0.
Mktvalue = market value of equity at the end of the prior quarter. If unavailable, *Mktvalue* is calculated at the fiscal year-end immediately prior. *LMktvalue* indicates the logarithm transformation of *Mktvalue*.
BM = book to market ratio at the end of the prior quarter. If unavailable, *BM* is calculated at the fiscal year-end immediately prior. *LBM* indicates the logarithm transformation of *BM*.
Growth = short-term earnings growth, calculated as $(eps_{i(t+2)} - eps_{i(t+1)})/\lvert eps_{i(t+1)}\rvert$, where $eps_{i(t+1)}$ ($eps_{i(t+2)}$) is the firm's one-year-ahead (two-year-ahead) mean forecast of earnings.
Beta = market beta estimated using the market model with a minimum of 30 out of 60 monthly returns prior to the month in which *COC* is estimated.
COC = $\sqrt{(eps_{i(t+2)} - eps_{i(t+1)})/p_{it}}$, where $eps_{i(t+1)}$ ($eps_{i(t+2)}$) is the firm's one-year-ahead (two-year-ahead) mean forecast of earnings and p_{it} is the current price from IBES summary files. *COC* is estimated in the month following the current earnings announcement.
Fog = the number of years of education required to comprehend the earnings press release, computed as 0.4[(words/sentences) + 100(three or more syllable words/words)].

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Appendix

See Table A.1.

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