How firms strategically disclose information through selected channels

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Abstract: This paper examines firms' use of different disclosure channels (earnings conference call and earnings press release) and corresponding investor reactions. By drawing from a theory about e-communication, we predict that earnings conference calls induce less processing costs to investors than earnings press releases, and hence its use increases the stock price impact and decreases the communicational ambiguity of information. Consistently, when comparing these channels, we find that firms distribute positive information to earnings conference calls. Firms that use positive tone in earnings conference calls increase the stock market reaction sixfold compared to earnings press releases. When firms distribute information to channels, the tone and readability of their calls improve while these characteristics of earnings press releases remain unchanged. Also, firms tend to distribute more positive information to conference calls when future performance is good but less when earnings exceed benchmarks, indicating that firms try to manage investors' expectations.

Keywords: qualitative disclosure, conference calls, earnings press releases, linguistic tone, textual analysis, management language, stock market reaction

JEL-classification: G10, G14, G40, G41

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1. Introduction

The use of rhetoric to amplify the impact of good news and reduce it for bad news is a central element to firms' disclosure strategies. Theories predict that firms apply various rhetoric strategies to increase or dampen the announcement effect of information releases over disclosure channels – such as press releases or conference calls. While numerous studies find empirical evidence for this, it remains unclear how managers use the distribution of the information to channels as rhetoric strategy. This void exists since current theories focus on the news' content or rhetoric while ignoring the potential influence of the disclosure channel. If the channel choice has no effect on the price impact of the information, firms would disclose a uniform set of information over all channels to save resources. However, prior research agrees that channels like conference calls offer incremental information to other disclosure channels like press releases (e.g. Frankel et al. (1999); Matsumoto et al. (2011)). This raises the questions of why firms choose to distribute incremental information to a distinct channel and how we must rethink the theory of market reactions to news – content and transmission – to understand this behavior.

In this paper, we answer both questions by using the firms' earnings announcement setting (press release vs. conference call) to study their information distribution decision. By comparing earnings press releases (EPRs) with earnings conference calls (ECCs) of S&P500 companies over 14 years (2004 - 2018), we provide evidence that firms indeed consider the distribution of information to channels in their news disclosure decision and that they distribute positive immaterial information to the channels that are easy to process for investors, like ECCs. Our analyses show that such distribution of positive news to ECCs can increase the resulting stock market reaction sixfold compared to EPRs. At the same time, we do not find conclusive evidence that EPRs become more negative. These findings are robust to different information distribution measures and to controlling for firm-fixed and year-fixed effects.

We conclude that the reasons behind this behavior are twofold. First, managers know which information they must disclose. Managers withhold negative but disclose positive immaterial information since it is costless, and they do not face litigation risk for omitting or placing additional immaterial information. Second, managers know that investors face less processing costs when consuming ECCs than EPRs since it is cognitively less demanding, and results in less communicational ambiguity. Hence, the optimal disclosure strategy for managers is disclosing positive immaterial information that likely provokes “multiple and conflicting interpretations” exclusively over ECC (Daft and Lengel (1986); Skinner (2019)). Thereby, they can cost efficiently influence the stock price as investors can easily process these positive immaterial pieces of information to reassess the firm value.

We derive this the second reason by applying the media naturalness hypothesis by Kock (2005). Evolution optimized humans’ physiology to process predominantly information communicated over the face-to-face channel. Hence, humans face higher processing costs if the information channel differs from the so-called “natural” face-to-face channel. In line with this argument, the ECC channel is associated with more processing costs but less than the electronic reporting (e.g., press release) channel than the face-to-face channel (face-to-face < conference call < press release).

We show that the media naturalness hypothesis predicts the observed managers’ and investors’ behavior. Since managers try to influence processing costs for investors when distributing information to channels, we predict and find that it relates to channel readability. ECCs are more readable when firms distribute information to EPRs and ECCs. This relation may be driven by their desire for facilitating “clarity and understanding” for investors (Graham et al. (2005)). Further, since firms try to influence the information processing costs for investors depending on future firm performance (Li (2008)), we test and find that the distribution of information to channels predicts future firm performance. For this test, we split firm performance into earnings and non-earnings measures since Graham et al. (2005) document that managers consider earnings to be more important while the general finance literature emphasizes the importance of cash flows for investment decisions. For the non-earnings measures (i.e. cash flows and operating performance), we find a positive relation between the distribution of information and future firm performance. This finding underlines that firms want to disclose positive information in an impactful and unequivocal manner and consider the channel choice as an instrument to achieve it. For the earnings measures (i.e. earnings per share), we predict a concave relation between firm performance and information distribution, since increased positive news disclosure raises investor expectations and not meeting them is costly for firms (Skinner (1994); Rogers et al. (2011)). Our analysis confirms that notion and shows that firms distribute less positive information to ECCs when exceeding earnings benchmarks; a behavior that increases investors' processing costs and lowers their expectations.

Lastly, we expect the market to efficiently reflect the disclosed information since the distribution of information to ECC reduces the processing costs of positive information. Hence, we analyze how information distribution to channels relates to return predictability by investigating how investors process distributed and not distributed information. A portfolio – that holds the quintile of firms that distribute the most information to channels – yields significant abnormal returns (equal to 5 % p.a.). This result implies that investors use the information to reassess the firm value but do it slowly. This is consistent with the theory of mosaic, under which an analyst can assemble pieces of non-public and immaterial information into the bigger picture that reveals a material conclusion in a time and resource intensive process (Becker (2000)).

Our paper contributes to several growing strands of literature while answering the question of why firms choose to distribute information to channels and how we must rethink the theory of market reactions to news. We contribute to the strand analysing disclosure strategies, by showing that information distribution extends the set of existing disclosure strategies, and that it is used to decrease informational asymmetry. Furthermore, our findings regarding the price impact of tone of EPRs and ECCs add new granularity to the literature of disclosure processing costs because previous studies analyze EPR and ECC separately. We find that stock returns are six times more sensitive to the tone of ECCs than that of EPRs which indicates that ECC's disclosure processing costs are lower compared to EPR's. Lastly, our paper also contributes to the large and fast-growing textual analysis field by using similarity measures to compare both channels (EPRs and ECCs). We thereby extend the similarity measures use which was limited to one channel in previous research.

2. Theoretical explanations for information distribution

Following Dye (2001), the theory of disclosure generally assumes that firms use an array of disclosure strategies to dampen (increase) the stock price effects of negative (positive) information (e.g., Merkl-Davies and Brennan (2007); Davis and Tama-Sweet (2012)). One of these options may be to choose the best suitable channel. Various channels are available – SEC filings, press releases, or conference calls – for disclosing information and researchers acknowledge that these channels differ in format (text vs. speech), opportunities for interaction, and language (e.g., Mayew (2012); Skinner (2019)). These differences have motivated numerous studies which document that channels like conference calls offer incremental information to other disclosure channels like press releases (e.g. Frankel et al. (1999); Matsumoto et al. (2011)). Nevertheless, theories regarding corporate disclosures hold limited predictive power concerning the optimal disclosure channel choice for firms, since standard models mostly presume efficient markets, implying that prices reflect information regardless of the channel (e.g., Fama (1970)).

If information processing is costless for investors, then why do some firms disclose more information over one than another specific channel? Variations in the distribution of information to channels are probably not random, as firms' management supervises the corporate disclosures preparation with great care (e.g., Graham et al. (2005); Huang et al. (2014)). Also, Loughran and McDonald (2011a) report that the resources that firms put into legal and technical writing of registration statements roughly equals that put into accounting. Therefore, to investigate why managers intend to distribute information to one channel or another, we develop two arguments.

2.1. Levelling argument

The theory of (semi-)efficient markets generally predicts that the market interprets any new information without being influenced by the channel (e.g., Fama (1970)). Under this assumption, a firm cannot select a disclosure channel that influences investors' processing costs and would waste resources doing so. Hence to save resources, this firm would disclose a uniform set of information over all channels instead of distributing information to certain channels. Providing uniform information sets is cost-efficient for two reasons. First, it minimizes litigation risk compared to other means of sampling – like randomly selected information sets for each channel – since when not doing so, firms may not disclose material information or disclosing it inappropriately. Second, uniform information sets do not require additional resources of accountants, lawyers, and executives to decide what the best information distribution decision is and to adjust the information's format to the channel. Therefore, we predict that firms disclose uniform information sets when markets are efficient, and we name this notion the "levelling argument".

Researchers use the levelling argument as an assumption in their argument and method. For instance, Kimbrough (2005) and Matsumoto et al. (2011) state that earnings conference calls essentially repeat the information of the earnings press releases at the call's beginning. Also, Price et al. (2012) use the tone of the ECC presentation section as a proxy for the tone of the EPR in their empirical analysis.

2.2. Separation argument

Contrary, our second "separation argument" points towards channels being a significant lever to influence how investors process information by recognizing several findings in the behavioral finance literature. Assuming that processing costs vary across channels and that investors are limited in their processing capacity (e.g., Blankespoor et al. (2020)), firms – that distribute information to channels – can influence investors' processing costs. Low processing costs, for instance, can increase the stock price reaction towards a news release.

Recent empirical evidence documents that managers adjust information disclosure along different characteristics: optimizing sentiment (e.g., Huang et al. (2014)), readability (e.g., Li (2008)), information visibility (e.g., Hollander et al. (2010); Skinner (2019); Cohen et al. (2020)), or disclosure timing (e.g., Edmans et al. (2018)). The reason for this is that the stock price reaction is a central concern for managers due to its direct impact on the firm's cost of capital, ongoing managerial compensation agreements, or career options (Graham et al. (2005)). If the choice of disclosure channels extends the latitudes of managerial rhetoric to influence stock price, we expect it to be subject to similar economic relations. In the following, we present further mechanics behind this reasoning.

2.2.1. Media naturalness hypothesis

Our separation argument assumes that investors have limited processing capacity and that channels vary in the inherent processing costs they add to the disclosed information. While the former assumption has been extensively studied in the field of finance (e.g., Blankespoor et al. (2020)), we cannot rely on previous work to understand why different channels might induce different processing costs for investors (otherwise we derive the levelling argument again). Therefore, we draw from the "media naturalness hypothesis" by Kock (2005) from the management communication research area. The media naturalness hypothesis is based on evolutionary theory and argues that electronic communication media induce processing costs to humans (regardless of the information) since they are not the most natural face-to-face communication channel. This means that with face-to-face communication, the recipient can process information with the least cognitive effort, communicational ambiguity, and the highest physiological arousal (summarized as low processing costs). Consequently, *ceteris paribus*, a decrease in the naturalness of a communication channel (its degree of similarity to the face-to-face channel) leads to increased processing costs (increase in cognitive effort, communication ambiguity, and a decreased physiological arousal for the recipient).

When applying the media naturalness hypothesis on corporate disclosures, we understand that the managements' channel choice adds to the processing costs. With high costs, investors might fail to process all information within low naturalness channels. This results in communicational ambiguity, and a delayed and muted stock price reaction to information within a less natural channel. Therefore, managers distribute positive information to more natural channels since they try to match the information with the channels' processing cost to highlight positive information unequivocally in more natural channels. We name this the "separation argument".

2.2.2. Applicability of the media naturalness hypothesis

The media naturalness hypothesis builds on the fact that we humans relied for 99 % of our evolutionary cycle on face-to-face communication characterized by five distinct features: 1) co-location (being next to the other person), and 2) synchronicity (receiving/sending information without latency) as well as communication through observing/making, 3) facial expressions, 4) body language, and 5) sounds (including speech, which uses a variety of sound combinations). Humans had cognitively, physiologically, and genetically adapted over the millennia to process information from channels that exhibit these characteristics (Kock (2005)). In contrast to the face-to-face channel, newly-tapped e-communication channels match some of these characteristics to lower degrees and, therefore, burden the information's receiver with higher processing costs. Therefore, a more natural channel facilitates, *ceteris paribus*, a more efficient understanding of messages that provoke multiple interpretations or differences in understanding.

We apply this theory to rank the processing costs of corporate disclosure channels for investors like sending electronic documents, filing with the SEC, holding conference calls, etc. This enables us to make predictions about how corporate communication channels may be used under the separation argument for the following reasons. First, most corporate information is disclosed over either an electronic press release, SEC filing or telephone (conference) call, and hence, corporate disclosure channels fall mostly into the e-communications category. The level of naturalness of corporate disclosure channels, including telephone calls and electronic reports, has been studied in numerous empirical studies (e.g., Kock (2005); Cho et al. (2011)) and the main conclusion is that e-reports are less natural than conference calls. E-reports are neither synchronous nor allow for co-location, the observation of sounds, facial expressions, or body language. Hence, they do not match any of the five characteristics of the face-to-face channel and cause higher cognitive load and communicational ambiguity while the physiological arousal is lower. In contrast, telephone (conference) calls are more natural since they are a synchronous channel that allows for interaction (hearing/speaking), while not being co-located or allowing to see/make facial expressions or body language. Therefore, the media naturalness hypothesis allows us to conjecture that conference calls are more natural compared to the e-report but less natural compared to the face-to-face channel.

Second, the media naturalness hypothesis may help to predict managers' information distribution decision of negative or positive information to channels since they and investors are subject to processing costs due to time and brain-power constraints. This makes the consumption of disclosures an active economic choice for investors who expect a competitive return to processing (Blankespoor et al. (2020)). This return to acquiring new information can be influenced by managers who distribute information to different channels. Assuming the media naturalness hypothesis holds, managers would benefit from a content-"channel naturalness" matching since they could increase the overall processing costs for negative news, rendering the information consumption uneconomical for some investors. Apart from increasing or dampening the stock market impact of news, managers may also strive for decreasing stock price volatility. According to Graham et al. (2005), the predictability of earnings for investors concerns managers, who therefore disclose information in a way that facilitates clear and understandable information. One reason for this is that better earnings predictability reduces information risk to investors and results in a lower cost of equity. Hence, since news disclosure impacts investors' assessment of future firm performance and since the disclosure over less natural channels may lead to communicational ambiguity (Kock (2005)), managers abstain from communicating complex and value relevant information these channels. Therefore, the media naturalness hypothesis allows us to make predictions about the optimal disclosure channel choice for managers for a given piece of information.

However, the corporate disclosure setting differs from the e-communication setting in numerous important ways. The critical assumption that a channel's purpose is to transmit new information may not hold in the corporate setting. For example, Cohen et al. (2020) find that firms copy up to 85 % of text from previous years 10-K filing and paste it in the following year's 10-K. The authors argue that mandated filings with regular cadence are mostly informative when analyzing them with previous filings. In the same vein, Brown and Tucker (2011) report that "(w)hile MD&A disclosures have become longer over time, they have become more like what investors saw in the previous year (...) Moreover, we find that the price responses to MD&A modifications have weakened over time (...) suggesting a decline in MD&A usefulness." Hence, corporate communication over mandated periodical reports may not qualify as a communication channel according to the media naturalness hypothesis.

Another assumption is that the information receiver is a human being and not a computer. Since investors increasingly apply algorithms to enter or exit stock positions during news events (O'Hara (2015); Rogers et al. (2017); Skinner (2019)) and algorithms have lower information processing costs than humans (Allee et al. (2018)), it is unclear whether managers choose channels to optimize for algorithmic or human recipients. However, we expect the media naturalness hypothesis to be useful for understanding firms' channel choice since its merits overweigh the shortfalls.

3. Hypotheses development

It is an empirical question which of our two conflicting arguments (levelling vs. separation) describes managerial behavior best. Since the levelling argument follows from falsifying of the separation argument, we test the latter using two hypotheses. The first hypothesis under the separation argument argues that the stock market reacts differently to information distributed to channels with higher or lower degrees of naturalness. Since investors are capacity constrained and information processing is costly, managers can influence their total information processing costs by distributing information to channels. This results in a delayed and muted stock price reaction to information within less natural channels. In contrast, under the levelling argument, investors have the same processing costs for all disclosure channels which results in stock price reactions of comparable speeds and magnitude among them.

H1: The stock market reaction towards information within less natural channels is delayed and muted compared to more natural channels.

The second hypothesis tests whether managers distribute positive information to more natural channels since they try to match it to the channels' processing cost to highlight positive information in more natural channels.

Within the quarterly reporting setting, firms have two sets of information: one that they need to disclose due to the regulatory environment (Graham et al. (2005)), and one that is the residual between the minimal disclosure requirement and the information set that firms plan to disclose. Since, managers know which information they must disclose, they might withhold negative immaterial information as it is costless, and managers do not face litigation risk for omitting immaterial information. Therefore, we ague that firms have mainly immaterial positive information to distribute to channels.

With those two sets at hand, firms may distribute information to channels with higher or lower degrees of naturalness by, first, placing an uniform information set to all disclosure channels, to meet the minimum disclosure requirements of regulators and investors. This is the optimal disclosure decision for material information (positive or negative) as this strategy dominates the other three available options.[1] The material information disclosure exclusively over EPR may induce more extensive questioning or "interrogations" by analysts during the question and answer portion of a ECC which may lead to unwanted information disclosure (e.g., Mayew (2012)). Similarly, not disclosing the information or disclosing it exclusively over ECC may increase litigation risk as shareholders who did not enter the call may file a lawsuit since the firm did not comply to the regulations around Fair Disclosure. Further, this is the cost-minimal disclosure strategy for material information since it requires the least resources to populate all channels (no lawyers and IR staff necessary to adapt disclosure to channel). Beyond that minimum set, firms start distributing the residual information by selectively adding further pieces of positive (negative) information to the more (less) natural channel until all information is placed.

[1] Information is defined as "material" if there is a substantial likelihood that a reasonable investor would consider the information important in making an investment decision, according to the SEC (https://www.sec.gov/rules/final/33-7881.htm).

Hence, we argue that high levels of information distribution to channels are associated with higher positivity for the more natural channel. In contrast, under the levelling argument, resource-constrained managers decide against distributing information to channels since investors process it from all channels equally.

H2: An increasing information distribution to channels is associated with higher positivity for the more natural channel.

4. Hypotheses-specific test design

4.1. Choice of channels

To test our hypotheses, we use the quarterly earnings announcement and analyze managements' decision to distribute information to channels. During this event, firms disclose periodical publications over different channels with different naturalness during a short period of time and this unique setting suits our research question. We exclude quarterly reports (10-Ks) since firms are required by the SEC to disclose EPRs and ECCs within a short time-window of 48 hours, whereas quarterly reports filings lag behind these two channels by up to 90 days (Securities and Exchange Commission (2002)). Due to this time-lag, practitioners and academics consider EPRs and ECCs to be the most relevant periodical disclosure channels. The empirical findings of Brown and Tucker (2011) provide evidence to this argument since they document a decline in price reaction to MD&A disclosures over time, suggesting that managers increase the use of boilerplate disclosure. Furthermore, the content and style of EPRs and ECCs are relatively unregulated compared to quarterly reports, which reduces noise in our data that stems from boilerplate language.

To analyze the information that firms intend to disclose, we focus on the ECCs' presentation part and exclude the Q&A section since analysts may force a firm to deviate from its intended disclosure strategy and disclose more information than planned. Therefore, by comparing EPRs to the ECCs' presentations, we gain insights into firms' choice of distributing information to a more natural (ECC) or less natural (EPR) channel.

4.2. Measuring textual similarity as proxy for information distribution to channels

Under the separation argument and within the quarterly reporting setting, firms have two sets of information: one that they need to disclose due to the regulatory environment (Graham et al. (2005)), and one that is the residual between the minimal disclosure requirement and the information set that firms plan to disclose.

Using those two sets, firms may distribute information to channels with higher or lower degrees of naturalness by, first, placing a uniform information set to all disclosure channels, to meet the minimum disclosure requirements of regulators and investors. This is the optimal disclosure decision for material information (positive or negative) as this strategy dominates the other three available.[2] The material information disclosure exclusively over EPR may induce more extensive questioning or "interrogations" by analysts during the question and answer portion of a ECC which may lead to unwanted information disclosure (e.g., Mayew (2012)). Similarly, not disclosing the information or disclosing it exclusively over ECC may increase litigation risk as shareholders who did not enter the call may complain that the firm did not comply to the regulations around Fair Disclosure. Further, this is the cost-minimal disclosure strategy for material information since it requires the least resources to populate all channels (no lawyers and IR staff necessary to adapt disclosure to channel).

[2] Information is defined as "material" if there is a substantial likelihood that a reasonable investor would consider the information important in making an investment decision, according to the SEC (https://www.sec.gov/rules/final/33-7881.htm).

Beyond that minimum set, firms start distributing the residual information by selectively adding further positive (negative) pieces of information to the more (less) natural channels until all information is placed. Hence, for every additionally distributed piece of information, the information within the channels becomes less similar, but for periods with little news exceeding the minimal threshold, the information within channels remains similar. We capture channel distribution by modifying two textual similarity measures from the field of linguistics that compare EPRs and ECCs – cosine similarity and the Jaccard coefficient. These similarity approaches were already applied in previous studies about SEC filings and ECCs; e.g., see Lee (2016); Cohen et al. (2020) for analyzing 10-K, Cicon (2014) for ECCs, and Hanley and Hoberg (2010) for S-1. We interpret higher values of our measures as a proxy for firms distributing more information between the channels.

The term *Info* represents our key variables *Info_Cosine* or *Info_Jaccard*. *Info_Jaccard* differs from *Info_Cosine* as it regards two documents as more similar if a word occurs in both at least once. In contrast, *Info_Cosine* regards texts as more similar if words occur in both documents the same number of times. Hence, *Info_Jaccard* is more sensitive to word diversity, and *Info_Cosine* more sensitive to word repetitions.

Following Cicon (2014), we compute *Info_Cosine* as $1 - \cos(\theta)$ between two documents – D_1 and D_2 – as follows: Let $\overrightarrow{d_1}$ and $\overrightarrow{d_2}$ be the set of words occurring in D_1 and D_2, respectively. Define the word frequency vectors $D_k^{(TF)}$ of any document D_k as:

$$D_k^{(TF)} = [nD_k(t_1),\ nD_k(t_2),\ \ldots,\ nD_k(t_n)], \tag{1}$$

where k is a given document and thereby, $nD_k(t_i)$ the number of occurrences of word t in D_k. Then, *Info_Cosine* is defined as:

$$Info\_Cosine = 1 - \cos(\theta) = 1 - \frac{D_1^{(TF)} \cdot D_2^{(TF)}}{\left\|D_1^{(TF)}\right\| \times \left\|D_2^{(TF)}\right\|}, \tag{2}$$

where the dot product, ·, is the scalar product and $||\ ||$ is the Euclidean norm. By doing so, we measure the normed distance of both vectors.

We compute our second measure *Info_Jaccard* as one minus the intersection of the two word-sets divided by the union of the two word-sets

$$Info\_Jaccard = 1 - \frac{D_1^{(TF)} \cap D_2^{(TF)}}{\left|D_1^{(TF)} \cup D_2^{(TF)}\right|}. \tag{3}$$

By construction, we cannot identify whether *Info*'s values are higher due to D_1 being different from D_2 or *vice versa*. This commutative feature is due to the bidirectional mathematical operations in each measure's numerator. To illustrate how we assess information distribution and how the two measures differ, we offer an anecdotal example in Table A. 3 of the Online Appendix 1 and an example of the computation of *Info_Cosine* and *Info_Jaccard* in the Online Appendix 2.

4.3. Measuring tone as proxy for information in a channel

We rely on extensive previous literature on quantifying qualitative information by using the linguistic tone as our proxy. This implies the simplifying assumption that positive or negative words in predetermined dictionaries are equally informative, whereas other words are uninformative. To measure tone, we use positive and negative word counts from the financial reporting-specific wordlists developed by Loughran and McDonald (2011b). we do not count a positive word if there are negation words ("no," "not," "none," "neither," "never," and "nobody") immediately before it. Next, we subtract positive and negative words and scale its difference by the number of total words. The final measure represents the net positivity per word in an channel where a higher number of positive than negative words results in a positive value for tone and *vice versa*. A greater number of total words in an channel results in a smaller value for tone.

4.4. H1 – Stock returns

To investigate our first hypothesis, we examine how the impact of information on the stock return differs between channels with lower or higher degrees of naturalness (EPRs vs. ECCs). For that, we calculate cumulative abnormal returns (*CAR*) to extract the stock price reaction using the Fama-French five-factor model as described in Fama and French (2015) as our benchmark. We vary the time window between 1 day (*CAR*(-1, 1)) and 30 days (*CAR*(-1, 30)) around the ECC date to examine the relationship between tone of channels and the contemporaneous stock returns or the post-earnings-announcement returns. Furthermore, we control for the time difference of the disclosure releases, which correspond to the time the market has for processing a channel before the next is published. We do so to increase the comparability of tone's impact on stock returns between EPRs and ECCs. Since tone's impact on returns varies with the time it has been public to the market (e.g., Borochin et al. (2018)), inaccurate interpretations could arise when comparing two tone-effects which have been released at different points in time. We control for the impact of the time difference between EPRs and ECCs on the return impact of tone by using an interaction term between tone and the dummy variable *Diff_Day_Discl*. This dummy variable takes on the value of 1 if a firm releases its EPR and the ECC *not* within 24 hours before the market closes at 16:00 EST and 0 otherwise. The base effect of tone resulting from the interaction shows its impact on stock returns if the EPR and the ECC are disclosed before the same day's market close. Therefore, it reflects the disclosure-time adjusted impact of tone on stock returns. The firm-level cross-sectional regression analysis has the following form:

$$\begin{aligned} CAR(m, p)_{i,q} = \beta_0 &+ \beta_1(Diff\_Day\_Discl_{i,q} \times Tone\_EPR_{i,q}) + \beta_2 Tone\_EPR_{i,q} \\ &+ \beta_3(Diff\_Day\_Discl_{i,q} \times Tone\_ECC_{i,q}) + \beta_4 Tone\_ECC_{i,q} \\ &+ \beta_5 Controls\_CAR_{i,q} + i_i + \tau_q + \varepsilon_{i,q}, \end{aligned} \tag{4}$$

where *CAR* represents the cumulative abnormal return measures for time-window starting on day *m* to *p*. The sum of the coefficients β_1 and β_2 (β_3 and β_4) estimates EPRs' (ECCs') tone impact on abnormal stock returns if a firm does not release its EPR and the ECC within 24 hours before the market closes. In line with the literature regarding tone and stock market reactions, we control for various variables within the vector *Controls_CAR* namely, *MtB*, *Leverage*, *RoA_Q0*, *log*(*Volume*), *Volatility*, *AFE*, *log(Assets)*, *Is_Annual_Report*. The dummy variables i and τ capture the firm-fixed and year-fixed effects, respectively. Table A.2 in the Online Appendix 1 provides the definitions for all variables. The standard errors are reflected in ε. Index q stands for a year-quarter and index i for a company in our sample. For our comparative analysis, we focus on the magnitude, sign, and significance of coefficients β_2 and β_4 and to verify Hypothesis H1 – that stock market reactions are larger in more natural channels – we require β_4 to be larger than β_2.

4.5. H2 – Tone differences between EPRs and ECCs

To assess our second hypothesis, we examine how the tone of EPRs and ECCs change if firms distribute information to these channels. Under the separation argument, managers believe that more natural channels (ECCs) are better suited to disclose positive information than less natural channels (EPRs). Therefore, we expect information distribution (*Info*) to relate negatively to the tone of EPRs (*Tone_EPR*) and positively to the tone of ECCs (*Tone_ECC*) and we investigate this link using the following regression model:

$$Info_{i,q} = \beta_0 + \beta_1 Tone\_ECC_{i,q} + \beta_2 Tone\_EPR_{i,q} + \beta_3 Controls_{i,q} + i_i + \tau_q + \varepsilon_{i,q}. \quad (5)$$

The coefficient β_0 represents the model's intercept, β_1 represents the model's sensitivity towards *Tone_ECC*, while β_2 stands for the sensitivity for *Tone_EPR*. The coefficient β_3 summarizes the different sensitivities for control variables. We follow prior literature on tone and performance and include the vector *Controls* containing *MtB, Leverage, AFE, RoA_Q0, Sales_Growth, Cash_StInv, CF_Op_Q0, log(Assets), log(Age), Std_Inv, Std_CF_Op, Std_Net_Sales, Num_Analysts, Is_Annual_Report.* All remaining parameters are the same as in the previous section. To verify that firms disclose positive information over more natural rather than less natural channels when distributing information (Hypothesis 2), we require the estimated coefficient β_1 to be positive and β_2 to be negative.

5. Data and variables

5.1. Sample construction

We include all S&P 500 index's constituents between 2004 and 2018. All firms are included for the entire sample period if they were an index constituent once to mitigate potential survivorship bias. We obtain the firms' 8-K reports from the SEC's EDGAR platform. Using an open-source parsing library (detailed in Table A. 1 in the Online Appendix 1), we download and parse 8-K reports to obtain our EPR data. Following Arslan-Ayaydin et al. (2016), we consider the text within exhibit 99.1 to be relevant for an EPR. Next, we download all available ECCs in the Thomson Reuters Street Events database and separate the presentation part from the Q&A part. We merge the subsamples if information is disclosed over both channels within a time window of max. 48 hours and stem all text data using the Porter stemming algorithm (Porter (1980)). The stock prices and financial data are obtained from Thomson Reuters Eikon. To construct excess returns for stocks, we rely on Fama & French's web site's daily and monthly factors and choose the conference call date as our earnings announcement reference date.

5.2. Summary Statistics

We present the composition of our sample in Table 1. Panel A shows that our planned sample starts with 28,563 observations but shrinks down to 17,314 due to missing data points or conflicts from merging databases. Panel B shows the distribution of the observations across years, which indicates that our observations do not cluster within any particular year. We winsorize all variables at the 1 % and 99 % percentile to reduce the influence of outliers.

<<< Table 1 >>>

Table 2 displays the corresponding descriptive statistics for the news release describing variables (Panel A), firm-financial variables (B), and stock performance variables (Panel C). The mean of *Info_Cosine* (0.37) is lower compared to *Info_Jaccard* (0.69). This divergence of the measures suggests that EPRs and ECCs use different words but have similar word frequencies in both channels. Consistent with the previous research, the distribution of *Tone_EPR* is negatively skewed – larger values are to the left than to the right of the median. This observation suggests that EPRs tend to be more pessimistic on average which is consistent to e.g., Feldman et al. (2010).

In contrast, *Tone_ECC* is positively skewed and positive on average. This goes in line with our documented readability of EPRs and ECCs. The average complexity of the language measured by the Gunning Fog index is higher for EPRs than ECCs which is intuitive as written language tends to be more complex than spoken language. The average number of words within ECCs is 3,685, while it is 2,541 for EPRs.

<<<Table 2>>>

Table 3 reports the correlations between the text-based measures. Both *Info* measures correlate highly and positively (0.61). However, they seem to be low correlated with other measures of informative content like tone (e.g., corr(*Info_Cosine*, *Tone_EPR*) = -0.09) and readability (e.g., corr(*Info_Cosine*, *Fog_EPR*) = -0.15). The correlation between *Tone_EPR* and *Tone_ECC* of 0.40 indicates that both channels' positivity is weakly linearly connected.

<<<Table 3>>>

6. Results

6.1. H1 – Stock returns

Table 4 compares the effects of *Tone_EPR* and *Tone_ECC* on abnormal stock returns by applying Equation (4). We can corroborate three saliences from our results regarding Hypothesis 1. First, we observe that tone of ECCs (Model 2, 3, 5, and 6) has a greater effect on abnormal stock returns than within EPRs (Model 1, 3, 4, and 6) in terms of magnitude, statistical significance, and explanatory power. When focusing on the (-1,1)-day time window (Model 1-3) and the difference in the coefficients, we find that the coefficient for *Tone_ECC* (1.5760 in Model 2) is almost double as high its value for *Tone_EPR* (0.8890 in Model 1). This difference is significant as the 95 % confidence intervals of the coefficients do not overlap and persists over longer time windows (Model 4-6). When controlling for both tone variables (Model 3), we find that *Tone_ECC* is six times more impactful than *Tone_EPR* (1.5090 vs. 0.2259). To translate this into a practical perspective, an increase of *Tone_EPR* by its standard deviation (0.0062) implies a 0.14 % increase of *CAR*(-1, 1), compared to a 1.1 % increase implied by *Tone_ECC*'s standard deviation (0.0073). Models 2 and 3 further underline the low economic relevance of *Tone_EPR* for predicting abnormal returns, since the adjusted R^2 is lower or does not increase after *Tone_EPR*'s addition.

Second, we document that the stock price sensitivity towards *Tone_EPR* increases while it decreases for *Tone_ECC* over time. The coefficient value for *Tone_EPR* is approximately 50 % higher in Model 6 ((-1,30) time window) compared to Model 3 ((-1,1) time window), while the coefficients of *Tone_ECC* remain equally high for both models.

Third, we find for the first time by analyzing the interaction term (*Diff_Day_Discl* × *Tone_ECC*) that firms can increase the impact of positive information on stock returns by disclosing it during a different trading session than the EPR; for example, if a firm releases an EPR in the morning but holds an ECC after the market closes. In economic terms, the stock return impact of a standard deviation increase of *Tone_ECC* rises to 1.52 %[3].

<<<Table 4>>>

[3] = "β_3 × Std(*Tone_ECC*) × *Diff_Day_Discl* + β_4 × Std(*Tone_ECC*)" = (0.5761 × 0.0073 × 1 + 1.5090 × 0.0073)

From the above findings, we deduce that the effect of tone on abnormal stock returns is greater for ECCs than EPRs since investors react more efficiently to information (proxied by tone) contained in ECCs than in EPRs which is consistent with our separation argument. Investors experience higher processing costs in the less natural channel (EPR) and process the contained information less efficient as in the more natural channel (ECC), resulting in a muted and delayed reaction.

6.2. H2 – Tone differences between EPRs and ECCs

Figure 1 provides the first evidence that managers disclose positive information via more and negative information via less natural channels by displaying the relationship between the tone of each channel (*Tone_EPR*, *Tone_ECC*) ordered by their percentiles. The key findings are that the tone spread (ECC – EPR) increases if information distribution to channels increases since the ECCs' slope is positive, whereas the EPRs' slope is negative. For instance, a decile jump in *Info_Cosine* corresponds to 0.7 net positive words less in an EPR[4], whereas 0.8 more in an ECC. This observation is persistent for the different measures of information distribution (Panel A for *Info_Cosine* and Panel B for *Info_Jaccard*) and indicates that the tone of EPRs and ECCs corresponds to information distribution to channels in opposite ways.

<<<Figure 1>>>

We continue to test for Hypothesis 2 by applying Equation (5) and display further evidence for firms disclosing positive information in more natural (ECCs) and negative information in less natural channels (EPRs) in Table 5. It examines the relationship between information distribution and tone of ECCs and EPRs and shows positive and significant coefficients for *Tone_ECC* for both information distribution measures, which is in line with our prediction.

[4] = "Coefficient value × Decile(*Info_Cosine*) × Mean(*Words_EPR*)" = (-0.0000182 × 10 × 3,685)

However, for *Tone_EPR*, we find the coefficients for both information distribution measures to be negative but only to be significant for *Info_Cosine*.

The values of the coefficients suggest that information distribution is an economically significant predictor for tone. For instance, a firm – whose information distribution (proxied, e.g., by *Info_Cosine*) is one standard deviation higher than that of an otherwise identical firm – will have 528 more net positive words per ECC[5]. Overall, these results are consistent with our Hypothesis 2 that firms disclose positive information over more natural channels.

The absence of a significant relationship between *Tone_EPR* and *Info_Jaccard* can be explained by its computation method. It counts every occurring word only once and is more sensitive to word diversity. Since firms use less different negative than positive words, the results may be driven by this textual characteristic of EPRs. Nevertheless, since the relationship between negative news disclosure and information distribution is not robust against the measurement method choice, we conclude that the processing cost reduction for positive news disclosure drives the information distribution decision of firms.

This observation is in line with several previous studies like Asay et al. (2018), who find that changes in the readability of disclosures are mainly driven by attempts to write more readable good news reports (meaning decrease processing costs) as opposed to intentional obfuscation of poor performance (increasing processing costs). It is also consistent with theories which conjecture that managers have an incentive to disclose good and withhold bad news by disclosing positive information only if it is above a positivity threshold (e.g., Verrecchia (1983)).

<<<Table 5>>>

[5] = "Coefficient value × Std(*Info_Cosine*) × Mean(*Words_ECC*)" = (0.1079 × 1.3275 × 3,685). The corresponding value for *Info_Jaccard* is 122.

6.3. Additional analyses

The main results of our empirical analyses have supported our hypotheses and are, so far, in line with our idea of the separation argument. Now, we present additional analyses to further substantiate the separation argument and the notion that information distribution is driven by managers disclosing positive information in the more natural. We do so by investigating mechanics behind the separation argument (tone, readability, operating performance, expectation management, agency costs, and portfolio theory).

6.3.1. Information distribution and tone spread

Under the separation argument firms must distribute a set of information to channels with higher or lesser degree of naturalness. This means that before firms distribute information, all channels contain the same minimum amount of information and if more information must be distributed, the more natural channel will become more positive (the content will differ). An empirical consequence of this is that the correlation of the tone between channels is high with no distribution (similar minimum content) and low with more distribution to channels (similar minimum content and dissimilar additional content).

In this section, we provide evidence that our theorized process of adding information to the initial set describes actual managerial behavior. We analyze whether information distribution (*Info*) moderates the relation of EPRs' tone (*Tone_EPR*) to ECCs' tone (*Tone_ECC*) and predict that when *Info* is low, the correlation between *Tone_EPR* and *Tone_ECC* is the highest and that the correlation decreases with higher *Info* levels.

To show the basic relationship between the tone variables and *Info*, we model the relation with and without controls and show the results in Table 6. Since the interaction *Info* × *Tone_ECC* is negative, we document that the impact of ECCs' tone on EPRs' decreases when firms distribute more information to channels. This finding is statistically significant at the 1 % level in all model specifications for both information distribution measures (Model 1-

2) while controlling for firm-fixed, year-fixed effects, and other firm-level controls (Model 3-4).

To put this result into a practical perspective, we use the most restrictive model (Model 3). If a firm does not distribute information to channels (*Info_Cosine* = 0), a one standard deviation increase in *Tone_ECC* yields to 12.65 more net positive words in an EPR[6]. However, if *Info_Cosine* has the value of its sample mean, a one standard deviation increase in *Tone_ECC* translates into only a 5.66 increase in net positive words in an EPR.[7] Thus, these findings are not only statically significant but also practically relevant indicating that "average" companies use 6.98 (12.65 – 5.66) net positive words less in their EPR compared to companies that do not distribute.

<<<Table 6>>>

To follow this process more gradually, we analyze the marginal effects of varying levels of information distribution (*Info*) and *Tone_ECC* on *Tone_EPR*. Figure 2 illustrates changes in *Tone_EPR* as a function of *Tone_ECC* for five different levels of *Info* (1^{st}, 25^{th}, 50^{th}, 75^{th}, and 99^{th} percentile). The slopes show that higher levels of *Info* create a flatter line profile for *Tone_ECC*'s impact on *Tone_EPR* and *vice versa*. Thus, the impact of ECCs' tone on EPRs' tone decreases (but not becoming negative) if firms distribute more information to channels. Overall, this analysis supports the notion that firms disclose the same uniform set of information over all disclosure channels (high coefficient when no distribution) and further distribute positive information to channels (coefficient decreases when distributing).

<<<Figure 2>>>

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[6] = "Coefficient value base effect × Std(*Tone_ECC*) × Mean(*Words_EPR*)" = (0.6818 × 0.0073 × 2,541). The corresponding value for *Info Jaccard* is 23.06.

[7] = "((Coefficient value base effect × Std(*Tone_ECC*)) + ("Coefficient value interaction" × Mean(*Info_Cosine*) × Std(*Tone_ECC*)) × Mean(*Words_EPR*)" = ((0.6818 × 0.0073) + (-1.0044 × 0.0073 × 0.3748)) × 2,541)

6.3.2. Information distribution and readability

Li (2008) documents a linear relation between news' readability and firm performance and concludes that managers delay the bad news processing by making it more complex to read. Complex to read information increases the information processing costs for investors since less readable news requires more time and resources to extract relevant information (e.g., Bloomfield (2002)). However, the interpretation of Li (2008) that the linear relation between readability and firm performance is driven by negative news disclosure is questioned by Asay and Hales (2018). They argue that managers actually strive to make good news more readable.

To be able to answer this open question around the mechanics behind the variation of readability (bad news vs. good news), we assess how the readability of channels relates to information distribution. Since the readability of news directly impacts its processing costs, we expect that the more natural channel (ECC) is easier to read because it contains more positive information. Following the textual analysis literature, we rely both on the Gunning Fog index (*Fog*, higher values indicate lower readability) and the Flesch-Kincaid readability index (*Flesch*, higher values indicate higher readability) as our proxies for readability of EPRs and ECCs (Loughran and McDonald (2016)).

Table 7 displays the results across Panel A (ECCs) and Panel B (EPRs). Regarding ECCs, we find a positive relationship between the readability of ECCs' presentation parts and information distribution – supporting the finding of Asay et al. (2018). Technically, the coefficient on *Flesch* is positive and on *Fog* negative for both information distribution measures. When focusing on EPRs' readability, the results are not conclusive as *Info_Jaccard* has no significant relation with any proxy of readability.

<<<Table 7>>>

6.3.3. Information distribution and operating performance

Positive news disclosure due to a firm's elevated prospects may be a supporting factor for the information distribution decision. There is a consensus in literature that positive firm performance relates to positive information disclosure since good performing firms are willing to signal their positive prospects. This disclosure behavior of a firm can be explained by the expectations-adjustment hypothesis where managers use disclosures to align investors' expectations of future performance with their assessment (Ajinkya and Gift (1984); King et al. (1990); Davis et al. (2012)). Firms might do so to increase, e.g., analyst coverage (Bhushan (1989), (1994); Lang and Lundholm (1996)) or reduce its cost of capital by lowering informational asymmetry between themselves and investors (Graham et al. (2005); Asay et al. (2018)).

In the same vein, according to the credibility argument, analysts demand additional disclosures when performance is good to assess the credibility and persistence of the firm's performance (Hutton et al. (2003); Matsumoto et al. (2011)). Since reducing uncertainty about a firm's prospects for analysts is a concern of managers (Graham et al. (2005)) and because of analysts' elevated information demand if firm performance is good, it is likely that information distribution increases when firm performance increases.

While lowering the informational asymmetry by disclosing the demanded information, firms might also consider the channel when planning their disclosure because they want to keep processing costs low. Since we argue that good firm performance relates to increased positive news disclosure and that more natural channels are better suited for positive news disclosure, we expect firms to distribute information to ECCs when firm performance is good.

We proxy firms' operating performance (*Perf*) using two metrics from their current, next, and second-next quarter – cash flows from operations scaled by the last quarter total assets (*CF_Op*) and return on assets (*RoA*) following Barber and Lyon (1996). We divide earnings before interest and taxes by last quarter's total assets since this metric is less affected by industry-specific depreciation patterns (like in the real estate or utility sector) or managerial discretion. We regress our operating performance measures on information distribution (*Info*) while controlling for the predictive power of tone on firm performance and tabulate the results in Table 8.

Panel A and B show the result of our regression of current and future firm performance proxied by *RoA* and *CF_Op* on both measures for information distribution and a set of controls. Regarding *RoA* in Panel A, the coefficients for both distribution measures are positive for the current and next quarter. However, our findings around the second next quarter are inconclusive as the coefficient on *Info_Cosine* is insignificant. Regarding *CF_Op* in Panel B, we find positive and but insignificant coefficients for both distribution measures for the current quarter, but positive and significant ones for the next and second next quarter.

The magnitude of our findings suggests that the use of information distribution is an economically significant predictor of next quarter's firm performance. For instance, a firm – whose information distribution (proxied, e.g., by *Info_Cosine*) is one standard deviation higher than that of an otherwise identical firm – will have a 0.22 % higher *CF_Op_Q1* (= 0.1079 × 0.0209). Overall, these results – that information distribution increases when a firm's prospects are good – are consistent with our notion that firms distribute mostly positive information. Therefore, we conclude that firm performance is a factor influencing information distribution.

<<<Table 8>>>

6.3.4. Information distribution and expectation management

The risk of not reaching investors' expectations may be a factor that reduces a firms' use of information distribution. Firms take on higher risk when disclosing positive information as it influences the expectations of investors and analysts (Rogers et al. (2011)). Expectations rise when firms disclose optimistic statements or exhibit unusual linguistic optimism, or optimism not predicted by fundamentals (D'Augusta and DeAngelis (2020)). Not meeting investors' or analysts' expectations has consequences for firms as they may face litigation in a lawsuit while being accused of over-optimism (Skinner (1994); Rogers et al. (2011)). To counteract the risk of litigation and to avoid accusations of over-optimism, firms might be more conservative with the emphasis they put on positive compared to negative performance. Conservative disclosure may be especially prevalent when firms beat earnings benchmarks, as managers attempt to dampen expectations of future earnings performance (Matsumoto (2002); Richardson et al. (2004); D'Augusta and DeAngelis (2020)).

Consequently, we expect that if firms beat earnings' expectations, they face the risk of over-emphasizing positive performance and therefore disclose – and also – distribute less information. We use two proxies relating to the risk of over-emphasizing positive firm performance to test our proposed relationship between information distribution and expectation management. First, we follow surveyed evidence by Graham et al. (2005) (how much of this quarter's earnings exceeded prior-year earnings (*DEARN*)) and second, empirical evidence by D'Augusta and DeAngelis (2020) (how much of this quarter's earnings exceeded analyst forecasts (*AFE*)). Both variables are scaled by the firm's marketvalue and can take both positive and negative values.

To test the link between expectation management and the separation argument, we adapt an asymmetric responsiveness model introduced by Basu (1997) and applied by the accounting conservatism literature (D'Augusta and DeAngelis (2020)). We regress *Info* on *AFE* or *DEARN* and interact both variables with a dummy variable that takes the value 1 if performance is above expectations and 0 otherwise.

Table 9 presents the results relating to whether information distribution depends upon the expectation management motive. The coefficients on the interactions between both *AFE*

(Model 1-2) and *DEARN* (Model 3-4) as well as their respective benchmark exceedance indicator variable are negative and statistically significant at any conventional level in all our test specifications. We also observe insignificant relationships between earnings performance measures (*AFE*, *DEARN*) and information distribution (*Info*) when firm performance is below expectations. This finding suggests that based on earnings, firms only modulate information distribution when they beat their benchmark by distributing less information to channels. Our reading of this finding is that firms generally take on the risk of elevating investor expectations with additional disclosure but avoid it in riskier situations such as when earnings exceed benchmarks. Overall, this result is consistent with our notion that expectation management influences information distribution negatively.

<<<Table 9>>>

6.3.5. Information distribution and agency costs

The presence of agency conflicts may be a supporting or limiting factor for firms' use of information distribution and in the following we provide arguments for both readings. The relation between information distribution and agency costs might be positive since firms – which are plagued by agency problems – employ opportunistic managers that use disclosure strategies to induce investor reactions (Huang et al. (2014); Edmans et al. (2018); Breuer et al. (2020)). Investor reactions are influenced by information disclosures, which can be controlled by firms' top management. Prior findings suggest that opportunistic managers use their discretion over corporate disclosure to achieve personal financial and non-financial goals like increasing compensation (e.g., Noe (1999); Edmans et al. (2018)), remaining in corporate control (e.g., Healy and Palepu (2001); Graham et al. (2005)) or signaling talent (e.g., Trueman (1986)). In line with these findings, we expect that firms distribute information to channels if they have severe agency problems like investing inefficiently (e.g., Jensen and Meckling (1976)), managing earnings (Bergstresser and Philippon (2006); Cornett et al. (2008)), or using deceptive trust rhetoric (Breuer et al. (2020)).

However, the relation between information distribution and agency costs might also be negative, since managers understand that information distribution reduces informational asymmetry between investors. Lower informational asymmetry increases investors' chance to uncover potential opportunistic management behavior, which may not be in managers' interest (Jo and Kim (2007)). Consequently, the association between information distribution and agency cost producing behavior would be negative. Managers distribute less information when evidence for agency costs exist and *vice versa*. Jo and Kim (2007) provide empirical observations supporting this notion as they document a negative nexus between disclosure frequency and earnings management. Another explanation for a negative relation of information distribution and agency costs might be that information distribution is a proxy for the absence of agency problems as cases of genuinely meant disclosure certainly exist.

Given this directional uncertainty of the effect of agency costs on information distribution, we conduct the following empirical analysis on three actions taken by management that proxy opportunistic behavior. One action may be accruals management, a tool to manipulate the investor's perception of a firm. A possibility is that managers manipulate reported earnings to their advantage before corporate events (Teoh et al. (1998a), (1998b); Erickson and Wang (1999); Kasznik (1999)) or to maximize their compensation (Xie (2001); Bergstresser and Philippon (2006); Cornett et al. (2008)). In the same vein, we expect managers who manipulate earnings to seize their discretion over information distribution. To test this conjecture, we estimate the absolute value of discretionary accruals ($|DA|$) while accounting for firm performance using the modified Jones model described by Huang et al. (2014).

Alternatively, firms' inefficient investment may be rooted in agency problems (e.g., Breuer et al. (2020)). These agency problems lead to firms not following the shareholder optimal investment strategy as opportunistic managers consider their financial and non-financial utility in the investment decision (e.g., Jensen and Meckling (1976)). Hence, if information distribution allows inference about managerial opportunism, we expect it to be related to investment efficiency, too. To test this conjecture, we classify a firm as investing inefficiently (IE) by following the approach of Biddle et al. (2009).

Lastly, managers who engage in opportunistic behavior may alter their rhetoric, for example, by (falsely) conveying trustworthiness to investors. Conveying trustworthiness is a significant proxy for agency problems as Breuer et al. (2020) document that managers using more trust words invest less efficiently or exhibit poor operating performance. Both observations are known as deteriorating effects of present agency conflicts. If information distribution extends the latitudes of deceiving managerial rhetoric, we expect it to be related to the use of trust words. To test this conjecture, we compute a similar metric as for tone, using the trust word list by Audi et al. (2016). We count the number of trust words divided by the number of total words in the presentation part of an ECC's transcript (*Trust*).

Table 10 reports our tests for the association between information distribution and agency problems using the three alternative proxies for agency costs: investment inefficiency, discretionary accruals, and trust words. The coefficients on inefficient investment *IE* are negative for *Info_Cosine* but insignificant for *Info_Jaccard*, which provides inconclusive evidence for information distribution being negatively related to inefficient investment. The coefficients on discretionary accruals *DA* are negative for *Info_Cosine* (*Info_Jaccard*), suggesting that, *ceteris paribus*, distributing information relates to lower earnings management. Regarding the ratio of trust words *Trust*, we find significant and positive coefficients on both information distribution measures, meaning that the usage of trust-related words increases when distributing information in ECCs. In practical terms, a one standard deviation increase of *Info_Cosine* implies a 0.12 words increase of trust words in an ECC's presentation, which is almost negligible. Therefore, we argue the use of trust words is only weakly related to information distribution, which may most likely be explained by cases of genuinely meant trust rhetoric that go along with information distribution rather than agency conflicts.

Overall, the findings suggest that firms distribute information when tangible agency costs (like inefficient investment or earnings management) are low. These results are also consistent with managers making more shareholder optimal decisions when informational asymmetry is low as suggested by Jo and Kim (2007). Therefore, we conclude that information distribution is more likely to be a proxy for the absence rather than the presence of agency problems.

<<<Table 10>>>

6.3.6. Information distribution and portfolio returns

The market compensates capacity-constrained investors with the marginal value of the information they process and impound into prices (e.g., Grossman and Stiglitz (1976)). Therefore, since our results suggest that information distribution is associated with to genuinely informative and positive news in the natural channel, it should not predict future stock returns. Predictions should not be possible since investors obtain positive information over the disclosure channel with the least processing costs. An empirical consequence of this reasoning is that a portfolio based on information distribution cannot yield abnormal returns as firms' stock prices reflect the information's value.

We test this assertion by closely following Cohen et al. (2020) to construct these portfolios. For each month, we compute quintiles based on *Info* (low to high distributor) of the last calendar year. Those quintiles form five portfolios. Stocks enter the portfolio on the first day of the next month after the ECC, which induces a time lag in our portfolio construction but decreases eventual trading costs from rebalancing. Note that we rebalance and equally weight our portfolio every month, and firms remain in the portfolio for three months. We calculate abnormal returns over three approaches: excess returns (return minus the one-month return of the T-Bill), Fama-French three-factor alpha, and Fama-French five-factor alpha.

Table 11 reports the average monthly returns in basis points. Quintile 1 (Q1) corresponds to firms whose ECCs are most like their EPRs, and hence, this portfolio consists of the "low distributors." Quintile 5 (Q5) corresponds to firms whose ECCs differ most from their EPRs, and thus this portfolio represents the "high distributors."

Our results show that a long portfolio earns a large and significant abnormal return ranging between 43 and 131 basis points per month. The result is unaffected by controlling for the Fama-French factors (market, size, and value) and the two additional factors (momentum and profitability). These findings suggest that systematic loadings on commonly known risk factors do not drive these portfolios' returns and that firms who distribute information experience higher future returns. Firms that do not distribute information are associated with no abnormal returns. Notably, this finding holds for both our *Info* measures, indicating that the particular way how we compute the differences between ECCs and EPRs does not drive the results. The strong positive abnormal returns suggest that managers indeed disclose genuine positive information and support our initial findings of the positive relation information distribution with operating performance and tone. Additionally, the magnitude of positive abnormal returns suggests that managers potentially disclose material information that benefits from the reduced communicational ambiguity of information distribution. This is consistent with the theory of mosaic, under which an analyst can assemble pieces of non-public and immaterial information into the bigger picture that reveals a material conclusion in a resource intensive process (Becker (2000)). Further, our findings provide evidence relevant to the pending petition by Adam M.

Altman, who argues that ECCs must be filed with the SEC to comply with Regulation Fair Disclosure as it may contain material information[8].

<<<Table 11>>>

7. Conclusion

Existing financial research and theories assume that investors process information regardless of the disclosure channel and thereby contradict recent findings that document incremental informativeness of disclosure channels like earnings conference calls. The contradiction arises since firms would not provide incremental information over a particular channel if they do not expect a positive return on their effort in distributing this information. To understand this disclosure behavior, we draw from the communication literature to state two opposing arguments for and against the usefulness of distributing information – levelling vs. separation.

We find evidence for our separation argument since we document positive relations between the positivity of information and the channel's ease of processing for investors. This means that firms distribute positive news to channels that induce less processing cost to investors leading to larger and timelier stock market reactions. Indeed, we test for this behavior on the quarterly earnings announcement period, when firms must disclose information over earnings press releases (EPR) and earnings conference calls (ECC) with little time difference. In particular, we show that the distribution of positive information in ECCs increase the stock market reaction six times greater than for EPRs.

Since our evidence suggests that abnormal returns are possible despite managers efforts to decrease investors' processing costs, we also examine how information distribution relates

[8] See Pending petition of the Law Firm Adam Altman Ltd. with the SEC regarding mandating ECC transcript disclosure over the SEC EDGAR system. (https://www.sec.gov/rules/petitions/2019/petn4-742.pdf)

to the readability of EPRs and ECCs. We find that ECCs are more readable and that the readability improves when firms distribute information. This positive relation may be driven by the wish to facilitate "clarity and understanding" for investors (Graham et al. (2005)). Furthermore, information distribution predicts future firm performance by an economically significant margin, which underlines that firms want to disclose positive information in an impactful and unequivocal manner and want to achieve this by choosing the most suitable channel. Our empirical findings are robust to different information distribution measures and controlling for firm-fixed and year-fixed effects.

Overall, our study is consistent with information distribution being another rhetoric of managers but has some limitations too. We acknowledge that our study is a first step in exploring disclosure strategies that involve two channels. Although our results support the notion that stock price sensitivity towards the more natural channel drives the distribution decision, we recognize that our analyses are tests of association and not causality. Thus, it is inadequate to regard our results as evidence that all the investigated factors cause information distribution. Nevertheless, the results are in line with such a reading.

Our study has implications for academics and practitioners, especially because investors do not seem to exploit the potential of observable information distribution. A possible route for future analysis might be that ECCs – which are the drivers of information distribution's positive effect – contain immaterial information which help deriving material conclusions. This is criticized by shareholder rights organizations and subject to the ongoing discussion at the SEC[9]. Examining which factors influence the information dissemination from ECCs into asset prices may, therefore, be a natural next step.

[9] See Pending petition of the Law Firm Adam Altman Ltd. with the SEC regarding mandating ECC transcript disclosure over the SEC EDGAR system. (https://www.sec.gov/rules/petitions/2019/petn4-742.pdf)

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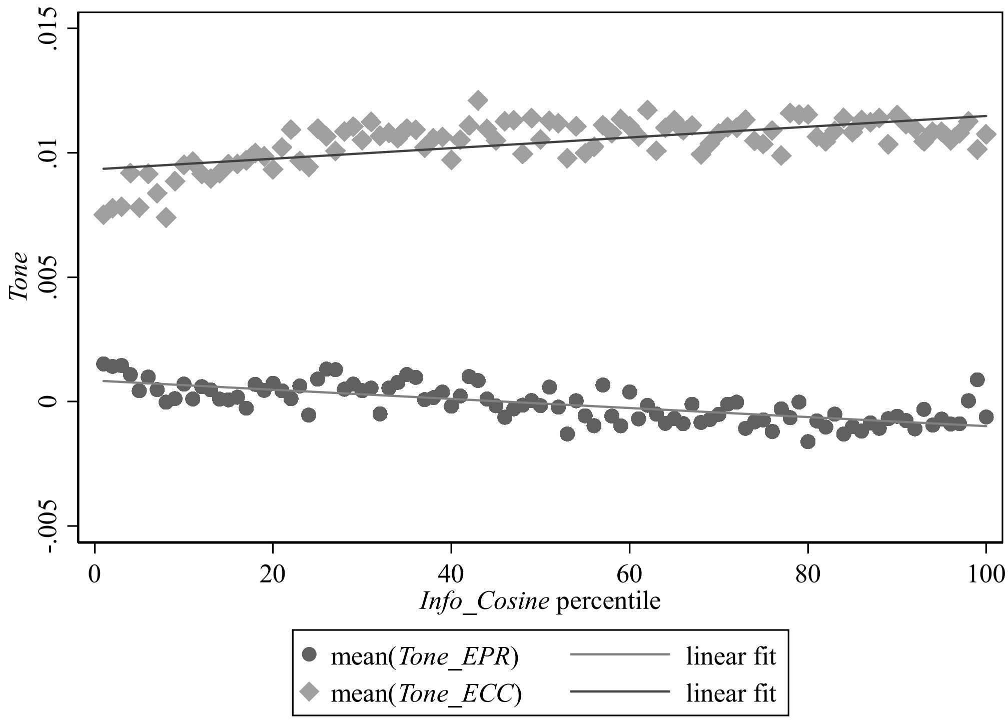
Figures

Figure 1

Effect of information distribution on the change in disclosure tone in EPR and ECC

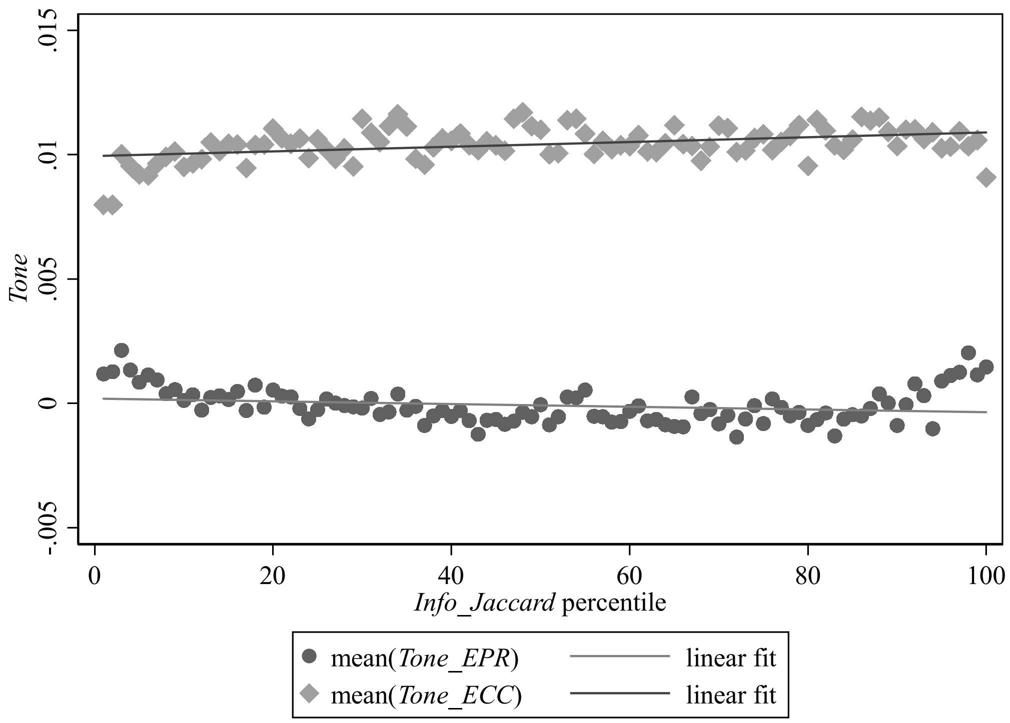
Panel A: ***Info_Cosine***



mean(*Tone_EPR*)=0.0008403-0.0000182·*Info_Cosine*

mean(*Tone_ECC*) = 0.0093392-0.0000214·*Info_Cosine*

Panel B: *Info_Jaccard*



mean(*Tone_EPR*) = 0.0001920-0.0000054·*Info_Jaccard*

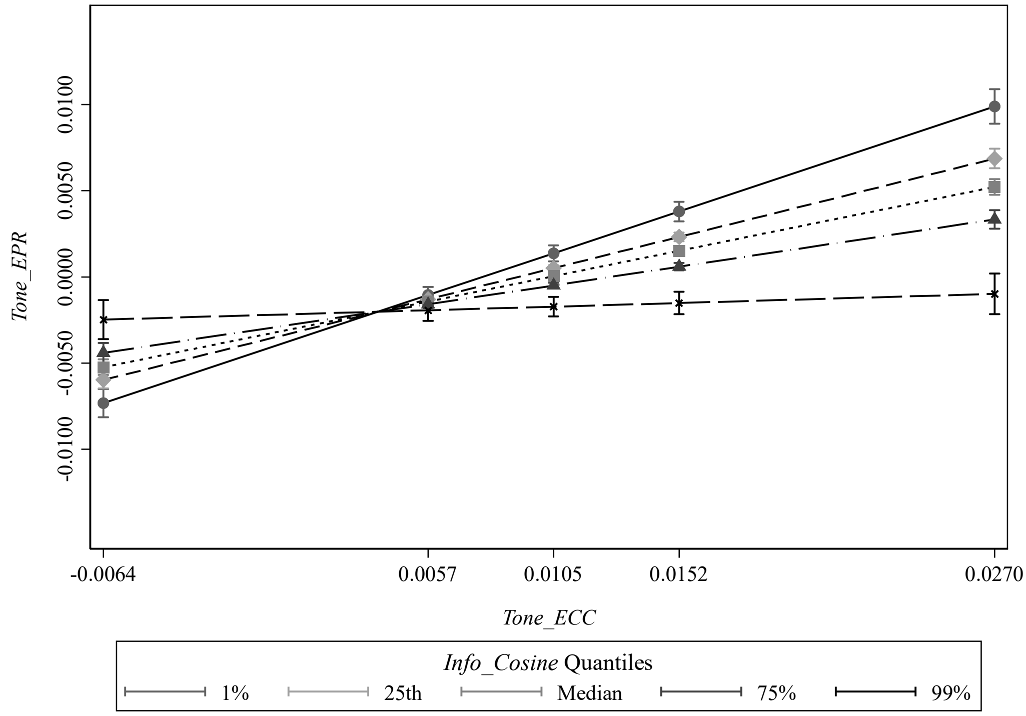
mean(*Tone_ECC*) = 0.00993770-0.0000095·*Info_Jaccard*

This Figure shows the change in disclosure tone of EPRs and ECCs for the change in information distribution. Panel A displays the results for *Info_Cosine* and Panel B for *Info Jaccard*, respectively.

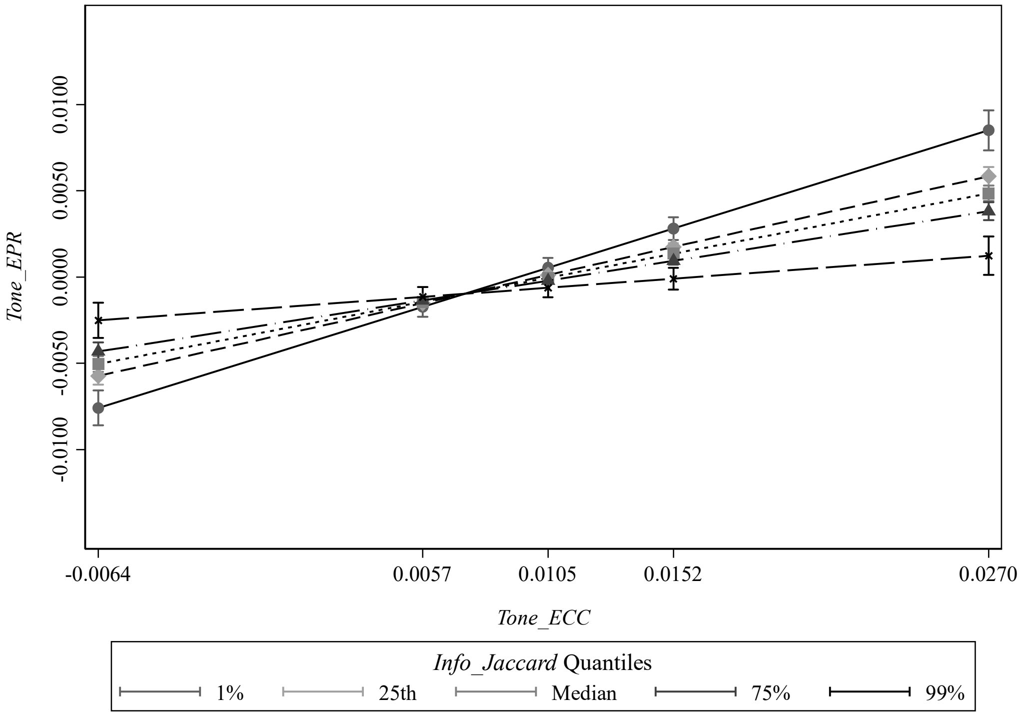
Figure 2

Plotted interaction effects of information distribution on the relation between the tone of ECC tone and the tone of EPR

Panel A: *Info_Cosine*



Panel B: *Info_Jaccard*



This figure outlines the marginal effects of individual information distribution measures for five different percentiles (1 %, 25 %, 50 %, 75 %, and 99 %) in conjunction with the tone of ECCs (*Tone_ECC*) on the tone of EPRs (*Tone_EPR*). Panel A displays the results for *Info_Cosine* as information distribution measure and Panel B for *Info_Jaccard*, respectively.

Tables

Table 1

Sample composition and distribution across the years

Panel A: Sample attribution	
Number of earnings conference calls in the sample period (2005 – 2018)	28,563
Minus automated match of earnings conference calls with Form 8-K	-4,069
Minus automated match of CIK number with Thomson Reuters database	-12
Drop if extreme values for financial variables and missing variables	-7,178
Final sample size	17,314

Panel B: Final sample distribution across years

Year	**No. of firms**	**No. of obs.**	**% of obs.**
2004	157	163	1 %
2005	274	796	5 %
2006	312	934	5 %
2007	333	1,067	6 %
2008	351	1,181	7 %
2009	370	1,263	7 %
2010	379	1,304	8 %
2011	396	1,331	8 %
2012	384	1,311	8 %
2013	400	1,398	8 %
2014	408	1,422	8 %
2015	408	1,413	8 %
2016	416	1,393	8 %
2017	408	1,408	8 %
2018	370	930	5 %
Sum	549	17,314	100 %

This table describes the construction of our sample, beginning with the theoretical largest sample size. Panel A displays the sample attribution, and which computational step eliminates observations. Panel B displays the final sample and the number of observations per year. "No." stands for number and "obs." stands for observations. We exclude observations with EPR or ECC containing fewer than 250 words. We exclude observations with extreme values, which might indicate implausible accounting information or major corporate events like mergers.(*Inv* < −0.5 and *Inv* > 2, *RoA_Q0* < −0.5 and *RoA_Q0* > 2 , *Sales_Growth* < −0.5 and *Sales_Growth* > 1, *Cash_StInv* < 0 and *Cash_StInv* > 1, *Leverage* < 0 and *Leverage* > 100, *MtB* > 100, *CF_Op_Q0* < −1 and *CF_Op_Q0* > 2). Table A. 2 in the Online Appendix 1 provides the definitions for all variables.

Table 2

Descriptive statistics

Variable	*N*	Mean	Std	P1	P25	P50	P75	P99
				Panel A: News release variables				
Tone_EPR	17,314	-0.0001	0.0062	-0.0162	-0.0036	0	0.0035	0.0159
Tone_ECC	17,314	0.0104	0.0073	-0.0077	0.0057	0.0105	0.0152	0.0277
Info_Cosine	17,314	0.3748	0.1079	0.1597	0.2966	0.3675	0.4485	0.6465
Info_Jaccard	17,314	0.688	0.0578	0.5456	0.651	0.6876	0.7258	0.824
Flesch_CC	17,314	28	24	0	0	40	51	66
Fog_CC	17,314	14	2.9197	9.1	11	13	17	17
Flesch_EPR	17,314	25	11	0	19	26	33	47
Fog_EPR	17,314	16	1.5216	12	15	16	17	17
Trust	17,314	0.0006	0.0009	0	0	0.0004	0.0009	0.004
Words_CC	17,314	3,685	1,248	1,230	2,780	3,589	4,491	6,909
Words_EPR	17,314	2,541	1,213	782	1,641	2,305	3,169	64,00
Diff_Day_Discl	17,314	0.1155	0.3196	0	1	1	1	1
Is_Annual_Report	17,314	0.2324	0.4223	0	0	0	0	1
				Panel B: Financial variables				
RoA_Q0	17,314	0.038	0.0231	-0.0083	0.0233	0.035	0.0492	0.1061
CF_Op_Q0	17,314	0.0592	0.0611	-0.0694	0.0199	0.0486	0.0907	0.2426
AFE	17,314	0.001	0.0178	-0.0176	0	0.0006	0.0017	0.0232
AFE_Above	17,314	0.7172	0.4504	0	0	1	1	1
DEARN	15,234	0.0035	0.0697	-0.1081	-0.0026	0.0012	0.0051	0.134
DEARN_Above	17,314	0.6594	0.4739	0	0	1	1	1
MtB	17,314	1.6217	1.3571	0.117	0.7446	1.2342	2.0294	6.96
Leverage	17,314	0.278	0.1843	0.0005	0.1453	0.2539	0.3882	0.7847
log(Market_Cap)	17,314	23	1.1660	21	22	23	24	26
Cash_StInv	17,314	0.1407	0.1514	0.0016	0.0323	0.087	0.1938	0.6762
log(Assets)	17,314	23	1.2273	20	22	23	24	26
log(Age)	17,314	3.0665	0.991	0.1451	2.5519	3.0987	3.7233	4.7587
Num_Analysts	17,314	17	7.81	3	12	17	22	38
Sales_Growth	17,314	0.0245	0.1445	-0.3662	-0.0343	0.0181	0.0749	0.5317
DA	15,486	0.0617	0.0886	0.0003	0.0136	0.0341	0.0721	0.4328
IE	16,728	0.4553	0.498	0	0	0	1	1
Std_Net_sales	17,314	611	1,400	12	92	224	558	6,406
Std_Inv	17,314	0.0187	0.0191	0.0006	0.0073	0.013	0.023	0.0904
Std_CF_Op	17,314	0.0471	0.0241	0.0092	0.032	0.0431	0.0574	0.1322
				Panel C: Stock performance variables				
log(Volume)	17,314	14	1.2022	12	14	14	15	17
Volatility	17,314	0.0187	0.0111	0.0068	0.0117	0.0156	0.0221	0.0632
CAR(-1, 1)	17,314	0.003	0.0669	-0.1864	-0.03	0.0023	0.0374	0.1851
CAR(-1, 30)	17,314	0.0033	0.1016	-0.2777	-0.0494	0.0038	0.0568	0.2771

This table shows the descriptive statistics on all variables employed in our tabulated analyses after winsorizing. Panel A displays all variables describing the news release, Panel B all financials, and Panel C all the stock return data that we used in our analyses. The definition of the control variables is presented in Table A. 2 in the Online Appendix 1. *N* is the number of observations, Std stands for standard deviation, P1 is the 1st, P25 the 25th, P50 the median, P75 the 75th, and P99 the 99th percentile of each variable's distribution. *N* is set to the maximal available number of observations for each variable.

Table 3

Correlations of news release variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	*Info_Cosine*	1	0.6072	0.0829	-0.0868	0.1610	-0.1482	-0.3568	0.2908	-0.0349	-0.0679	0.0560
(2)	*Info_Jaccard*		1	0.0423	-0.0268	0.0264	-0.0050	-0.0646	0.1378	-0.0147	-0.0815	0.0688
(3)	*Tone_ECC*			1	0.4001	0.1122	-0.1035	-0.0974	0.0869	0.0300	-0.0032	-0.0539
(4)	*Tone_EPR*				1	-0.0680	0.0710	0.2064	-0.1689	0.0142	-0.0461	-0.0127
(5)	*Flesch_CC*					1	-0.9464	-0.2720	0.2201	0.0069	0.0298	-0.0497
(6)	*Fog_CC*						1	0.2758	-0.2086	-0.0114	-0.0327	0.0525
(7)	*Flesch_EPR*							1	-0.7389	0.0316	-0.0400	-0.0205
(8)	*Fog_EPR*								1	-0.0347	0.0072	0.0169
(9)	*Trust*									1	-0.0271	-0.0211
(10)	*Words_CC*										1	-0.0270
(11)	*Words_EPR*											1

This table reports the Pearson correlation coefficients of news release variables.

Table 4

Tone and stock returns

	(1) CAR(-1, 1)	(2) CAR(-1, 1)	(3) CAR(-1, 1)	(4) CAR(-1, 30)	(5) CAR(-1, 30)	(6) CAR(-1, 30)
Tone_EPR	0.8890***		0.2259*	0.9984***		0.3365*
	(6.8984)		(1.6959)	(5.5836)		(1.7872)
Diff_Day_Discl × Tone_EPR	-0.0625		-0.3740	0.1298		-0.0790
	(-0.1901)		(-1.0403)	(0.2966)		(-0.1571)
Tone_ECC		1.5760***	1.5090***		1.5987***	1.4998***
		(15.2689)	(13.8548)		(11.1732)	(9.9333)
Diff_Day_Discl × Tone_ECC		0.4525**	0.5761**		0.3449	0.3777
		(2.1222)	(2.2851)		(1.1243)	(1.0215)
Diff_Day_Discl	0.0004	-0.0043	-0.0054*	-0.0016	-0.0051	-0.0054
	(0.2116)	(-1.4366)	(-1.7540)	(-0.6012)	(-1.1780)	(-1.1860)
MtB	0.0048***	0.0042***	0.0043***	0.0027*	0.0021	0.0022
	(4.6799)	(4.1856)	(4.2280)	(1.9123)	(1.5251)	(1.5533)
Leverage	0.0166**	0.0121	0.0123	0.0014	-0.0031	-0.0028
	(2.2884)	(1.5764)	(1.6095)	(0.1567)	(-0.3368)	(-0.3037)
RoA_Q0	0.0361	0.0260	0.0223	0.2096***	0.2030***	0.1965***
	(0.9047)	(0.6435)	(0.5589)	(3.2259)	(3.0972)	(3.0071)
log(Volume)	-0.0087***	-0.0083***	-0.0082***	-0.0094***	-0.0090***	-0.0090***
	(-6.3558)	(-6.0348)	(-6.0167)	(-5.3132)	(-5.0545)	(-5.0351)
Volatility	0.2881***	0.4149***	0.4168***	0.5731***	0.6947***	0.6984***
	(2.7354)	(3.8969)	(3.9233)	(3.6502)	(4.4390)	(4.4582)
AFE	2.2322***	2.0801***	2.0729***	2.2616***	2.1165***	2.1064***
	(9.8328)	(9.4104)	(9.3814)	(7.8847)	(7.5027)	(7.4455)
log(Market_Cap)	0.0030	0.0035*	0.0033	0.0041	0.0047*	0.0043*
	(1.5430)	(1.7496)	(1.6349)	(1.5961)	(1.8011)	(1.6729)
Annual_Report	0.0006	0.0004	0.0004	0.0001	-0.0002	-0.0002
	(0.5194)	(0.3145)	(0.3251)	(0.0535)	(-0.0929)	(-0.0924)
Firm Dummies	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES
Intercept	0.0579	0.0367	0.0414	0.0126	-0.0107	-0.0031
	(1.1260)	(0.6976)	(0.7844)	(0.1970)	(-0.1634)	(-0.0471)
Observations	17,314	17,314	17,314	17,314	17,314	17,314
R^2	0.087	0.101	0.101	0.050	0.056	0.056
Adj. R^2	0.057	0.071	0.071	0.018	0.024	0.024

This table presents our regression results, evaluating the influence of the tone of EPRs and ECCs on abnormal stock returns. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 5

Information distribution and tone

	(1) *Info_Cosine*	(2) *Info_Jaccard*
Tone_ECC	1.3275***	0.5733***
	(6.5877)	(5.3293)
Tone_EPR	-1.6693***	-0.2450
	(-5.3214)	(-1.3981)
MtB	-0.0020	0.0015
	(-0.9335)	(1.3877)
Leverage	-0.0054	-0.0017
	(-0.2840)	(-0.1658)
RoA_Q0	0.1531**	0.1475***
	(1.9867)	(3.4829)
AFE	-0.2590**	-0.0414
	(-2.0481)	(-0.5869)
Annual Report	-0.0126***	-0.0029***
	(-6.5668)	(-2.7967)
Cash_StInv	-0.0369**	-0.0274**
	(-2.0032)	(-2.5764)
CF_Op_Q0	0.0048	-0.0132
	(0.2732)	(-1.2994)
log(Assets)	-0.0166***	-0.0050*
	(-2.8799)	(-1.8182)
Std_Inv	-0.5814***	-0.0904
	(-2.8200)	(-0.7886)
Std_CF_Op	-0.0875	-0.0135
	(-0.6072)	(-0.1848)
log(Age)	0.0005	0.0020
	(0.0521)	(0.5576)
Num_Analysts	-0.0000	0.0001
	(-0.0045)	(0.5015)
Sales_Growth	-0.0078*	-0.0049**
	(-1.7273)	(-2.0398)
Std_Net_sales	-0.0000	-0.0000
	(-0.4953)	(-0.2200)
Firm Dummies	YES	YES
Year Dummies	YES	YES
Intercept	0.8246***	0.8040***
	(6.2998)	(12.9511)
Observations	17314	17314
R^2	0.668	0.638
Adj. R^2	0.657	0.626

This table presents the results of our OLS regression evaluating the influence of informativeness and other determinants on *Tone_EPR*. Table 1 provides details on our sample construction and Table A. 2 in the Online Appendix 1 provides definitions for all variables. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 %, and 10 % level, respectively.

Table 6

Information distribution and tone spread

	(1) *Tone_EPR*	(2) *Tone_EPR*	(3) *Tone_EPR*	(4) *Tone_EPR*
Tone_ECC	0.7067***	1.2738***	0.6818***	1.2433***
	(17.7677)	(9.9469)	(17.5342)	(9.7783)
Info_Cosine	0.0041***		0.0039***	
	(2.8597)		(2.7693)	
Info_Cosine × Tone_ECC	-1.0390***		-1.0044***	
	(-10.1046)		(-10.0124)	
Info_Jaccard		0.0108***		0.0101***
		(4.1372)		(3.8717)
Info_Jaccard × Tone_ECC		-1.4041***		-1.3778***
		(-7.5598)		(-7.5064)
MtB			0.0002**	0.0003***
			(2.1884)	(2.6332)
Leverage			-0.0017*	-0.0017*
			(-1.8121)	(-1.7284)
AFE			0.0182**	0.0224***
			(2.2498)	(2.6873)
RoA_Q0			0.0269***	0.0272***
			(5.9693)	(5.9281)
Sales_Growth			0.0000	0.0001
			(0.0300)	(0.2971)
Cash_StInv			0.0010	0.0013
			(0.8901)	(1.1797)
CF_Op_Q0			-0.0033***	-0.0034***
			(-3.0316)	(-3.0656)
log(Assets)			0.0007***	0.0008***
			(2.7875)	(3.0676)
log(Age)			-0.0007*	-0.0007*
			(-1.7311)	(-1.9053)
Std_Inv			-0.0116	-0.0084
			(-1.1912)	(-0.8550)
Std_CF_Op			-0.0045	-0.0055
			(-0.6908)	(-0.8356)
Std_Net_sales			0.0000	0.0000
			(0.4286)	(0.5721)
Num_Analysts			-0.0000	-0.0000
			(-0.9590)	(-0.8863)
Annual_Report			0.0001	0.0002
			(0.7852)	(1.5090)
Firm Dummies	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Intercept	-0.0006	-0.0064***	-0.0176***	-0.0253***
	(-0.8363)	(-3.4667)	(-2.9435)	(-3.9539)
Observations	17,314	17,314	17,314	17,314
R^2	0.600	0.590	0.608	0.598
Adj. R^2	0.587	0.576	0.595	0.585

This table presents our regression results, evaluating the influence of information distribution and other determinants on the tone of EPRs. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 7
Information distribution and readability

	Panel A: ECC			
	(1)	(2)	(3)	(4)
	Info_Cosine	***Info_Jaccard***	***Info_Cosine***	***Info_Jaccard***
Flesch_CC	0.0002**	0.0001***		
	(2.4002)	(3.2390)		
Fog_CC			-0.0011*	-0.0008**
			(-1.7778)	(-2.3440)
Tone_ECC	1.3347***	0.5791***	1.3379***	0.5805***
	(6.6181)	(5.3855)	(6.6467)	(5.3994)
Tone_EPR	-1.6747***	-0.2494	-1.6705***	-0.2458
	(-5.3393)	(-1.4213)	(-5.3269)	(-1.4021)
MtB	-0.0020	0.0014	-0.0020	0.0014
	(-0.9398)	(1.3804)	(-0.9432)	(1.3745)
Leverage	-0.0056	-0.0019	-0.0057	-0.0019
	(-0.2980)	(-0.1871)	(-0.3013)	(-0.1880)
AFE	-0.2577**	-0.0403	-0.2568**	-0.0399
	(-2.0481)	(-0.5755)	(-2.0400)	(-0.5683)
RoA_Q0	0.1549**	0.1489***	0.1550**	0.1488***
	(2.0152)	(3.5195)	(2.0164)	(3.5132)
Sales_Growth	-0.0081*	-0.0051**	-0.0081*	-0.0051**
	(-1.7933)	(-2.1428)	(-1.8065)	(-2.1402)
Cash_StInv	-0.0359*	-0.0266**	-0.0362**	-0.0269**
	(-1.9594)	(-2.5268)	(-1.9786)	(-2.5511)
CF_Op_Q0	0.0033	-0.0144	0.0035	-0.0141
	(0.1879)	(-1.4188)	(0.1992)	(-1.3857)
log(Assets)	-0.0162***	-0.0047*	-0.0163***	-0.0048*
	(-2.8274)	(-1.7330)	(-2.8426)	(-1.7644)
log(Age)	0.0008	0.0023	0.0008	0.0022
	(0.0897)	(0.6330)	(0.0872)	(0.6182)
Std_Inv	-0.5824***	-0.0913	-0.5934***	-0.0987
	(-2.8205)	(-0.8011)	(-2.8694)	(-0.8639)
Std_CF_Op	-0.0883	-0.0141	-0.0866	-0.0129
	(-0.6151)	(-0.1942)	(-0.6028)	(-0.1771)
Std_Net_sales	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.4804)	(-0.1970)	(-0.4945)	(-0.2170)
Num_Analysts	-0.0000	0.0001	0.0000	0.0001
	(-0.0216)	(0.4743)	(0.0088)	(0.5212)
Annual_Report	-0.0124***	-0.0027***	-0.0125***	-0.0027***
	(-6.4546)	(-2.6172)	(-6.4666)	(-2.6605)
Firm Dummies	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Intercept	0.8153***	0.7964***	0.8366***	0.8123***
	(6.2335)	(12.9063)	(6.3918)	(13.0468)
Observations	17,314	17,314	17,314	17,314
R^2	0.668	0.639	0.668	0.638
Adj. R^2	0.657	0.627	0.657	0.626

This table presents the results of our regression evaluating the influence of information distribution on readability. Panel A displays the relationship between information distribution and ECCs' readability, while Panel B displays the relationship between information distribution and EPRs' readability. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Continued

Panel B: EPR				
	(5)	(6)	(7)	(8)
	Info_Cosine	***Info_Jaccard***	***Info_Cosine***	***Info_Jaccard***
Flesch_EPR	-0.0023***	-0.0001		
	(-11.4978)	(-0.5829)		
Fog_EPR			0.0101***	0.0011
			(8.3964)	(1.5325)
Tone_ECC	1.1475***	0.5682***	1.2195***	0.5618***
	(5.9547)	(5.3127)	(6.2396)	(5.2485)
Tone_EPR	-1.1146***	-0.2294	-1.4388***	-0.2205
	(-3.7586)	(-1.3133)	(-4.6686)	(-1.2487)
MtB	-0.0018	0.0015	-0.0021	0.0014
	(-0.9109)	(1.3930)	(-1.0079)	(1.3698)
Leverage	-0.0125	-0.0019	-0.0093	-0.0021
	(-0.6734)	(-0.1843)	(-0.5076)	(-0.2065)
AFE	-0.2931**	-0.0423	-0.2797**	-0.0435
	(-2.3622)	(-0.6006)	(-2.2232)	(-0.6157)
RoA_Q0	0.1741**	0.1481***	0.1680**	0.1491***
	(2.4647)	(3.4981)	(2.2310)	(3.5051)
Sales_Growth	-0.0091**	-0.0049**	-0.0089**	-0.0050**
	(-2.0979)	(-2.0560)	(-1.9942)	(-2.0912)
Cash_StInv	-0.0340*	-0.0273**	-0.0409**	-0.0278***
	(-1.9495)	(-2.5655)	(-2.3153)	(-2.6407)
CF_Op_Q0	0.0057	-0.0131	0.0109	-0.0125
	(0.3418)	(-1.2992)	(0.6318)	(-1.2356)
log(Assets)	-0.0173***	-0.0050*	-0.0157***	-0.0049*
	(-3.1939)	(-1.8268)	(-2.8089)	(-1.7863)
log(Age)	0.0015	0.0021	0.0012	0.0021
	(0.1815)	(0.5676)	(0.1407)	(0.5849)
Std_Inv	-0.5588***	-0.0898	-0.5648***	-0.0887
	(-2.9106)	(-0.7822)	(-2.8075)	(-0.7759)
Std_CF_Op	-0.0154	-0.0114	-0.0620	-0.0108
	(-0.1135)	(-0.1580)	(-0.4381)	(-0.1484)
Std_Net_sales	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.8894)	(-0.2390)	(-0.6832)	(-0.2588)
Num_Analysts	0.0001	0.0001	-0.0001	0.0001
	(0.1126)	(0.5064)	(-0.1703)	(0.4635)
Annual_Report	-0.0099***	-0.0028***	-0.0111***	-0.0027***
	(-5.2116)	(-2.7018)	(-5.8896)	(-2.6498)
Firm Dummies	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Intercept	0.8884***	0.8058***	0.6531***	0.7858***
	(7.1367)	(12.9669)	(5.0672)	(12.4745)
Observations	17,314	17,314	17,314	17,314
R^2	0.685	0.638	0.676	0.638
Adj. R^2	0.675	0.626	0.665	0.626

Table 8

Information distribution and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Information distribution and return on assets					
	RoA_Q0	***RoA_Q1***	***RoA_Q2***	***RoA_Q0***	***RoA_Q1***	***RoA_Q2***
Info_Cosine	0.0040**	0.0047**	0.0039			
	(2.2409)	(2.4008)	(1.6351)			
Info_Jaccard				0.0080***	0.0134***	0.0132***
				(2.5964)	(3.5707)	(3.2628)
Tone_EPR	0.1442***	0.1162***	0.1598***	0.1394***	0.1118***	0.1567***
	(5.0929)	(3.6582)	(3.1693)	(4.9707)	(3.5225)	(3.1673)
Tone_ECC	0.0456**	0.1063***	0.0858***	0.0460**	0.1046***	0.0833***
	(2.3605)	(4.3356)	(2.9698)	(2.3289)	(4.2802)	(2.8604)
RoA_Qm1	0.4882***			0.4876***		
	(17.3154)			(17.3097)		
RoA_Q0		0.4624***			0.4614***	
		(13.2387)			(13.2175)	
RoA_Q1			0.4051***			0.4039***
			(6.5447)			(6.5218)
MtB	0.0042***	0.0046***	0.0052***	0.0042***	0.0046***	0.0052***
	(11.3325)	(10.3551)	(6.9878)	(11.2973)	(10.3311)	(7.0043)
Leverage	-0.0079***	-0.0020	0.0023	-0.0079***	-0.0020	0.0022
	(-3.9833)	(-0.9298)	(0.5901)	(-3.9851)	(-0.9393)	(0.5879)
Sales_Growth	0.0417***	-0.0009	-0.0061**	0.0417***	-0.0009	-0.0061**
	(16.5186)	(-0.3768)	(-2.4796)	(16.5115)	(-0.3643)	(-2.4705)
Cash_StInv	-0.0078***	-0.0074**	-0.0043	-0.0077***	-0.0072**	-0.0041
	(-2.7125)	(-2.4390)	(-1.2790)	(-2.6748)	(-2.3660)	(-1.2105)
log(Assets)	-0.0027***	-0.0008	-0.0021**	-0.0027***	-0.0008	-0.0021**
	(-4.1468)	(-1.2566)	(-2.1381)	(-4.2157)	(-1.2825)	(-2.1292)
log(Age)	0.0010	0.0011*	0.0002	0.0010	0.0011*	0.0002
	(1.6051)	(1.7394)	(0.3323)	(1.6003)	(1.7179)	(0.3042)
Std_Inv	-0.0368*	-0.0090	0.0076	-0.0385*	-0.0105	0.0066
	(-1.6770)	(-0.4285)	(0.3216)	(-1.7743)	(-0.5061)	(0.2830)
Std_CF_Op	0.0001	0.0041	-0.0087	-0.0001	0.0038	-0.0090
	(0.0039)	(0.2193)	(-0.4283)	(-0.0080)	(0.2055)	(-0.4433)
Std_Net_sales	0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
	(1.1010)	(-1.4182)	(-0.4434)	(1.0985)	(-1.4478)	(-0.4573)
Num_Analysts	0.0001	0.0000	-0.0000	0.0001	0.0000	-0.0000
	(1.4622)	(0.3311)	(-0.3127)	(1.4434)	(0.2991)	(-0.3440)
Annual_Report	-0.0003	-0.0025***	0.0017***	-0.0003	-0.0025***	0.0017***
	(-0.6255)	(-5.0416)	(4.2216)	(-0.6742)	(-5.0700)	(4.2100)
Firm Dummies	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES
Intercept	0.0761***	0.0393***	0.0701***	0.0730***	0.0325**	0.0627***
	(4.9910)	(2.6592)	(2.8930)	(4.6837)	(2.1618)	(2.6268)
Observations	16,777	17,314	17,292	16,777	17,314	17,292
R^2	0.786	0.721	0.706	0.786	0.721	0.706
Adj. R^2	0.779	0.712	0.696	0.779	0.712	0.696

This table presents the results of our regression evaluating the influence of information distribution on firm performance. Panel A displays the relationship between information distribution and return on assets, while Panel B displays the relationship between information distribution and cash flows. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Continued

Panel B: Information distribution and cash flows						
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	CF_Op_Q0	***CF_Op_Q1***	***CF_Op_Q2***	***CF_Op_Q0***	***CF_Op_Q1***	***CF_Op_Q2***
Info_Cosine	0.0085	0.0209***	0.0167**			
	(1.0545)	(3.5313)	(2.1864)			
Info_Jaccard				0.0038	0.0294**	0.0528***
				(0.2689)	(2.5064)	(3.9588)
Tone_EPR	-0.0528	0.0155	0.2793**	-0.0661	-0.0121	0.2637**
	(-0.4136)	(0.1462)	(2.1886)	(-0.5108)	(-0.1151)	(2.0635)
Tone_ECC	-0.0979	0.0696	0.0631	-0.0893	0.0797	0.0542
	(-1.1677)	(0.9700)	(0.7357)	(-1.0647)	(1.1085)	(0.6303)
CF_Op_Qm1	0.0346			0.0344		
	(1.5826)			(1.5782)		
CF_Op_Q0		0.4793***			0.4796***	
		(25.4464)			(25.3968)	
CF_Op_Q1			0.1216***			0.1214***
			(4.1143)			(4.1108)
MtB	0.0097***	0.0080***	0.0134***	0.0096***	0.0079***	0.0133***
	(6.6348)	(7.1356)	(9.3981)	(6.6187)	(7.0833)	(9.3626)
Leverage	-0.0566***	-0.0114*	-0.0158**	-0.0567***	-0.0115*	-0.0158**
	(-6.1622)	(-1.8321)	(-2.0836)	(-6.1704)	(-1.8532)	(-2.0846)
Sales_Growth	0.0277***	0.0143**	0.0105	0.0276***	0.0142**	0.0105
	(3.9485)	(2.4146)	(1.5916)	(3.9407)	(2.4066)	(1.5931)
Cash_StInv	0.0848***	-0.0221***	-0.0206**	0.0846***	-0.0221***	-0.0197*
	(6.4750)	(-2.7356)	(-2.0299)	(6.4628)	(-2.7224)	(-1.9421)
log(Assets)	0.0017	0.0002	-0.0021	0.0016	-0.0000	-0.0021
	(0.6317)	(0.1143)	(-0.9508)	(0.5856)	(-0.0061)	(-0.9607)
log(Age)	0.0014	0.0051**	-0.0022	0.0014	0.0050**	-0.0023
	(0.4495)	(2.3502)	(-0.9114)	(0.4502)	(2.3533)	(-0.9512)
Std_Inv	0.1103	-0.0297	0.0546	0.1053	-0.0391	0.0499
	(1.4609)	(-0.3907)	(0.6978)	(1.3844)	(-0.5198)	(0.6433)
Std_CF_Op	-0.0180	-0.1355***	0.0119	-0.0185	-0.1370***	0.0105
	(-0.2311)	(-2.6300)	(0.1704)	(-0.2383)	(-2.6812)	(0.1506)
Std_Net_sales	0.0000	0.0000	0.0000*	0.0000	0.0000	0.0000*
	(1.3043)	(0.3783)	(1.9222)	(1.3025)	(0.3540)	(1.9361)
Num_Analysts	0.0006***	0.0003**	0.0001	0.0006***	0.0003**	0.0001
	(2.8497)	(2.0938)	(0.5766)	(2.8347)	(2.0577)	(0.5386)
Annual_Report	0.0525***	-0.0690***	-0.0124***	0.0524***	-0.0692***	-0.0124***
	(25.6030)	(-26.0449)	(-7.3272)	(25.6165)	(-26.0817)	(-7.3910)
Firm Dummies	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES
Intercept	-0.0526	0.0482	0.0766	-0.0482	0.0419	0.0476
	(-0.7823)	(1.1976)	(1.4745)	(-0.7038)	(1.0098)	(0.9011)
Observations	16,777	17,314	17,292	16,777	17,314	17,292
R^2	0.556	0.601	0.432	0.556	0.600	0.433
Adj. R^2	0.541	0.587	0.413	0.540	0.587	0.414

Table 9
Information distribution and expectation management

	(1) *Info_Cosine*	(2) *Info_Jaccard*	(3) *Info_Cosine*	(4) *Info_Jaccard*
AFE	0.4284	0.2139		
	(1.4779)	(1.3127)		
AFE_Above	0.0010	0.0017**		
	(0.7371)	(1.9806)		
AFE_Above × AFE	-1.1014**	-0.4353*		
	(-2.4450)	(-1.8156)		
DEARN			0.0683	0.0855***
			(1.4900)	(3.3739)
DEARN_Above			0.0018	0.0023***
			(1.2741)	(2.8149)
DEARN_Above × DEARN			-0.1576**	-0.1382***
			(-2.2059)	(-4.0369)
MtB	-0.0022	0.0016	-0.0024	0.0014
	(-1.0563)	(1.5324)	(-1.1182)	(1.3393)
Leverage	-0.0004	0.0006	-0.0018	-0.0007
	(-0.0223)	(0.0558)	(-0.0850)	(-0.0649)
RoA_Q0	0.1188	0.1450***	0.1225	0.1136***
	(1.5133)	(3.4129)	(1.5827)	(2.6268)
Sales_Growth	-0.0065	-0.0042*	-0.0102**	-0.0049**
	(-1.4128)	(-1.6911)	(-2.2504)	(-2.0581)
Cash_StInv	-0.0375**	-0.0271**	-0.0244	-0.0157
	(-2.0070)	(-2.5266)	(-1.2833)	(-1.5551)
CF_Op_Q0	0.0078	-0.0130	0.0079	-0.0129
	(0.4276)	(-1.2434)	(0.4116)	(-1.2320)
log(Assets)	-0.0190***	-0.0056**	-0.0189***	-0.0047
	(-3.2179)	(-2.0171)	(-2.8825)	(-1.6209)
log(Age)	0.0019	0.0019	0.0048	0.0019
	(0.2071)	(0.5084)	(0.3874)	(0.3947)
Std_Inv	-0.6003***	-0.1039	-0.6579***	-0.0774
	(-2.8856)	(-0.8974)	(-2.7639)	(-0.6139)
Std_CF_Op	-0.1022	-0.0218	-0.1009	-0.0380
	(-0.7004)	(-0.2972)	(-0.6570)	(-0.4991)
Std_Net_sales	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.5689)	(-0.2570)	(-0.6183)	(-0.3889)
Num_Analysts	-0.0000	0.0001	0.0002	0.0001
	(-0.0040)	(0.4882)	(0.3290)	(0.3072)
Annual_Report	-0.0128***	-0.0028***	-0.0136***	-0.0028***
	(-6.4680)	(-2.6480)	(-6.6865)	(-2.6920)
Firm Dummies	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Intercept	0.8813***	0.8173***	0.8762***	0.8097***
	(6.5730)	(12.9650)	(5.8420)	(12.3127)
Observations	17,314	17,314	15,234	15,234
R^2	0.659	0.631	0.686	0.655
Adj. R^2	0.648	0.619	0.675	0.643

This table presents the results of our regression evaluating the influence of exceeding performance benchmarks on information distribution. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 10

Information distribution and agency problems

	(1)	(2)	(3)	(4)	(5)	(6)
	IE	***IE***	***DA***	***DA***	***Trust***	***Trust***
Info_Cosine	-0.7434*		-0.0260*		0.0003**	
	(-1.7090)		(-1.8962)		(2.1053)	
Info_Jaccard		-0.8051		-0.0492**		0.0006**
		(-1.0787)		(-2.1173)		(2.5006)
Tone_ECC	-7.4385	-7.9505	-0.0779	-0.0832	-0.0010	-0.0010
	(-1.4857)	(-1.5823)	(-0.5374)	(-0.5709)	(-0.6951)	(-0.6433)
Tone_EPR	-5.0161	-3.8832	-0.0391	-0.0014	-0.0001	-0.0005
	(-0.8205)	(-0.6337)	(-0.1949)	(-0.0071)	(-0.0724)	(-0.2768)
MtB	-0.0478	-0.0458	-0.0012	-0.0011	-0.0000	-0.0000
	(-0.9863)	(-0.9478)	(-0.5268)	(-0.4921)	(-0.3590)	(-0.4564)
Leverage	0.2481	0.2469	0.0069	0.0070	0.0001	0.0000
	(0.6066)	(0.6010)	(0.5279)	(0.5305)	(0.3537)	(0.3448)
AFE	-3.1830	-3.0143	0.1097	0.1127	-0.0016	-0.0017
	(-0.7525)	(-0.7109)	(0.7781)	(0.7970)	(-0.9554)	(-0.9927)
RoA_Q0	-5.9077**	-5.9085**	0.0449	0.0477	0.0007	0.0007
	(-2.4194)	(-2.4176)	(0.4916)	(0.5246)	(1.1552)	(1.0998)
Sales_Growth	0.5045*	0.5067*	-0.0157**	-0.0157**	-0.0000	-0.0000
	(1.8838)	(1.8951)	(-2.1556)	(-2.1599)	(-1.1452)	(-1.1309)
Cash_StInv	-1.1377**	-1.1261**	0.0014	0.0011	0.0003	0.0003
	(-2.4456)	(-2.4054)	(0.0837)	(0.0628)	(1.4690)	(1.4890)
CF_Op_Q0	9.2835***	9.2680***	0.1375***	0.1372***	0.0000	0.0000
	(9.1344)	(9.1189)	(3.9052)	(3.9115)	(0.0607)	(0.1118)
log(Assets)	-0.2264*	-0.2185*	0.0275***	0.0277***	-0.0000	-0.0000
	(-1.7685)	(-1.6995)	(5.5071)	(5.5513)	(-1.1922)	(-1.2706)
log(Age)	-0.1112	-0.1124	-0.0016	-0.0016	0.0000	0.0000
	(-0.6940)	(-0.7038)	(-0.4094)	(-0.4069)	(0.0960)	(0.0808)
Std_Inv	7.5243	7.8417	-0.1214	-0.1097	0.0001	0.0000
	(1.3820)	(1.4286)	(-0.8629)	(-0.7792)	(0.0753)	(0.0063)
Std_CF_Op	5.4316*	5.4654*	0.0353	0.0380	0.0002	0.0002
	(1.7763)	(1.7791)	(0.3739)	(0.4023)	(0.1867)	(0.1658)
Std_Net_sales	0.0001	0.0001	0.0000*	0.0000*	0.0000	0.0000
	(1.0347)	(1.0348)	(1.9276)	(1.8971)	(0.2643)	(0.2541)
Num_Analysts	0.0384***	0.0386***	0.0000	0.0000	0.0000***	0.0000***
	(3.4928)	(3.4841)	(0.1347)	(0.1459)	(2.8944)	(2.8542)
Annual_Report	0.5641***	0.5706***	0.0177***	0.0179***	-0.0001***	-0.0001***
	(6.9316)	(7.0172)	(7.1838)	(7.2210)	(-3.9120)	(-4.0386)
Firm Dummies	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES
Intercept	3.7452	3.7971	-0.5570***	-0.5387***	0.0011	0.0009
	(1.2289)	(1.2072)	(-4.9755)	(-4.6811)	(1.3342)	(1.0531)
Observations	16,007	16,007	14,740	14,740	17,314	17,314
R^2			0.277	0.277	0.369	0.369
Adj. R^2			0.251	0.251	0.348	0.348

This table presents the results of our regression evaluating the influence of information distribution on agency problems. Table A. 2 in the Online Appendix 1 provides the definitions for all variables. Standard errors are clustered at the firm level, and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 11

Information distribution and abnormal portfolio returns

	Panel A: *Info_Cosine*		**Panel B: *Info_Jaccard***	
	Q1	**Q5**	**Q1**	**Q5**
Excess	0.0089	0.0131	0.0094	0.0129
t-statistics	2.2171	3.4225	2.4120	3.4730
Alpha 3F	0.0006	0.0048	0.0012	0.0047
t-statistics	0.4143	3.3258	0.9662	3.3367
Alpha 5F	0.0000	0.0044	0.0005	0.0043
t-statistics	-0.0123	2.9702	0.3974	2.9933

This table reports calendar-time portfolio returns for high and low "distributors." We compute quintiles based on the prior year's distribution of similarity measures across our sample for both information distribution measures. Stocks then enter the equal-weighted quintile portfolios in the month after the public release of one of their ECC. Stocks are held in the portfolio for three months. We report excess returns (return minus risk-free rate), Fama-French three-factor alphas (market, size, and value), and five-factor alphas (market, size, value, profitability, and investment). Panel A reports portfolio return using *Info_Cosine*, and Panel B using *Info_Jaccard*. The *t*-statistics are reported below the estimates.

Online Appendix 1

Additional Tables

Table A. 1

Data sources and third-party tools used

Third-party element	Access
SEC Edgar database	https://www.sec.gov/edgar/searchedgar/companysearch.html
SEC filing parser	https://github.com/alions7000/SEC-EDGAR-text (code version: 72615f6)
Risk factor data	https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
L&M wordlist	https://sraf.nd.edu/textual-analysis/resources

This table gives an overview of our data sources and third-party tools used.

Table A. 2

Variable Definitions

Variable	Definition
AFE	(I/B/E/S EPS median of analysts' forecasts in quarter t) - (Actual EPS in quarter t) / (stock price at ECC date).
AFE_Above	Dummy variable, which is equal to one if *AFE* >0.
Annual_Report	Dummy variable, which is equal to one if quarter t is the fiscal year end.
CAR(-1, 1)	Cumulative abnormal returns between -1 day to +1 day.
CAR(-1, 30)	Cumulative abnormal returns between -1 day to +30 day.
Cash_StInv	(Cash and short-term investments in quarer t) / (*Assets* in quarter t-1).
CF_Op_Qt	(Cash from operating activities in quarter t) / (*Assets* in quarter t).
DA	Discretionary accruals calculated using the two-digit SIC industry cross-sectional modified Jones model.
DEARN	((Net income before extraordinary items in quarter t) - (net income before extraordinary items in quarter t - 4))/ (company market cap in quarter t - 4).
DEARN_Above	Dummy variable, which is equal to one if *DEARN* > 0.
Flesch_CC	Flesch readability index for the presentation part of ECCs.
Flesch_EPR	Flesch readability index for EPRs.
Fog_CC	Fog index for the presentation part of ECCs.
Fog_EPR	Fog index for EPRs.
IE	Dummy variable, which is equal to one, if the firm-quarter observation is classified as investing efficiently, and zero, if it is classified as investing inefficiently.
Info_Cosine	1 - Cosine_Similarity(EPR, ECC).
Info_Jaccard	1 - Jaccard_Coefficient(EPR, ECC).
Inv	(Purchase of fixed assets in quarter t) / (*Assets* in quarter t-1).
Leverage	(Book value of total debt in quarter t) / (*Assets* quarter t).
log(Age)	Logarithm of company's age in years in quarter t.
log(Assets)	Logarithm of *Assets* in quarter t.
log(Market_Cap)	Logarithm of market value of equity at ECC date.
log(Volume)	Logarithm of total shares traded in quarter at ECC date.
MtB	(Market capitalization in quarter t) / (*Assets* in quarter t).
Num_Analysts	Number of analysts following the firm in quarter t.
RoA_Qt	(Earnings before interest, taxes, depreciation, and amortisation in quarter t) / (*Assets* in quarter t).
Sales_Growth	(Net sales in quarter t) / (net sales in quarter t - 1) - 1.
Diff_Day_Discl	Dummy variable, which is equal to one if EPR and ECC are disclosed before the market closes on the same day.
Std_CF_Op	Standard deviation of *CF_Op* over the last five years.
Std_Inv	Standard deviation of *Inv* over the last five years.
Std_Net_sales	Standard deviation of net sales over last five years.
Tone_ECC	(#positive words - #negative words) / (*Words_ECC*).
Tone_EPR	(#positive words - #negative words) / (*Words_EPR*).
Trust	(Total number of trust words used in the ECC in quarter t) / (*Words_CC* quarter t).
Volatility	Standard deviation of stock returns between -90 and -10 days before ECC date.
Words_ECC	Total number of non-numeric words in ECC in quarter t.
Words_EPR	Total number of non-numeric words in EPR in quarter t.

This table defines the variables used in our tabulated analyses. All variables are winsorized 1 % of each tail.

Table A. 3

Similarity Text Example

<table>
<tr><th>Panel A:
Q2 2017 Facebook Inc Earnings Press Release (07/26/2017 16:07 PM EST)</th><th>Panel B:
Q2 2017 Facebook Inc Earnings Conference Call (07/26/2017 05:00 PM GMT)</th></tr>
<tr><td>MENLO PARK, Calif. – July 26, 2017 – Facebook, Inc. (NASDAQ: FB) today reported financial results for the quarter ended June 30, 2017.

"We had a good second quarter and first half of the year," said Mark Zuckerberg, Facebook founder and CEO. "Our community is now two billion people and we're focusing on bringing the world closer together."

Second Quarter 2017 Financial Highlights

[TABLE]

Second Quarter 2017 Operational and Other Financial Highlights

Daily active users (DAUs) – DAUs were 1.32 billion on average for June 2017, an increase of 17 % year-over-year.
Monthly active users (MAUs) – MAUs were 2.01 billion as of June 30, 2017, an increase of 17 % year-over-year.
Mobile advertising revenue – Mobile advertising revenue represented approximately 87 % of advertising revenue for the second quarter of 2017, up from approximately 84 % of advertising revenue in the second quarter of 2016.
Capital expenditures – Capital expenditures for the second quarter of 2017 were $1.44 billion.
Cash and cash equivalents and marketable securities – Cash and cash equivalents and marketable securities were $35.45 billion at the end of the second quarter of 2017.
Headcount – Headcount was 20,658 as of June 30, 2017, an increase of 43 % year-over-year.

[END]</td><td>Mark Zuckerberg, Facebook Inc - Founder, Chairman of the Board and CEO:

Thanks, Deborah, and thanks, everyone, for joining today.
This quarter, we reached an important milestone for our community. 2 billion people now use Facebook every month, and more than 1.3 billion people use it daily. We also saw good results on the business with total revenue growing by 45 % year-over-year to $9.3 billion and advertising revenue up 47 % to $9.2 billion.
We're proud of the progress we're making, and it also comes with a responsibility to make sure that we have the most positive impact on the world that we can. That's why, last month, we updated Facebook's mission. For the past decade, we focused on making the world more open and connected. We have a lot more to do here to give people a voice and help everyone stay connected with their family and friends, but now I believe we have a responsibility to do even more. Our new mission is to bring the world closer together.
A big part of this mission is building community. Communities give us a sense that we're part of something bigger than ourselves, that we're not alone and that we have something better ahead to work toward. Last month, we had our first ever Facebook Communities Summit to talk about our product road map focused on building what we call meaningful communities. Meaningful communities on Facebook are groups that quickly become an important part of your social network experience and your real-world support structure. And right now, over 100 million people are members of these groups, from new parents to people suffering from rare diseases. So these groups often span online and offline and bring people together physically as well as over the Internet.
Our goal is to help more than 1 billion people join meaningful communities, and part of this involves helping people discover the right groups, which is why we're building technology like AI to better understand people's interests and suggest groups that might be meaningful to them. And in the 6 months after we started working on this, we've already helped more than 50 % more people join meaningful communities than had before that. So we have a lot more to do here.

[2.792 more words]</td></tr>
</table>

This table presents an example of an EPR and the corresponding ECC showing Facebook's use of channels after their second quarter 2017. Panel A shows the text of an EPR, while Panel B shows the transcript of a ECC presentation. The placeholder [TABLE] stands for a removed HTML-table and [END] for the text's end. The computed information distribution measures are: *Info_Cosine* = 0.6800 and *Info_Jaccard* = 0.7816.

Online Appendix 2

Mathematical explanation of information distribution measures

For a textual and numerical example, consider these three short texts:

D_A: We gained new customers.

D_B: We gained new customers globally.

D_C: We expect higher competition.

Based on this example, D_A is very similar to D_B but less similar to D_C.

The informativeness of D_A and D_B is calculated by, first, taking the union $\mathrm{T}(D_A, D_B)$:

$\mathrm{T}(D_A, D_B)$ = [we, gained, new, customers, globally]

The term frequency vectors of D_A and D_B are:

$D_A^{(TF)} = [1, 1, 1, 1, 0]; D_B^{(TF)} = [1, 1, 1, 1, 1]$

The *Info_Cosine* score of D_A and D_B is therefore:

$$Info\_Cosine(D_A, D_B) = 1 - \frac{(1\times1+1\times1+1\times1+1\times1+0\times1)}{(\sqrt{1^2+1^2+1^2+1^2})\times(\sqrt{1^2+1^2+1^2+1^2+1^2})} = 0.11$$

Similarly, the informativeness of D_A and D_C is:

$\mathrm{T}(D_A, D_C)$ = [we, gained, new, customers, expect, higher, competition]

$D_A^{(TF)} = [1, 1, 1, 1, 0, 0, 0]; D_C^{(TF)} = [1, 0, 0, 0, 1, 1, 1]$

$$Info\_Cosine(D_A, D_C) = 1 - \frac{(1\times1+1\times0+1\times0+1\times0+0\times1+0\times1+0\times1)}{(\sqrt{1^2+1^2+1^2+1^2})\times(\sqrt{1^2+1^2+1^2+1^2})} = 0.75$$

Info_Cosine reflects the larger difference between D_A and D_C than between D_A and D_B.

Using the same D_A, D_B, and D_C as above, the Jaccard similarities are

$$Info\_Jaccard(D_A, D_B) = 1 - \frac{|\{\text{we, gained, new, customers}\}|}{|\{\text{we, gained, new, customers, globally}\}|} = \frac{1}{5} = 0.2$$

$$Info\_Jaccard(D_A, D_B) = 1 - \frac{|\{\text{we}\}|}{|\{\text{we, gained, new, customers, expect, higher, competition}\}|} = \frac{6}{7} = 0.86$$