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Research

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The negativity of managerial word choice (managerial tone) in conference calls is a telltale indicator of a company's future. Specifically, increases in negativity—what we term "bleak tone changes"—strongly predict lower future earnings and increased uncertainty. Decreases in negativity, however, only weakly predict the opposite. To isolate the explanatory power of managerial tone, we controlled for negativity changes in the earnings press release and analysts' questions. Analysts and investors underreact when they extract value-relevant information from negativity changes. Consequently, a negativity-based trading strategy generates abnormal returns.

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CE Credits: 1

Effective analysts and investors distill information from whatever sources are available. Quarterly earnings releases receive detailed attention from market participants. Company managers typically hold an earnings conference call to accompany such releases. In the call, they present the corporate financial and other results and answer questions from financial analysts. What can analysts and investors infer from managerial communication in these calls? And what do they, in fact, infer?

Detailed analyses in our study of 100,000 conference calls that accompanied earnings releases from 2003 to 2016 show that increases in managerial negativity, what we term "bleak tone changes," strongly predict lower future earnings and increased uncertainty. We found this result to be true after controlling for information in the earnings press release and various other factors. Analysts adjust their earnings forecasts in response to bleak tone changes, and market prices move, but

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these reactions are insufficient. Hence, a profitable negativity-based trading strategy is available. “Bright tone changes”—that is, decreases in negativity—predict positive responses but only weakly.

Linguistic tone (the relative frequency of negative and positive words) and vocal cues during an earnings conference call engender stock market reactions (see, e.g., Mayew and Venkatachalam 2012; Price, Doran, Peterson, and Bliss 2012; Brockman, Li, and Price 2015).[1] Investors who consider incorporating measures of tone into their investment choices will want to know the reasons for this effect. What drives the short-term market reaction to conference call tone? Does managerial tone convey value-relevant news about cash flows or discount rates? Or does it reflect sentiment or tactics that fool the market? Prior literature provides no satisfactory answers to these questions.

Prior studies of tone in conference calls that found links between tone and earnings and uncertainty did not control for the earnings press release and analysts’ questions during the call. Without such controls, however, investors cannot know what information is added by *managerial* tone in conference calls.[2]

If one casts a wider net and considers those studies that jointly examined the predictive power of other corporate communications for earnings and stock returns, one finds varying conclusions. Some results indicate that managers signal value-relevant information with their tone in earnings press releases. Others indicate, to the contrary, that managers mislead the market with such releases.[3] We make no attempt here to resolve these contradictory findings. We do argue, however, that to understand whether managerial tone in conference calls conveys value-relevant information, one must investigate stock returns together with their drivers: earnings and uncertainty. Moreover, one must examine analyst forecast revisions. Throughout, one must control for the tone of the earnings press release and analysts’ questions.

The literature’s major findings identifying stock price reactions to linguistic tone were established a while ago. In particular, Mayew and Venkatachalam (2012) studied conference calls in 2007, and Price et al. (2012) and Brockman et al. (2015) covered the years 2004–2007. Do these results still hold for a more current sample? In a pattern of coevolution, the behaviors of managers and the market may respond to discoveries in the finance literature, just as the literature responds to those behaviors. Another new factor has entered the system. In recent years, many executives have become active on social media (see, e.g., Chen, Hwang, and Liu 2019). This development may have made conference calls less relevant than in the past. Alternatively, the linguistic component in conference calls may be a fundamental characteristic of corporate communication, no less important today than it was a decade ago. These observations make an examination of the role of linguistic tone in a contemporary sample important.

We performed our tests in the context of earnings conference calls for companies with available transcripts from 2003 through 2016. Presentations and answers were considered separately. The analysis, following prior literature, focused on *negativity changes*, measured as current-quarter negativity minus prior-quarter negativity. The analysis entailed two important features.

First, to determine how changes in managerial negativity convey incremental information, our approach controlled for the traditional factors—namely, quantitative earnings surprise, company uncertainty, and stock returns during the most recent quarter—but in addition, it controlled for the negativity changes in both the earnings press release and analysts’ questions. These last two controls are critical for teasing out the additional information that *managerial* speech provides. Earlier studies showed that stock market participants *do react* to conference calls (Frankel, Johnson, and Skinner 1999; Bowen, Davis, and Matsumoto 2002; Bushee, Matsumoto, and Miller 2003); indeed, they react even during calls (Matsumoto, Pronk, and Roelofsen 2011). We sought to shed light on *what* (e.g., cash flow news, discount rate news, or rather, non-information-driven managerial sentiment) drives stock market reactions. We also sought to determine whether that reaction is too weak, too strong, or roughly appropriate.

Second, we examined asymmetrical effects of upticks (*bleak changes*) and downticks (*bright changes*) in the negativity of tone. We expected an increase in a manager’s negativity to carry value-relevant information (because the manager overcame the natural tendency to speak positively).

We found that negativity changes in conference calls significantly predict both future earnings and uncertainty. (In the study, uncertainty was represented by the standard deviation of analysts’ postcall forecasts for earnings in the next quarter.) Bleak tone changes strongly predict both lower future earnings and higher uncertainty. In contrast, bright tone changes predict only weakly in the opposite direction. Our results clearly indicate that the negativity change in the presentation section of the call yields additional explanatory power beyond the negativity change in the earnings press release. These results refute the view that conference call presentations simply rephrase the information the press release contains. In addition, negativity changes in managers' answers yielded information beyond such changes in the conference call presentation, earnings press release, and analysts' questions. In short, analysts' questions obtain or extract additional value-relevant information from managers.

Information becoming available from managerial tone does not mean that analysts receive or respond to it. How do analysts and the market respond? First, we found that after managerial tone changes, sell-side analysts revise their forecasts for the next quarter. Analysts respond less than fully, however, to the information; that is, they underreact. Moreover, in line with the results from our earnings and uncertainty regressions, we found that analysts adjust their estimates more strongly in response to bleak tone changes than in response to bright tone changes. Second, the market reacts negatively to bleak tone changes. But the market also underreacts. Thus, stock price movements tend to persist in their initial direction. This behavior is consistent with the incomplete adjustment by analysts.

In our study, we carried out a calendar-time portfolio strategy that exploited the price drift following managerial negativity changes. Our contributions in this context are (1) to document the economic magnitude of systematic underreaction to tone within a large, recent cross-section of stocks and (2) to demonstrate that the overall drift is driven primarily by initial underreaction to bleak changes. The strategy generated risk-adjusted returns of around 0.3% per month. For practical purposes, these findings are mostly relevant for portfolios that are able to underweight stocks with bleak changes relative to an index. The tone-changes trading strategy performed more strongly for stocks for which less price efficiency was expected, such as for companies with little institutional ownership or few analysts.[4]

Our major finding is that bleak tone changes portend bad developments well beyond other available information, but neither the analysts nor the market recognizes how bad.

Reading Managerial Tone

Company managers have numerous ways to communicate with the market. The analysis here focuses on earnings conference calls. Three questions arise at the outset: Why (and to whom) might conference calls provide *additional* useful information beyond what is already known at the time of the call? Which parts of conference calls should investors and analysts attend to most closely? And which features of the call merit attention?

First, that conference calls should yield information over and above the content of the earnings press release is hardly obvious *ex ante*. In theory, the releases might well reveal all that the managers wish to convey. For this reason, controlling for the tone of those earnings press releases is critical.[5]

We do not posit that all analysts, much less all market participants, follow conference calls. In fact, some market participants are likely to process any value-relevant information from conference calls whereas others focus on other sources of information about the fundamental value of a company.

Second, conference calls have two components: (1) prepared remarks by company managers and (2) a more spontaneous section during which managers respond to questions from analysts. Managers presumably pursue multiple objectives in conference calls, including promoting the company and its valuation, establishing and safeguarding credibility, avoiding litigation for misleading or insufficiently informing investors, and addressing challenges brought by investors or other stakeholders. These ends must be pursued while avoiding the release of confidential information.

Should prepared remarks by managers in conference calls reveal more than impromptu remarks? First principles do not tell us. Prepared remarks provide a more confident way to convey the intended message than do impromptu remarks. Managers can (and do), of course, also prepare answers to likely questions. Some answers, however, become garbled; some questions come as a surprise; and some managers do not prepare effectively. Thus, when answering questions, managers may reveal some information they later wish they had not, much the way witnesses in a trial might inadvertently reveal information under cross-examination. Finally, a manager may wish to communicate some information in a nonpurposeful manner—that is, to keep the information separate from the prepared remarks. Providing information in response to a question preserves seemliness and plausible deniability about intent. Prepared answers to likely questions can be used to provide indirect tips.

Empirics, not theory, will reveal which parts of the conference call powerfully predict company fundamentals and thus, presumably, elicit stock price reactions. Therefore, we analyzed presentations and answers separately, and we also separated answers from analyst questions. In addition to managerial tone, tone in analysts' questions can be informative (see, e.g., Chen, Nagar, and Schoenfeld 2018). Therefore, to extract the incremental information content from managerial negativity changes, we controlled for the negativity change in analysts' questions.

Third, which characteristics of the conference call, if any, should investors (and analysts) pay attention to? The literature has used *linguistic tone* (the relative frequency of negative and positive words), which is the measure that we used.[6] Why might this crude variable be useful? For example, when a materially negative outlook is conveyed, it is likely to be accompanied by the use of negative words, but analysts and investors may simply react to concrete numbers (e.g., decreased operating margins) by inputting them into their valuation spreadsheets. The *tone*, however, provides a way to infer additional information. Counting negative and positive words as an indicator hardly means that tone will be the most informative indicator. Once machine learning and artificial intelligence advance sufficiently, we expect extensive details of the call to be examined.[7] This study provides a way to determine whether a simple approach yields informative results and should serve as a precursor to more sophisticated analyses in the future.

We expected bleak changes to predict more strongly than bright changes for several reasons. First, significant constraints presumably operate to keep managers from boosting their negativity. That is, managers should not say or would prefer not to say some things about negative news, but they could say these things comfortably about positive news. Second, managers may accord with the widely observed finding of *prospect theory* (Kahneman and Tversky 1979) that individuals use reference points from recent experience when evaluating outcomes. In our speech context, the recent experience for managers would be how negative the financials were in the prior quarter. *Loss aversion*, a primary component of prospect theory, posits that payoffs in the loss domain count two to three times as much as payoffs in the gain domain. Presumably, then, an increase in negativity (a bleak change) would be perceived as a loss—in contrast to the gain represented by a bright change. If so, more news will be needed to induce managers to speak with a bleak change than with a bright change. Alternative theories, however, such as litigation-risk aversion, could explain why bright tone changes would be more informative.[8] In short, whether bleak or bright changes are more telling is an empirical question.[9] Also, empirics will show whether analysts and the market understand how bleak and bright changes might differ in their information content.

Methods and Data

This section introduces the methods and data used in the study.

Methods. We had two main goals: (1) to examine the relationship between conference call negativity changes and proxies for company fundamentals and (2) to determine how negativity changes affect analysts' and investors' expectations. To pursue our goals, we ran regressions of earnings, uncertainty, analyst forecast revisions, forecast errors, and stock returns on various tone measures and controls. The explanatory variables in all the regressions were standardized to have a zero mean and a standard deviation of 1. This process facilitated an immediate comparison of the relative economic effects of various variables. We estimated panel regressions with company, industry, and quarter fixed effects. To account for autocorrelation in the error terms, we clustered standard errors at the company level.[10]

In an additional analysis, we examined monthly calendar-time portfolio strategies constructed to exploit any investor underreaction to managerial tone. This analysis allowed us to quantify the magnitude of investor returns from our findings while avoiding look-ahead bias.

Sample. We drew data from multiple sources. We obtained conference call transcripts from Thompson Reuters StreetEvents. We used analyst forecast data from Institutional Brokers' Estimate System (IBES), company fundamentals from Compustat, and price data from the Center for Research in Security Prices (CRSP). Our sample includes all US common stocks traded on the NYSE, AMEX, or NASDAQ for which earnings conference call transcripts and analyst data were available.

The sample period is 2003 through 2016; the beginning of the sample was determined by the availability of conference call transcripts. We extracted earnings press releases from companies' 8-K filings, which we downloaded via the US SEC's EDGAR system.[11]

All variables displayed in the tables in the main text are defined in **Table A1** in Appendix A. Definitions of variables that served as additional controls and summary statistics of all variables are in the Supplemental Online Appendix (SOA).

Variables and Summary Statistics.

We discuss in the following subsections how we measured tone of speech and tone of press releases, our decision to focus on negativity change, and the dependent variables we used to assess how tone changes predict company fundamentals and how analysts and investors respond to tone changes, company-level control variables, and other examined characteristics of managerial speech.

Measuring tone of speech and tone of press releases. We identified managerial speech characteristics through written transcripts of conference calls. To capture tone, we used the word lists compiled by Loughran and McDonald (2011). Those lists contain 2,329 negative, 354 positive, and 297 uncertain words.[12]

Various individuals speak in the conference calls. The CEO usually speaks approximately half of the time; Li, Minnis, Nagar, and Rajan (2014) analyzed who speaks when on conference calls. Our main analysis considered the tone of all management members jointly, and we usually refer to these members collectively as "the manager." The results were similar when we computed our tone measures for only CEO speech. Our focus was on what managers say. We computed our negativity indicators separately for the manager's prepared presentation and for the manager's answers because these parts of the call are fundamentally different. Questions from knowledgeable analysts may also be informative, and we thus investigated the analysts' negativity as well as that of the managers.

$Negativity_{jt}$ measures the tone of managers or analysts of company j in the conference call of quarter t. It is defined as

$$Negativity_{jt} = \frac{Negative\ words_{jt} - Positive\ words_{jt}}{Negative\ words_{jt} + Positive\ words_{jt} + 1}. \tag{1a}$$

This net negativity measure has also been used in prior studies (see, e.g., Price et al. 2012; Henry and Leone 2016). As an alternative, we also computed negativity as the ratio of negative words to total words—that is,

$$Negativity\ (alt)_{jt} = \frac{Negative\ words_{jt}}{Total\ words_{jt}}. \tag{1b}$$

The negative word frequency measure in Equation 1b ignores positive words, which offers advantages and disadvantages.

On the one hand, positive words are more ambiguous than negative words because negation (e.g., "no," "not," "none," "neither," "never," "nobody," "*n't") mostly occurs with positive words and capturing all negations is difficult (see Loughran and McDonald 2016). These characteristics may help explain the findings in Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008), who documented for a sample of media articles that negative words are more informative than positive words. Thus, the results of the prior literature do not necessarily imply that increases in negativity are more informative than decreases in negativity.

On the other hand, the ratio of negative to total words ignores the fact that a manager may simply use more negative *and* positive words overall. The measure of negativity in Equation 1a thus accounts for the total number of "sentiment" words (i.e., both positive and negative words) a manager uses. In the main text, we present all results using net negativity, Equation 1a. We also checked, however, whether the results held if we used Equation 1b as our measure of negativity (see the SOA). Note that when using the measure in Equation 1b, bright tone changes (downticks in negativity) occur only when managers use fewer negative words, but when using the definition in Equation 1a, such changes can also be driven by an increase in the number of positive words. Therefore, comparing the results for the two measures allowed us to test whether information content rather than estimation noise (resulting from the difficulty of accurately adjusting for negation of positive words) explains the differences in the relative predictive power of bleak tone changes (upticks in negativity) and bright tone changes (downticks in negativity) that we documented.

Where we measured positive words, we exercised care to correct for negation by excluding a positive word from the count when a negation word ("no," etc.) occurred among the three words preceding it (except when a comma or a period appeared in that range). In addition, as noted by Allee and DeAngelis (2015), certain words should not be counted if followed by certain other words. These words are "good" (in, e.g., "good morning"), "effective" (in, e.g., "effective income"), "efficiency" (in, e.g., "efficiency ratio"), and "closing" (in, e.g., "closing remarks"). Therefore, we applied the Allee and DeAngelis (2015) screens for these "special" words.[13]

We coded *negativity in earnings press release* to serve as a control variable. Whichever negativity measure we used for conference calls, whether Equation 1a or Equation 1b, we used also for the press release. Even though both the earnings press release and the conference call presentation were carefully scripted, we found the correlation of negativity in these two communications to be fairly low (0.41 when using net negativity and 0.46 when using negative word frequency). The correlation between the quarter-to-quarter changes in the two variables is even lower (0.27 and 0.28, respectively). These low correlations alone make it likely that conference call presentations provide information beyond what is already known from the press release.

The average negativity values are –0.31 and –0.24 for, respectively, presentations and answers. That the values are negative is not surprising because managers are, arguably, naturally inclined to use more positive than negative words in a conference call. The disparity between presentations and answers may reflect the tendency of CEOs to buff up assessments in presentations, perhaps because they think they can do so more judiciously in prepared remarks. A major factor tilting answers toward negativity, however, is likely to be the negative cast of analysts' questions (average negativity of +0.12). Indeed, the correlation between negativity changes in analysts' questions and negativity changes in managerial answers is positive and higher than the correlation between negativity changes in analysts' questions and negativity changes in presentations (0.23 vs. 0.12). Analysts' strong negative tilt suggests that they differentially ask about concerns, about the validity of the remarks made in the formal presentations, and about the company's past performance and future prospects.

Negativity changes, bleak tone changes, and bright tone changes. Some managers may be generally more positive than others (see, e.g., Davis, Ge, Matsumoto, and Zhang 2015), and the market probably builds expectations about the tone of particular managers. Thus, we would expect innovations in negativity to provide a stronger signal than plain negativity. We focused on *negativity change*:

$$Negativity\ change_{jt} = Negativity_{jt} - Negativity_{jt-1}, \quad (2)$$

where t indicates the quarter. Demers and Vega (2010); Feldman, Govindaraj, Livnat, and Segal (2010); Davis, Piger, and Sedor (2012); and Henry and Leone (2016) also focused on tone changes.

We isolated the incremental information conveyed by negativity changes by controlling for a series of company and tone characteristics. An alternative, also intuitive approach, is to first compute abnormal negativity, derived as the residual from auxiliary first-pass regressions of tone on past tone and company characteristics, and then use that measure in the main regressions. Unreported results (available on request) show that we obtained similar findings by using this approach.

Using changes provides several advantages over the abnormal tone approach. First, a change measure removes systematic company-specific misclassifications of words (Feldman et al. 2010; Loughran and McDonald 2016). Second, using a change measure is nonparametric, whereas the abnormal tone approach relies on the functional form in the first-pass regression. Third—and an important aspect from a practical perspective—using a change measure avoids look-ahead bias; that is, it avoids using information not available at the time investment decisions are made. This aspect is particularly important when one examines how tone can be used in a trading strategy when the information is available to analysts and investors at a certain time.

Negativity change is denoted by NC, with NC_P and NC_A denoting negativity changes in, respectively, presentations and answers. Define $1\{NC > 0\}$ as an indicator variable that equals 1 if the corresponding negativity change is positive and equals zero otherwise. Similarly, $1\{NC \leq 0\}$ is an indicator variable that equals 1 if the corresponding negativity change is negative and equals zero otherwise. A *bleak tone change* (uptick in negativity) is defined as the absolute value of $NC_P \times 1\{NC_P > 0\}$ for presentations and as the absolute value of $NC_A \times 1\{NC_A > 0\}$ for answers. Analogously, a *bright tone change* (downtick in negativity) is defined as the absolute value of $NC_P \times 1\{NC_P \leq 0\}$ for presentations and as the absolute value of $NC_A \times 1\{NC_A \leq 0\}$ for answers.

To reduce the influence of outliers, we winsorized negativity changes at the 1% and 99% levels. Similarly, we winsorized bleak changes and bright changes at the 99% level.

Dependent variables. We had two principal questions about the implications of tone changes. (1) How do they predict company fundamentals? (2) How, if at all, do analysts and investors respond to tone changes? We assessed the relationship of tone changes with company fundamentals by using the following variables:

- *Earnings change in quarter t + 1* is earnings in quarter t + 1 minus earnings in the same quarter the previous year, divided by the volatility of earnings changes over the prior 20 quarters. (This formulation follows, e.g., Bernard and Thomas 1989 and Tetlock et al. 2008.)
- *Postcall forecast dispersion* is the standard deviation of analysts' forecasts for quarter t + 1 earnings tallied three days after the conference call of quarter t, divided by the absolute value of the mean consensus earnings forecast outstanding three days after the conference call of quarter t, multiplied by 100.
- *Consensus forecast change* is the change in analysts' mean consensus forecast for earnings in quarter t + 1 from the day before the conference call to three days after the call, divided by the absolute value of earnings in quarter t + 1, multiplied by 100.
- *Consensus forecast error* is the difference between the postcall forecast (the consensus forecast for quarter t + 1 outstanding three days after the conference call for quarter t) and the actual earnings in quarter t + 1, divided by the absolute value of earnings in quarter t + 1, multiplied by 100.
- We calculated daily excess stock returns in percentages following Daniel, Grinblatt, Titman, and Wermers (1997; hereafter, DGTW). DGTW provided monthly portfolio returns. We applied DGTW's methodology to daily returns to compute DGTW characteristic-adjusted stock returns. CAR[t,t + k] is the cumulative DGTW characteristic-adjusted stock return from day t through day t + k, where t = 0 on the conference call day. We computed both the two-day CAR[0,1] and the 59-day CAR[2,60]. We complemented the daily DGTW returns with both monthly raw returns and monthly DGTW returns (which we calculated by using the same procedure as for the daily returns). These variables are the main dependent variables of interest in the calendar-time tests that follow.

To reduce the influence of outliers, we trimmed continuous dependent variables (the standardized change in earnings, forecast change, forecast error, and the CARs) at the 1% and 99% levels. For postcall forecast dispersion, we carried out one-sided trimming at the 99% level. (Results proved similar if we winsorized instead.) Importantly, we did not trim the monthly raw and DGTW returns in the calendar-time tests.

Company-level control variables. The regression specifications controlled for a series of variables that we expected to be related to changes in company fundamentals, analyst reactions, and/or stock returns. Specifically, they included the company's earnings change in quarter t, mean earnings surprise in quarter t, size in quarter t, book-to-market in quarter t, stock return in quarter t, monthly volatility in quarter t, and precall forecast dispersion. All control variables were winsorized at the 1% and 99% levels except precall forecast dispersion, which was winsorized at the 99% level.

Additional examined characteristics of managerial speech. Several additional patterns of speech were expected to be value relevant and so were included as additional explanatory variables: length of the conference call, inconsistency in tone, uncertain words, strong modal words (words expressing level of confidence, such as "always,'' "definitely," "never," and "will"), words having to do with finance, the frequency of numbers, sentence complexity, and atypical tenses.

The *length of a conference call* may indicate that a company has more explaining to do. Therefore, we controlled for the log of the number of words in presentations, answers, and analyst questions. *Inconsistency in tone* is the absolute difference in negativity between presentations (prepared speech) and answers (improvised speech). Inconsistency may indicate troubles ahead but may also indicate that the manager's answers are particularly informative. Using the Loughran and McDonald (2011) classification, we also coded the use of *uncertain* and *strong modal* words or constructions. Uncertain words may harm investors' ability to value a stock (in the spirit of Loughran and McDonald 2013). Modal words express levels of confidence (e.g., "always"). (We did not analyze weak modal words separately because they are a subset of the uncertain-word list.) We also included the *frequency of financial words* (as identified in Matsumoto et al. 2011) and the *frequency of numbers* (as suggested by Zhou 2018). As a measure of *sentence complexity*, we calculated the number of words per sentence.[14]

Finally, we accounted for *atypical tenses*. Arguably, presentations should primarily announce and explain past results. Answers should clarify missed points, explain the current situation, or preview the future. In the SOA, we show that, normally, approximately half of the phrases in presentations use the past tense whereas in answers, close to two-thirds of the phrases use the present tense. The use of the future tense is relatively rare; fewer than 10% of the verbs used in any of the presentations and answers used the future tense, although much present tense discussion is implicitly about the future. If sentences in a presentation use the past tense an unusually small number of times, the managers may be trying to divert attention from actual outcomes to potential future events. We defined *atypical tense* as the weighted average percentage of the manager's verbs not in the past tense in the presentation and the manager's verbs not in the present or future tense in the answers, where the weights were the numbers of verbs in the two respective parts of the conference call.

We winsorized all these speech characteristics variables at the 1% and 99% levels.

Do Managerial Negativity Changes Predict Earnings and Uncertainty?

If managerial negativity changes help predict earnings and uncertainty, stock market reactions to negativity changes in the appropriate direction would probably reflect rational information processing. We report in this section our investigation of the predictive power of managerial tone changes for earnings and uncertainty. Analyst and stock market reactions are the subject of the following sections.

Future Earnings. Do managers reveal information about future earnings of the company by the tone they use, purposefully or inadvertently, in the conference call? If yes, then negativity changes will predict earnings changes in the next quarter. Moreover, tone changes will predict earnings changes even after one controls for hard information, such as the current quarter's earnings surprise and negativity changes in the earnings press release.

The first main result of this analysis is that negativity changes, beyond publicly available information, strongly predict future changes in earnings, as measured by the next quarter's earnings minus those from the same quarter a year earlier. **Table 1** tells the tale. It contains results of panel regressions for the second quarter of 2003 through the second quarter of 2016 (2003:Q2–2016:Q2). The first column shows that the negativity change in either presentations or answers relates negatively to future changes in earnings, even after we controlled for relevant factors. Those factors are the negativity changes of the earnings press release and analysts' questions, the current change in earnings, the earnings surprise, and a large set of other controls that includes company, industry, and quarter fixed effects.[15]

We separately investigated bleak tone changes (negativity upticks) and bright tone changes (negativity downticks). The results in columns 2 and 3 of Table 1 show that, as expected, bleak tone changes in presentations and/or answers strongly predict negative future earnings changes. The effects of bright tone changes are much weaker.

All these results held after we controlled for the negativity change in the earnings press release and in analyst questions, either of which alone also significantly predicts future earnings changes. The SOA shows Fama–MacBeth (1973) regressions to reestimate the specifications of columns 2 and 3 of Table 1 to allow the effect of tone changes to vary over time. As previously, bleak tone changes predicted earnings changes more strongly than did bright tone changes.

In summary, when managers speak more negatively than they have previously, earnings tend to do worse, even after accounting for the hard information contained in the earnings announcement and the negativity changes of the press release and analysts' questions. Bleak tone changes predict more powerfully than bright tone changes.

Uncertainty. Greater uncertainty about a company's future should drive up the discount rate that the market applies to the company's future earnings and, therefore, depress its stock price. Thus, we were concerned with how the tone in a manager's speech affects uncertainty following the conference call (proxied by how dispersed analysts' estimates were right after the call).[16]

Columns 4–6 of Table 1 show that bleak changes predict greater dispersion of forecasts regarding

Table 1. Do Managerial Negativity Changes Help Predict Earnings and Uncertainty? Panel Regressions, 2003:Q2–2016:Q2 (*t*-statistics in parentheses)

	Earnings Change in Quarter $t + 1$			Postcall Forecast Dispersion		
Tone Change	1	2	3	4	5	6
Negativity change in presentations	−0.021			0.810		
	(−5.57)			(4.80)		
Negativity change in answers	−0.011			0.094		
	(−2.87)			(0.56)		
Bleak tone change in presentations		−0.028			0.886	
		(−6.85)			(4.66)	
Bright tone change in presentations		−0.001			−0.085	
		(−0.29)			(−0.49)	
Bleak tone change in answers			−0.019			0.443
			(−4.61)			(2.25)
Bright tone change in answers			−0.003			0.188
			(−0.74)			(1.02)
Negativity change in earnings press release	−0.012	−0.012	−0.017	0.261	0.259	0.445
	(−3.48)	(−3.51)	(−5.02)	(1.77)	(1.76)	(3.14)
Negativity change in analysts' questions	−0.005	−0.007	−0.007	0.078	0.095	0.137
	(−1.56)	(−2.17)	(−2.01)	(0.51)	(0.63)	(0.90)
Observations	70,997	70,997	70,997	71,714	71,714	71,714
R^2	0.305	0.305	0.305	0.266	0.266	0.266

Notes: "Earnings Change in Quarter $t + 1$" is earnings in quarter $t + 1$ minus earnings in the same quarter in the previous year, standardized by the volatility of earnings changes over the prior 20 quarters. "Postcall Forecast Dispersion" is the standard deviation of analysts' forecasts outstanding three days after the conference call. All variables are defined in Table A1 of Appendix A. All specifications include further controls: earnings change in quarter t; earnings surprise in quarter t; size in quarter t; book-to-market in quarter t; stock return in quarter t; monthly volatility in quarter t; precall forecast dispersion; ln(Words in the presentation); ln(Words in the answers); inconsistency in tone; % uncertain words; % strong modal words; % financial words; % atypical tense; complexity; % numbers in total words; and company, quarter, and industry fixed effects. These variables are defined in the SOA, which also presents the regression output displaying the coefficients on all controls. All explanatory variables were standardized to have a zero mean and a standard deviation of 1. The underlying standard errors were clustered on the company level and are robust to heteroskedasticity.

the next quarter, measured within three days after the conference call. In contrast, bright tone changes either do not significantly predict uncertainty (when comparing negativity with the prior quarter, as in Table 1) or predict a decrease in uncertainty but with a much smaller absolute effect than bleak tone changes (when taking into account information from the past four quarters in the computation of negativity changes; see the SOA).

In short, if managers speak with increased negativity, greater uncertainty is around the corner.

Do Analysts Respond to Managerial Negativity Changes?

The stock market requires an avenue for becoming informed about tone. No doubt some stock market investors simply listen to the conference call directly and respond. For a much larger audience of investors, the sell-side analysts—the professionals who are allowed to ask questions on these calls—are the messengers who distill and deliver information from the call.[17] That is, analysts report on the tea leaves that managers scatter before them with their written and spoken words. In this section, we examine the analysts' response to managerial negativity changes.

To be clear, we are not positing that analysts conduct the types of statistical analyses conducted here or even that they comb through press releases and transcripts to count words. Rather, we conjecture that they listen and read carefully and secure an impression as to whether the manager has spoken more or less negatively. If, in fact, analysts do respond, that response will reveal that at least some such informal process is at work. No doubt, some technologically sophisticated analysts do more, and machine learning is sure to enhance such processes in the future.

The results of this analysis, shown in **Table 2**, make clear that analysts do react to negativity changes in the appropriate direction—namely, the direction that those changes imply for future earnings.[18] Thus, they adjust their forecasts downward when the manager speaks more negatively, even after observables (column 1) have been controlled for. Recall that the explanatory variables are standardized to have a zero mean and a standard deviation of 1. The coefficient of –1.854 in column 1 implies that, on average, a 1 standard deviation increase in the negativity change in the presentation section of the conference call reduces the consensus earnings forecast for the next quarter by 1.85%, a sizable effect. Notably, these results held after we controlled for the negativity change in the earnings press release and in analysts' questions (both of which also have the expected negative sign) and for our rich set of other speech

Table 2. Do Analysts Respond to Managerial Negativity Changes? Panel Regressions, 2003:Q2–2016:Q2 (*t*-statistics in parentheses)

	Consensus Forecast Change			Consensus Forecast Error		
Tone Change	1	2	3	4	5	6
Negativity change in presentations	–1.854			1.148		
	(–14.42)			(4.96)		
Negativity change in answers	–0.618			0.809		
	(–5.00)			(3.35)		
Bleak tone change in presentations		–1.744			0.930	
		(–11.41)			(3.35)	
Bright tone change in presentations		0.545			–0.559	
		(4.33)			(–2.23)	
Bleak tone change in answers			–0.821			0.352
			(–5.65)			(1.33)
Bright tone change in answers			0.216			–0.776
			(1.65)			(–3.02)
Negativity change in earnings press release	–0.752	–0.759	–1.179	0.656	0.672	0.925
	(–6.24)	(–6.30)	(–9.73)	(2.89)	(2.96)	(4.14)
Negativity change in analysts' questions	–0.929	–1.049	–1.069	0.509	0.667	0.600
	(–7.98)	(–9.05)	(–9.17)	(2.29)	(3.06)	(2.73)
Observations	70,850	70,850	70,850	70,801	70,801	70,801
R^2	0.073	0.073	0.069	0.035	0.035	0.035

Notes: The analyst "Consensus Forecast Change" is in percentage of the absolute earnings in quarter $t + 1$. The analyst "Consensus Forecast Error" is in percentage of absolute earnings in quarter $t + 1$. All variables shown in this table are defined in Table A1 of Appendix A. All specifications include further controls, as noted in Table 1. These variables are defined in the SOA, which also presents the regression output displaying the coefficients on all controls. All explanatory variables were standardized to have a zero mean and a standard deviation of 1. The underlying standard errors are clustered on the company level and are robust to heteroskedasticity.

characteristics. Furthermore, in line with the earnings predictability regressions, columns 2 and 3 show that analysts adjust absolutely more strongly following bleak tone changes than following bright tone changes.

Do analysts' forecasts fully capture the tone of managers' speech? To answer that question, we related errors in those forecasts to the magnitude of the managers' negativity changes. Column 4 of Table 2 shows that when managers talk more negatively in presentations and answers, forecast errors (expected earnings above actual earnings) increase. Thus, analysts fail to fully incorporate all information from conference calls in their forecasts.[19] Column 5 also makes evident that analysts underreact more to bleak than to bright tone changes in presentations. With regard to answers, the results are mixed. A bright tone change appears stronger in the panel regressions in Table 2, column 6, but weaker in the Fama–MacBeth regressions (reported in the SOA). In any case, the big difference between the coefficients of bleak changes and bright changes in the forecast change regressions still suggests a stronger overall bleak-change effect for answers as well as for presentations.[20]

In summary, the results for future earnings and earnings forecasts support the idea that managerial negativity changes convey information regarding future earnings and that analysts incorporate that information. However, although analysts' estimates respond notably, they do so insufficiently.

Do Investors Respond to Managerial Negativity Changes?

Given that analysts revise their forecasts following managerial tone signals and given that analysts underreact to changes in negativity, we expected stock prices to respond in the same direction. Presumably, stock market participants are able to distill information from the negativity of conference calls, either directly or with the assistance of analysts, which implies that stock prices should move accordingly. Whether they move in a timely manner, however, and correct for analyst underreaction is unclear. We next sought to investigate these issues.

Immediate Stock Market Reactions.

Columns 1–3 of **Table 3** reveal the immediate stock market reaction to negativity changes. For these results, CAR[0,1], the abnormal returns on the day of the conference call plus the following day, was regressed on managerial negativity changes in the conference call. As a baseline, column 1 shows that negativity changes (in both presentations and answers) strongly negatively predict the short-term stock market reaction around the earnings announcement. This result is consistent with prior studies (e.g., Mayew and Venkatachalam 2012; Price et al. 2012; Lee 2016).

Our novel results separate the effects of bright tone changes and bleak tone changes (see columns 2 and 3). The market's immediate response to bleak tone changes is far stronger than to bright tone changes, which is consistent with our previous results. For example, column 2 implies that a 1 standard deviation increase in bright tone changes in presentations leads to a short-run abnormal stock return of 0.34%. The equivalent bleak tone change leads to a –0.55% abnormal return. Column 3, addressing answers, shows similarly that bleak changes are much more powerful than bright changes. All these findings resulted after we controlled for the negativity changes of the earnings press release and analysts' questions.

The full tables in the SOA show that the use of uncertain words, complex sentences, strong modal words, and fewer numbers is associated with negative short-term stock reactions, as is the use of financial words. The share price also responds negatively to the use of the wrong tense—that is, the manager using the past tense in the answers part of the earnings call or talking in the present or future tense in the presentation part of the earnings call. Interestingly, when managers' presentations and answers were lengthy, the market seemed to sense trouble ahead. All of these results are broadly consistent with the findings for future earnings, analyst responses, and/or analyst uncertainty. For example, a higher fraction of uncertain words foreshadows lower future earnings, induces analysts to reduce their earnings forecasts, and predicts higher uncertainty.

Overall, conference call negativity changes robustly determine immediate stock price reactions. **Figure 1** presents binned scatterplots connecting these results with the other results obtained so far. For each plot, all observations were sorted into 20 equal-sized bins of the explanatory variable. Each dot represents the average value within that bin of the variable on the vertical axis. The horizontal and vertical axes show residualized values, which

Table 3. Do Investors Respond to Managerial Negativity Changes? Panel Regressions, 2003:Q2–2016:Q2 (*t*-statistics in parentheses)

	CAR[0,1]			CAR[2,60]		
Tone Change	1	2	3	4	5	6
Negativity change in presentations	−0.706			−0.100		
	(−24.28)			(−1.68)		
Negativity change in answers	−0.316			−0.107		
	(−11.56)			(−1.82)		
Bleak tone change in presentations		−0.548			−0.165	
		(−17.20)			(−2.49)	
Bright tone change in presentations		0.338			−0.029	
		(11.33)			(−0.47)	
Bleak tone change in answers			−0.438			−0.030
			(−13.92)			(−0.45)
Bright tone change in answers			0.057			0.110
			(1.94)			(1.68)
Negativity change in earnings press release	−0.299	−0.305	−0.461	−0.034	−0.035	−0.057
	(−11.25)	(−11.48)	(−17.34)	(−0.61)	(−0.64)	(−1.06)
Negativity change in analysts' questions	−0.638	−0.699	−0.690	−0.064	−0.085	−0.073
	(−23.64)	(−25.98)	(−25.39)	(−1.17)	(−1.56)	(−1.32)
Observations	70,521	70,521	70,521	70,617	70,617	70,617
R^2	0.092	0.090	0.083	0.028	0.028	0.028

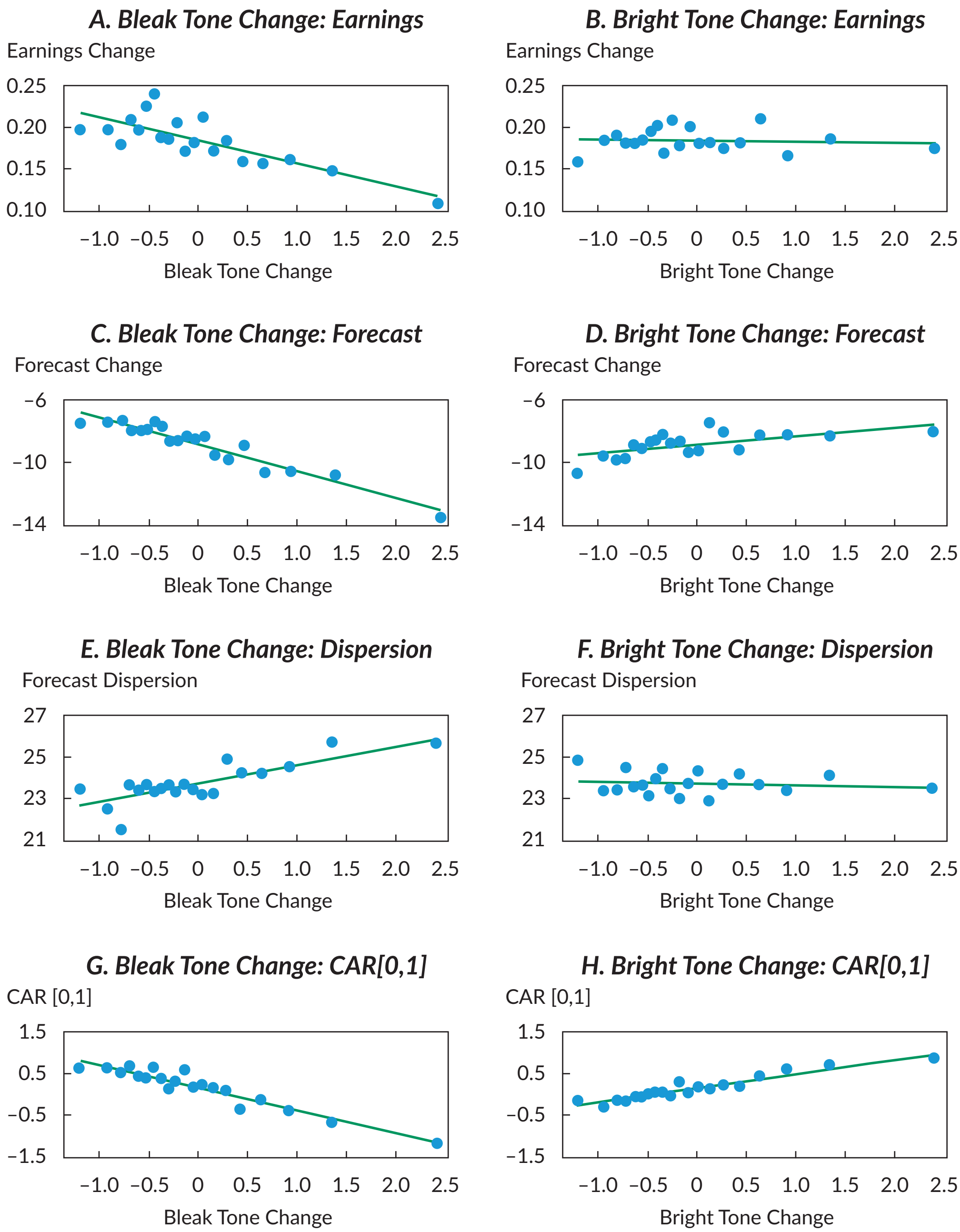
Notes: "CAR[0,1]" is the two-day [0,1] cumulative DGTW characteristic-adjusted stock return on and after the conference call date, in percentage. "CAR[2,60]" is the 59 trading day [2,60] cumulative DGTW characteristic-adjusted stock return in percentage from 2 days after the conference call date through the 60th day after that date. All variables are defined in Table A1 of Appendix A. All specifications include further controls, as noted in Table 1. All explanatory variables were standardized to have a zero mean and a standard deviation of 1. The underlying standard errors are clustered on the company level and are robust to heteroskedasticity.

explains why values on the horizontal axis can be negative. Specifically, all plots controlled for both the control variables and fixed effects used in Tables 1, 2, and 3. These plots show what bleak tone changes (Panels A, C, E, and G) and bright tone changes (Panels B, D, F, and H) in presentations portend for future earnings (Panels A and B), how analysts adjust their forecasts (Panels C and D), analyst uncertainty (Panels E and F), and how investors immediately respond (Panels G and H). The slopes in the figures on the left-hand side are much steeper than those on the right. That is, consistent with the results for earnings, earnings forecast changes, and uncertainty, the market's immediate response to bleak tone changes is much stronger than its response to bright tone changes.

Event-Time Returns beyond Initial Market Response. What happens as the days and weeks pass after the conference call? Of course, if the market efficiently prices in all information contained in managerial negativity changes, there will be no relationship, in principle, between negativity changes and postcall returns. Alternatively, return reversals may result, as would happen if managerial statements were crafted to trick the market.[21] Finally, if analysts underestimated the news revealed by managerial speech patterns, clear indications might occur of return continuation.

To investigate whether rational pricing, reversal, or continuation pertains, we analyzed how stock prices behaved in the quarter following a conference call. We

Figure 1. Responses to Bleak and Bright Tone Changes in Presentations: Earnings, Analyst Behavior, and Stock Prices



Notes: The binned scatterplots illustrate the explanatory power of tone changes in presentations for future earnings, analyst forecast changes, forecast dispersion (an indicator of uncertainty), and immediate stock price reaction. The four plots on the left concern bleak tone changes; the plots on the right concern bright tone changes.

used DGTW characteristic-adjusted excess returns, which allowed us to control jointly for size, value, and momentum in stock returns. Column 4 of Table 3 shows postcall drift in the 2–60 trading days after the conference call. Controlling for the earnings surprise, the negativity change in the earnings press release, and all other controls used previously, we found that negativity changes in both presentations and answers, on average, negatively explain postcall cumulative returns; that is, persistence occurs in stock price movements.[22]

Moreover, columns 5 and 6 of Table 3 suggest that the drift in excess returns predicted by tone changes in presentations is stronger after bleak than after bright tone changes. For answers, bleak tone changes predict no drift; bright changes predict some. Nevertheless, even for answers, bleak tone changes explain more of the total effect—that is, initial reaction plus drift.[23] These findings are consistent with the findings of Hong, Lim, and Stein (2000), who found stronger price drifts following negative news. Hong et al. suggested that a possible explanation for their results is that managers are unlikely to quickly update investors with negative information and that the delay results in the information diffusing slowly in the markets. Importantly, however, we show that bleak tone changes actually do predict fundamentals (earnings and uncertainty) more strongly than do bright tone changes. Thus, our results suggest not that investors are necessarily underreacting more strongly to negative information that managers fail to communicate but that managers' bleak talk is more informative than their bright talk.

In summary, even after we controlled for the negativity change in the press release and for the earnings surprise, companies experiencing bleak tone changes in their conference calls underperform the benchmark comprising other companies with similar characteristics. Managerial tone conveys valuable and valued information. The drift that follows, however, indicates that the market slowly incorporates the information. From a practical investment perspective, the question now becomes whether the predictive ability of negativity changes can be exploited.

Calendar-Time Tests.

To test whether investors can profit from the predictive ability of negativity changes, we started by constructing a calendar-time portfolio strategy to capture the lags in the incorporation of negativity changes into stock prices. Then, to control for alternative sources of return predictability, we used a regression to examine the predictive power of tone changes.[24]

Portfolio strategy. At the beginning of each month, we ranked stocks into quintile portfolios based on their most recent quarter-to-quarter change in negativity. Stocks with a price at or below $5 at portfolio formation were excluded, which assured that low-priced, illiquid stocks would not drive our results. For each of the five portfolios, we computed equal-weighted excess returns (in excess of the one-month T-bill rate) for the subsequent month.[25] A portfolio that was long (short) stocks with low (high) negativity changes thus reflects the profits to systematic underreaction to tone in conference calls.

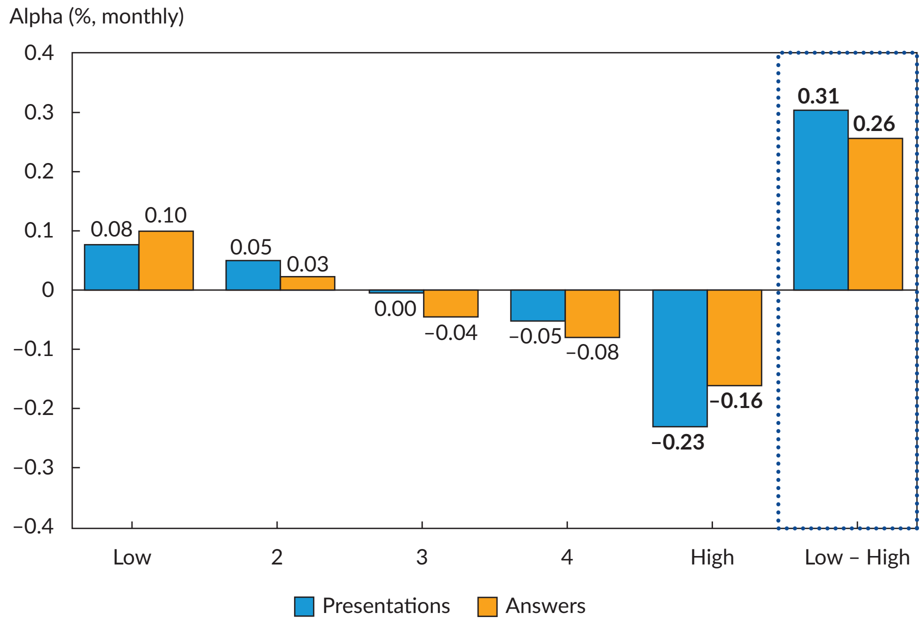
Figure 2 summarizes the results. Monthly risk-adjusted returns (alphas) from the Carhart (1997) four-factor model decreased after a quarter-to-quarter boost in negativity. The long–short portfolio, which was long (short) stocks with low (high) negativity changes, generated monthly alphas of 0.31% and 0.26% for, respectively, presentations and answers. These alphas are highly statistically significant; the *t*-statistics are well above 3.[26] As shown in **Table A2** in Appendix A, excluding stocks in the lowest market-capitalization tercile (of the sample) reduced the profitability of the long–short strategy. The returns remained, however (at least for presentations), statistically and economically significant. Finally, we also computed value-weighted portfolio returns, which are insignificant.

Overall, these results indicate that negativity changes are quickly incorporated into stock prices for the largest stocks in our sample.[27] The profitability of the strategy is not limited, however, to small-capitalization stocks, which suggests that, in practical terms, negativity changes in presentations and answers may well add value to existing factor-based trading strategies, which have become prominent in recent years. Typically, such long-only strategies use characteristics (factors) to overweight stocks with favorable characteristics and underweight stocks with unfavorable characteristics. For example, momentum strategies overweight stocks with strong past performance and underweight stocks with weak past performance. In a similar vein, investors can benefit by underweighting positions in companies that exhibit upticks in negativity. Although positions in small-cap companies make up, by definition, only a small fraction of the overall portfolio of an investor diversified in the market, positions in medium-sized and large companies can be useful for this purpose.

Fama–MacBeth regressions. To further examine the predictability of returns, we next estimated Fama–MacBeth regressions of monthly stock returns on the most recent quarter-to-quarter changes in negativity and controls. To facilitate comparability with the event-time regression results, we established the next month's DGTW return as the main dependent variable of interest. (The results were similar when we used raw returns.)

Column 1 of **Table 4** suggests that negativity changes help to significantly predict future characteristic-adjusted returns. Columns 2 and 3 show that, consistent with the event-time results, bleak tone changes predict more strongly than bright tone changes. The results held after controlling for size, book-to-market,

Figure 2. Abnormal Returns to Negativity Changes in Calendar-Time Tests, May 2003–July 2016



Notes: Portfolio 1 (Low) contained the stocks with the lowest negativity changes, whereas Portfolio 5 (High) contained the stocks with the highest negativity changes. Low – High is the strategy that was long Portfolio 1 and short Portfolio 5. Alpha is the intercept from a time-series regression of monthly portfolio excess returns on the Carhart (1997) four-factor model. Numbers shown in bold indicate statistical significance at the 1% level. The underlying standard errors accounted for heteroskedasticity and autocorrelation up to 12 months.

momentum, the most recent earnings surprise, negativity changes in the earnings press release and analyst questions, and all remaining control variables from specification 6 of Table 3.[28]

In summary, our calendar-time strategies involving conference call tone changes reaped significant profits.[29] Negativity changes prove to be a robust predictor of the cross-section of stock returns. Importantly, the effect is explained neither by the earnings surprise nor by tone changes in the earnings press release and analyst questions.

Additional Results

In the SOA, we provide results of a number of additional analyses. First, we show that bleak tone changes based on the negativity frequency ratio (i.e., negative words to total words, as per Equation 1b) are stronger predictors of earnings and uncertainty as well as of analysts' and investors' responses than are bright tone changes. These results strengthen our conclusion that positive and negative tone changes are inherently different in terms of information content. Second, we provide results of an examination of the role of media, managerial incentives, and differences in tone informativeness among companies. Third, to check for robustness, we provide results of an additional series of changes to our main specifications.

Conclusion

Successful analysts and investors are high-class sleuths who search for and distill the information from clues wherever they may be found. Most analysts and investors start by looking at objective numbers, but success requires much more. For the study reported here, we asked what information analysts and investors might glean from managerial word choice in conference calls and whether they act on that information.

Our conclusion is, in short, that analysts and investors already find and respond to such information. Specifically, they look to changes in managers' use of linguistic tone. When a more negative tone is used, analysts lower their earnings estimates. When a less negative tone is used, analysts raise their estimates, but to a lesser extent. First, kudos to these analysts; such managerial word choices prove to be telltale signs of future earnings—and in the right direction. And kudos to the market, because it, too, moves in the right direction in response to these subtle clues. But the kudos are limited. Both analysts and the market underrespond. In short, a drift occurs

Table 4. Calendar-Time Tests: Fama–MacBeth Regressions, May 2003–July 2016 (*t*-statistics in parentheses)

	DGTW Characteristic-Adjusted Stock Return in Month $t + 1$		
Tone Change	1	2	3
Negativity change in presentations	−0.035		
	(−1.93)		
Negativity change in answers	−0.055		
	(−2.76)		
Bleak tone change in presentations		−0.051	
		(−2.40)	
Bright tone change in presentations		−0.001	
		(−0.02)	
Bleak tone change in answers			−0.047
			(−1.88)
Bright tone change in answers			0.023
			(1.00)
Negativity change in earnings press release	−0.023	−0.023	−0.030
	(−1.08)	(−1.11)	(−1.41)
Negativity change in analysts' questions	−0.056	−0.069	−0.056
	(−3.33)	(−4.03)	(−3.44)
Avg. *N*	1,339	1,339	1,339
R^2	0.072	0.072	0.072

Notes: The dependent variable is in percentage. For the explanatory variables, we used the most recent value at the beginning of month $t + 1$. The table further includes size in month t, book-to-market in month t, momentum, return reversal, and all the remaining variables from specification 6 of Table 3, excluding size and book-to-market in quarter t. All variables shown are defined in Table A1 in Appendix A. All explanatory variables were standardized to have a zero mean and a standard deviation of 1. The specifications include stocks with beginning-of-month prices above $5. The t-statistics are based on standard errors accounting for heteroskedasticity and autocorrelation up to 12 months (Newey and West 1987).

after the initial response, and this drift can lead to profitable trading strategies. The alert reader will recognize that such underreaction is a cousin of the well-known post-earnings-announcement drift.

What lessons should analysts and investors learn from our findings? First, they should have confidence that where currently they may be responding to company communications subtly, or even subconsciously, they are probably responding appropriately. Second, in light of the vast dollars at stake and the plummeting cost of capturing and processing information, they would do well to automate some of their tea leaf reading and test it on a statistical basis. Third, we conducted this analysis in the dawn of the era of machine learning and artificial intelligence. In the coming years, almost certainly, much more extensive analyses will be conducted of the hints that managers provide to the investment community—consciously or inadvertently—when they speak. Our article should encourage analysts, and those who employ them, to push further into investigations of language and psychology.

The presentations by managers during conference calls are studiously prepared; their tone is carefully chosen. The answers, although rehearsed for likely questions, must be somewhat impromptu. Our analysis shows that the tone of these calls provides incremental information over and above the earnings press release and analysts' questions. The estimates of analysts and the prices of stocks respond to the tone of the words managers use—in particular to any change in tone from the prior quarter or the prior four quarters. Our study also provides conclusive evidence that bleak tone changes are much more informative than bright tone changes.

There are lessons here too for managers. Many, no doubt, are aware that their tone conveys information. Many others may be naive on this subject. But all should understand what messages analysts and the market are distilling from their tone and consider whether they might wish to adjust their speech patterns.

Investment markets in the past two decades have been kind to those who were experts in recognizing patterns in prices. The next two decades may reward individuals who are experts in uncovering clues in previously hard-to-discern places, including patterns in human speech, which massive data availability and nearly costless processing have opened up for investigation.

Appendix A

Table A1. Variable Definitions

Bleak tone change	Defined as the absolute value of $NC_P \times 1\{NC_P > 0\}$ and the absolute value of $NC_A \times 1\{NC_A > 0\}$ for, respectively, presentations and answers. $1\{NC > 0\}$ is an indicator variable that is equal to 1 if the corresponding negativity change is positive and is equal to zero if the negativity change is negative.	Authors' calculation
Bright tone change	Defined as the absolute value of $NC_P \times 1\{NC_P \leq 0\}$ and the absolute value of $NC_A \times 1\{NC_A \leq 0\}$ for, respectively, presentations and answers. $1\{NC \leq 0\}$ is an indicator variable that is equal to 1 if the corresponding negativity change is negative and is equal to zero if the negativity change is positive.	Authors' calculation
CAR[0,1]	The two-day [0,1] cumulative DGTW characteristic-adjusted stock return on and after the conference call date, in percentage. DGTW characteristic-adjusted returns are defined as raw daily returns minus the returns on a portfolio of all CRSP common stocks in the same size, book-to-market, and one-year momentum quintiles.	CRSP, WRDS, Authors' calculation
CAR[2,60]	The 59 trading day [2,60] cumulative DGTW characteristic-adjusted stock return in percentage from 2 days after the conference call date through the 60th day after that date.	CRSP, WRDS, Authors' calculation
CAR[0,60]	The 61 trading day [0,60] cumulative DGTW characteristic-adjusted stock return in percentage from the day of the conference call through the 60th day after that date.	CRSP, WRDS, Authors' calculation
Consensus forecast change	The change in the analysts' consensus forecast for earnings in quarter $t + 1$ from the day before the conference call to three days after the call, divided by the absolute earnings in quarter $t + 1$, multiplied by 100.	IBES
Consensus forecast error	The difference between the post-conference-call forecast (the forecast for quarter $t + 1$ outstanding 3 days after the conference call for quarter t) and the actual earnings in quarter $t + 1$, divided by the absolute earnings in quarter $t + 1$, multiplied by 100.	IBES
Earnings change in quarter t	Earnings in quarter t minus earnings in the same quarter in the previous year, standardized by the volatility of earnings changes over the prior 20 quarters (we required at least 10 quarters in the computation).	IBES
Negativity in presentations, answers, analyst questions ($N_P/N_A/N_Q$)	The ratio $(n - p)/(n + p + 1)$, where n and p are the numbers of negative and positive words, respectively, used in the conference call. We computed negativity for presentations, answers, and analyst questions separately. In the SOA, we present an alternative using the ratio *n/words*, where *words* is the total number of words in the respective section of the call. We used the word list of Loughran and McDonald (2011) to compute both measures.	Authors' calculation

(continued)

Table A1. Variable Definitions (continued)

Negativity change in presentations, answers, analyst questions (NC_P/NC_A/NC_Q)	The change in the respective negativity measure from quarter *t* – 1 to quarter *t*.	Authors' calculation
Negativity change in earnings press release	The change in the negativity of the earnings press release from quarter *t* – 1 to quarter *t*. Negativity in the press release is defined as the ratio $(n - p)/(n + p + 1)$, where *n* and *p* are the numbers of negative and positive words, respectively, used in the earnings press release. In the SOA, we present an alternative using negativity frequency—that is, the ratio *n/words*, where *words* is the total number of words in the press release. We used the word list of Loughran and McDonald (2011) to compute both measures.	Authors' calculation
Postcall forecast dispersion	The standard deviation of analysts' forecasts for earnings in the quarter *t* + 1 outstanding 3 days after the conference call for quarter *t*, divided by the absolute value of the mean consensus forecast outstanding 3 days after the conference call for quarter *t*, multiplied by 100.	IBES

Note: Definitions of all variables used in the study are provided in the SOA.

Table A2. Calendar-Time Tests: Abnormal Returns to Negativity Changes, May 2003–July 2016 (*t*-statistics in parentheses)

	Negativity Change in Presentations				Negativity Change in Answers			
	Mean Negativity Change	Excess Return	Alpha (CH)	Alpha (CH)	Mean Negativity Change	Excess Return	Alpha (CH)	Alpha (CH)
1 (Low)	−0.294	1.013	0.078	0.010	−0.384	1.046	0.101	−0.014
	(−60.18)	(2.16)	(1.47)	(0.20)	(−89.31)	(2.09)	(1.46)	(−0.23)
2	−0.107	1.001	0.054	−0.031	−0.139	0.941	0.026	−0.032
	(−22.40)	(2.04)	(0.92)	(−0.53)	(−35.56)	(2.04)	(0.54)	(−0.54)
3	−0.003	0.965	−0.004	−0.061	−0.003	0.911	−0.043	−0.094
	(−0.66)	(2.04)	(−0.11)	(−1.31)	(−0.95)	(1.97)	(−0.79)	(−1.76)
4	0.101	0.899	−0.053	−0.080	0.132	0.889	−0.079	−0.110
	(18.58)	(1.89)	(−0.81)	(−1.15)	(35.74)	(1.78)	(−1.43)	(−1.64)
5 (High)	0.300	0.701	−0.228	−0.204	0.377	0.794	−0.158	−0.118
	(43.06)	(1.47)	(−3.66)	(−3.72)	(82.29)	(1.72)	(−2.82)	(−2.65)
Low – High (1 – 5)	−0.594	0.313	0.306	0.214	−0.761	0.252	0.259	0.104
	(−87.28)	(3.48)	(3.47)	(3.35)	(−123.36)	(4.10)	(3.40)	(1.68)
Small caps	incl.	incl.	incl.	excl.	incl.	incl.	incl.	excl.

Notes: CH stands for the Carhart (1997) model. "Small caps incl. (excl.)" means that stocks in the lowest market-cap tercile were included (excluded). Alpha is the intercept from a time-series regression of monthly portfolio excess returns on the Carhart four-factor model. The underlying standard errors account for heteroskedasticity and autocorrelation up to 12 months.

Authors' Note

The views expressed in this article are those of the authors and do not necessarily reflect the views of Swiss Rock Asset Management.

A previous version of this article was titled "Reading Managerial Tone: How Analysts and the Market Respond to Conference Calls."

Editor's Note

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Notes

1. For surveys, see Li (2011), Henry and Leone (2016), and Loughran and McDonald (2016).

2. For example, in his investigation of managerial spontaneity in conference calls, Lee (2016) included the net positivity of the overall conference call (managers and analysts together) as a control variable. This variable is associated with higher future earnings, higher analyst forecasts, and lower bid–ask spreads. His analysis, however, did not consider the tone of the earnings press release.

3. Some studies have shown that changes in positivity in earnings press releases predict higher returns on assets (Davis, Piger, and Sedor 2012) and that where future returns are harder to assess, this effect is stronger (Demers and Vega 2010). In contrast, Huang, Teoh, and Zhang (2014) provided evidence that an abnormally positive tone in earnings releases predicts lower earnings in the following years. The frequency of negative words in 10-K filings has been found to correlate positively with positive future earnings surprises (Loughran and McDonald 2011). Regarding uncertainty, agreement is greater. More favorable disclosures in 10-K and 10-Q filings are associated with less dispersion in analysts' estimates and lower stock volatility (Kothari, Li, and Short 2009; Loughran and McDonald 2011).

4. Additional results and robustness checks are relegated to the Supplemental Online Appendix (SOA).

5. Matsumoto et al. (2011) controlled for market reaction at the time of the press release to document that the earnings call provides incremental information (as measured by the absolute abnormal return during the call). By considering companies that announced earnings after trading hours and held a conference call during the next business day, Brochet, Kolev, and Lerman (2018) were able to document that additional information relevant for nonannouncing industry peers was contained in the conference call. Our interest here is in seeing whether the linguistic tone of the call remains informative once one has controlled for the corresponding feature in the press release.

6. Conference calls have allowed researchers to study strategic casting of analyst questions (Mayew 2008; Cohen, Lou, and Malloy 2013), evasive tactics of managers (Hollander, Pronk, and Roelofsen 2010; Gow, Larcker, and Zakolyukina 2019), vocal dissonance (Hobson, Mayew, and Venkatachalam 2012), deceptive words (Larcker and Zakolyukina 2012), analyst questions and information acquisition (Mayew, Sharp, and Venkatachalam 2013), communication patterns within the management team (Li, Minnis, Nagar, and Rajan 2014), short selling (Blau, DeLisle, and Price 2015), managerial time horizons (Brochet, Loumioti, and Serafeim 2015), language barriers between managers and call listeners (Brochet, Naranjo, and Yu 2016), industry window dressing (Chen, Cohen, and Lou 2016), contrastive words (Palmon, Xu, and Yezegel 2016), euphemistic language (Suslava 2017), extreme language (Bochkay, Chava, and Hales [forthcoming]), humor (Call, Flam, Lee, and Sharp 2019), vague talk (Dzieliński, Wagner, and Zeckhauser 2019), managerial extraversion (Green, Jame, and Lock 2019), and intangibles talk (Filipović and Wagner 2019).

7. Frankel, Jennings, and Lee (2018) applied several machine-learning techniques to conference calls and concluded that these techniques capture a fraction of the narrative content that a sophisticated reader would gather from a disclosure.

8. Managers are eager to avoid litigation risk. Thus, they may be inclined to downplay positive news and to quickly convey negative news. In that case, they would speak more positively only when their signal is highly informative. That phenomenon, in turn, would make bright tone changes more telling. An additional factor might be that, because managers are reluctant to voluntarily disclose bad news (and risk being fired) but are eager to reveal good news (e.g., to increase their reputations), whenever their negativity takes an uptick, their word choice may be mostly based on nonfundamentally relevant factors (e.g., their mood) rather than value-relevant information. If so, bleak tone changes would carry little information; bright tone changes would be more informative.

9. Prior literature has examined the relative importance of the frequency of negative words versus the frequency of positive words. These findings do not necessarily imply, however, that increases in negativity are more informative than decreases in negativity. See the section "Variables and Summary Statistics" for details.

10. Industry fixed effects are based on the 12 Fama–French industry classifications, as found on Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The SOA shows that the results are robust to using industry-quarter or CEO fixed effects instead of company, industry, and quarter fixed effects and to clustering standard errors by company and by quarter. We also show that the results held for Fama and MacBeth (1973) regressions with industry fixed effects.

11. In line with Loughran and McDonald (2011), we used the Wharton Research Data Services (WRDS) CIK file to link

the SEC's CIK identifier to our CRSP/Compustat/IBES merged sample.

12. We used the 2017 version. The current version is available at https://sraf.nd.edu/.

13. See the discussion in the SOA of whether the words "question" and "questions" should be excluded from the list of negative words. Although they were kept on the list in this study, excluding them did not affect our results.

14. Several papers have studied the readability of corporate communications (e.g., Li 2008; Loughran and McDonald 2014). Loughran and McDonald (2016) highlighted that the parsing of business documents into sentences is error prone. This danger is somewhat smaller in the context of conference calls, which do not contain, for example, tables. We were careful not to count decimal points as sentence-ending periods.

15. The results for the control variables are not shown to conserve space, but they are included in the full tables in the SOA. When managers used more uncertain words, more strong modal words, and more complex sentences, future earnings dropped, on average. The frequency of numbers is positively associated with future changes in earnings (although the coefficient is noisy).

16. Greater analyst uncertainty could reflect either higher systematic risk or idiosyncratic risk or both. Even idiosyncratic risk may be priced—that is, may affect discount rates—when investors are not fully diversified (see, e.g., Merton 1987).

17. Based on data on investor requests for transcripts, Heinrichs, Park, and Soltes (2019) concluded that institutional investors do not necessarily "consume" conference calls, even if they hold large positions. Only analysts can ask questions. Although some buy-side analysts participate (see Jung, Wong, and Zhang 2018), only 5% of questions are asked by these analysts.

18. Managers, analysts, and investors interact in settings other than conference calls. Solomon and Soltes (2015) cited survey evidence showing that 97% of CEOs of publicly traded companies meet privately with investors. Private conversations of analysts and management are also frequent (Green, Jame, Markov, and Subasi 2014; Soltes 2014). Even more intense interactions occur at longer analyst/investor "days" hosted by companies that wish to provide information (Kirk and Markov 2016). Analysts also sometimes hold private calls with managers just after the public conference calls. Thus, analyst reports after conference calls often contain topics that were not discussed in the call (Huang, Lehavy, Zang, and Zheng 2018). The result we have documented may thus arise in part from analysts following up with managers to clarify why the managers spoke particularly positively or negatively. In this way, the analysts hope to obtain more specific information to support their forecast changes.

19. This finding runs parallel to the result in Bradshaw, Richardson, and Sloan (2001) that analysts do not fully incorporate accruals into their earnings forecasts.

20. The sum of the postcall forecast error and forecast change is equal to the precall forecast error. Thus, the sum of the respective coefficients reflects the effect of negativity changes on the precall forecast error. A large effect suggests stronger informativeness for future earnings—that is, a larger amount of information not yet reflected in analysts' expectations prior to the call. As can be seen from Table 2, this sum is always larger for bleak changes.

21. Some modest reversal may occur in the medium term for another reason. As we have shown, bleak changes drive up uncertainty and have the potential to increase the discount rate applied to the company's stock. Thus, companies whose stock prices dipped in the short run could expect an increase in expected returns.

22. Our results confirm the average postcall drift pattern found by Price et al. (2012) for a pseudo-random sample of 2,880 conference calls in the 2004–07 period. In their event-time tests, Price et al. used size-adjusted returns as the dependent variable and then controlled for company variables; in our analysis, we used the (arguably) "tougher" benchmark of DGTW characteristic-adjusted excess returns. We considered managers' answers and analyst questions separately, whereas Price et al. pooled these two elements of the Q&A session. Brockman et al. (2015) emphasized the role of analyst tone in explaining stock-price drift. Henry and Leone (2016) presented graphs illustrating return continuation after the initial positive reaction to positive tone changes in earnings press releases. Our drift results are in contrast to the results of Huang et al. (2014), who examined earnings press releases from 1997 to 2007. Using raw returns (and controlling for company characteristics), they identified reversions, which, they argued, are consistent with managers' fooling the market.

23. See the analysis of CAR[0,60] in the SOA.

24. Most of the prior literature relied on event-time returns. In contrast to event-time returns, the calendar-time approach avoids such problems as cross-correlation, clustering of events, and look-ahead bias. The calendar-time approach is, therefore, better suited for investigating the feasibility of abnormal returns and resulting deviations from market efficiency (see, e.g., Mitchell and Stafford 2000).

25. The risk-free rate and the size, value, and momentum factors were downloaded from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

26. The results when we used DGTW characteristic-adjusted returns were similar. For presentations (answers), the monthly Carhart model alpha equaled 0.29% (0.23%), with all t-statistics well above 3.

27. In the SOA, we provide a more detailed examination of how proxies for information-processing constraints, such as company size, analyst coverage, and institutional ownership, affect the profitability of the long–short strategy. We found that the returns to negativity changes in presentations and answers decreased with each of the

following: market capitalization, institutional ownership, and analyst coverage.

28. The regressions included all remaining controls except for size and book-to-market in quarter *t*; these two variables were already included at the monthly frequency.

29. Note that we did not consider trading costs. The strategy was rebalanced monthly, and the profits were concentrated in relatively small-cap stocks. Thus, significant trading costs could be incurred and deplete the strategy's profits.

References

Allee, Kristian D., and Matthew D. DeAngelis. 2015. "The Structure of Voluntary Disclosure Narratives: Evidence from Tone Dispersion." *Journal of Accounting Research* 53 (2): 241–74.

Bernard, Victor L., and Jacob K. Thomas. 1989. "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research* 27: 1–36.

Blau, Benjamin M., Jared R. DeLisle, and S. McKay Price. 2015. "Do Sophisticated Investors Interpret Earnings Conference Call Tone Differently than Investors at Large? Evidence from Short Sales." *Journal of Corporate Finance* 31: 203–19.

Bochkay, Khrystyna, Sudheer Chava, and Jeffrey Hales. Forthcoming. "Hyperbole or Reality? Investor Response to Extreme Language in Earnings Conference Calls." *Accounting Review.*

Bowen, Robert M., Angela K. Davis, and Dawn A. Matsumoto. 2002. "Do Conference Calls Affect Analysts' Forecasts?" *Accounting Review* 77 (2): 285–316.

Bradshaw, Mark T., Scott A. Richardson, and Richard G. Sloan. 2001. "Do Analysts and Auditors Use Information in Accruals?" *Journal of Accounting Research* 39 (1): 45–74.

Brochet, François, Kalin Kolev, and Alina Lerman. 2018. "Information Transfer and Conference Calls." *Review of Accounting Studies* 23 (3): 907–57.

Brochet, François, Maria Loumioti, and George Serafeim. 2015. "Speaking of the Short-Term: Disclosure Horizon and Managerial Myopia." *Review of Accounting Studies* 20 (3): 1122–63.

Brochet, François, Patricia Naranjo, and Gwen Yu. 2016. "The Capital Market Consequences of Language Barriers in the Conference Calls of Non-U.S. Firms." *Accounting Review* 91 (4): 1023–49.

Brockman, Paul, Xu Li, and S. McKay Price. 2015. "Differences in Conference Call Tones: Managers versus Analysts." *Financial Analysts Journal* 71 (4): 24–42.

Bushee, Brian J., Dawn A. Matsumoto, and Gregory S. Miller. 2003. "Open versus Closed Conference Calls: The Determinants and Effects of Broadening Access to Disclosure." *Journal of Accounting and Economics* 34 (1–3): 149–80.

Call, Andrew C., Rachel W. Flam, Joshua A. Lee, and Nathan Y. Sharp. 2019. "Analysts' and Managers' Use of Humor on Public Earnings Conference Calls." Working paper. Available at https://ssrn.com/abstract=3425509.

Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52 (1): 57–82.

Chen, Hailiang, Byoung Hwang, and Baixiao Liu. 2019. "The Emergence of 'Social Executives' and Its Consequences for Financial Markets." Working paper. Available at https://ssrn.com/abstract=2318094.

Chen, Huaizhi, Lauren Cohen, and Dong Lou. 2016. "Industry Window Dressing." *Review of Financial Studies* 29 (12): 3354–93.

Chen, Jason V., Venky Nagar, and Jordan Schoenfeld. 2018. "Manager-Analyst Conversations in Earnings Conference Calls." *Review of Accounting Studies* 23 (4): 1315–54.

Cohen, Lauren, Dong Lou, and Christopher Malloy. 2013. "Playing Favorites: How Firms Prevent the Revelation of Bad News." NBER Working Paper 19429 (September).

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. 1997. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance* 52 (3): 1035–58.

Davis, Angela K., Weili Ge, Dawn Matsumoto, and Jenny Li Zhang. 2015. "The Effect of Manager-Specific Optimism on the Tone of Earnings Conference Calls." *Review of Accounting Studies* 20 (2): 639–73.

Davis, Angela K., Jeremy M. Piger, and Lisa M. Sedor. 2012. "Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language." *Contemporary Accounting Research* 29 (3): 845–68.

Demers, Elizabeth A., and Clara Vega. 2010. "Soft Information in Earnings Announcements: News or Noise?" Working paper. Available at https://ssrn.com/abstract=1153450.

Dzieliński, Michał, Alexander F. Wagner, and Richard J. Zeckhauser. 2019. "Straight Talkers, Vague Talkers, and the Value of Firms." Working paper. Available at https://ssrn.com/abstract=2965108.

Fama, Eugene F., and James D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–36.

Feldman, Ronen, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal. 2010. "Management's Tone Change, Post Earnings Announcement Drift and Accruals." *Review of Accounting Studies* 15 (4): 915–53.

Filipović, Zoran, and Alexander F. Wagner. 2019. "The Intangibles Song in Takeover Announcements: Good Tempo, Hollow Tune." Working paper. Available at https://ssrn.com/abstract=3330623.

Frankel, Richard, Jared Jennings, and Joshua Lee. 2018. "Using Natural Language Processing to Assess Text Usefulness to Readers: The Case of Conference Calls and Earnings Prediction." Working paper. Available at https://ssrn.com/abstract=3095754.

Frankel, Richard, Marilyn Johnson, and Douglas J. Skinner. 1999. "An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium." *Journal of Accounting Research* 37 (1): 133–50.

Gow, Ian D., David F. Larcker, and Anastasia A. Zakolyukina. 2019. “Non-Answers during Conference Calls.” Working paper. Available at https://ssrn.com/abstract=3310360.

Green, T. Clifton, Russell Jame, and Brandon Lock. 2019. “Executive Extraversion: Career and Firm Outcomes.” *Accounting Review* 94 (3): 177–204.

Green, T. Clifton, Russell Jame, Stanimir Markov, and Musa Subasi. 2014. “Access to Management and the Informativeness of Analyst Research.” *Journal of Financial Economics* 114 (2): 239–55.

Heinrichs, Anne, Jihwon Park, and Eugene Soltes. 2019. “Who Consumes Firm Disclosures? Evidence from Earnings Conference Calls.” *Accounting Review* 94 (3): 205–31.

Henry, Elaine, and Andrew J. Leone. 2016. “Measuring Qualitative Information in Capital Markets Research: Comparison of Alternative Methodologies to Measure Disclosure Tone.” *Accounting Review* 91 (1): 153–78.

Hobson, Jessen L., William J. Mayew, and Mohan Venkatachalam. 2012. “Analyzing Speech to Detect Financial Misreporting.” *Journal of Accounting Research* 50 (2): 349–92.

Hollander, Stephan, Maarten Pronk, and Erik Roelofsen. 2010. “Does Silence Speak? An Empirical Analysis of Disclosure Choices during Conference Calls.” *Journal of Accounting Research* 48 (3): 531–63.

Hong, Harrison G., Terence Lim, and Jeremy Stein. 2000. “Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies.” *Journal of Finance* 55 (1): 265–95.

Huang, Allen, Reuven Lehavy, Amy Y. Zang, and Rong Zheng. 2018. “Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach.” *Management Science* 64 (6): 2833–55.

Huang, Xuan, Siew Hong Teoh, and Yinglei Zhang. 2014. “Tone Management.” *Accounting Review* 89 (3): 1083–113.

Jung, Michael J., M.H. Franco Wong, and Frank Zhang. 2018. “Buy-Side Analysts and Earnings Conference Calls.” *Journal of Accounting Research* 56 (3): 913–52.

Kahneman, Daniel, and Amos Tversky. 1979. “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47 (2): 263–91.

Kirk, Marcus, and Stanimir Markov. 2016. “Come on Over: Analyst/Investor Days as a Disclosure Medium.” *Accounting Review* 91 (6): 1725–50.

Kothari, S.P., Xu Li, and James E. Short. 2009. “The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis.” *Accounting Review* 84 (5): 1639–70.

Larcker, David F., and Anastasia A. Zakolyukina. 2012. “Detecting Deceptive Discussions in Conference Calls.” *Journal of Accounting Research* 50 (2): 495–540.

Lee, Joshua. 2016. “Can Investors Detect Managers’ Lack of Spontaneity? Adherence to Predetermined Scripts during Earnings Conference Calls.” *Accounting Review* 91 (1): 229–50.

Li, Feng. 2008. “Annual Report Readability, Current Earnings, and Earnings Persistence.” *Journal of Accounting and Economics* 45 (2–3): 221–47.

———. 2011. “Textual Analysis of Corporate Disclosures: A Survey of the Literature.” *Journal of Accounting Literature* 29: 143–65.

Li, Feng, Michael Minnis, Venky Nagar, and Madhav Rajan. 2014. “Knowledge, Compensation, and Firm Value: An Empirical Analysis of Firm Communication.” *Journal of Accounting and Economics* 58 (1): 96–116.

Loughran, Tim, and Bill McDonald. 2011. “When Is a Liability Not a Liability?” *Journal of Finance* 66 (1): 35–65.

———. 2013. “IPO First-Day Returns, Offer Price Revisions, Volatility, and Form S-1 Language.” *Journal of Financial Economics* 109 (2): 307–26.

———. 2014. “Measuring Readability in Financial Disclosures.” *Journal of Finance* 69 (4): 1643–71.

———. 2016. “Textual Analysis in Accounting and Finance: A Survey.” *Journal of Accounting Research* 54 (4): 1187–230.

Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen. 2011. “What Makes Conference Calls Useful? The Information Content of Managers’ Presentations and Analysts’ Discussion Sessions.” *Accounting Review* 86 (4): 1383–414.

Mayew, William J. 2008. “Evidence of Management Discrimination among Analysts during Earnings Conference Calls.” *Journal of Accounting Research* 46 (3): 627–59.

Mayew, William J., Nathan Y. Sharp, and Mohan Venkatachalam. 2013. “Using Earnings Conference Calls to Identify Analysts with Superior Private Information.” *Review of Accounting Studies* 18 (2): 386–413.

Mayew, William J., and Mohan Venkatachalam. 2012. “The Power of Voice: Managerial Affective States and Future Firm Performance.” *Journal of Finance* 67 (1): 1–43.

Merton, Robert C. 1987. “A Simple Model of Capital Market Equilibrium with Incomplete Information.” *Journal of Finance* 42 (3): 483–510.

Mitchell, Mark L., and Erik Stafford. 2000. “Managerial Decisions and Long-Term Stock Price Performance.” *Journal of Business* 73 (3): 287–329.

Newey, Whitney K., and Kenneth D. West. 1987. “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica* 55 (3): 703–8.

Palmon, Dan, Ke Xu, and Ari Yezegel. 2016. “What Does ‘but’ Really Mean? Evidence from Managers’ Answers to Analysts’ Questions during Conference Calls.” Working paper. Available at https://ssrn.com/abstract=2831809.

Price, S. McKay, James S. Doran, David R. Peterson, and Barbara A. Bliss. 2012. “Earnings Conference Calls and Stock Returns: The Incremental Informativeness of Textual Tone.” *Journal of Banking & Finance* 36 (4): 992–1011.

Solomon, David H., and Eugene Soltes. 2015. “What Are We Meeting For? The Consequences of Private Meetings with Investors.” *Journal of Law & Economics* 58 (2): 325–55.

Soltes, Eugene. 2014. “Private Interaction between Firm Management and Sell-Side Analysts.” *Journal of Accounting Research* 52 (1): 245–72.

Suslava, Kate. 2017. “‘Stiff Business Headwinds and Unchartered Economic Waters’: The Use of Euphemisms in Earnings Conference Calls.” Working paper. Available at https://ssrn.com/abstract=2876819.

Tetlock, Paul C. 2007. “Giving Content to Investor Sentiment: The Role of Media in the Stock Market.” *Journal of Finance* 62 (3): 1139–68.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy. 2008. “More than Words: Quantifying Language to Measure Firms’ Fundamentals.” *Journal of Finance* 63 (3): 1437–67.

Zhou, Dexin. 2018. “Do Numbers Speak Louder than Words?” Working paper. Available at https://ssrn.com/abstract=2898595.