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published in
International Review of Financial Analysis
2018

DOI (link to publisher)
10.1016/j.irfa.2018.02.002

document version
Publisher's PDF, also known as Version of record

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Link to publication in VU Research Portal

citation for published version (APA)
Boudt, K., Thewissen, J., & Torsin, W. (2018). When does the tone of earnings press releases matter? *International Review of Financial Analysis*, *57*, 231-245. https://doi.org/10.1016/j.irfa.2018.02.002

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Download date: 13. Dec. 2021

International Review of Financial Analysis 57 (2018) 231–245

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

When does the tone of earnings press releases matter?☆

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ARTICLE INFO

Keywords:
Textual sentiment
Firm performance
Investor reaction
Tone informativeness
Information asymmetry

ABSTRACT

The tone of a firm's financial disclosure is increasingly used as a variable in panel data regressions to predict future performance and explain investors' reaction at earnings announcement. We investigate when tone is informative, and argue that the informativeness of tone increases with the information asymmetry between firms and investors. Using a sample of over 50,000 earnings press releases of about 1800 U.S. public firms between 2004 and 2015, we find that firm growth, size, age, complexity and forecast inaccuracy are key drivers of tone informativeness. The effect is economically significant, since, compared to the reference case of a transparent firm, we find that the slope coefficient of tone doubles or even quadruples in panel data regressions when the firm operates in an environment with high information asymmetry.

1. Introduction

Earnings press releases are an important voluntary communication channel for firms to reduce the information asymmetry between managers and stakeholders in a timely manner. In fact, several studies show that the tone of earnings press releases (*i.e.*, the difference between the number of positive and negative words) is a reliable signal of future earnings (Miller & Piotroski, 2002), and that the market positively reacts to the tone over the short and long term (Arslan-Ayaydin, Boudt, & Thewissen, 2016; Henry, 2008). Whereas much of prior research tests the presence of predictive and explanatory power of tone, the primary focus of this paper is to examine the relationship between information asymmetry and its informativeness.

This paper is key to increase our understanding of the role that financial narratives play in investors' assessments of firm performance, and to what extent qualitative information contains incremental information to that of quantitative data. This topic has become increasingly important for investors, regulators and other stakeholders as there is growing scepticism on the usefulness of financial narratives. For instance, in 2013, the Chairman of the International Accounting Standards Board (IASB), Hans Hoogervorst, expressed his fear that financial narratives may become compliance documents, rather than a means of conveying useful information (Reuters, 2013). Additionally, Loughran and McDonald (2017) study the server log of the SEC and show that firm disclosures are only limitedly requested by investors, questioning the importance investors attach to first-hand qualitative data. As such, our analysis is central in ascertaining whether the tone of financial narratives is relevant to the market.

We contribute to the literature by investigating the effect of information asymmetry on the informativeness of tone in predicting future firm performance and explaining the investors' reaction. We test this by using a sample of 53,000 earnings press releases by 1,829 published U.S. firms, written within the period 2004–2015. Consistent with the literature, we find that, on average, the tone of press releases contains information to predict future return-on-assets and explain cumulative abnormal returns at earnings announcement. However, the significance of this relationship is not systematic. In fact, we find that the tone of earnings press releases contains significant explanatory power for about 25% of the firms in our sample at a traditional level of 10%. This result points out the presence of differences in informativeness of tone across firms.

Next, we unravel to what extent information asymmetry affects these differences. We hypothesize and find that, when a firm is smaller, younger and in a higher growth stage, tone is more informative. Furthermore, we provide evidence that tone informativeness also increases in case of higher analysts' forecast inaccuracy and activity in multiple segments, both geographically or cross-business. Qualitative information in firms' disclosures is thus differentially informative to the

☆ This research was carried out thanks to financial support of the ICM-FWO - Intercollegiate Center for Management Science (Grant No. 11C8918N), and the Hercules Foundation (Project No. AKUL/11/02). We are very grateful to Naciye Sekerci for valuable comments and suggestions, as well as attendants at the 2016 Corporate Finance Day, 2017 Accounting Day, 2017 conference on Discourse approaches to financial communication (DAFC), and 2018 Annual Conference of the Midwest Finance Association (MFA).
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https://doi.org/10.1016/j.irfa.2018.02.002
Received 29 September 2017; Received in revised form 25 January 2018; Accepted 4 February 2018
Available online 10 February 2018
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market, and its information value is a positive function of the level of information asymmetry between managers and investors.

The strong cross-sectional differences in tone informativeness imply that the slope coefficient of tone, obtained through traditional panel data regressions, needs to be interpreted with caution. We therefore extend the traditional explanatory and predictive panel data approach, by adding interaction terms between tone and the several hypothesized proxies for information asymmetry. Our results indicate that, compared to the reference case of a transparent and established firm, the prediction accuracy of tone towards future performance and the investor reaction substantially increases in size as the degree of information asymmetry is higher.

This paper proceeds as follows. Section 2 reviews the literature on disclosure tone and information asymmetry, and develops the hypotheses. Section 3 introduces the general methodological approach to indicate heterogeneity, whereas Section 4 entails the data collection and variable description. Section 5 reports our main findings, whereas in Section 6, we adjust traditional panel data regression and study how tone informativeness changes with increasing information asymmetry. Section 7 concludes.

2. The heterogeneity of tone informativeness and its determinants

There exists strong evidence that the market uses qualitative information from earnings press releases to infer inside information of managers. In practice, tone is a proxy for the information content of any financial narrative, and is used in a broad field of research as an independent variable in panel data regressions and predictive performance models (Davis, Piger, & Sedor, 2012; Davis & Tama-Sweet, 2012; Engelberg, 2008; Henry, 2008; Loughran & McDonald, 2011). For instance, Davis et al. (2012) document the positive correlation between the tone of earnings press releases and the firm's future performance. Based on this result, they evidence the immediate positive effect of tone on the three-day cumulative abnormal returns around earnings announcement. Henry (2008), Arslan-Ayaydin et al. (2016) and Price, Doran, Peterson, and Bliss (2012) also report that the tone of earnings press releases is significantly positively correlated with short window contemporaneous returns around the date that the disclosures are made, even after controlling for a firm's financial information and earnings surprises.

The aforementioned studies measure tone as the relative difference between the number of positive and negative words, and is included in panel data models as follows:

$$Y_{i,q,t} = \alpha + \delta \cdot Tone_{i,q,t} + \beta \cdot X_{i,q,t} + \varepsilon_{i,q,t}, \tag{1}$$

where $Y_{i,q,t}$ is the dependent variable for firm i in quarter q of year t. $X_{i,q,t}$ represents the information set for firm i available at the time of the earnings press release, and $Tone_{i,q,t}$ is the tone of the earnings press release. As such, we can infer the information value of tone with respect to the dependent variable as:

$$\delta = \frac{\partial E\left[Y_{i,q,t} | X_{i,q,t}\right]}{\partial Tone_{i,q,t}}. \tag{2}$$

Panel data regressions, such as Eq. (1), obtain a single δ for the whole sample. This average effect can be considered a bad advisor of the information value of tone for firms that are opaque, compared to the average firm.

It is common knowledge that firm stakeholders tend to attach more value to actively gathering information when there is a higher information asymmetry. In fact, Hartmann-Wendels (1987) and Veronesi (1999) find that investors, operating in an uncertain environment, attach more value to new information that becomes available. Neilson (2016) shows that, when the difficulty of interpreting changes in earnings increases, investors attempt to gather more information at the firm-level. This points out that the investors' value towards news increases with firm-level opaqueness. Furthermore, using dividend announcements as events, Jung (2007) reports that investors react more strongly to the announcements when information asymmetry is higher. In a similar vein, Demers and Vega (2010) show that firms display strong differences in their reported textual content, and document that this is also reflected in the market reaction to the soft information in the earnings press release. In particular, they find that the market responds more to soft information for high-tech firms, for high price-earning ratios and R&D firms, as well as for firms with a low accounting quality. Finally, Diamond (1985) and Hakansson (1977) evidence that higher transparency at the firm-level lowers the benefits of highly informed investors to actively gather information, and increases the benefits for less informed investors. Overall, their research suggests that the marginal value of information is higher when greater information asymmetry is at play.

If the sensitivity of the investors' response to information is a positive function of the level of information asymmetry, we argue that tone informativeness should differ across firms as a function of information asymmetry. Simply put, we conjecture that investors and other stakeholders allocate more value to the qualitative content provided in the press releases of an opaque and risky firm, than that of a transparent and low-risk firm. Our first hypothesis therefore aims to test for cross-sectional differences of tone informativeness and to what extent the tone of firms' financial narratives has explanatory power to predict future firm performance and explain investors' reaction:

H1a. *The tone informativeness of earnings press releases to predict future operational performance is heterogeneous across firms.*

H1b. *The tone informativeness of earnings press releases to explain investors' reaction at earnings announcement is heterogeneous across firms.*

Our following hypotheses test whether information asymmetry drives the information value of tone. We proxy for information asymmetry with a set of commonly used variables from prior literature, more specifically; firm size, age, growth, forecast inaccuracy and operational complexity. We describe each variable below in more detail.

2.1. Size, age and growth

The inverse relationship between information asymmetry and firm size has been well documented (Fama & Schwert, 1977; Ross, 1977; Vermaelen, 1981). Younger firms generally have higher information asymmetry than their elder counterpart, have lower analyst coverage and are thus more risky for investors. Baeyens and Manigaart (2003) report that information asymmetry decreases over the lifetime of a firm and Berger and Udell (1998) show that firms in different life cycle stages have strong differences in funding possibilities. Mature firms are more reliable since they are covered more by analysts, and thus have greater ability to raise funds from the market. Smith and Watts (1992) also argue that the degree of information asymmetry is larger for firms with significant growth opportunities. If firm size, age and growth stage are important drivers of information asymmetry, we expect that the incremental information contained in earnings press releases of such opaque firms, are of greater value to investors. We thus pose that the impact of qualitative information is higher for smaller, younger growth firms.

H2a. *Ceteris paribus, the smaller, younger and more growth-oriented the firm is, the higher the signaling power of tone in predicting future performance.*

H2b. *Ceteris paribus, the smaller, younger and more growth-oriented the firm is, the higher the marginal sensitivity of investors' reaction towards tone.*

2.2. Forecast error

Elton, Gruber, and Gultekin (1981), Atiase and Bamber (1994) and Christie (1981) show that analysts' forecast accuracy is a strong proxy for information asymmetry and find that firms with higher levels of information asymmetry regarding the firm's cash flows tend to have larger forecast errors. Kimbrough (2005) finds that additional information surrounding forecasts, obtained from conference calls, reduces forecast underreactions and the strength of market reactions. We similarly expect that the additional information contained within earnings press releases is more informative in cases of higher earnings' uncertainty.

H3a. *Ceteris paribus, the more inaccurate the analysts' forecast error of a firm's earnings, the more positive the signaling power of tone in predicting future performance.*

H3b. *Ceteris paribus, the more inaccurate the analysts' forecast error of a firm's earnings, the more positive the marginal sensitivity of investors' reaction to tone.*

2.3. Operational complexity

In the final hypothesis, we posit that the operational complexity dims the market's view on earnings, resulting in reduced transparency. Barinov, Park, and Yildizhan (2016) find that the post-earnings announcement drift is stronger for firms with a more complex operational structure. In addition, they show that the sensitivity of earnings announcement returns to the earnings surprise is significantly stronger for complex firms, indicating higher market reaction to earnings surprises. Firms, active in multiple business segments and geographical segments, are more demanding towards the corporate level and are therefore more vulnerable towards inefficiencies (Bushman, Qi, Engel, & Smith, 2004). Jennings, Seo, and Tanlu (2014) find that geographical diversification decreases the quality of management forecasts, because increasing firm complexity obscures the ability to gather and process data. In addition, Gilson, Healy, Noe, and Palepu (2001) show that increasing operational complexity leads to an increase in asymmetry of information between firm insiders and outside investors. In line with their findings, we believe that higher operational complexity dims both the management's as well as the market's assessment of future earnings. Consequently, these firms have higher levels of information asymmetry and we thus expect the market to attach more value to the tone of these firm's earnings press releases. We pose that:

H4a. *Ceteris paribus, the operational complexity of a firm is positively associated with the signaling power of tone in predicting future performance.*

H4b. *Ceteris paribus, the operational complexity of a firm is positively associated with the marginal sensitivity of the investors' reaction towards tone.*

3. A two-step approach to analyse heterogeneity of tone informativeness

In this section we develop a two-step framework that reveals the presence of differences in tone informativeness across firms, and encovers its drivers. This methodology is inspired by the two-step approach of Fama and MacBeth (1973), extensively used within the literature of asset pricing (see, e.g., Goyal, 2012; Jagannathan, Schaumburg, & Zhou, 2010; Roll, 1977).

3.1. Estimating tone informativeness and its determinants

Tone proxies for the information content in any qualitative narrative. As shown in Eq. (1), tone is generally used as an independent variable in panel data regression and predictive performance models (see, e.g., Davis et al., 2012; Davis & Tama-Sweet, 2012; Henry, 2008; Loughran & McDonald, 2011). In order to obtain each firm's value of tone informativeness, δ_i, rather than performing one singular panel data regression, we run the following ordinary least squares estimation for the N firms in our dataset separately:

$$Y_{i,q,t} = \alpha_i + \delta_i \cdot Tone_{i,q,t} + \beta_i \cdot X_{i,q,t} + \varepsilon_{i,q,t}, \tag{3}$$

where $Y_{i,q,t}$ represents future performance or investors' reaction at quarter q of year t. In Appendix A we show that the investors' reaction to tone can be rational under a dividend discount model. Note that contrary to the panel data model in Eq. (1), the tone informativeness parameter in Eq. (3) is firm-specific, as indicated by the subscript i. Note also that, under Eq. (3), the tone informativeness of firm i is given by:

$$\delta_i = \frac{\partial E\,[Y_{i,q,t} | X_{i,q,t}]}{\partial Tone_{i,q,t}}. \tag{4}$$

Performing separate firm regressions allows us to obtain a measure of each firm's sensitivity to tone, both in predicting future performance and explaining the investors' reaction. The newly obtained sample of firm-specific informativeness measures, enables us to study its heterogeneity and identify its drivers.

3.2. Step 1 – testing the homogeneity assumption of the firms' δ

To verify whether tone informativeness is different across firms, we start by testing for its homogeneity. More specifically, we look at the tone informativeness parameter defined in Eq. (4) for all N firms separately and question whether:

$$H_0: \quad \delta_1 = \delta_2 = \delta_3 = \ldots = \delta_N. \tag{5}$$

The firm-by-firm regressions proposed in Eq. (3), are a direct way to obtain unbiased estimates of each firm's sensitivity to tone (or tone informativeness): δ_i. The obtained sample of N estimated firm-specific $\widehat{\delta_i}$s serves as the sample statistic to test the hypothesis of homogeneity in Eq. (5). We derive the distribution of the test statistic under the Gauss-Markov assumption that the homoscedastic and serially uncorrelated regression error term has mean zero, and is independent of the regressors. We then have that each firm's $\widehat{\delta_i}$ is (asymptotically) normally distributed around the actual (true) δ_i. Given that $\widehat{SE}_{\widehat{\delta_i}}$ is a consistent estimated standard error of $\widehat{\delta_i}$, we have that:

$$\frac{\widehat{\delta_i} - \delta_i}{\widehat{SE}_{\widehat{\delta_i}}} \sim N(0, 1), \tag{6}$$

for $T \to \infty$. The unknown in this equation is δ_i. Under H_0 of homogeneity and following the law of large numbers, we have that the cross-sectional average of the estimated exposure coefficient converges to δ_i:

$$\bar{\delta} = \frac{1}{N}\sum_{i=1}^{N} \widehat{\delta_i} \longrightarrow \delta_i, \tag{7}$$

for $N \to \infty$. Asymptotically, when the number of firms N and the number of time series observations T becomes infinitely large, we have that the standardized estimated δ follows a standard normal distribution under the null of homogeneity:

$$\delta_i^{ST} = \frac{\widehat{\delta}_i - \bar{\delta}}{\widehat{SE}_{\widehat{\delta}_i}} \sim N(0, 1). \tag{8}$$

Typically, we'll have that $T/N \to 0$, since the number of firms in our sample, N, is much larger than the amount of time-points, T. In the empirical analysis, we obtain the estimated standard error, $\widehat{SE}_{\widehat{\delta}_i}$, by using the Newey-West heteroskedasticity and autocorrelation consistent standard errors (HAC). H_0 (see, Eq. (5)) can then simply be verified by a test of normality. Rejecting the normality provides evidence against the null of equality of the firm's δ_i and indicates the existence of substantial differences across firm's tone informativeness.

In Appendix B, we conduct a simulation analysis to document the statistical validity of the proposed test for heterogeneity.[1] We show that

[1] We thank the reviewer for this suggestion.

Table 1
Number of firms and observations per industry.

		Sample		S&P 1500	S&P 500
SIC	Division	# Observations	% Firms	% Firms	% Firms
01–09	Agriculture, Forestry, Fishing	45	0%	0%	0%
10–17	Mining & Construction	2187	4.5%	5.7%	7.4%
20–39	Manufacturing	22,206	41.1%	39.3%	40%
40–49	Transportation & Public Utilities	4371	8,5%	9.8%	14.2%
50–59	Wholesale Trade & Retail Trade	5403	10%	11.3%	9.8%
60–67	Finance, Insurance & Real Estate	10,380	20%	18.7%	17.4%
70–89	Services	7953	15.7%	15.2%	11.2%
91–99	Public Administration & Others	122	0.2 %	0%	0%
Total:		52,667			

This table displays the number of observations and share of firms per industry using the two-digit SIC-codes. The S&P 1500 and S&P 500 composition is computed at the beginning of 2010, about midway throughout our sample period.

this method correctly rejects normality in cases of a heterogeneous δ with increasing N and T, under the similar dimensions as our data sample. We refer the reader to the Appendix for more details.

3.3. Step 2 – analysing the determinants of the cross-sectional variation in δ_i^{ST}

The previous step shows the existence of differences within tone informativeness across firms, but it does not indicate what drives these differences. We propose to model the information value of tone, δ_i^{ST}, as a linear function of relevant independent variables:

$$\delta_i^{ST} = \gamma_0 + \gamma_i \cdot Z_i + \varepsilon_i, \tag{9}$$

where the error term, ε_i, is assumed to have zero mean.[2]

Note however, that in the firm-by-firm regressions of Eq. (3) multiple time observations for each variable ($t = 1,\ldots,T$) are used to obtain one firm-specific measure of tone informativeness, δ_i^{ST}. Because we only have one dependent variable per firm, we need to transform the set of time varying control variables ($X_{i,q,t}$ in Eq. (3)) to a cross-sectional set (Z_i in Eq. (9)). Simply put, we average $X_{i,q,t}$ to obtain Z_i. Finding statistical significance of the estimated regressor coefficients, in the cross-sectional regression, further confirms the heterogeneity of informativeness and sheds light on its drivers.

4. Data

4.1. Sample description

Our sample consists out of U.S. data of publicly listed firms for the period of 2004Q1 up to 2015Q4. We download all possible earnings press releases available under the 8-K forms which are stored on the website of the SEC, as proposed by Section 406 of the Sarbanes-Oxley act of 2002. To further ensure data reliability, we do not consider earnings press releases, written before 2004. The earnings press releases are freely available and found under exhibit 99.1: " < TYPE > EX 99.1", or similar.[3]

In a second stage the downloaded press releases, which are stored as html-pages and contain the earnings press releases, are re-encoded into a more readable format. We follow the practice in accordance with the literature of parsing the text according to the following steps (Arslan-Ayaydin et al., 2016; Davis et al., 2012; Davis & Tama-Sweet, 2012; Henry, 2008; Loughran & McDonald, 2011):

i. Remove graphics.
ii. Re-encode characters such as   (blank space) or &amp (&) back to their original ASCII form.
iii. Remove all text appearing within < TABLE > HTML tags, where more than 15% of the non-blank characters are numbers.

We impose a threshold in terms of minimum number of words in the press releases to ensure that our sample only contains valid press releases and no misfilings. Davis et al. (2012) suggest that the reliability of the data collection increases if the minimal text length is 100 words, however we use a minimal length of 200 words as an extra imposed restriction because of the high amount of available press releases.[4] This leads to a total amount of 157,423 firm-quarter earnings press releases. We furthermore include data of a financial or accounting nature for which Compustat, CRSP and I/B/E/S are required. Because of missing data within the firm-quarter observations, the dataset is reduced to 60,710 observations. In order to ensure a sufficient number of firm-specific observations needed to capture each firm's tone informativeness, we keep firms with at least 15 unique quarter-year observations. We obtain a final sample of 52,667 earnings press releases from 1829 unique firms, with an average of about 29 observations per firm.[5] Out of these 1829 firms, about 70% (1274 firms) have been part of the S&P 1500 and about 27% (488 firms) have been part of the S&P 500 throughout the period of 2004–2015.

Table 1 presents the share of firms and observations of each industry in the total sample, alongside the composition of the S&P 1500 and S&P 500 for presentation purposes. The majority of firms within our dataset are active in manufacturing (about 41%). Financial firms and firms active in the service industry are also well represented in the sample. Public administration firms along with agricultural firms are marginally

[2] If γ_i is zero, it nests the special case of equal δ across firms. Z_i controls for several firm characteristics.

[3] Not all earnings press releases are filed under the same TYPE. Other similar abbreviations are used consistently throughout the filings, such as; "99-1", "99.01", etc. These cases were downloaded as well, and manually verified in terms of containing an earnings press release.

[4] Using a minimum threshold of 100 words does not alter our conclusions.

[5] In our robustness tests, this dataset is further reduced to firms for which there are at least 20 and 25 quarter-year observations. These datasets contain 46,663 and 30,607 observations respectively. Results remain qualitatively similar.

Table 2
Variable definitions.

Variable	Variable description
Panel A – Dependent variables	
$FUTROA_{i,q,t}$	Next quarter's ROA_i for firm i, with respect to quarter q of year t.
$CAR[-1;+1]_{i,q,t}$	The cumulative abnormal returns for firm *i* within a short term time-window around the announcement date of the press release of quarter *q* in year *t*. The cumulative abnormal returns are acquired using a market model that is estimated over a window of [d-315; d-63].
Panel B – Control variables	
$Tone_{i,q,t}$	The overall tone of the earnings press release of firm *i* of year *t*, in *q*; The tone is measured by: $Tone_{i,q,t} = \frac{PW_{i,q,t} - NW_{i,q,t}}{TW_{i,q,t}}$, where TW represents the total amount of words in the press release. Different libraries are used to define the amount of positive words (PW) and negative words (NW): Loughran & McDonald, Henry and their centered average.
$ROA_{i,q,t}$	(ROA of firm *i* in quarter *q* of year *t*, before extraordinary items) / (total assets at the quarter start).
$RET_{i,q,t}$	Buy-and-hold returns of firm *i* of quarter *q* of year t, for the 12 month period, ending three months after the fiscal year end.
$\sigma_{RETi,q,t}$	Standard deviation for firm *i* of RET_i over the last 12 months ending three months after the fiscal year-end, *t*.
$\sigma_{ROAi,q,t}$	Standard deviation of *ROA* over the last 5 years.
$MC_{i,q,t}$	Logarithm of the market capitalization of firm *i* on the last day of the quarter *q* of year *t* (in $ mil), i.e. $P_{i,d,q,t} \cdot CSHO_{i,q,t}$, where $P_{i,d,q,t}$ represent the price of firm *i* on day *d* of quarter *q* of year *t* and $CSHO_{i,q,t}$ is the number of common shares outstanding of firm *i* at the end of quarter *q* of year *t*.
$BTM_{i,q,t}$	log(1 + Book-To-Market ratio for firm *i* in quarter *q* of year *t*).
$BUSseg_{i,q,t}$	log(1 + # of Business Segments of firm *i* in quarter q of year t).
$GEOseg_{i,q,t}$	log(1 + # of Geographical Segments of firm *i* in quarter q of year t).
$AGE_{i,t}$	log(1 + # years since firm *i* first appears in CRSP monthly file, relative to time *t*).
$LOSS_{i,q,t}$	1 if ROA is negative for firm *i* in quarter *q* of year t, 0 otherwise.
$\Delta(ROA_{i,q,t})$	Change in (ROA for firm *i* in quarter *q* of year *t* before extraordinary items) /(beginning total assets).
$FE_{i,q,t}$	(*I/B/E/S* actual earnings per share (*EPS*) - median of most recent analysts forecasts) / (stock price at the fiscal year-end, for firm *i* in quarter *q* of year *t*).
$MedianCons_{i,q,t}$	Median of the analyst forecasts for one-year-ahead *EPS* stock price at the fiscal year-end, divided by the current stock price.

present (less than 1%).[6]

4.2. Variables

We next give the definition of future performance and investors' reaction, tone of earnings press releases, proxies for information asymmetry and the control variables. Table 2 lists the variables used in this study.

4.2.1. Future performance and investors' reaction

As presented in Eq. (3), we use firm-by-firm regressions to obtain estimates of each firm's sensitivity of future firm performance and investors' reaction to the tone of earnings press releases. To proxy for future performance, we use the next quarter's return on assets, $FUTROA_{i,q,t}$. The investors' reaction is estimated following prior literature as the cumulative abnormal returns, or CAR (Arslan-Ayaydin et al., 2016; Davis et al., 2012; Demers & Vega, 2014). $CAR_{i,q,t}$ is computed by taking the difference between the observed value of the firm's returns and the expected value computed using a market model. This market model regresses the firm returns on the market returns to obtain the ordinary least squares estimate of the intercept ($\alpha_{i,q,t}$) and the slope coefficient ($\beta_{i,q,t}$). Using data from a window starting 315 days before the announcement and ending 62 days before the date of the announcement, the ordinary least squares estimates of $\alpha_{i,q,t}$ and $\beta_{i,q,t}$ are obtained, denoted as $\widehat{\alpha}_{i,q,t}$ and $\widehat{\beta}_{i,q,t}$. The daily differences in a three-day window around the announcement date, d^*, are then summed, and form the cumulative abnormal returns:

$$CAR[-1;+1]_{i,q,t} = \sum_{j=-1}^{+1} R_{i,d^*+j,q,t} - \widehat{\alpha}_{i,q,t} - \widehat{\beta}_{i,q,t} \cdot R_{M,d^*+j,q,t}, \tag{10}$$

where $R_{i,d^*+j,q,t}$ represents the firm *i*'s returns on day $d^* + j$ of quarter *q* of year *t*, and $R_{M,d^*+j,q,t}$ represents the market's returns.

4.2.2. Tone

Through a bag-of-words approach, we use predefined libraries of positive and negative words to construct our measure of tone. This method simply counts the number of positive and negative words within any narrative such that an overall degree of positivity is obtained, proxying the information content of the press release (Henry, 2008; Loughran & McDonald, 2011, 2013). Several ways of constructing tone came forth from the literature. For example Sadique, In, and Veeraraghavan (2008) opt for using positive tone and negative tone, measured by the number of positive and negative words in the narrative section, as separate measures. Davis et al. (2012) define net optimism as the difference between the number of positive words and negative words. In this paper however, we follow Brockman and Cicon (2013), Demers and Vega (2014) and Arslan-Ayaydin et al. (2016) by defining the tone as the spread between the number of positive and negative words, relative to the total amount of words in the earnings press release:

$$Tone_{i,q,t} = \frac{PW_{i,q,t} - NW_{i,q,t}}{TW_{i,q,t}}, \tag{11}$$

where $PW_{i,q,t}$ represents the number of positive words for firm *i*, in quarter *q* of year *t*, $NW_{i,q,t}$ represents the number of negative words and $TW_{i,q,t}$ refers to the total number of words in the earnings press release.

There are numerous available word lists to categorize words as being positive and negative, but using finance related libraries generally leads to less biased results in the analysis of earnings press releases (Arslan-Ayaydin et al., 2016; Loughran & McDonald, 2011). We therefore limit ourselves to two of the more established dictionaries developed within this finance literature: the positive and negative wordlists by Henry (2008) and the ones by Loughran and McDonald (2011) (see, e.g., Doran, Peterson, & Price, 2010; Ferguson, Philip, Lam, & Guo, 2014; Huang, Teoh, & Zhang, 2014; Garcia, 2012; Loughran & McDonald, 2011, 2013). Although both the Henry and Loughran & McDonald libraries are specifically designed for finance applications, we further avoid our results to be driven by choice of library and define an overall measure of sentiment which is the centered average of both libraries' tone, denoted as $Tone_{i,q,t}$.[7]

[6] Additionally, Table 1 points out that the industry-wise composition of our sample of 1829 firms is strongly aligned with the S&P-composition (midway throughout our sample period), indicating that our sample is a proper representation of the U.S. market.

[7] We still perform robustness tests using the library of Henry (2008) (denoted as $Tone^{HEN}_{i,q,t}$) and the library of Loughran and McDonald (2011) ($Tone^{LM}_{i,q,t}$) separately, for which we post the model validations in Table 9. The conclusions remain qualitatively similar. The correlations between $Tone_{i,q,t}$, $Tone^{HEN}_{i,q,t}$, and $Tone^{LM}_{i,q,t}$, range between 40% and 80%. The positive correlations indicate that the different measurements capture the underlying tone similarly.

Table 3
Summary statistics.

Panel A - summary statistics of the dependent variables, tone measures and controls

	Mean	Std. dev.	Q1	Median	Q3
$FUTROA_{i,q,t}$	0.006	0.043	0.002	0.010	0.021
$CAR[-1;+1]_{i,q,t}$	0.001	0.079	−0.037	0.0004	0.040
$Tone_{i,q,t}$	0.000	0.842	−0.498	−0.058	0.425
$Tone_{i,q,t}^{HEN}$	0.034	0.032	0.012	0.027	0.046
$Tone_{i,q,t}^{LM}$	−0.014	0.218	−0.127	0	0.106
$AGE_{i,t}$	22.814	18.602	10	17	30
$MC_{i,q,t}$ (in mil.)	7.947	22.121	0.509	1.482	5.212
$BTM_{i,q,t}$	0.569	0.489	0.267	0.473	0.763
$FE_{i,q,t}$	−0.019	0.156	−0.056	0.057	0.223
$BUSseg_{i,q,t}$	5.126	5.259	1	3	9
$GEOseg_{i,q,t}$	6.423	7.450	1	4	9
$ROA_{i,q,t}$	0.006	0.041	0.002	0.010	0.021
$RET_{i,q,t}$	0.132	0.495	−0.139	0.077	0.309
$\sigma_{ROAi,q,t}$	0.015	0.028	0.003	0.006	0.014
$\sigma_{RETi,q,t}$	0.023	0.015	0.013	0.018	0.027
$LOSS_{i,q,t}$	0.200	0.400	0	0	0
$\Delta(ROA_{i,q,t})$	−0.001	0.030	−0.005	−0.001	0.002
$MedianCons_{i,q,t}$	0.008	0.028	0.006	0.013	0.018

Panel B - average tone per calendar year

Year	# Observations	# Firms	$Tone_{i,q,t}$	$Tone_{i,q,t}^{HEN}$	$Tone_{i,q,t}^{LM}$
2004	1191	739	0.344	0.047	0.031
2005	3101	1058	0.306	0.043	0.043
2006	3508	1215	0.139	0.040	0.030
2007	4287	1448	0.075	0.039	0.014
2008	5115	1622	−0.155	0.032	−0.039
2009	5380	1689	−0.320	0.020	−0.073
2010	5532	1726	0.060	0.035	−0.012
2011	5341	1693	0.069	0.036	−0.014
2012	5339	1630	−0.162	0.031	−0.032
2013	5324	1589	−0.125	0.029	−0.035
2014	5068	1526	−0.099	0.031	−0.033
2015	3443	1426	−0.096	0.026	−0.045

This table reports the summary statistics of our sample. Panel A gives the descriptive statistics for the observations within the sample and Panel B shows the evolution of the number of observations, number of firms and tone-measures over time. Note that certain variables are logarithmized in the regressions (e.g., # of business segment, *BUSseg*, and Market capitalization, *MC*). We however present the non-transformed variable for interpretation purposes.

4.3. Descriptive statistics

Table 3 presents the summary statistics of the relevant variables. On average $FUTROA_{i,q,t}$ and $CAR[-1;+1]_{i,q,t}$ are positive with a respective value of 0.006 and 0.001 and a high standard deviation, indicating a broad and diversely performing dataset. While the tone proxy following the library of Henry (2008) ($Tone_{i,q,t}^{HEN}$) is positive, the average of the Loughran and McDonald (2011) measure ($Tone_{i,q,t}^{LM}$) is slightly negative. This is consistent with prior literature (see, e.g., Baginski, Demers, Wang, & Yu, 2011; Loughran & McDonald, 2013) as the number of negative words in the Loughran and McDonald (2011) library far exceeds the number of positive words. Our main independent variable $Tone_{i,q,t}$ is obtained by averaging and scaling the sum of $Tone_{i,q,t}^{LM}$ and $Tone_{i,q,t}^{HEN}$. The variable $Tone_{i,q,t}$ therefore has an average of exactly zero by construction. Panel B, in Table 3 shows the evolution of our different tone measures throughout the years. During the financial crisis (especially in 2009) we find tone to be at its lowest point. After 2010, $Tone_{i,q,t}^{HEN}$ increases in value but does not return back to pre-crisis levels. $Tone_{i,q,t}^{LM}$ even remains negative.

Furthermore, we find that the average age ($AGE_{i,t}$) is about 22 years. The average and median of $BTM_{i,q,t}$ are lower than one with a high standard deviation, implying that the dataset contains over- as well as undervalued firms. The analysts' forecast error ($FE_{i,q,t}$) is negative on average indicating that analysts tend to overestimate earnings of firms within the dataset. Finally, there is a strong spread in terms of operational complexity, $BUSseg_{i,q,t}$ and $GEOseg_{i,q,t}$, indicating strong differences in firm's operating structures.

Table 4 displays the Pearson correlations of the dependent ($FUTROA_{i,q,t}$ and $CAR[-1;+1]_{i,q,t}$), several proxies for $Tone_{i,q,t}$, as well as the control variables. Overall, the correlation table points out that several of the variables used in the regressions are significantly correlated with one another, making multivariate analysis an appropriate way for investigating the posed hypotheses. The different measures of tone are highly correlated with one another, between the ranges of 40% and 80%. Moreover, Table 4 indicates a significant positive correlation between tone and the independent variables, which is consistent with prior research (see, e.g., Arslan-Ayaydin et al., 2016; Henry, 2008; Loughran & McDonald, 2011). We also find that the tone is significantly and positively correlated with the forecast error ($FE_{i,q,t}$) and the number of geographical and business segments ($BUSseg_{i,q,t}$, $GEOseg_{i,q,t}$). Additionally, we report a negative correlation between $BTM_{i,q,t}$ and the different proxies for tone, which is in accordance with the postulated hypothesis. In terms of $AGE_{i,t}$, we find a negative correlation in terms of $Tone_{i,q,t}^{LM}$, but a positive one for the others.

5. Results of the two-step approach

Hereafter, we elaborate on the framework developed in Section 3.

Table 4
Correlation table.

	$FUTROA_{i,q,t}$	$CAR[-1;+1]_{i,q,t}$	$Tone_{i,q,t}$	$Tone^{HEN}_{i,q,t}$	$Tone^{LM}_{i,q,t}$	$AGE_{i,t}$	$MC_{i,q,t}$	$BTM_{i,q,t}$	$FE_{i,q,t}$
$CAR[-1;+1]_{i,q,t}$	0.100***								
$Tone_{i,q,t}$	0.176***	0.074***							
$Tone^{HEN}_{i,q,t}$	0.172***	0.058***	0.842***						
$Tone^{LM}_{i,q,t}$	0.124***	0.067***	0.842***	0.418***					
$AGE_{i,t}$	0.138***	−0.003	0.033***	0.098***	− 0.043***				
$MC_{i,q,t}$	0.103***	−0.004	0.080***	0.135***	0.054***	0.258***			
$BTM_{i,q,t}$	− 0.057***	0.041***	− 0.178***	− 0.120***	− 0.180***	0.037***	− 0.103***		
$FE_{i,q,t}$	0.079***	0.175***	0.104***	0.051***	0.123***	0.003	0.016***	− 0.105***	
$BUSseg_{i,q,t}$	0.090***	0.009*	0.089***	0.097***	0.053***	0.178***	0.094***	0.036***	0.031***
$GEOseg_{i,q,t}$	0.108***	0.018***	0.080***	0.055***	0.079***	0.084***	0.087***	− 0.077***	0.032***
$ROA_{i,q,t}$	0.671***	0.095***	0.202***	0.180***	0.160***	0.139***	0.106***	− 0.019***	0.173***
$RET_{i,q,t}$	0.143***	− 0.051***	0.166***	0.145***	0.135***	− 0.046***	0.008	− 0.232***	0.085***
$\sigma_{RETi,q,t}$	− 0.284***	0.003	− 0.166***	− 0.171***	− 0.109***	− 0.229***	− 0.164***	0.169***	− 0.144***
$\sigma_{ROAi,q,t}$	− 0.279***	− 0.013**	− 0.096***	− 0.123***	− 0.039***	− 0.157***	− 0.092***	− 0.086***	− 0.014**
$LOSS_{i,q,t}$	− 0.459***	− 0.098***	− 0.234***	− 0.196***	− 0.199***	− 0.166***	− 0.120***	0.031***	− 0.205***
$\Delta(ROA_{i,q,t})$	0.018***	0.015***	0.041***	0.031***	0.038***	0.010*	0.008	− 0.028***	−0.003
$MedianCons_{i,q,t}$	0.430***	0.033***	0.160***	0.147***	0.123***	0.136***	0.092***	− 0.018***	0.170***

	$BUSseg_{i,q,t}$	$GEOseg_{i,q,t}$	$ROA_{i,q,t}$	$RET_{i,q,t}$	$\sigma_{RETi,q,t}$	$\sigma_{ROAi,q,t}$	$LOSS_{i,q,t}$	$\Delta(ROA_{i,q,t})$
$GEOseg_{i,q,t}$	0.270***							
$ROA_{i,q,t}$	0.095***	0.113***						
$RET_{i,q,t}$	0.006	0.011*	0.128***					
$\sigma_{RETi,q,t}$	− 0.046***	0.016***	− 0.296***	− 0.207***				
$\sigma_{ROAi,q,t}$	− 0.044***	0.004	− 0.348***	−0.002	0.271***			
$LOSS_{i,q,t}$	− 0.086***	− 0.043***	− 0.620***	− 0.124***	0.333***	0.323***		
$\Delta(ROA_{i,q,t})$	−0.003	−0.003	0.048***	0.027***	− 0.032***	− 0.035***	− 0.083***	
$MedianCons_{i,q,t}$	0.118***	0.062***	0.519***	0.131***	− 0.359***	− 0.275***	− 0.529***	0.003

This table reports the Pearson correlation for the different performance measures, tone measurements and financial and accounting control variables. *, **, *** Denote statistical significance at the 10%, 5%, and 1% level based on a two-tailed t-test, respectively.

This section starts by constructing the models that predict future firm performance, and investors' reaction, through which we obtain each firm's informativeness of tone. Furthermore, we test the normality of the obtained sample of informativeness estimates. In the next step we use a cross-sectional model, indicating the drivers of tone informativeness.

5.1. Differences across tone informativeness

We estimate the informativeness of tone in signaling future firm performance for each firm separately, using a model in which we include the current profitability ($ROA_{i,q,t}$, $RET_{i,q,t}$, and $LOSS_{i,q,t}$), operating and business risk ($\sigma_{ROA_{i,q,t}}$ and $\sigma_{RET_{i,q,t}}$), firm size ($MC_{i,q,t}$), growth

Table 5
Estimation results of the firm-by-firm regressions.

Equation		$\beta_{0,i}$	δ_i	$\beta_{1,i}$	$\beta_{2,i}$	$\beta_{3,i}$	$\beta_{4,i}$	$\beta_{5,i}$	$\beta_{6,i}$	$\beta_{7,i}$	$\beta_{8,i}$	$\overline{Adj.\ R^2}$
Panel A - average coefficients and significance levels in predicting future performance ($FUTROA_{i,q,t}$)												
Eq. (12)	$\overline{\hat{\beta}}$	− 0.013	**0.158**	0.114	− 0.033	0.002	0.000	− 0.021	0.072	0.004	0.0013	**0.335**
	$\overline{SE_{\beta}}$	0.161	**1.402**	0.459	0.085	1.402	0.015	0.502	0.616	0.020	0.427	
	+ Significant at 1%	4.98%	**3.34%**	8.64%	3.06%	2.24%	2.35%	1.75%	2.95%	5.3%	2.68%	
	+ Significant at 5%	12.36%	**10.11%**	16.4%	7.65%	6.23%	6.94%	6.34%	9.19%	13.12%	7.6%	
	+ Significant at 10%	19.03%	**17.61%**	21.92%	10.93%	10.93%	12.03%	11.65%	15.75%	19.03%	11.26%	
	− Significant at 1%	4.21%	**1.26%**	3.12%	3.61%	1.69%	1.59%	4.48%	1.37%	3.44%	3.44%	
	− Significant at 5%	11.1%	**4.59%**	6.89%	11.37%	6.01%	5.3%	10.22%	5.74%	9.35%	8.26%	
	− Significant at 10%	15.91%	**8.69%**	11.59%	17.82%	10.99%	9.9%	15.58%	10.88%	14%	11.86%	
Panel B - average coefficients and significance levels in explaining investors' reaction ($CAR[-1;+1]_{i,q,t}$)												
Eq. (13)	$\overline{\hat{\beta}}$	− 0.040	**1.193**	0.355	0.092	0.092						**0.093**
	$\overline{SE_{\beta}}$	0.075	**3.771**	2.717	0.172	0.056						
	+ Significant at 1%	0.55%	**3.34%**	3.28%	4.76%	26.9%						
	+ Significant at 5%	2.52%	**10.5%**	9.62%	15.86%	43.79%						
	+ Significant at 10%	5.08%	**17.44%**	15.04%	25.1%	55.82%						
	− Significant at 1%	5.03%	**0.82%**	2.52%	0.71%	0.44%						
	− Significant at 5%	14.71%	**3.88%**	6.78%	3.01%	1.2%						
	− Significant at 10%	25.21%	**7.76%**	10.39%	6.07%	2.19%						

This table reports the average OLS coefficient estimates and average robust standard errors, together with the frequency of significantly positive and negative coefficients using the one-sided *t*-test at the 1%, 5% and 10% levels, and the average adjusted R^2. Results for the parameter of interest (δ_i) are indicated in bold. Results are presented for predicting the future performance (Panel A) and explaining the investors' reaction (Panel B).

($BTM_{i,q,t}$) and the forecast error ($FE_{i,q,t}$):

$$\text{For a given } i: \quad FUTROA_{i,q,t} = \beta_{0,i} + \delta_i \cdot Tone_{i,q,t} + \beta_{1,i} \cdot ROA_{i,q,t} + \beta_{2,i} \cdot BTM_{i,q,t} + \beta_{3,i} \cdot FE_{i,q,t} + \beta_{4,i} \cdot RET_{i,q,t} + \beta_{5,i} \cdot \sigma_{ROA_{i,q,t}} + \beta_{6,i} \cdot \sigma_{RET_{i,q,t}} + \beta_{7,i} \cdot MC_{i,q,t} + \beta_{8,i} \cdot LOSS_{i,q,t} + \varepsilon_{i,q,t}, \tag{12}$$

where δ_i in the firm-by-firm regressions represents informativeness of $Tone_{i,q,t}$ in predicting $FUTROA_{i,q,t}$ for firm i. This approach leads to consistent estimates of tone informativeness but has the drawback of a relatively high estimation uncertainty because of the limited number of available earnings press releases per firm. Nevertheless, as shown in Subsection 3.2, these firm-by-firm OLS estimates of δ_i are useful, since they can be combined into a test of homogeneity.

We run a similar regression, to estimate the regression coefficient of tone in explaining the investors' reaction to the earnings press release, as proxied by the $CAR[-1;+1]_{i,q,t}$. In our model, we follow Arslan-Ayaydin et al. (2016) by adding control variables for the firm's profitability and growth, as well as the value of the forecast error to capture the hard information of the earnings press release. The resulting regression model is given by:

$$\text{For a given } i: \quad CAR[-1;+1]_{i,q,t} = \beta_{0,i} + \delta_i \cdot Tone_{i,q,t} + \beta_{1,i} \cdot ROA_{i,q,t} + \beta_{2,i} \cdot BTM_{i,q,t} + \beta_{3,i} \cdot FE_{i,q,t} + \varepsilon_{i,q,t}, \tag{13}$$

where δ_i represents the informativeness of $Tone_{i,q,t}$ in explaining $CAR[-1;+1]_{i,q,t}$ for firm i.

Table 5 reports a summary of the estimation results for all 1829 firm-by-firm regressions. Panel A displays the estimation results for Eq. (12) and Panel B reports the results for Eq. (13). We find that the average $Adj.\ R^2$ of the regressions is 33.5% (9.3%) when predicting $FUTROA_{i,q,t}$ (explaining $CAR[-1;+1]_{i,q,t}$). Consistent with previous literature, the tone of earnings press releases contains information to predict future performance and investors' reaction (Davis et al., 2012; Henry, 2008; Loughran & McDonald, 2011), but this relationship is for most firms not statistically significant: only around 25% of the coefficients are significant at a confidence level of 10% (17.61% + 8.69% for $FUTROA_{i,q,t}$ and 17.44% + 7.76% for $CAR[-1;+1]_{i,q,t}$). This low significance can be explained by the limited number of available press releases per firm. The number of earnings press releases per firm varies between 15 and 45, with an average value of 29 observations. This also explains why the average standard error, $\overline{\widehat{SE}_\beta}$ (1.402 and 3.771) is large relative to the average informativeness $\overline{\hat{\delta}}$ (0.158 and 1.193). When pooling the information across the $N = 1829$ firms, as shown in the next section, the standard error is substantially reduced.[8] Table 5 also points out that the true δ_i is generally positive for both future performance and earnings reaction because the percentage of significant positive δ_is at the one-sided test at the 10% and 5% levels are significantly higher than the obtained significant negative δ_is and higher than their respective type 1 significance levels.

Fig. 1 displays the histograms of the obtained informativeness estimates. We find that, a large proportion of the obtained exposure coefficients is economically and statistically close to zero; in particular in the case of δ_{FUTROA_i}. Furthermore, both histograms display positive skewness, with longer and heavier tails to the right, which corresponds to the positive average coefficients of δ_i (0.158 and 1.193 for δ_{FUTROA_i} and $\delta_{CAR[-1;+1]_i}$ respectively) in Table 5. Altogether, the histograms visually deviate from normality, which is in line with our first hypothesis. We formally evaluate the null hypothesis of homogeneity with the normality test procedure proposed in Subsection 3.2, on the

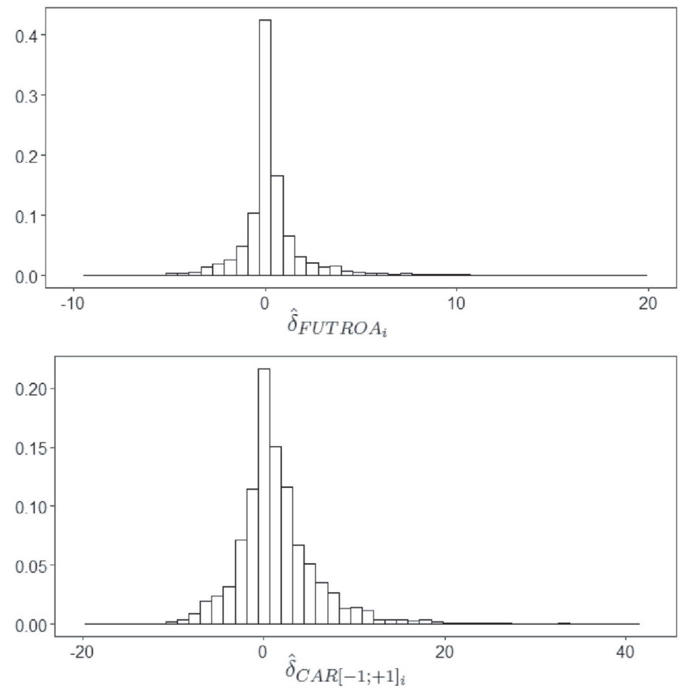

Fig. 1. Histogram of the obtained tone informativeness estimates $\hat{\delta}_{FUTROA_i}$ and $\hat{\delta}_{CAR[-1;+1]_i}$. This figure displays the histograms of the obtained estimates of the firm-specific tone exposure coefficients $\hat{\delta}_i$ from the separate firm-specific regressions, represented in Eq. (3). The upper histogram displays the distribution of tone informativeness in terms of predicting future firm performance ($\hat{\delta}_{FUTROA_i}$), whereas the lower histogram displays the tone informativeness in terms of explaining the investors' reaction ($\hat{\delta}_{CAR[-1;+1]_i}$).

standardized informativeness coefficients δ_i^{ST}. Panel A of Table 6 reports the results for the Anderson-Darling, Jarque-Bera and the Kolmogorov-Smirnov tests. Each test controls for different criteria of normality but in all cases the null hypothesis of homogeneity is rejected. This result is in line with H1a and H1b and complements prior literature by showing that tone indeed contains information value, but also that there are substantial cross-sectional differences within informativeness.

5.2. Information asymmetry and tone informativeness

We now study the firm characteristics that can explain the heterogeneity in the tone exposure coefficients. We do this first by using a split-sample analysis and t-tests. We then take a multivariate regression approach.

As shown in Subsection 3.3, we, first transform our control variables into a cross-sectional dataset. To better visualize the cross-sectional variability of tone exposure coefficients, we report in Table 7 a split sample of the exposure coefficients according to the information asymmetry dimensions following our hypotheses. We define firms with high information asymmetry as firms that belong to the bottom quartile of smallest ($\overline{MC_i}$), youngest ($\overline{AGE_i}$) and most growth-oriented ($\overline{BTM_i}$) firms, and the top quartile of firms having high forecast inaccuracy ($|\overline{FE_i}|$) and operational complexity ($\overline{GEOseg_i}$ / $\overline{BUSseg_i}$). Table 7 shows no statistical difference between small and large firms in terms of δ_{FUTROA_i}, but find that the exposure coefficient is statistically larger for young and growth-oriented firms. Additionally, we show that a larger forecast inaccuracy, and operational complexity are associated with a statistically larger informativeness coefficient. In terms of the investors' reaction, we find a statistically larger coefficient for firms that are smaller and younger, but find no statistical difference in terms of growth-orientation. We furthermore find a statistical larger tone

[8] Roughly speaking, by pooling across the 1,829 firms, the standard error is shrunk by a factor of $1/\sqrt{1{,}829}$, as can be seen in Eq. 3 of Petersen (2009).

Table 6
The cross-section of firm-by-firm estimators of the tone informativeness: heterogeneity and its drivers.

	$\delta^{ST}_{FUTROA_i}$	$\delta^{ST}_{CAR[-1;+1]_i}$
Panel A – testing for homogeneity by verifying the normality of the sample of δ_i^{ST} s.		
Anderson-Darling	17.064	1.953
	(0)	(0)
Jarque-Bera	65.900	9.355
	(0)	(0.009)
Kolmogorov-Smirnov	0.114	0.099
	(0)	(0)
Panel B – regression results: drivers of the information value of tone.		
(Intercept)	− **2.746*****	**0.568***
	(0.649)	(0.297)
$\overline{MC_i}$	0.023	− **0.090*****
	(0.058)	(0.025)
$\overline{AGE_i}$	− **0.188*****	− **0.199*****
	(0.071)	(0.043)
$\overline{BTM_i}$	− **0.401****	− 0.182
	(0.192)	(0.136)
$\overline{\lvert FE_i \rvert}$	**0.184*****	0.000
	(0.066)	(0.052)
$\overline{BUSseg_i}$	**0.653*****	− 0.033
	(0.082)	(0.042)
$\overline{GEOseg_i}$	**0.449*****	**0.069****
	(0.059)	(0.034)
$\overline{ROA_i}$	**16.811*****	2.627
	(2.433)	(1.654)
$\overline{RET_i}$	0.269	0.060
	(0.298)	(0.199)
$\overline{\sigma_{ROAi}}$	**14.716*****	3.326
	(3.686)	(2.062)
$\overline{\sigma_{RETi}}$	**17.379***	**15.916*****
	(10.143)	(5.802)
$\overline{LOSS_i}$	**1.403*****	− 0.035
	(0.291)	(0.216)
$\overline{\Delta ROA_i}$	− 0.048	− 0.012
	(0.051)	(0.041)
$\overline{MedianCons_i}$	− 5.710	1.022
	(3.868)	(2.826)
R^2	0.185	0.063
Adj. R^2	0.179	0.057
Num. obs.	1829	1829
F statistic	12.038	9.525
p-value	0.000	0.000
VIF	1.227	1.067

Panel A – This table reports the results of the Anderson-Darling, Kolmogorov-Smirnov and Jarque-Bera tests in determining whether the sample of firm-specific sensitivities (δ_i^{ST}s, obtained by the firm-by-firm regressions in Eqs. (12) and (13)) of future performance and investors' reaction to tone follow a normal distribution. The statistic of each test is reported with the accompanying p-value in parentheses. Panel B – This table reports the impact of information asymmetry on the tone sensitivity as shown in Eq. (14). This cross-sectional dataset is obtained by averaging each firm's observations over all time periods. Obtained robust standard errors are presented in parenthesis. *, **, *** Denote statistical significance at the 10%, 5%, and 1% level based on a two-tailed t-test, respectively.

exposure in terms of forecast inaccuracy and geographical complexity.

After obtaining a sample of cross-sectional values of tone informativeness (δ_is) and standardizing this sample, as shown in Eq. (8), we construct a model that reveals its relationship with information asymmetry. Again, note that we transform our dataset ($X_{i,q,t}$ in Eq. (3)) to a cross-sectional one (Z_i in Eq. (9)). As posed in the second hypothesis, we control for firm size, age and growth. We proxy for firm size by taking the logarithm of the market capitalization, $\overline{MC_i}$. To capture the age of the firm, we use the logarithm of the number of years since a firm first appeared in the CRSP database: $\overline{AGE_i}$. We control for firm growth using

Table 7
Comparison of informativeness coefficients for firms with high and low information asymmetry.

	δ_{FUTROA_i}			$\delta_{CAR[-1;+1]_i}$		
	≤ Q25	≥ Q75	*t*-Stat	≤ Q25	≥ Q75	*t*-Stat
$\overline{MC_i}$	0.230	0.050	0.873	1.533	0.828	**2.727*****
$\overline{AGE_i}$	0.420	0.016	**2.191****	1.349	0.729	**3.056*****
$\overline{BTM_i}$	0.292	−0.036	**2.093*****	1.163	1.133	1.048
$\overline{\lvert FE_i \rvert}$	0.069	0.613	− **1.981****	1.099	1.219	− **1.689***
$\overline{BUSseg_i}$	−0.025	0.292	− **2.501****	1.234	0.811	1.164
$\overline{GEOseg_i}$	−0.047	0.253	− **1.901***	0.373	1.282	− **3.578*****

This table reports a comparison of tone exposure coefficients, as estimated using Eq. (3), for firms with high and low information asymmetry. Firms with high (low) information asymmetry are defined as per our hypotheses, using a cross-sectional dataset Z_i in Eq. (9). More specifically, information asymmetry is defined by the bottom (top) quartile of small ($\overline{MC_i}$), young ($\overline{AGE_i}$), and growth-oriented firms ($\overline{BTM_i}$), or the highest (lowest) quartile of firms with a high forecast inaccuracy ($\overline{\lvert FE_i \rvert}$), and the firm's operational complexity ($\overline{BUSseg_i}$ / $\overline{GEOseg_i}$). '≤Q25' ('≥Q75') represents the mean of the bottom (top) quartile. *, **, *** Denote statistical significance at the 10%, 5%, and 1% level based on a two-tailed t-test, respectively.

the logarithm of the book-to-market ratio, or $\overline{BTM_i}$. We expect $\overline{MC_i}$, $\overline{AGE_i}$, and $\overline{BTM_i}$ to be negatively associated with tone informativeness. The older and bigger the firm is the less asymmetric the firm is and the less incremental information press releases contain. Similarly, as $\overline{BTM_i}$ increases, the less undervalued the firm is and the less the market is in need for additional information to correctly assess its financial performance.

The third hypothesis poses that the higher the absolute forecast error ($\overline{\lvert FE_i \rvert}$) is, the more uncertain stakeholders are concerning the firm's true earnings, and the more informative tone is.[9] Lastly, in Hypotheses 4a and 4b, we test whether a firm's operational complexity dims both the managers' view as well as the market's capacity to evaluate future performance. The operational complexity is measured by the logarithm of the number of business segments the firm is active in, $\overline{BUSseg_i}$, and the amount of geographical segments, $\overline{GEOseg_i}$. We expect the operational complexity to be positively associated with tone informativeness.

We extend the information set of the cross-sectional regression even further, by controlling for the profitability ($\overline{ROA_i}$, $\overline{\Delta(ROA_i)}$, and $\overline{LOSS_i}$), the operational and business risk ($\overline{\sigma_{ROA_i}}$ and $\overline{\sigma_{RET_i}}$), and the forecast consensus ($\overline{MedianCons_i}$). More precisely, the overall cross-sectional model takes up the following form:

$$\begin{aligned}\text{For } i = 1,\ldots,N: \quad \delta_i^{ST} = {} & \gamma_0 + \gamma_1 \cdot \overline{MC_i} + \gamma_2 \cdot \overline{AGE_i} + \gamma_3 \cdot \overline{BTM_i} \\ & + \gamma_4 \cdot \overline{\lvert FE_i \rvert} + \gamma_5 \cdot \overline{BUSseg_i} + \gamma_6 \cdot \overline{GEOseg_i} \\ & + \gamma_7 \cdot \overline{ROA_i} + \gamma_8 \cdot \overline{RET_i} + \gamma_9 \cdot \overline{\sigma_{ROA_i}} \\ & + \gamma_{10} \cdot \overline{\sigma_{RET_i}} + \gamma_{11} \cdot \overline{LOSS_i} + \gamma_{12} \cdot \overline{\Delta(ROA_i)} \\ & + \gamma_{13} \cdot \overline{MedianCons_i} + \varepsilon_i \end{aligned} \tag{14}$$

Table 6 reports that firm size ($\overline{MC_i}$) is negatively associated with the information value of tone for $\delta^{ST}_{CAR[-1;+1]_i}$, indicating that the larger the firm is, the less informative tone is in explaining the investors' reaction. This result is consistent with Vermaelen (1981), in that larger firms have a lower level of information asymmetry. We however find no significant association between $\overline{MC_i}$ and $\delta^{ST}_{FUTROA_i}$. Secondly, we report

[9] Since the forecast error can be positive (underestimation by analysts) or negative (overestimation by analysts) we opt to use the average of the absolute values in order to capture the magnitude with which analysts wrongly estimated the earnings.

Table 8
Robustness – determinants of tone informativeness by library.

	Henry (2008)		Loughran and McDonald (2011)	
	$\delta^{ST,HEN}_{FUTROA_i}$	$\delta^{ST,HEN}_{CAR[-1;+1]_i}$	$\delta^{ST,LM}_{FUTROA_i}$	$\delta^{ST,LM}_{CAR[-1;+1]_i}$
(Intercept)	**− 6.518*****	0.520	**− 1.918*****	**0.773*****
	(1.165)	(0.316)	(0.427)	(0.297)
$\overline{MC_i}$	0.107	**− 0.129*****	0.041	**− 0.128*****
	(0.094)	(0.026)	(0.033)	(0.025)
$\overline{AGE_i}$	**− 0.525*****	**− 0.234*****	− 0.078	**− 0.116*****
	(0.128)	(0.044)	(0.049)	(0.042)
$\overline{BTM_i}$	**− 0.824****	− 0.207	− 0.100	**− 0.391*****
	(0.340)	(0.134)	(0.146)	(0.145)
$\overline{\lvert FE_i \rvert}$	**0.311****	− 0.000	**0.113***	− 0.006
	(0.134)	(0.048)	(0.058)	(0.051)
$\overline{BUSseg_i}$	**1.421*****	0.070	**0.345*****	0.035
	(0.165)	(0.046)	(0.062)	(0.040)
$\overline{GEOseg_i}$	**0.932*****	**0.139*****	**0.273*****	**0.083****
	(0.107)	(0.037)	(0.046)	(0.034)
$\overline{ROA_i}$	**36.548*****	**4.058****	**12.360*****	2.370
	(4.342)	(1.605)	(2.187)	(1.708)
$\overline{RET_i}$	0.711	− 0.107	0.159	0.099
	(0.482)	(0.206)	(0.245)	(0.198)
$\overline{\sigma_{ROAi}}$	**41.406*****	2.698	**8.221*****	2.719
	(5.286)	(2.089)	(2.773)	(2.442)
$\overline{\sigma_{RETi}}$	**39.278****	**19.191*****	**16.233****	**10.712***
	(18.034)	(6.147)	(7.395)	(5.672)
$\overline{LOSS_i}$	**3.496*****	0.037	**0.788*****	− 0.282
	(0.498)	(0.222)	(0.253)	(0.204)
$\overline{\Delta(ROA_i)}$	0.021	− 0.015	0.004	− 0.018
	(0.094)	(0.042)	(0.048)	(0.044)
$\overline{MedianCons_i}$	− 3.478	2.938	**− 7.224****	− 0.961
	(6.414)	(2.653)	(3.335)	(2.708)
R^2	0.252	0.093	0.115	0.058
Adj. R^2	0.246	0.087	0.108	0.051
Num. obs.	1829	1829	1829	1829
F-statistic	15.613	13.269	8.226	8.358
p-value	0.000	0.000	0.000	0.000
VIF	1.337	1.103	1.129	1.061

This table reports the exposure of tone sensitivity to relevant control variables and proxies for information asymmetry. It revisits the framework represented in Table 7, using different dictionaries: the positive and negative wordlists of Henry ($Tone^{HEN}_{i,q,t}$) and Loughran & McDonald ($Tone^{LM}_{i,q,t}$) This cross-sectional dataset is obtained by averaging each firm's available observations over all time observations. Models are constructed using White correction for heteroskedasticity. Obtained robust standard errors are presented in parenthesis. *, **, *** Denote statistical significance at the 10%, 5%, and 1% level based on a two-tailed t-test, respectively.

that $\overline{AGE_i}$ is significantly and negatively associated with both measures of δ_i^{ST} at the 1%-level. Older firms contain lower levels of information asymmetries than younger firms (Baeyens & Manigaart, 2003), which decreases the incremental value of tone for investors. $\delta^{ST}_{FUTROA_i}$ is also significantly and negatively affected by the firm's growth-level, $\overline{BTM_i}$. Since the more growth-oriented the firm is, the more information asymmetric the firm tends to be (Smith & Watts, 1992), and as such, the more tone is informative as a signal for future performance. We thus find evidence that firm size, age, and growth stage influence tone informativeness.

We find strong evidence in favor of H3a ($\delta^{ST}_{FUTROA_i}$), with the coefficient of $\overline{\lvert FE_i \rvert}$ being positive and significant. Under high forecast inaccuracy, tone is more informative in predicting future performance, further confirming the inverse relationship between information asymmetry and forecast inaccuracy (Atiase & Bamber, 1994; Kimbrough, 2005). In terms of $\delta^{ST}_{CAR[-1;+1]_i}$, we find an insignificant coefficient. Additionally, $\overline{\sigma_{RET_i}}$ is significantly and positively associated with both measures of tone informativeness. We can also conclude that the risk environment of the firm influences the sensitivity towards the informativeness of qualitative information.

Finally, we find that the sign of $\overline{GEOseg_i}$ is positive and significant for $\delta^{ST}_{FUTROA_i}$ and $\delta^{ST}_{CAR[-1;+1]_i}$, however $\overline{BUSseg_i}$ is only positive and significant for the prior. Overall, these findings indicate that the tone of earnings press releases is more informative in cases of higher operational complexity, complementing the findings of Gilson et al. (2001). These results confirm Hypotheses 4a and 4b and show that the tone of earnings press releases is more informative in cases of higher operational complexity.

5.3. Robustness checks

To show that our results are robust we repeat the regression of Eq. (14) for alternative dictionary specifications. Recall that our main results are obtained using the averaged value of tone, coming from both the positive and negative word lists of Henry (2008) and Loughran and McDonald (2011) and that we recquire at least 15 observations per firm. As shown in Table 8, we find that our conclusions remain robust when using $Tone^{HEN}_{i,q,t}$ and $Tone^{LM}_{i,q,t}$ individually. We even find higher significance in predicting the sensitivity of the cumulative abnormal returns to the tone when using the Henry (2008) library. When using $Tone^{LM}_{i,q,t}$, we fail to find support for H2a, but find strong support for H3b.

Furthermore, we test for raising the minimal number of time-series observations per firm, and find that the cross-sectional regressions remain significant if we impose the requirement of having at least 20 and 25 observations per firm. We report the model validations for alternative dictionaries and the minimum observation length in Table 9 and find qualitatively similar results to Table 6 which are available upon request.

Overall, our findings from the cross-sectional analysis suggest that information asymmetry is a key driver of tone informativeness. The information value of tone increases as the firm is younger, smaller and in a high-growth stage. In addition, a larger forecast error and operational complexity also drive the informativeness.

6. A panel data model with heterogeneity in tone informativeness

The results of Table 6 suggest that tone informativeness differs across firms as a function of information asymmetry. The two-step regression approach, however, is only feasible as an ex post analysis since it requires to first estimate the exposure over a sufficiently long estimation sample, and to regress those estimates on historical averages. To study how informativeness changes in cases of high information asymmetry, we recommend to use a panel data approach, as it allows to directly model the cross-section and time series variation. In doing so, the results of a panel data regression give more insight into the size of informativeness and how it changes for different levels of information asymmetry.

Hypotheses 2a–4b pose that informativeness is a function of firm size, age, growth level, forecast accuracy, and operational and geographical diversification. We experimented with various functional forms, and concluded that a parsimonious approach is to introduce dummy variables, that control whether an observation exceeds a certain threshold value of information asymmetry. The following longitudinal approach estimates one panel data regression, including interaction terms between tone and data-driven dummy variables:

$$\begin{aligned} Y_{i,q,t} = {} & \alpha + \delta_0 \cdot Tone_{i,q,t} + \gamma \cdot Tone_{i,q,t} \cdot I(MC_{i,q,t} < Q_A^{MC}) \\ & + \zeta \cdot Tone_{i,q,t} \cdot I(BTM_{i,q,t} < Q_B^{BTM}) \\ & + \theta \cdot Tone_{i,q,t} \cdot I(AGE_{i,t} < Q_C^{AGE}) + \lambda \cdot Tone_{i,q,t} \cdot I(\lvert FE_{i,q,t} \rvert > Q_D^{\lvert FE \rvert}) \\ & + \nu \cdot Tone_{i,q,t} \cdot I(BUSseg_{i,q,t} > Q_E^{BUSseg}) \cdot I(GEOseg_{i,q,t} > Q_F^{GEOseg}) \\ & + \beta \cdot X_{i,q,t} + \varepsilon_{i,q,t}, \end{aligned} \tag{15}$$

Table 9
Robustness – validation of sensitivity to tone for alternative dictionaries and minimum observations per firm.

Dictionary		Average tone		Henry (2008)		Loughran and McDonald (2011)	
Min. obs.		$\delta^{ST}_{FUTROA_i}$	$\delta^{ST}_{CAR[-1;+1]_i}$	$\delta^{ST,HEN}_{FUTROA_i}$	$\delta^{ST,HEN}_{CAR[-1;+1]_i}$	$\delta^{ST,LM}_{FUTROA_i}$	$\delta^{ST,LM}_{CAR[-1;+1]_i}$
15	F-statistic	12.038	9.525	15.613	13.269	8.226	8.358
	p-Value	0	0	0	0	0	0
	R^2	0.185	0.063	0.252	0.093	0.115	0.058
	Num. obs.	1829	1829	1829	1829	1829	1829
20	F-statistic	10.624	9.646	12.342	12.374	8.760	6.857
	p-Value	0	0	0	0	0	0
	R^2	0.216	0.084	0.238	0.106	0.172	0.057
	Num. Obs.	1476	1476	1476	1476	1476	1476
25	F-statistic	10.650	8.575	9.679	11.069	6.851	7.086
	p-Value	0	0	0	0	0	0
	R^2	0.228	0.109	0.239	0.121	0.173	0.078
	Num. obs.	1113	1113	1113	1113	1113	1113

This table reports the validation of several robustness models. Each model revisits the framework of Table 7, modelling the exposure of our sample of firm-specific sensitivities of future performance and investors' reaction to tone, albeit using different libraries and with increasing restriction to the minimal amount of each firm's observations (Min. obs.). For each firm we report the F-statistic, p-value, R^2 and the minimal number of observations required per firm.

where $\varepsilon_{i,q,t}$ represents the error term with zero mean, $X_{i,q,t}$ represent a set of control variables, including firm-, industry-, year- and quarter-dummies. $Y_{i,q,t}$ represents either the future performance measure $FUTROA_{i,q,t}$ or the investors' reaction $CAR[-1;+1]_{i,q,t}$. The dummy variables are '1' if a certain condition is met and '0' otherwise. Whether an observation meets the condition depends on the benchmark values A through F. For example, if A in $I(MC_{i,q,t} < Q_A^{MC})$ is 0.1, then this dummy is '1' for observations belonging to the 10% smallest (as measured by $MC_{i,q,t}$) amongst all observations up to that point in time t.[10] As such, if condition A is met, the overall tone exposure coefficient becomes $\delta_0 + \gamma$. The cut-off values A through F are not arbitrarily chosen but estimated as to optimize the in-sample $Adj.\ R^2$ of the panel data regression. In doing so, Eq. (16) shows that each firm's total coefficient of $Tone_{i,q,t}$ depends on the degree of its information asymmetry:

$$\begin{aligned}\frac{\partial E[Y_{i,q,t}|I_{i,q,t}]}{\partial Tone_{i,q,t}} &= \delta_0 + \gamma\cdot I(MC_{i,q,t} < Q_A^{MC}) + \zeta\cdot I(BTM_{i,q,t} < Q_B^{BTM}) \\ &\quad + \theta\cdot I(AGE_{i,t} < Q_C^{AGE}) + \lambda\cdot I(|FE_{i,q,t}| > Q_D^{|FE|}) \\ &\quad + \nu\cdot I(BUSseg_{i,q,t} > Q_E^{BUSseg})\cdot I(GEOseg_{i,q,t} > Q_F^{GEOseg}).\end{aligned} \tag{16}$$

Models (1) and (3) of Tables 10 and 11 compare the power of tone in predicting future operational performance and explaining investors' reaction with and without these dummies respectively. Using an ANOVA-test, we find a significant statistical improvement of the $Adj.R^2$ when controlling for information asymmetry.

These models further capture the economic significance of considering heterogeneity of tone informativeness. When predicting future performance, the baseline model of Table 10 has an overall tone informativeness coefficient of 0.888, but when taking information asymmetry into account this value drops to 0.283. This again confirms that the tone informativeness is lower for symmetric and transparent firms and that the overall slope coefficient increases with the degree of information asymmetry. For small firms ($MC_{i,q,t}$), the informativeness of tone triples when predicting future operational performance (0.283 + 0.712 = 0.995). We find similar increases for our other dummy variables. The tone coefficient of younger ($AGE_{i,t}$) and more growth-oriented firms ($BTM_{i,q,t}$) is larger in size. The total effect therein even quadruples (0.283 + 1.026) and triples (0.283 + 0.454) respectively. Consistent with our prior findings, Model (3) also reports a significant and positive effect when the absolute value of the forecast error ($|FE_{i,q,t}|$) is high (0.283 + 1.067). One caveat however, concerns the operational complexity. The dummy-variable indicates a negative sign, which is contrary to our expectations. Models (2) and (4) incorporate control variables and additionally control for various fixed effects. We find that the overall values of tone informativeness decreases, and even turn insignificant in terms of firm size ($MC_{i,q,t}$). We still find a statistically more significant model when controlling for information asymmetry and find that the informativeness coefficient remains a function of $BTM_{i,q,t}$, $|FE_{i,q,t}|$ and $AGE_{i,t}$.

Models (1) and (3) in Table 11 show that $MC_{i,q,t}$, $AGE_{i,t}$ and $|FE_{i,q,t}|$ strongly increase tone informativeness when explaining investors' reaction. Whereas the tone of a more symmetric firm contains a coefficient of 0.477, the coefficient of a small firm, a young firm, and a firm with highly inaccurate forecast earnings increases with 0.315, 0.247, and 1.146 respectively. We additionally find negative and insignificant coefficients in terms of growth stage and having a high operational complexity. When controlling for various fixed effects and control variables, we report that the dummies remain statistical significant. In terms of growth stage, there is a negative and significant coefficient accompanying $BTM_{i,q,t}$, which is contrary to our expectations. Using an ANOVA-test, Model (4) outperforms Model (2), indicating that tone heterogeneity causes an increase in statistical performance.

Overall, the panel data results indicate that considering information asymmetry is key in understanding how and when qualitative information matters. The signaling power of tone increases heavily when firms are growth-oriented, younger and when forecast inaccuracy increases. When explaining the investors' reaction, firm size, age (forecast inaccuracy) strongly decrease (increase) the information value of tone.

7. Conclusion

Studying tone informativeness is of paramount importance for understanding the extent to which qualitative information can incrementally explain market movements, relative to quantitative information. We find that tone informativeness substantially differs across firms and that it is driven by the firm's level of information asymmetry.

Through an extensive empirical analysis, using sample of 52,667 earnings press releases over the period of 2004Q1 up to 2015Q4, we show that the tone of earnings press releases is only informative for about one quarter of the firms in our sample. We further evidence that the tone of earnings press releases is especially informative for smaller, younger, and growth-oriented firms. Similarly, we find an increase in the information value of tone for firms with a higher analysts' forecast inaccuracy and a higher operational complexity. Finally, we show that

[10] By introducing this time constraint we prevent a potential forward looking bias.

Table 10
Signaling future performance under homogeneity and heterogeneity of the tone informativeness coefficients in panel data regressions.

$FUTROA_{i,q,t}$	Homogeneity		Heterogeneity	
	Model (1)	Model (2)	Model (3)$^{+++}$	Model (4)$^{+++}$
(Intercept)	**0.006*****	**0.015****	**0.006*****	**0.015****
	(0.000)	(0.006)	(0.000)	(0.006)
$Tone_{i,q,t}$	**0.888*****	**0.161*****	**0.283*****	**0.090*****
	(0.019)	(0.029)	(0.000)	(0.026)
$Tone_{i,q,t} \cdot I\,(MC_{i,q,t} < Q_{0.25}^{MC})$			**0.712*****	0.063
			(0.055)	(0.046)
$Tone_{i,q,t} \cdot I\,(BTM_{i,q,t} < Q_{0.1}^{BTM})$			**1.026*****	**0.079***
			(0.051)	(0.041)
$Tone_{i,q,t} \cdot I\,(AGE_{i,t} < Q_{0.1}^{AGE})$			**0.454*****	**0.097***
			(0.062)	(0.052)
$Tone_{i,q,t} \cdot I\,(\lvert FE_{i,q,t}\rvert > Q_{0.8}^{\lvert FE\rvert})$			**1.067*****	**0.283*****
			(0.066)	(0.051)
$Tone_{i,q,t} \cdot I\,(BUSseg_{i,q,t} > Q_{0.9}^{BUSseg})$ $\cdot I\,(GEOseg_{i,q,t} > Q_{0.75}^{GEOseg})$			**− 0.327***	**− 0.255***
			(0.181)	(0.138)
$RET_{i,q,t}$		**0.005*****		**0.005*****
		(0.000)		(0.000)
$ROA_{i,q,t}$		**0.295*****		**0.294*****
		(0.005)		(0.005)
$MC_{i,q,t}$		− 0.000		− 0.000
		(0.000)		(0.000)
$BTM_{i,q,t}$		**− 0.011*****		**−0.010*****
		(0.000)		(0.000)
$\sigma_{ROA_{i,q,t}}$		**0.032*****		**0.033*****
		(0.006)		(0.006)
$\sigma_{RET_{i,q,t}}$		**− 0.050*****		**− 0.043*****
		(0.011)		(0.011)
$FE_{i,q,t}$		− 0.000		**− 0.000*****
		(0.000)		(0.000)
$LOSS_{i,q,t}$		**− 0.003*****		**− 0.002*****
		(0.000)		(0.000)
Firm fixed effects	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes
Year fixed effects	No	Yes	No	Yes
Quarter fixed effects	No	Yes	No	Yes
R^2	0.031	0.576	0.050	0.576
Adj. R^2	0.031	0.560	0.049	0.561
Num. obs.	52,667	52,667	52,667	52,667
F-statistic	1674.305	37.245	457.376	37.203
p-Value	0	0	0	0
VIF	1.032	2.357	1.052	2.360

This table reports the results of panel data regressions for predicting future operational complexity $FUTROA_{i,q,t}$ under homogeneity (Models 1–2) and heterogeneity (Models 3–4). The heterogeneity is controlled for by using interaction variables proxying for firms with high levels of information asymmetry. These are defined by our hypothesis as size ($MC_{i,q,t}$), age ($AGE_{i,t}$), growth stage ($BTM_{i,q,t}$), operational complexity ($BUSseg_{i,q,t}$ and $GEOseg_{i,q,t}$) and earnings uncertainty ($FE_{i,q,t}$). The benchmarks for the dummy variables are obtained as those maximizing the Adj. R^2. Models 2 and 4 extend Models 1 and 3, by controlling for industry-, year-, quarter-, and firm-fixed effects. All models are constructed using White correction for heteroscedasticity. Robust standard errors are presented in parenthesis. *, **, *** Denote statistical significance at the 10%, 5%, and 1% level based on a two-tailed t-test, respectively. +, ++, +++ Denote the statistical significance at the 10% level with which there is a reduction in residual sum of squares between the homogeneity (Models 1–2) and heterogeneity (Models 3–4) assumption based upon ANOVA-testing.

the hypothesized drivers of tone informativeness can be directly included into longitudinal models to predict firm performance and explain the investors' reaction. These generalized panel models show that the slope coefficient of tone can easily double and even quadruple in absolute size, indicating that tone is a more informative signal of future performance when firm transparency is low. This also explains the higher reaction of investors to the qualitative information of earnings press releases, in such an opaque environment. These results confirm that the marginal impact of the information contained in earnings press releases is higher for firms with a higher level of information asymmetry.

Whereas our primary focus in this paper lies on earnings press releases, there are several other corporate disclosures available with which firms communicate to outside stakeholders, such as CEO letters (Boudt & Thewissen, 2018) and conference calls (Price et al., 2012). An interesting avenue for future research would therefore be to disentangle the tone informativeness of different types of corporate disclosures in a comparative study, and to investigate whether the relationship established in this paper can be extrapolated to other types of narratives.

Table 11
Explaining investors' reaction under homogeneity and heterogeneity of the tone informativeness coefficients in panel data regressions.

$CAR[-1,+1]_{i,q,t}$	Homogeneity		Heterogeneity	
	Model (1)	Model (2)	Model (3)$^{+++}$	Model (4)$^{+++}$
(Intercept)	**0.001*****	− 0.025	**0.002*****	− 0.026
	(0.000)	(0.017)	(0.000)	(0.017)
$Tone_{i,q,t}$	**0.700*****	**0.829*****	**0.477*****	**0.803*****
	(0.041)	(0.056)	(0.056)	(0.071)
$Tone_{i,q,t} \cdot I(MC_{i,q,t} < Q_{0.33}^{MC})$			**0.315*****	**0.248****
			(0.105)	(0.125)
$Tone_{i,q,t} \cdot I(BTM_{i,q,t} < Q_{0.25}^{BTM})$			− 0.124	**− 0.468***
			(0.097)	(0.252)
$Tone_{i,q,t} \cdot I(AGE_{i,t} < Q_{0.15}^{AGE})$			**0.274****	**0.493*****
			(0.120)	(0.143)
$Tone_{i,q,t} \cdot I(\lvert FE_{i,q,t}\rvert > Q_{0.8}^{\lvert FE\rvert})$			**1.146*****	**0.249***
			(0.127)	(0.139)
$Tone_{i,q,t} \cdot I(BUSseg_{i,q,t} > Q_{0.66}^{BUSseg})$			− 0.341	− 0.406
$\cdot I(GEOseg_{i,q,t} > Q_{0.7}^{GEOseg})$			(0.344)	(0.377)
$ROA_{i,q,t}$		**0.075*****		**0.073*****
		(0.013)		(0.013)
$BTM_{i,q,t}$		**0.024*****		**0.025*****
		(0.001)		(0.001)
$FE_{i,q,t}$		**0.009*****		**0.009*****
		(0.000)		(0.000)
Firm fixed effects	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes
Year fixed effects	No	Yes	No	Yes
Quarter fixed effects	No	Yes	No	Yes
R^2	0.006	0.087	0.008	0.088
Adj. R^2	0.005	0.054	0.008	0.054
Num. obs.	52,667	52,667	52,667	52,667
F statistic	291.648	2.617	69.865	2.635
p-value	0	0	0	0
VIF	1.006	1.008	1.046	1.090

This table reports the results of panel data regressions for explaining investors' reaction $CAR[-1;\ +1]_{i,q,t}$ under homogeneity (Models 1–2) and heterogeneity (Models 3–4). The heterogeneity is controlled for by using interaction variables proxying for firms with high levels of information asymmetry. These are defined by our hypothesis as size ($MC_{i,q,t}$), age ($AGE_{i,t}$), growth stage ($BTM_{i,q,t}$), operational complexity ($BUSseg_{i,q,t}$ and $GEOseg_{i,q,t}$) and earnings uncertainty ($FE_{i,q,t}$). The benchmarks for the dummy variables are obtained as those maximizing the Adj. R^2. Models 2 and 4 extend Models 1 and 3, by controlling for industry-, year-, quarter-, and firm-fixed effects. All Models are constructed using White correction for heteroscedasticity. Robust standard errors are presented in parenthesis.

Appendix A. Tone informativeness and investors' reaction

To illustrate the relationship between investors' reaction and tone, suppose that investors value the firm using the dividend discount model, such that the value for firm i, $V_{i,q,t}$, is given by:

$$V_{i,q,t} = \frac{D_{i,q,t} \cdot (1 + g_{i,q,t})}{r_{i,q,t} - g_{i,q,t}}, \tag{A.1}$$

where $D_{i,q,t}$ represents the current dividend per share, $r_{i,q,t}$ refers to the required rate of return and $g_{i,q,t}$ is the dividend growth rate. The investor uses the available information to determine the factor that maps the value of the dividend per share into the firm value per share. Using a loglinear model and separating the available information set into the tone of the earnings press release ($Tone_{i,q,t}$) and the other relevant variables ($X_{i,q,t}$), we obtain:

$$\frac{1 + g_{i,q,t}}{r_{i,q,t} - g_{i,q,t}} = \exp(\alpha_i + \delta_i \cdot Tone_{i,q,t} + \beta \cdot X_{i,q,t} + \varepsilon_{i,q,t}). \tag{A.2}$$

Combining Eqs. (A.1) and (A.2) gives that:

$$\log V_{i,q,t} = \log D_{i,q,t} + \alpha_i + \delta_i \cdot Tone_{i,q,t} + \beta \cdot X_{i,q,t} + \varepsilon_{i,q,t}. \tag{A.3}$$

We subtract the firm value of the previous time period from both sides:

$$\log V_{i,q,t} - \log V_{i,q-1,t} = \log D_{i,q,t} + \alpha + \delta \cdot Tone_{i,q,t} + \beta \cdot X_{i,q,t} + \varepsilon_{i,q,t} - \log V_{i,q-1,t}. \tag{A.4}$$

Note that the left-hand side of Eq. (A.4) expresses the return $R_{i,q,t}$. Taking the partial derivative of the conditionally expected return with respect to tone yields δ_i, as in Eq. (4).

Appendix B. Simulation study of finite sample properties of the proposed test for heterogeneity

We use a simulation analysis to verify the statistical validity of the proposed test for heterogeneity for various values of N and T. The observations are simulated as follows. First we draw a hypothetical independent tone variable $Tone_{i,t}$ from the uniform distribution between -1 and 1. Then we draw an idiosyncratic error term $u_{i,t}$ from the normal distribution with mean zero and standard deviation of 0.5. We then compute the performance measure as follows:

$$Y_{i,t} = \alpha_i + \delta_i \cdot Tone_{i,t} + u_{i,t}, \tag{B.1}$$

where $Y_{i,t}$ represents the dependent variable (i.e. ROA or $CAR[-1;+1]$) and the intercept, α_i, is fixed at 0.5. Under the assumption of homogeneity, all firms have the same δ fixed at 1. Under the setup of heterogeneity, we assume that half of the firms take a δ_i of 0.1 and the other half a δ_i of 1.

Next, we run firm by firm regressions and obtain the sample of N estimated $\hat{\delta}$s, and standardize following Eq. (8). We then test for the sample normality using the Anderson-Darling test (with a confidence level of 95%).[11] We repeat this process 1000 times and count the number of times normality is rejected. Results are reported in Table 12. We show that, with increasing N and T, the rejection rate of normality tends to 100% in the heterogeneous case, and approximates the 5% nominal size level in case of homogeneity. We indicate in bold the situation that is most representative for our sample, where we have $N = 1{,}829$ firm entities and on average about $T = 29$ observations per firm, and we find that there is consistent rejection of normality in the heterogeneous case.

Table 12
Rejection rate of normality under heterogeneity and homogeneity.

	Heterogeneity				Homogeneity			
	T							
N	20	25	29	50	20	25	29	50
10	0.078	0.102	0.108	0.270	0.040	0.064	0.048	0.052
50	0.242	0.540	0.670	0.972	0.060	0.060	0.062	0.050
100	0.550	0.764	0.910	1.000	0.064	0.076	0.046	0.058
500	1.000	1.000	1.000	1.000	0.064	0.070	0.052	0.048
1000	1.000	1.000	1.000	1.000	0.068	0.066	0.054	0.051
1829	1.000	1.000	**1.000**	1.000	0.072	0.064	**0.054**	0.047
2000	1.000	1.000	1.000	1.000	0.078	0.064	0.055	0.048

This table reports the overall rejection rate of the obtained test of homogeneity, following a simulated relationship between a dependent variable $Y_{i,t}$ and an independent variable $Tone_{i,t}$, under both a heterogeneous and homogeneous relationship. The bold situation indicates similar dimensions to our data sample.

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[11] We repeat this for the Jarque-Bera test and Kolmogorov-Smirnov test and find qualitatively similar results.

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