It's not what you say, but how you say it – Managerial charisma and agitation in earnings conference calls

by

Wolfgang Breuer*, Andreas Knetsch** and Sami uddin***

November 15, 2021

Abstract

Using a machine learning-based software, we identify two patterns of managerial communication in the question-and-answer (Q&A) part of conference calls: Charismatic communication represents an effort of managers to convey a positive picture of the firm's situation. Agitated communication is a result of managers being stressed or tense. Our empirical evidence shows that market participants react favorably to charismatic rhetoric, even though it does not convey any useful information on the firm's economic information. In fact, charismatic communication prompts stronger stock market reactions than the actual content of the Q&A part. Moreover, we demonstrate that managers are more agitated when they present earnings figures that are more inflated by means of discretionary accruals.

Keywords: Textual Analysis; Managerial Rhetoric; Managerial Affective States; Stock Market Reactions; Earnings Management

*Wolfgang Breuer, RWTH Aachen University, Department of Finance
Templergraben 64, 52056 Aachen, Germany. Fon: +49 241 8093505, Fax: +49 241 8093539,
eMail: wolfgang.breuer@bfw.rwth-aachen.de.

**Andreas Knetsch, RWTH Aachen University, Department of Finance
Templergraben 64, 52056 Aachen, Germany. Fon: +49 241 8093505, Fax: +49 241 8092163,
eMail: andreas.knetsch@bfw.rwth-aachen.de.

***Sami uddin RWTH Aachen University, Department of Finance
Templergraben 64, 52056 Aachen, Germany. Fon: +49 241 8093505, Fax: +49 241 8092163,
eMail: samiuddinkhanbabar@bfw.rwth-aachen.de

We are very grateful for the support provided by Precire GmbH. We especially thank Anja Linnenbürger for helpful discussions and feedback.

1. Introduction

Textual analysis has become an integral method in finance and accounting. Firms' public disclosure documents have naturally provided the most recognized subject of study to answer numerous research questions by means of textual analysis. Among the most prominent issues are the questions of how stock markets react to firms' public disclosures (e.g., Henry, 2008; Huang et al., 2014a; Price et al., 2012) and the attempt to reveal fraudulent or deceptive managerial behavior (e.g., Burgoon et al., 2016; Larcker and Zakolyukina, 2012; Throckmorton et al., 2015). A common notion of studies investigating these and other issues has been that firms' public disclosure documents contain valuable qualitative information on the firm's situation that is not reflected in the disclosures' quantitative figures. However, more recent work has started to challenge this view. It interprets language in public disclosure documents as the result of rhetorical intentions of managers and their affective states.

Kearney and Liu (2014) review the literature on sentiment analysis – defined as the degree of positivity or negativity of texts. They highlight the common understanding that the sentiment in firms' public disclosures captures relevant qualitative information about the firm's situation (e.g., Henry, 2008). More recent work has however explored the possibility that managers use the sentiment in public disclosures to deceive market participants. Huang et al. (2014a) demonstrate in this vein, that the sentiment in earnings press releases does not contain valuable information about firms' prospects beyond that contained in financial figures. Instead, managers use the sentiment in earnings press releases to prompt market reactions in line with their ulterior motives.

Likewise, studies on the ability of texts to reveal deceptive managerial behavior have foremost focused on identifying words or phrases that are indicative of situations or circumstances in which deceptive behavior is more likely (e.g., Loughran and Mcdonald, 2011a, 2011b). More recently, researchers have analyzed patterns in managerial communication that indicate affective states or rhetorical attempts which relate to deceptive behavior (e.g., Mayew and Venkatachalam, 2012; Breuer et al., 2020).

Machine learning techniques have become a common tool in textual analysis of financial documents, their application has however been focused on quantifying the qualitative information about the firm's situation contained in texts. Machine learning techniques have been applied under this paradigm to both research questions in textual analysis mentioned above: predicting stock market reactions to public disclosures (e.g., Li, 2010; Barth et al., 2020) and detecting deceptive managerial behavior (e.g., Humpherys et al., 2011; Throckmorton et al., 2015).

Prior work has investigated different rhetorical facets of public disclosure language like complexity, extremity, metaphorical language, concreteness, tentativeness, and unscriptedness by relying on basic word count and manual coding (e.g., Guo et al., 2020; Bochkay et al., 2020; König et al., 2018; Pan et al., 2018; Graf-Vlachy et al., 2020; Lee, 2016). Only little work exists that utilizes machine learning techniques to quantify rhetorical features of managerial language (Barth et al., 2020). Our study adds to this emerging strand of research. We utilize machine learning to quantify linguistic characteristics, which are a result of rhetorical efforts or affective states of managers.

Numerous approaches for using machine learning techniques in textual analysis exist. One of the most popular relies on researchers training algorithms to classify texts as positive or negative based on their own evaluations of training data (e.g., Antweiler and Frank, 2004; Li, 2010). This approach has however been criticized for being opaque and not replicable (Loughran and Mcdonald, 2016). We use a commercially available pre-trained algorithm, called Precire, which evaluates how texts are perceived by laypeople along 22 dimensions. Our approach is thus fully replicable and effectively measures rhetorical characteristics rather than the informational content of texts.

We specifically study the question-and-answer (Q&A) section of conference calls, since we expect that affective states and rhetorical efforts of managers are especially relevant in these unscripted conversations. Using Common Factor Analysis, we converge the 22 dimensions of managerial communication resulting from the evaluation by Precire. We interpret the two most relevant factors yielded by this procedure as charismatic communication, defined as communication involving the rhetorical intent of the communicator aimed at influencing the perception of the target (Lewis, 1981), and agitated communication, which is characterized by the affective state of an individual being tense or stressed at the time of communication.

In line with our first hypothesis, we find that stock market participants are susceptible to charismatic communication. Our results show that the effect of managerial charisma on stock market reactions strongly outweighs that of the qualitative information conveyed in the Q&A section. This finding highlights the importance of managerial rhetoric. Moreover, we confirm that charismatic communication does not convey any valuable information on the firm's situation. Our findings thus also demonstrate that market participants are deceived by managerial rhetoric.

The second hypothesis argues that presenting deceptive information elicits feelings of fear, guilt, and stress in managers. Thus, they appear to be more agitated when they present earnings figures which are more inflated by means of accruals-based earnings management. This conjecture is also supported by our empirical results.

Overall, these findings highlight the relevance of the view that managerial language not only conveys information but also – if not foremost – is a rhetorical means of managers and depends on the manager’s affective state. We also demonstrate the potential of machine learning approaches to measure aspects of managerial rhetoric.

The remainder of this paper is organized as follows. Section 2 gives an overview of the relevant literature on textual analysis. Section 3 explains our sample selection, the measurement of rhetorical features by Precire, and how we identify the two patterns of “charismatic” and “agitated” communication. Section 4 develops our hypotheses. Section 5 explains the construction of our variables. Section 6 presents the empirical analyses. Finally, Section 7 concludes.

2. Literature Review

Various studies have established that tone in firms’ public disclosure documents can help predict future operating performance and triggers stock market reaction (e.g., Henry, 2008; Feldman et al., 2010; Loughran and Mcdonald, 2011; Price et al., 2012; Huang et al., 2014a; Li et al., 2019; Chen et al., 2018; Mayew et al., 2020; Bochkay et al., 2020).

However, other work also highlights that managers use this potential of tone to mislead market participants. Rogers et al. (2011) find that firms with a more optimistic tone face more lawsuits, hence depicting more perceived deception or misrepresentation. Huang et al. (2014a) establish a measure of abnormal positive tone which is found to be negatively related to future operating performance and positively related to earnings management. The authors establish that abnormal tone deceives investors and that managers use abnormal tone for strategic purposes.

Beyond the positivity of tone or sentiment, managers employ other features of text to influence investors’ perception. Barth et al. (2019) investigate managers providing more irrelevant or imprecise information in conference calls. This behavior is more pronounced when analysts ask tougher questions, reported earnings are inflated, or operating performance has been poor. According to Sinha (2016) market reactions depend more strongly on the structure of a press release than on its content. Graham et al. (2005) find that finance executives tend to strategically bundle bad news with other news. Similarly, Allee and Deangelis (2015) find that managers deliberately disperse positive and negative words within conference calls to trigger more favorable stock market reactions. Cicon (2017) investigates the cosine-similarity index of the two parts of conference calls. Higher similarity indicates less incremental informativeness of the Q&A section and prompts less favorable market reactions. Larcker and Zakolyukina (2012) find that deceptive executives refer more frequently to general knowledge, and less frequently to shareholder value. They use more extreme positive emotion words and fewer anxiety words. The authors also show that managerial deception in terms of accounting falsification is better predicted by their linguistics-based measures than many measures of discretionary accruals.

Moreover, other studies have investigated characteristics of managerial language like its complexity (Guo et al., 2020a), use of metaphors (König et al., 2018), concreteness of language (Pan et al., 2018), tentativeness of language and comparative language (Graf-Vlachy et al., 2020), as well as the degree of unscriptednes in language (Lee, 2016) in public disclosure documents.

Beyond investigating texts, one strand of literature studies the vocal and verbal features of communication indicating managerial deception. For instance, Burgoon et al. (2016), investigate vocalistic and linguistic features of conference calls and find that these features are important factors in the identification of deceptive utterances. They also observe that the identification of deceptive utterances is more pronounced in the unscripted part of conference calls (Q&A) as compared to the scripted part (presentation). Throckmorton et al. (2015) confirm that quantitative financial information along with non-verbal vocal acoustic and linguistic cues yield significantly better results for financial fraud detection. Mayew and Venkatachalam (2012) analyze the audio of conference calls and find that managerial affective states help predict the financial prospects of the firm. The authors use commercially available software, called “Layered Voice Analysis” for their analysis. Similarly, using LVA, Hobson et al. (2012) find that vocal markers of cognitive dissonance are positively related with different misreporting proxies.

Machine learning approaches have become increasingly popular in textual analysis. One approach that has recently gained much encouragement is pointed out by Loughran and McDonald (2020). It uses machine learning to generate dictionaries, which can be employed in bag of words analyses (e.g., Garcia et al., 2020; Ke et al., 2019). However, the most popular technique in machine learning still is the naïve Bayesian approach. Researchers manually classify texts or parts of the text. The algorithm is then trained, based on this training data, and applied to the out-of-sample data. For instance, Antweiler and Frank (2004) use this approach to categorize internet stock messages as bearish, bullish or neutral. Li (2010) identifies positive, negative, uncertain, and neutral sentences in 10-Q filings. And Huang et al. (2014b) classify analyst reports as positive, negative, or neutral. Sinha (2016) uses a commercially available pre-trained machine learning algorithm. The author applies the Thomson Reuters NewsScope Engine in order to estimate the probabilities of the tone being negative, positive, or neutral.

Machine learning techniques have also been applied in textual analysis to identify deceptive behavior by managers (e.g., Humpherys et al., 2011; Throckmorton et al., 2015). Few studies also investigate manager’s personality traits by applying machine learning to corporate disclosures. Hrazdil et al. (2020) investigate the big five personality traits, and Harrison et al. (2020) look among others at conscientiousness, neuroticism, extraversion. Moreover, Li et al. (2021) measure characteristics of corporate culture using machine learning techniques.

Despite the increasing popularity of machine learning approaches in textual analysis, only little work exists that applies them to quantifying the rhetorical features of managerial language. To the best of our knowledge, the only exception is Barth et al. (2019), who use a machine learning approach to classify manager answers in conference calls as evasive.

3. Analyzing Conference Call Transcripts with Precire

We analyze our sample of conference calls with the technology of Precire. Precire is a company that specializes in analyzing textual documents with machine learnings algorithms. Precire's technology is based on the naïve Bayes approach and it evaluates how communication is perceived along 22 dimensions. To this end, Precire has trained a neural net using more than 38 million text evaluations, where laypeople submitted their impression of speech transcripts. The result of this training process is an algorithm that utilizes over 4 billion words and 110 million parameters to evaluate a text along the 22 dimensions. We list these dimensions together with their definitions of how individuals perceive a speech or conversation in order to score high on this dimension in Appendix 1.

We believe that the technology of Precire is suited especially well to analyze the rhetorical features or presentational format rather than the content of conference calls for several reasons: Firstly, the speeches or conversations used by Precire to train the neural net pertain to a wide range of topics, none of which are finance-, business-, or economics-related. Thus, the technology is unlikely to capture the economically relevant information contained in conference calls and instead captures the sensation a layperson would have when reading the conference call transcript. The conference call of Activision Blizzard Inc. for the third quarter of 2018 is a good example of this. It was ranked in the top 1 % of the conference calls in our sample on the dimension "positive". The President and Chief Operating Officer of Activision Blizzard Inc. responds to a question on how the launch of the game "Black Ops 4" is performing as follows:

"[…] Well, we're confident and we're energized by the performance of Black Ops 4. The launch, as I said, is off to a strong start on both console and PC. […] And the Call of Duty team is doing what it knows how to do well, which is build deeply engaging experience. […] And we added Blackout, which is a deeply appealing mode […]."

The words “energized”, “engaging”, or “appealing” are not considered in the finance-specific dictionaries of Loughran and McDonald (2011) or Henry (2008) used commonly in textual analysis of public disclosures. They do however create the impression of a successful product launch.

Secondly, the technology is advantageous to non-finance-specific bag of words approaches like the Harvard General inquirer as it considers the syntax of sentences in its evaluation. This advantage also becomes apparent when looking at the phrase “doing what it knows to do well”. The meaning of this phrase is very hard to capture by a bag of words approach. It leaves the reader with the impression that the Call of Duty team at Activision Blizzard Inc. is highly competent. We hope that the software of Precire is able to account for such subtleties of language which are based on syntax, figures of speech, and literary devices. Prior studies that have analyzed such nuances of language have relied on manual investigations of the text. König et al. (2018), for example, manually investigate metaphorical communication in conference calls. They thus only investigate a small sample of texts. Moreover, manual classifications tend to suffer from researcher subjectivity.

Thirdly, since Precire has trained its algorithm based on speeches and conversations, it is suited especially well to analyze conference calls, which constitute an oral format consisting of a speech part and a conversation (Q&A) part.

Using commercially available machine learning-based algorithms does however suffer from the limitation prominently warned by Loughran and Mcdonald (2016): The researchers do not know which textual characteristics drive the results of the textual analysis. This objection is certainly true in our case. Regarding the conference call cited above, we do not know whether “energized”, “engaging”, “appealing”, or the phrase “doing what it knows to do well” were actually considered to leave a positive impression on the reader by the algorithm. However, the two main reasons as to why blind trust in the classification of an algorithm is dangerous do not apply to our study. For one, as Loughran and Mcdonald (2016) point out, machine learning approaches where algorithms are trained by researchers to classify texts based on a training set of disclosure documents could possibly base their evaluation of the document on unintended characteristics the researchers are not aware of, like indicators of the firm's industry or a certain period. In this case, the results of the classification would be driven by these indicators of specific circumstances rather than the content or tone of the document as claimed by the researchers. Even though we are not aware of the textual characteristics driving the classification of conference calls when using the technology provided by Precire, we are not at risk of classifying conference calls based on indicators of specific firm circumstances, since the Precire algorithm was not trained for financial documents. For another, machine learning approaches often suffer from not being replicable, when researchers train the classification algorithm themselves. The algorithm we rely on has been trained by a third party, its classification of our sample conference calls is thus beyond our influence and fully replicable.

3.1 Sample Construction

We begin our analysis by constructing a large sample of conference call transcripts. To this end, we download conference call transcripts from Refinitiv from 2005 onwards for all firms which were part of the Russell 3000 index at some time during this period. Prior to 2005, electronic transcripts of analyst calls were not widely available (Price et al., 2012). Moreover, call transcripts from Refinitiv prior to 2005 are structured heterogeneously so that an automated distinction between their sections and speakers is difficult or impossible. We manage to download 119,804 conference call transcripts this way. We then isolate the presentation section and the Q&A section which we further separate into analyst questions and manager answers. Since not all transcripts follow the same convention on tagging sections and speakers, we lose some transcripts. Next, we require that the managers' answers in the Q&A section have a minimum length of 500 words. By setting this rather high minimum text length, we want to make sure that the Precire software can capture all relevant aspects of rhetoric contained in a text's syntax, which it might miss for shorter texts. This leaves us with 92,166 conference call transcripts over the fiscal years 2005 to 2020.

The managerial answers from the Q&A section of the conference call transcript are then analyzed by Precire. The result of this analysis are scores for each of the 22 dimensions, which can potentially range from 0 to 1. We display descriptive statistics for all 22 dimensions in Table 1.

<Insert Table 1 here.>

What first stands out are the small standard deviations on many dimensions. Thus, conference calls are rather homogenous with respect to many linguistic characteristics. Given the professional format of conference calls, this is to be expected.

Table 2 reports correlations among the 22 dimensions in our sample. The high correlations observed between many dimensions suggest a large degree of commonality between them. Given the specific context of conference calls, this is also to be expected. It is, for example, hard to imagine that a manager's communication in a conference call is "positive" but at the same time not "optimistic". Accordingly, these two dimensions display the highest correlation among all dimensions (95.01 %).

<Insert Table 2 here.>

3.2. Factor Analysis

In the light of many Precire dimensions being highly correlated and likely capturing common characteristics of communication in the specific context of conference calls, we use Common Factor Analysis (setting the initial communality estimates equal to the squared multiple correlations among the variables) to reduce the number of variables to consider in our analysis and focus on their underlying common pattern of communication.

Table 3 presents the resulting Eigenvalues and the Total Variance Explained of each factor. What stands out is that the first factor explains more than half of the variance of all variables. The second factor explains 16.9 % of the variance, and the third and fourth factors explain 10.7 % and 6.8 %, respectively. We follow the convention to exclude factors with Eigenvalues below 1.

<Insert Table 3 here.>

Table 4 presents the rotated matrix of factor loadings. We choose Varimax as our method of rotation, which, as an orthogonal rotation method, assumes that the factors are not correlated. Our results remain however qualitatively identical, if we relax this assumption and instead choose the Promax rotation method with a power of 4. The factor loadings describe the relevance of each Precire dimension for the four resulting factors. By construction, each factor quantifies a distinct pattern of communication. The next section describes these patterns of communication. It also establishes hypotheses that link the two factors with the highest Eigenvalues to specific manager behavior and how it is perceived by stock market participants.

<Insert Table 4 here.>

4. Hypotheses development

4.1 Charismatic communication and stock market reactions

Impression management constitutes the regulation of information about one's self, some event, or object, primarily for others (Schlenker and Weigold, 1992). On a grand level, impression management is "the packaging of information in order to lead target audiences to desired conclusions" (Gardner & Avolio, 1998). Gardner and Avolio (1998) argue that leaders deploy impression management strategies to portray their image in such a way that they are perceived as charismatic by their followers. According to Shamir et al. (1994), charismatic individuals are highly expressive and influence, mobilize, and persuade others through the use of rhetoric. They communicate their ideology transparently with the use of slogans and labels, draw a bright picture, exemplify values, and their vision of the future. Thus, charismatic communication is primarily related to the way how information is presented rather than the content of the information itself.

In what follows, we argue in detail that the dimensions which load strongly onto the first factor derived from our factor analysis describe "charismatic" communication. Charismatic communication is generally characterized by the rhetorical intent of the communicator which involves the use of certain attributes aimed at influencing the perception of the target (Lewis, 1981).

The dimension that loads most strongly onto the first factor is "positive". It has a factor loading of about 0.94 for this factor and loadings below 0.21 for any other factor. Positive language is defined as communication which is perceived as creating "a pleasant atmosphere through a positive and cheerful charisma". Similarly, "motivating" has a factor loading of 0.919 and is defined as "to excite the audience with enthusiasm and activity". Charismatic leaders create a charming atmosphere through the use of rhetoric which is aimed at mobilizing respondents to take some action. Therefore, managers involved in charismatic communication will use more positive and motivating language, which enables them to influence more easily the perceptions of market participants.

"Optimistic" has the third-highest factor loading of 0.917. It is perceived as the attribute of communication that motivates receivers to "draw positive conclusions and talk about positive expectations". The language used by charismatic leaders is aimed to connect past and current activities with future goals, which stimulates followers' hopes and trust in the leader and ultimately inspires followers to take action (Seyranian & Bligh, 2008).

Amongst all features, vision or reference to a bright future is a core component of charisma (Awamleh and Gardner, 1999). "Visionary" communication involves "to talk about great plans and a promising future". Charismatic language is aimed at portraying a promising image of the future by focusing on vague goals with 'utopian outcomes' (Shamir et al., 1993). The "visionary" dimension in our case has a factor loading of 0.82. Fanelli et al. (2009) study "CEOs charismatic visions" in letters to shareholders by means of manual content analysis. They find that projection of charismatic visions by CEOs positively effects analyst recommendations.

"Supportive" loads nearly as strong onto the first factor as visionary does. This dimension is characterized by showing "interest in the well-being of others, to encourage and to help them". De Vries et al. (2010) suggest that charismatic communication is characterized by a non-aggressive and supportive style of communication with the use of persuasion and argumentation. Similarly, friendly is a relevant dimension for the first factor. Friendliness implies "to communicate benevolently, likable and warmheartedly". Charismatic leaders are also perceived to give due consideration to others, listen to them, and demonstrate empathetic behavior.

"Composed" communication means "to communicate with little nervousness and stress". Since relaxed, composed, and dominant styles are associated with charismatic communication (e.g. Holladay and Coombs, 1994), we anticipate that managers communicating charismatically express themselves more calmly and composedly.

In sum, charismatic communication on part of managers is perceived as positive, motivating, optimistic, visionary, supportive, self-confident, friendly, composed, impressive, and goal-oriented by perceivers. Charismatic leaders resort to the use of metaphorical language (Tur et al., 2021), imagery (Fiol et al., 1999), fantasies, and mysticism (Bass, 1985). Many of these characteristics rely on the use of idiomatic language and figures of speech. Figurative language adds to the sense-giving attempt as it enhances meaning in the sender's rhetoric; it also develops and drives the stakeholders' perceptions (Cornelissen and Werner, 2014). Similarly, metaphorical communication is used to operationalize sensory experiences and familiarity for a relatively better persuasion outcome (Mio, 1997). Subject to this potential of metaphorical communication, senders try to synchronize their goals with the receivers' responses mostly anticipating a favorable response to the message communicated (Antonakis et al., 2011).

We investigate how and why investors react to a charismatic communication style. As highlighted in the literature review, investors respond to the tone in firms' public disclosure documents. The common interpretation for these stock market reactions to public disclosure document language is that investors interpret it on an incremental basis and expect additional information in these documents which otherwise cannot be included in quantitative information (Henry, 2008) In line with this reasoning, the existing work on textual analysis in finance and accounting focusses on extracting the informational content from public disclosure documents and quantifies it as "tone". Loughran and Mcdonald (2011) or Henry (2008) have developed the most prominent finance-specific dictionaries that serve the purpose of capturing the informational content in finance-related documents. These wordlists outperform general-purpose dictionaries developed in the fields of psychology and sociology like the Harvard-IV in predicting market reactions (e.g., Loughran and Mcdonald, 2011).

We challenge the assumption that stock market reactions to the language in public disclosure documents are solely or overwhelmingly prompted by the qualitative information contained in this communication. We propose that market participants also react to the rhetorical means, specifically the extent of charismatic communication. Conference calls provide ample discretion for managers to engage in rhetoric and convince stakeholders that the firm is efficiently managed (e.g., (Merkl-Davies & Brennan, 2007; Pan et al., 2018). Overall, we conjecture that a more charismatic communication style by managers in conference calls elicits a more positive impression of the firm and thus leads to more favorable stock market reactions.

H1: The extent of charismatic communication is positively related to stock market reactions following conference calls.

Testing this hypothesis is also interesting because it looks at a potential limitation of investor rationality. We argue that charismatic communication is just a rhetorical element and void of any economically relevant information. Thus, investors reacting to charisma would demonstrate that they are deceived by rhetorical means. In order to establish that charismatic communication, as measured by our first factor, does not convey any economically meaningful information, we test its ability to predict future firm performance following Huang et al. (2014a) in Section 6.2.

4.2 Agitated communication and earnings management

The psychology literature has proposed several explanations about how individuals behave in situations, where they are trying to deceive others. For instance, Elaad (2003) suggests that people believe they are worse liars than they actually are. Vrij (2008) suggests that the reasons for this distorted self-perception lie in (i) the "illusion of self-transparency", according to which people needlessly assume that their thinking and mental states are visible to others (Gilovich et al., 1998), (ii) people thinking of themselves as being more ethical than others perceive them (Kaplar & Gordon, 2004) where this pattern is also endorsed by cognitive dissonance theory (Festinger, 1957), and (iii) people remembering serious lies more often than "white lies" (Elaad, 2003).

Thus, deceiving or projecting an impression requires a lot of mental resources leading to a significant level of cognitive load. This cognitive load is attributed to the challenge of presenting fabricated content without arising any suspicion (Vrij, 2000), fear of detection (Buller and Burgoon, 1996; Bell and DePaulo, 1996), fear of reputation or credibility infringement, and most importantly, deceivers trying to avoid those cues which are generally associated with deceivers (Vrij, 2000). That's why according to the leakage hypothesis of Ekman and Friesen (1969), deception on part of individuals is expected to result in feelings of fear, stress, and guilt which are depicted in physical or behavioral signs. These behavioral signs are embedded in linguistic communication. According to Pennebaker, (2011, P. 140) **"**Our emotions influence our thinking, which is reflected in the ways we use function words". These function words in the form of negative emotion words represent the emotional state of the individual (Zhou et al., 2004; Toma and Hancock, 2012). The verbal cues reveal deceivers to be more tense, less convincing, and less pleasant (DePaulo et al., 2003). This state of being tensed or stressed is generally termed as 'Agitated'.

According to the "Diagnostic and Statistical Manual of Mental Disorders", agitation is defined as "excessive motor activity associated with a feeling of inner tension". Similarly, the International Psychogeriatric Association (IPA) defines agitation as an "excessive motor activity", characterized by restlessness and repetitious mannerisms. In general terms, people who are perceived to be restless or as suffering from inner tension are generally described as "agitated" by others.

We argue that the factor with the second-highest Eigenvalue in our factor analysis converges different dimensions that represent some aspect of "agitated communication", where high values of the second factor represent low levels of agitation. The dimensions that display the largest factor loadings for this factor in Table 4 are "structured" and "formal" with a factor loading of 0.92 each. Structured communication is defined as communication that follows "a common theme and a logical structure”. DePaulo et al. (2003) conclude from their meta-analysis that deceptive statements are less logically and ambivalently structured as compared to truthful statements. Similarly, “formal” is defined as “to communicate rationally and fact-based”. Generally, more concrete and factual statements are associated with a high reliability of the presenter. Since concrete language reduces investors’ uncertainty and facilitates channelling the informational needs of the investor (Doest and Semin, 2005), less factual or less objective language is perceived to be associated with deception as it may lead to suspicion and uncertainty.

“Intellectual” has a factor loading of 0.88. It refers to a communication style “with thought-out precision and complexity”. High degrees of cognitive complexity may be attributed to high levels of intellectual and mental sophistication (Graf-Vlachy et al., 2020). However, due to the cognitive load caused by communicating deceptive information, deceivers’ performance may drastically decline, as their mental preoccupation with numerous challenges may hamper their ability to yield detailed and sophisticated responses (DePaulo et al., 2003). We thus expect managers involved in obfuscation to be unable to use complex language.

The fourth dimension for (non-) agitated communication is “reliable” and has a factor loading of 0.87. Reliable means “to make binding statements and take responsibility”. Reliable communication is characterized by owning and taking responsibility for the statement being presented. Less reliable statements can be identified through various underlying patterns. For instance, presenters depicting a behavior to seek forgiveness or demonstrating remorse in their communication, reflect less reliable information. Similarly, feelings of guilt or anxiety demonstrate distancing from the deceptive statement. Furthermore, deceivers are likely to communicate in more evasive ways (Zuckerman et al., 1981). Linguistically, distancing or evasive communication is conducted by using fewer self-references and more negations indicating less responsibility towards the deceptive statement (DePaulo et al., 2003; Hancock et al., 2008). Larcker and Zakolyukina, (2012) confirm this pattern for accounting information. They observe that deceptive statements contain fewer personal pronouns indicating fewer self-references, with more extreme positive emotion words.

“Authoritative” communication is perceived “to set the tone and take control”. Besides feelings of guilt and anxiety, deceivers are also keen to observe their respondents so that they can align their stories accordingly (Buller & Burgoon, 1996). Such mental preoccupation restrains the deceiver so that he/she behaves less controlling or authoritative. Therefore, more agitation on the part of managers leads to a less controlling or authoritative attitude in conference calls.

“Goal-oriented” and “impressive” have factor loadings of 0.69 and 0.59, respectively. “Goal-oriented” is defined as “to make clear and concise statements”. Deceptive individuals who do not have the opportunity to plan and rehearse lies are relatively bad at generating compelling narratives (Vrij, 2000). Therefore, there is always a greater likelihood that the deceptive statements may have internal contradictions which imply that deceptive managers are unable to communicate in a more focused and goal-oriented fashion. Therefore, managers are also unable to deploy impressive rhetoric.

A “self-confident” style of communication is defined as “to be in the spotlight and not to avoid confrontation”. Similarly, a more confident and assertive style is associated with the precision of the underlying information (Price and Stone, 2004). However, managers speak with less conviction when presenting deceptive information, as indicated by them referring to superficial information and avoiding references to themselves (Larcker and Zakolyukina, 2012). We, therefore, argue that managers involved in deception are less willing to face confrontation.

In sum, the prior empirical and theoretical evidence supports the notion that the second factor measures the extent of agitation in managerial communication, which could stem from deceptive behavior. Burgoon et al. (2016) state that in the case of high-stakes settings, like conference calls, where deception can be costly, negative emotions like guilt or fear of detection are more likely to emerge while presenting deceptive information. Given that people display verbal signs of fear, stress, and guilt when engaging in deceptive behavior, we overall expect that conference call participants will perceive managerial language as more agitated when they are presenting information that is meant to deceive investors.

In order to establish a link between the pattern of communication measured by the second factor and deceptive managerial behavior, we look at earnings inflation by means of discretionary accruals. We argue that managers fear that their manipulation of accounting figures will be exposed when they answer questions from analysts in conference calls. The Q&A part of conference calls serves as an ideal setting for investigating verbal cues of managers that reveal them as being agitated, since – contrary to other public disclosures – managers might be faced with critical questions on their accounting figures to which they must oftentimes react spontaneously without a prepared statement (Burgoon et al., 2016). Our second hypothesis thus argues that the feelings of stress and fear, experienced by managers presenting inflated earnings, lead to verbal cues that are perceived as managers being more agitated:

H2: Managers appear to be more agitated in the conference call when discretionary accruals are higher.

5. Financial data and bag of words-based text measures

We denote the extent of perceived charisma in the conference call of firm *i* in quarter *t*, as quantified by the first factor from our factor analysis, as $Charisma_{i,t}$. $Agitated_{i,t}$ represents the level of perceived agitation, which is quantified as the inverted value of the second factor ($Agitated_{i,t} = Max(Second\ Factor_{i,t}) + Min(Second\ Factor_{i,t}) – Second\ Factor_{i,t}$).

All our financial data comes from Refinitiv. We primarily measure stock market reactions as the cumulative abnormal return over an event window starting on the day of the conference call and ending one trading day after the conference call ($CAR(0,1)_{i,t}$). We calculate abnormal daily returns as

$$(1)\ AR_{i,d} = R_{i,d} - \alpha_i - \beta_{1,i} R_{m,d} - \beta_{2,i} R_{s,d} - \beta_{3,i} R_{v,d} - \beta_{4,i} R_{r,d} - \beta_{5,i} R_{c,d}$$

where $R_{i,d}$ denotes firm *i*'s excess stock return on day *d*, with *d* being zero for the conference call day itself. α_i, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$, $\beta_{4,i}$, $\beta_{5,i}$ are the coefficient estimates from a regression of the daily excess stock return of firm *i* on the five Fama-French factors, $R_{m,d}$, $R_{s,d}$, $R_{v,d}$, $R_{r,d}$, and $R_{c,d}$, provided on Kenneth French's website. We estimate this regression over a time window of 252 trading days starting on the trading day before the conference call.

We employ two alternative measures of how stock market participants react to conference calls. Firstly, we look at the change in analyst recommendations following the conference call (e.g., König et al., 2018). Analyst recommendations are quantified on a scale ranging from 1 to 5, where 1 represents a strong buy recommendation and 5 stands for a strong sell recommendation. We calculate the difference in the mean analyst recommendation between the trading day before the conference call and one trading day after the conference call and multiply it with minus one to arrive at $RC(0,1)_{i,t}$, so that positive values of $RC(0,1)_{i,t}$ correspond to improvements in the mean analyst recommendation. Secondly, we look at abnormal trading volumes over the same event window ($CAV(0,1)_{i,t}$) (e.g., Barber and Odean, 2008; Price et al., 2012). We calculate the abnormal trading volume at day *d* as the trading volume at that day divided by the mean trading volume over the (-252, -1) time window. $CAV(0,1)_{i,t}$ is then calculated as the sum of the abnormal trading volumes on the day of the conference call and the following trading day.

We rely on an established measure of discretionary accruals to quantify the degree to which firms' financial performance is inflated by means of earnings management. We calculate our primary measure of discretionary accruals ($DiscAcc_{i,t}$) with the help of the model developed by Kothari et al., (2005), which is a modified version of the Jones, (1991) model that accounts for the effect of firm performance on accruals. Total accruals in quarter *t* are the difference in current assets excluding cash and short-term investments between quarter *t* and *t–1* reduced by the difference in current liabilities excluding the current portion of long-term debt between the same quarter minus depreciation and amortization in quarter *t*. We then calculate $DiscAcc_{i,t}$ as the residuals from the following regression model, which we estimate separately for each industry-quarter, based on the Fama-French 12-industry classification, with at least 15 observations:

$$(2)\quad \frac{TotalAccruals_{i,t}}{TotalAssets_{i,t-1}} = \beta_1 \cdot \frac{1}{TotalAssets_{i,t-1}} + \beta_2 \cdot \frac{\Delta NetSales_{i,t}}{TotalAssets_{i,t-1}}$$

$$+\beta_3 \cdot \frac{PropPlanEquip_{i,t}}{TotalAssets_{i,t-1}} + \beta_4 \cdot \frac{NetIncome_{i,t-1}}{TotalAssets_{i,t-2}} + \varepsilon_{i,t}$$

We also estimate $DiscAcc_{i,t}$ based on the original Jones, (1991) model as well as the modified Jones model developed by Dechow et al., (1995) Our results for these approaches are reported in the appendix and remain qualitatively similar.

Similar to Price et al. (2012), the vast majority of the conference calls in our sample are held on the same day or one day after the earnings press release (99.65 %). The remaining 0.35 % took place 2 to 9 trading days after the earnings press release. Our set of control variables thus includes the earnings per share surprise from the earnings press release of the respective conference call ($EPSsurprise_{i,t}$). Following prior work, we calculate this metric as the difference between the actual earnings per share reported for quarter t+1 and the average estimate prior to the respective earnings announcement scaled by the stock price two trading days prior to the announcement (e.g., Easton and Zmijewski, 1989).

Our other control variables are also inspired by Price et al. (2012) or Huang et al. (2014a). We also account for the firm's unadjusted stock market performance ($PreBHR_{i,t}$) as well as its unadjusted stock return volatility (*PreVola*$_{i,t}$) prior to the conference call. Moreover, we also control for the firm's abnormal stock performance (*PreAlpha*$_{i,t}$) as well as the part of its stock return volatility that is not explained by market-wide volatility (*PreRMSE*$_{i,t}$).

We use return on assets as a measure of operating performance, which is calculated as the net income before taxes scaled by total assets in the same quarter (*ROA*$_{i,t}$). *ΔROA*$_{i,t}$ indicates the change in operating performance compared to quarter *t–1* and *StdROA*$_{i,t}$ is a measure of volatility in past operating performance. A dummy variable indicates if the firm has incurred a loss in quarter *t* (*Loss*$_{i,t}$). We also control for firm size (*Size*$_{i,t}$) and age (*Age*$_{i,t}$). In order to capture publicly available information on the firms' prospects, we include the market-to-book ratio (*MTB*$_{i,t}$) as a common proxy for growth opportunities and the one-quarter-ahead earnings per share forecast (*EPSforecast*$_{i,t}$).

Beyond controlling for the quantitative information publicly available at the time of the earnings conference call, we also account for the qualitative information contained in the earnings press release prior to the respective conference call (*PresLM*$_{i,t}$), as prior work has highlighted the relevance of earnings press release tone for stock market reactions (e.g., Davis et al., 2012; Henry, 2008). We follow Price et al. (2012) and use the tone from the presentation section of the conference call as a proxy for the tone in the earnings press release. This approach is based on the observation that managers primarily reiterate the relevant information from the press release in the presentation section (Kimbrough, 2005; Matsumoto et al., 2011). We measure *PresLM*$_{i,t}$ by counting the negative and positive words in the presentation section using the word lists developed by Loughran and Mcdonald (2011). This dictionary was specifically devised to capture the financially relevant information in firms' public disclosure documents and has been used extensively in the finance and accounting literature. Henry and Leone (2016) demonstrate that finance-specific dictionaries better predict stock market reactions to earnings press releases than general-purpose wordlists. Originally, the Loughran and McDonald (2011) dictionary was derived to analyze 10-K filings. We do however use its updated version from March 2019, which the authors modified to account the peculiarities of conference calls.

Prior work demonstrates that the effect of the qualitative information contained in the Q&A section of conference calls on stock market reactions is substantial (e.g., Price et al., 2012). In order to isolate the effect of managerial charismatic rhetoric from that of the financial qualitative information conveyed in the Q&A section, we also control for the informational content of this part of the conference call using the Loughran and Mcdonald, (2011) dictionary ($Q\&ALM_{i,t}$). Moreover, we measure the Q&A section tone based on the Harvard IV dictionary ($Q\&AHIV_{i,t}$). This wordlist was developed with the goal of content analysis research on textual data for social sciences.

To construct the three bag of words-based measures of tone, we first count the occurrences of words on the positive or negative wordlists of Loughran & Mcdonald (2011) and Harvard IV, respectively. Following prior work (e.g., Price et al., 2012; Henry and Leone, 2016), we construct all bag of words-based tone measures as the difference between (weighted) positive and (weighted) negative words in the respective conference call part divided by the sum of (weighted) positive and (weighted) negative words.

Finally, we also include the natural logarithm of the total word count in the Q&A section as a control variable ($ln(words_{i,t})$).

After dropping observations for which financial information is missing, our final sample consists of 71,735 conference call observations over the years 2005 to 2019 from 2,488 different firms. Table 5 details all variable definitions, Table 6 presents descriptive statistics on all variables employed in our statistical analyses, and Table 7 provides their univariate correlations.

<Insert Table 5, 6, and 7 here.>

What stands out from Table 7 is that $Charisma_{i,t}$, and all three bag of words approaches to measure positive tone are highly correlated. This suggests that more favorable information is conveyed with a more charismatic demeanor.

6. Empirical Results

6.1 Charismatic rhetoric and stock market reactions

Our first hypothesis conjectures that stock markets react positively to charismatic communication by managers in the Q&A section. We thus estimate the following regression model using OLS with standard errors clustered on the firm-level:

$$(3)\, CAR_{(0,1)} = \alpha + \beta_1 \cdot Charisma_{i,t} + Controls_{j,i,t} + \tau_t + \delta_n + \varepsilon_{i,t},$$

where *j* indicates our control variables, τ_t represents quarter- and δ_n industry dummies. Table 8 presents the results of estimating this regression, where we display standardized beta coefficients, which allow for a direct comparison of the magnitude of the coefficients and *t*-statistics (in parentheses).

<Insert Table 08 here.>

Column 1 of Table 8 does not include any bag of words-based measure of the conference call content or sentiment. We observe a positive and highly significant coefficient estimate on $Charisma_{i,t}$ in this specification.

In Column 2, we add $PresLM_{i,t}$ to capture the extent to which the informational content of the earnings press release influences stock returns around the conference call. The coefficient estimate on $PresLM_{i,t}$ is positive and highly significant. The positive effect of $Charisma_{i,t}$ to stock market reactions does however persist. Column 3 further adds $Q\&ALM_{i,t}$ to capture the economically relevant qualitative information contained in the Q&A part of the conference call. We also observe a positive coefficient estimate on $Q\&ALM_{i,t}$. However, the positive effect on

$Charisma_{i,t}$ still persists. These results firmly support our Hypothesis H1. They demonstrate that investors react more positively to a more charismatic communication style by managers in the Q&A section of conference calls. Stock market participants are thus not only sensitive to the information conveyed in these conversations, which we measure using conventional finance-specific wordlists, but also to the rhetoric with which this information is conveyed. In fact, the effect of $Charisma_{i,t}$ is only about 14 % smaller than that on $PresLM_{i,t}$ and about 24 % smaller than that on $EPSsurprise_{i,t}$. Thus, the extent of charisma in managerial communication plays only a marginally smaller role in determining stock market reactions around conference calls than the qualitative or quantitative information contained in the earnings press release, respectively. Regarding the qualitative information conveyed in the Q&A section, the effect of $Charisma_{i,t}$ is more than three times larger than that on $Q\&ALM_{i,t}$. Thus, managerial charisma is far more important in determining stock market reactions to conference calls than the actual information conveyed in the Q&A section. It suggests that investors are highly susceptible to managerial efforts of rhetoric in conference calls.

We are also interested in the extent to which other linguistic characteristics than the choice of vocabulary with a positive connotation are relevant in determining stock market reactions. To this end, Column 4 includes $Q\&AHIV_{i,t}$ to capture the extent of positive vocabulary used by managers and does not consider $Charisma_{i,t}$. Since we are controlling for the informational content in the conference call using $PresLM_{i,t}$ and $Q\&ALM_{i,t}$, this approach can be interpreted as investigating the effect of positive vocabulary that does not convey any economically relevant information. We observe a positive and significant coefficient estimate on $Q\&AHIV_{i,t}$. This effect is however much smaller in terms of magnitude and significance as compared to $PresLM_{i,t}$ or $Q\&ALM_{i,t}$. Moreover, the effect is only about one-fourth in magnitude of the effect of $Charisma_{i,t}$ in the otherwise identical model in Column 3. Thus, rhetoric based on positive non-informative vocabulary relates positively to stock market reactions; it does however prompt much weaker reactions than other rhetorical efforts that are perceived as charismatic.

In Column 5, we estimate Model (3) using both $Charisma_{i,t}$ and $Q\&AHIV_{i,t}$ as independent variables. The coefficient estimate on $Charisma_{i,t}$ remains virtually unchanged as compared to the same model without $Q\&AHIV_{i,t}$ in Column 3. $Q\&AHIV_{i,t}$ is however largely absorbed by $Q\&AHIV_{i,t}$ and does not display a significant influence on stock market reactions in this model. This confirms that the use of vocabulary with a positive connotation is an aspect of charismatic rhetoric. Our findings for $Q\&AHIV_{i,t}$ also demonstrate that positive vocabulary only plays a minor role in influencing stock market reactions by means of charismatic rhetoric. Other features of rhetoric which are successfully captured by the software of Precire, like syntax or the use of idioms, are also of major importance. Overall, our findings thus also highlight the potential of machine learning-based approaches to quantify these aspects of rhetoric.

We use changes in analyst reactions, measured as $RC(0,1)_{i,t}$, as an alternative measure of stock market reactions to charismatic rhetoric in Model 3. Financial analysts are important actors in financial markets, whose recommendations affect stock prices (e.g., Francis & Soffer, 1997). Moreover, analysts effectively increase the transparency of firms and the informational efficiency of stock prices (e.g., Frankel et al., 2006; Lang et al., 2004) We thus investigate whether these highly trained professionals are also susceptible to charismatic rhetoric in Table 9.

<Insert Table 9 here.>

The results for this alternative measure of how stock market participants react to charismatic rhetoric are in large parts qualitatively similar to those for $CAR(0,1)_{i,t}$. As conjectured by Hypothesis H1, we observe a positive correlation between $Charisma_{i,t,}$ and $RC(0,1)_{i,t}$. We even observe that the effect of $Charisma_{i,t}$ on $RC(0,1)_{i,t}$ is slightly more relevant, when compared to the other major determinants of stock market reactions. Its coefficient estimate is about 13 % larger than on $PresLM_{i,t}$ or $EPSsurprise_{i,t}$ and more than 3.5 times larger than that on $Q\&ALM_{i,t}$. As before for stock market reactions, we observe that managerial charisma is far more relevant than the actual information in the Q&A section.

What also stands out is that $Q\&ALM_{i,t}$ does not show a significant effect on $RC(0,1)_{i,t}$ after controlling for $Charisma_{i,t}$. Thus, in contrast to what we find for stock market reactions, the information contained in the Q&A section does not seem to affect the impression of analysts, but only managerial rhetoric.

Finally, we look at abnormal trading volumes as an alternative measure of analyst reactions, in order to confirm the effect of $Charisma_{i,t}$ on actual trading behavior. We change regression model 3 in that we replace $CAV(0,1)_{i,t}$ as the dependent variable and substitute all independent variables by their absolute values. The latter change is due to trading volumes increasing when stock market participants judge a firm's situation as extremely positive or extremely negative, likewise. The result of estimating this model are presented in Table 10.

<Insert Table 10 here.>

We observe a positive and significant coefficient estimate on $Charisma_{i,t}$ in all models. The effect is again meaningful in size. It is about 55 % as relevant as the information contained in the earnings press release ($PresLM_{i,t}$). These results also endorse Hypothesis H1. We do not observe significant coefficient estimates on either $Q\&ALM_{i,t}$ or $Q\&AHIV_{i,t}$. This is consistent with our prior observation that the qualitative information or the choice of words in the Q&A section is not as relevant in determining stock market reactions as $Charisma_{i,t}$ is.

6.2 Charismatic rhetoric and future firm performance

As we explain in Section 3, the positive reactions of stock market participants to charismatic rhetoric have two possible interpretations. For one, $Charisma_{i,t}$ could contain valuable information about the firm's situation, which are not reflected in any of our quantitative measures of the firm's current situation and its prospects nor in the measures of qualitative information based on the bag of words approach. For another, $Charisma_{i,t}$ could be free of any information and solely constitute an attempt of managers to sway investors.

To establish the informational value of $Charisma_{i,t}$, we follow Huang et al., (2014a) and argue that $Charisma_{i,t}$ would positively predict a firm's future performance, if it conveys actually relevant information on the firm's prospects. If we observe a negative correlation, managers use rhetoric to actively mask poor firm situations. And if $Charisma_{i,t}$ is uncorrelated with future performance, it does not convey economically relevant information and is solely a rhetorical tool to influence investor perception.

We regress $ROA_{i,t+4}$ as a measure of firms' future operating performance on $Charisma_{i,t}$. In line with Huang et al. (2014a), we choose the four quarter- or one-year-ahead performance, rather than a one-quarter-time window, since one quarter might be too short for the information conveyed in the conference call to become relevant. We use the same control variables as in Model (3), including industry- and year-dummies. Adding $DiscAcc_{i,t}$, we also control for the extent of earnings inflation in quarter *t*, as Huang et al. (2014a) do. The results of estimating this model are presented in Table 11. Including $DiscAcc_{i,t}$ results in losing a large part of the observations. We thus present a version of Table 11 without $DiscAcc_{i,t}$ in Appendix. Our conclusions regarding the informational value of $Charisma_{i,t}$ are supported in these specifications.

<Insert Table 11 here.>

As in Huang et al. (2014), $DiscAcc_{i,t}$ displays a negative and highly significant coefficient estimate in all models. We do not control for any other measure of conference call content or tone than $Charisma_{i,t}$ in Column 1. We stepwise add $PresLM_{i,t}$, $Q\&ALM_{i,t}$, and $Q\&AHIV_{i,t}$ as additional independent variables in Columns 2 to 4. This approach allows us to draw conclusions about whether qualitative information of specific parts of rhetoric convey information about the firm's future performance.

The coefficient estimates on $Charisma_{i,t}$ are negative but insignificant in Columns 1 to 4. These results do not support the notion that $Charisma_{i,t}$ truthfully conveys information about the firm's situation.

Interestingly, $Q\&AHIV_{i,t}$ relates negatively and significantly to future performance in Column 4. This result indicates that managers use words with a positive connotation when they try to disguise that the firm is in a poor situation. It is consistent with managers using words with a positive connotation to mask poor firm performance, as they do with qualitative financial information (Huang et al., 2014a). Even though we cannot confirm a similar use of charismatic rhetoric, our results overall rule out that $Charisma_{i,t}$ contains genuine information on the firm's situation.

This finding establishes that market participants are in fact deceived by the charismatic rhetoric of managers. Market participants thus react irrationally to this facet of managerial communication. Despite $Charisma_{i,t}$ measuring nothing but "cheap talk", investors have a more favorable perception of the firm, if its managers charm them with a positive charisma.

6.3 Charismatic rhetoric during the financial crisis

During the financial crisis of 2008-2009 trust in firms and the capital market plummeted (e.g., Lins et al., 2017). We conjecture that market participants were thus more sceptical towards the rhetorical efforts of managers and rather relied on concrete information during these years. To test this claim, Table 12 displays the results of a seemingly unrelated estimation of Model (3) with standard errors clustered at the firm level separately for the years before the financial crisis, 2008-2009, and the years subsequent to the crisis.

<Insert Table 12 here.>

Column 1 to 3 present pre-crisis, during crisis and post-crisis values respectively. The coefficient estimate on $Charisma_{i,t}$ is largest before the financial crisis. It is more than twice as large as during the financial crisis. Following the financial crisis, the effect of $Charisma_{i,t}$ nearly recovered to the pre-crisis level. Chi-square statistics of 6.05 and 4.42 confirm at confidence levels of 1.4 % and 3.6 %, respectively, that the effect of $Charisma_{i,t}$ was smaller during the crisis years than before or after. These results confirm our conjecture that managers are less effective at charming market participants in a distrusting environment.

Regarding economically relevant qualitative information, the coefficient estimate on $Q\&ALM_{i,t}$ is largest during the crisis years. It is about three or two times as large as in the pre- or post-crisis years. However, the effect of $Q\&ALM_{i,t}$ is only statistically significant different between the pre-crisis and crisis years (Chi-square = 3.38; p = 6.6 %). We are unable to confirm a difference in the way $Q\&ALM_{i,t}$ relates to $CAR_{i,t}$ between the crisis and post-crisis years (Chi-square = 2.28; p = 13.1 %). We thus only find week evidence of concrete economically relevant information being considered more important during the financial crisis.

6.4 Agitated rhetoric and earnings management

Hypothesis H2 argues that managers are perceived as being more agitated in conference calls when the earnings figures for the corresponding quarter are more heavily inflated by means of earnings management. We test this conjecture by regressing $DiscAcc_{i,t}$ on $Agitated_{i,t}$ and our familiar set of controls including industry- and year quarter-dummies, as presented in Table 13.

<Insert Table 13 here.>

The results of this estimation in Column 1 of Table 13 show that $DiscAcc_{i,t}$ relates positively and highly significantly to $Agitated_{i,t}$. We add $PresLM_{i,t}$, $Q\&ALM_{i,t}$, $Q\&AHIV_{i,t}$, as well as $Charisma_{i,t}$ as control variables in Column 2. The positive relationship between perceived agitation and earnings management persists. These results firmly endorse Hypothesis H2. The level of perceived agitation of managers in the conference call is an effective indicator of the extent to which managers have inflated the reported earnings by means of discretionary accruals. This finding also establishes the potential of machine learning-based approaches to capture managerial affective states by means of textual analysis.

It is also worth noting that managers are perceived to be more agitated when they engage in more charismatic rhetoric. This is consistent with our above observation which suggests that charisma is used by managers to mask poor firm performance. It is thus similar to discretionary accruals in that both are used to present a distortedly favorable picture of the firm's situation. Consistently, both means of perception seem to trigger an agitated emotional state of the manager.

Managers also seem to be less agitated, when they reveal more positive information in the Q&A section. Contrary to the use of purely rhetorical means, the information revealed by managers in public disclosure statements can be subject to litigation since it can be considered "material" (e.g., Rogers et al., 2011; Huang et al., 2005). We thus argue that managers are less likely to present misleading facts than to engage in rhetorical efforts with the aim of deceiving market participants. Consequently, we believe that the information presented in the Q&A section is mostly genuine and interpret the negative relationship between $Q\&ALM_{i,t}$ and $Agitated_{i,t}$ as being due to managers feeling less agitated when they can respond to analysts questions by presenting positive information.

7. Conclusion

This study uses the commercially available machine learning-based software "Precire" to quantify patterns in managerial rhetoric of the Q&A section of analyst conference calls. We identify two dimensions of communication: Charismatic communication is characterized by the rhetorical intent of the managers and agitated communication reflects the affective state of the manager in conference calls.

Charismatic communication involves the rhetorical intent of the communicator aimed at influencing the perception of the target (Lewis, 1981), and agitated communication, is characterized by the affective state of an individual being tense or stressed at the time of communication.

Our empirical results show that market participants – investors and analysts alike – attach greater value to firms when their managers communicate more charismatically. As we also demonstrate that charismatic communication does not contain economically relevant information on the firm's situation, our findings show that market participants are susceptible to purely rhetorical means, which constitute nothing but "cheap talk". The observed effect of charismatic communication on stock market reactions is substantially larger than that of the qualitative information contained in the Q&A section. This finding is remarkable. It highlights that form is more important than substance in the discussion section of conference calls when it comes to stock market reactions.

We also observe that managers appear to be more agitated, when they present earning figures that are more inflated by means of discretionary accruals. This result is in line with the psychology literature that argues that individuals perceive feelings or guilt, stress, and fear, when they engage in deceptive behavior and that these feelings affect their linguistic patterns.

Beyond demonstrating the importance of managerial rhetoric and investor irrationalities, our study highlights the potential of machine-learning based approaches to quantify characteristics of managerial communication that stem from rhetorical efforts or affective states. Even though textual analysis has been employed with this goal in the finance and accounting literature, machine learning approaches have been focused on extracting qualitative information rather than rhetorical patterns or managers’ emotions from firm’s public disclosure documents.

References

Allee, K. D., & Deangelis, M. D. (2015). The structure of voluntary disclosure narratives: Evience from tone dispersion. *Journal of Accounting and Research*, *53*(2), 241–274.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *Journal of Finance*, *59*(3), 1259–1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

Awamleh, R., & Gardner, W. L. (1999). Perceptions of leader charisma and effectiveness: The effects of vision content, delivery, and organizational performance. *Leadership Quarterly*, *10*(3), 345–373. https://doi.org/10.1016/s1048-9843(99)00022-3

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, *21*(2), 785–818. https://doi.org/10.1093/rfs/hhm079

Barth, A., Mansouri, S., & Woebbeking, F. (2020). "Let me get back to you" - A machine learning approach to measuring non-answers. *Ssrn*, 1–45. https://doi.org/10.2139/ssrn.3567724

Barth, A., Mansouri, S., Woebbeking, F., & Zörgiebel, S. (2019). How to Talk down Your Stock Returns. *SSRN Electronic Journal*, 1–30. https://doi.org/10.2139/ssrn.3336671

Bass, B. M. (1985). Leadership and performance beyond expectations. In *Collier Macmillan*. Collier Macmillan. https://doi.org/10.1242/dev.115.3.717

Bell, K. L., & DePaulo, B. M. (1996). Liking and lying. *Basic and Applied Social Psychology*, *18*(3), 243–266. https://doi.org/10.1207/s15324834basp1803_1

Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2021). Using machine learning to detect misstatements. *Review of Accounting Studies*, *26*(2), 468–519. https://doi.org/10.1007/s11142-020-09563-8

Bochkay, K., Hales, J., & Chava, S. (2020). Hyperbole or reality? Investor response to extreme language in earnings conference calls. *Accounting Review*, *95*(2), 31–60. https://doi.org/10.2308/accr-52507

Breuer, W., Knetsch, A., & Salzmann, A. J. (2020). What Does It Mean When Managers Talk About Trust? *Journal of Business Ethics*, *166*(3), 473–488. https://doi.org/10.1007/s10551-018-4072-2

Buller, D. B., & Burgoon, J. K. (1996). Interpersonal deception theory. *Communication Theory*, *6*(3), 203–242. https://doi.org/10.1111/j.1468-2885.1996.tb00127.x

Burgoon, J., Mayew, W. J., Giboney, J. S., Elkins, A. C., Moffitt, K., Dorn, B., Byrd, M., & Spitzley, L. (2016). Which Spoken Language Markers Identify Deception in High-Stakes Settings? Evidence From Earnings Conference Calls. *Journal of Language and Social Psychology*, *35*(2), 123–157. https://doi.org/10.1177/0261927X15586792

Chen, J. V, Nagar, V., & Schoenfeld, J. (2018). Manager-analyst conversations in earnings conference calls. *Review of Accounting Studies*, *23*(4), 1315–1354. https://doi.org/10.1007/s11142-018-9453-3

Cicon, J. (2017). Say it again Sam: the information content of corporate conference calls. *Review of Quantitative Finance and Accounting*, *48*(1), 57–81.

https://doi.org/10.1007/s11156-015-0542-0

Cornelissen, J. P., & Werner, M. D. (2014). Putting Framing in Perspective: A Review of Framing and Frame Analysis across the Management and Organizational Literature. *Academy of Management Annals*, *8*(1), 181–235. https://doi.org/10.1080/19416520.2014.875669

Davis, A. K., Piger, J. M., & Sedor, L. M. (2012). Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language. *Contemporary Accounting Research*. https://doi.org/10.1111/j.1911-3846.2011.01130.x

de Vries, R. E., Bakker-Pieper, A., & Oostenveld, W. (2010). Leadership = communication? The relations of leaders' communication styles with leadership styles, knowledge sharing and leadership outcomes. *Journal of Business and Psychology*, *25*(3), 367–380. https://doi.org/10.1007/s10869-009-9140-2

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting Earnings Management. *The Accounting Review*, *70*(2), 193–225.

DePaulo, B. M., Malone, B. E., Lindsay, J. J., Muhlenbruck, L., Charlton, K., & Cooper, H. (2003). Cues to deception. *Psychological Bulletin*, *129*(1), 74–118. https://doi.org/10.1037/0033-2909.129.1.74

Doest, L. Ter, & Semin, G. (2005). Retrieval contexts and the concreteness effect: Dissociations in memory for concrete and abstract words. *European Journal of Cognitive Psychology*, *17*(6), 859–881. https://doi.org/10.1080/09541440540000031

Easton, P. D., & Zmijewski, M. E. (1989). Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics*, *11*(2–3), 117–141. https://doi.org/10.1016/0165-4101(89)90003-7

Ekman, P., & Friesen, W. V. (1969). Nonverbal Leakage and Clues to Deception † . *Psychiatry*, *32*(1), 88–106. https://doi.org/10.1080/00332747.1969.11023575

Elaad, E. (2003). Effects of feedback on the overestimated capacity to detect lies and the underestimated ability to tell lies. *Applied Cognitive Psychology*, *17*(3), 349–363. https://doi.org/10.1002/acp.871

Fanelli, A., Misangyi, V. F., & Tosi, H. L. (2009). In charisma we trust: The effects of CEO charismatic visions on securities analysts. *Organization Science*, *20*(6), 1011–1033. https://doi.org/10.1287/orsc.1080.0407

Feldman, R., Govindaraj, S., Livnat, J., & Segal, B. (2010). Management's tone change, post earnings announcement drift and accruals. *Review of Accounting Studies*, *15*(4), 915–953. https://doi.org/10.1007/s11142-009-9111-x

Festinger, L. (1957). A theory of social cognitive dissonance. *Standorf University Press*, 203.

Fiol, C. M., Harris, D., & House, R. (1999). Charismatic Leadership: Strategies For Effecting Social Change. *Leadership Quarterly*, *10*(3), 449–482. https://doi.org/10.1007/978-3-7908-2158-1_5

Francis, J., & Soffer, L. (1997). The Relative Informativeness of Analysts' Stock Recommendations and Earnings Forecast Revisions. *Journal of Accounting Research*. https://doi.org/10.2307/2491360

Frankel, R., Kothari, S. P., & Weber, J. (2006). Determinants of the informativeness of analyst research. *Journal of Accounting and Economics*. https://doi.org/10.1016/j.jacceco.2005.10.004

Gardner, W. L., & Avolio, B. J. (1998). The charismatic relationship: A dramaturgical perspective. *Academy of Management Review*, *23*(1), 32–58. https://doi.org/10.5465/AMR.1998.192958

Gilovich, T., Savitsky, K., & Medvec, V. H. (1998). The Illusion of Transparency: Biased Assessments of Others' Ability to Read One's Emotional States. *Journal of Personality and Social Psychology*, *75*(2), 332–346. https://doi.org/10.1037/0022-3514.75.2.332

Graf-Vlachy, L., Bundy, J., & Hambrick, D. C. (2020). Effects of an advancing tenure on CEO cognitive complexity. *Organization Science*, *31*(4), 936–959. https://doi.org/10.1287/orsc.2019.1336

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1–3), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002

Guo, W., Sengul, M., & Yu, T. (2020). Rivals' negative earnings surprises, language signals, and firms' competitive actions. *Academy of Management Journal*, *63*(3), 637–659. https://doi.org/10.5465/amj.2018.0397

Hancock, J. T., Curry, L. E., Goorha, S., & Woodworth, M. (2008). On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. *Discourse Processes*, *45*(1), 1–23. https://doi.org/10.1080/01638530701739181

Harrison, J. S., Thurgood, G. R., Boivie, S., & Pfarrer, M. D. (2020). Perception is reality: How ceos' observed personality influences market perceptions of firm risk and shareholder returns. *Academy of Management Journal*, *63*(4), 1166–1195. https://doi.org/10.5465/AMJ.2018.0626

Henry, E. (2008). Are investors influenced by how earnings press releases are written? *Journal of Business Communication*, *45*(4), 363–407. https://doi.org/10.1177/0021943608319388

Henry, E., & Leone, J. A. (2016). Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone. *Accounting Review*, *91*(1), 153–178. https://doi.org/10.2308/accr-51161

Hobson, J. L., Mayew, W. J., & Venkatachalam, M. (2012). Analyzing Speech to Detect Financial Misreporting. *Journal of Accounting Research*, *50*(2), 349–392. https://doi.org/10.1111/j.1475-679X.2011.00433.x

Holladay, S. J., & Coombs, W. T. (1994). Speaking of visions and visions being soken: An exploration of the effects of content and delivery on perceptions of leader and charisma. *Management Communication Quarterly*, *8*(2), 165–189.

Hrazdil, K., Novak, J., Rogo, R., Wiedman, C., & Zhang, R. (2020). Measuring executive personality using machine-learning algorithms: A new approach and audit fee-based validation tests. *Journal of Business Finance and Accounting*, *47*(3–4), 519–544. https://doi.org/10.1111/jbfa.12406

Huang, A. H., Y.zang, A., & Zheng, R. (2014). Evidence on the information content of text in analyst reports. *Accounting Review*, *89*(6), 2151–2180. https://doi.org/10.2308/accr-50833

Huang, X., Teoh, S. H., & Zhang, Y. (2014). Tone management. *Accounting Review*, *89*(3), 1083–1113. https://doi.org/10.2308/accr-50684

Humpherys, S. L., Moffitt, K. C., Burns, M. B., Burgoon, J. K., & Felix, W. F. (2011). Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems*, *50*(3), 585–594. https://doi.org/10.1016/j.dss.2010.08.009

James. W.Pennebaker. (2011). The secret life of pronouns: what our words say about us. In *Blommsburry Press NewYork*.

Jones, J. J. (1991). Earnings Management During Import Relief Investigations. *Journal of Accounting Research*, *29*(2), 193. https://doi.org/10.2307/2491047

Kaplar, M. E., & Gordon, A. K. (2004). The enigma of altruistic lying: Perspective differences in what motivates and justifies lie telling within romantic relationships. *Personal Relationships*, *11*(4), 489–507. https://doi.org/10.1111/j.1475-6811.2004.00094.x

Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, *33*, 171–185.

Kimbrough, M. D. (2005). The Effect of Conference Calls on Analyst and Market Underreaction to Earnings Announcements. *THE ACCOUNTING REVIEW*, *80*(1), 189–219.

König, A., Mammen, J., Luger, J., Fehn, A., & Enders, A. (2018). Silver bullet or ricochet? Ceos' use of metaphorical communication and infomediaries' evaluations. *Academy of Management Journal*, *61*(4), 1196–1230. https://doi.org/10.5465/amj.2016.0626

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), 163–197. https://doi.org/10.1016/j.jacceco.2004.11.002

Lang, M. H., Lins, K. V., & Miller, D. P. (2004). Concentrated control, analyst following, and valuation: Do analysts matter most when investors are protected least? *Journal of Accounting Research*. https://doi.org/10.1111/j.1475-679X.2004.t01-1-00142.x

Larcker, D. F., & Zakolyukina, A. A. (2012). Detecting Deceptive Discussions in Conference Calls. *Journal of Accounting Research*, *50*(2), 495–540. https://doi.org/10.1111/j.1475-679X.2012.00450.x

Lee, J. (2016). Can investors detect managers' lack of spontaneity? Adherence to predetermined scripts during earnings conference calls. *Accounting Review*, *91*(1), 229–250. https://doi.org/10.2308/accr-51135

Lewis, T. V. (1981). Charismatic communication and faith healers: Critical study of rhetorical behavior. *Dissertation Abstracts International*, *41*(8-A), 3322. https://digitalcommons.lsu.edu/gradschool_disstheses%0Ahttp://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=psyc2&NEWS=N&AN=1982-50014-001

Li, F. (2010). The information content of forward- looking statements in corporate filings-A naïve bayesian machine learning approach. *Journal of Accounting Research*, *48*(5), 1049–1102. https://doi.org/10.1111/j.1475-679X.2010.00382.x

Li, K., Mai, F., Shen, R., & Yan, X. (2021). Measuring Corporate Culture Using Machine Learning. *The Review of Financial Studies*, *34*(7), 3265–3315.

https://doi.org/10.1093/rfs/hhaa079

Li, M., Wu, H., Xiao, M., & You, J. (2019). Beyond cheap talk: management's informative tone in corporate disclosures. *Accounting and Finance*, *59*(5), 2905–2959. https://doi.org/10.1111/acfi.12554

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. *Journal of Finance*. https://doi.org/10.1111/jofi.12505

Loughran, T., & Mcdonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Loughran, T., & Mcdonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, *54*(4), 1187–1230. https://doi.org/10.1111/1475-679X.12123

Loughran, T., & McDonald, B. (2011). Barron's red flags: Do they actually work? *Journal of Behavioral Finance*, *12*(2), 90–97. https://doi.org/10.1080/15427560.2011.575971

Matsumoto, D., Pronk, M., & Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *Accounting Review*, *86*(4), 1383–1414. https://doi.org/10.2308/accr-10034

Mayew, W. J., Sethuraman, M., & Venkatachalam, M. (2020). Individual analysts' stock recommendations, earnings forecasts, and the informativeness of conference call question and answer sessions. *Accounting Review*, *95*(6), 311–337. https://doi.org/10.2308/TAR-2017-0226

Mayew, W. J., & Venkatachalam, M. (2012). The power of voice: Managerial affective states and future firm performance. *Journal of Finance*, *67*(1), 1–43. https://doi.org/10.1111/j.1540-6261.2011.01705.x

Merkl-Davies, D. M., & Brennan, N. M. (2007). Discretionary Disclosure Strategies in Corporate Narratives: Incremental Information or Impression Management? *Journal of Accounting Literature*, *26*, 116-196. http://hdl.handle.net/10197/2907

Mio, J. S. (1997). Metaphor and Politics. *Metaphor and Symbol*, *12*(2), 113–133. https://doi.org/10.1207/s15327868ms1202_2

Pan, L., McNamara, G., Lee, J. J., Haleblian, J. (John), & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal*, *39*(8), 2204–2225. https://doi.org/10.1002/smj.2733

Price, P. C., & Stone, E. R. (2004). Intuitive Evaluation of Likelihood Judgment Producers: Evidence for a Confidence Heuristic. *Journal of Behavioral Decision Making*, *17*(1), 39–57. https://doi.org/10.1002/bdm.460

Price, S. M. K., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking and Finance*, *36*(4), 992–1011. https://doi.org/10.1016/j.jbankfin.2011.10.013

Rogers, J. L., Van Buskirk, A., & Zechman, S. L. C. (2011). Disclosure tone and shareholder litigation. *Accounting Review*, *86*(6), 2155–2183. https://doi.org/10.2308/accr-10137

Schlenker, B. R., & Weigold, M. F. (1992). Interpersonal processes involving impression regulation and management. *Annual Review of Psychology*, *43*(1), 133–168. https://doi.org/10.1146/annurev.ps.43.020192.001025

Seyranian, V., & Bligh, M. C. (2008). Presidential charismatic leadership: Exploring the rhetoric of social change. *Leadership Quarterly*, *19*(1), 54–76. https://doi.org/10.1016/j.leaqua.2007.12.005

Shamir, B., Arthur, M. B., & House, R. J. (1994). The rhetoric of charismatic leadership: A theoretical extension, a case study, and implications for research. *Leadership Quarterly*, *5*(l), 25–42. https://doi.org/10.1108/S1479-357120180000009016

Shamir, B., House, R. J., & Arthur, M. B. (1993). The motivational effects of charismatic leadership: A self-concept based theory. *Organization Science*, *9*(4), 557–594. https://doi.org/10.1108/S1479-357120180000009009

Sinha, N. R. (2016). Underreaction to News in the US Stock Market. *Quarterly Journal of Finance*, *6*(2). https://doi.org/10.1142/S2010139216500051

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, *62*(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x

Throckmorton, C. S., Mayew, W. J., Venkatachalam, M., & Collins, L. M. (2015). Financial fraud detection using vocal, linguistic and financial cues. *Decision Support Systems*, *74*, 78–87. https://doi.org/10.1016/j.dss.2015.04.006

Toma, C. L., & Hancock, J. T. (2012). What Lies Beneath: The Linguistic Traces of Deception in Online Dating Profiles. *Journal of Communication*, *62*(1), 78–97. https://doi.org/10.1111/j.1460-2466.2011.01619.x

Tur, B., Harstad, J., & Antonakis, J. (2021). Effect of Charismatic Signaling in Social Media Settings: Evidence from TED and Twitter. *The Leadership Quarterly, In Press*, 101476.

Vrij, A. (2000). *Detecting lies and deceit: the psychology of lying and the implications for professional practice*. Wiley. https://doi.org/10.1002/acp.743.abs

Vrij, A. (2008). Detecting Lies and Deceit Pitfall and Opportunities. In *John Wiley & Sons, Ltd* (Second).

Zhou, L., Burgoon, J. K., Nunamaker, J. F., & Twitchell, D. (2004). Automating Linguistics-Based Cues for detecting deception in text-based asynchronous computer-mediated communication. *Group Decision and Negotiation*, *13*(1), 81–106. https://doi.org/10.1023/B:GRUP.0000011944.62889.6f

Zuckerman, M., Depaulo, B. M., & Rosenthal, R. (1981). Verbal and nonverbal communication of deception. In *Advances in Experimental Social Psychology* (Vol. 14, Issue C). https://doi.org/10.1016/S0065-2601(08)60369-X

Table 1 – Descriptive statistics of Precire dimensions

Variable	Mean	Standard Deviation	Minimum	10 % Quantile	Median	90 % Quantile	Maximum
aggressive	0.51	0.01	0.44	0.49	0.51	0.52	0.60
authoritative	0.58	0.01	0.52	0.57	0.58	0.59	0.63
composed	0.55	0.01	0.49	0.53	0.55	0.56	0.63
dramatic	0.47	0.01	0.38	0.45	0.47	0.49	0.54
empathic	0.49	0.02	0.43	0.47	0.49	0.51	0.58
formal	0.64	0.01	0.57	0.62	0.64	0.65	0.71
friendly	0.54	0.01	0.46	0.52	0.54	0.55	0.61
goal_oriented	0.62	0.01	0.55	0.60	0.62	0.63	0.67
impressive	0.56	0.02	0.47	0.53	0.56	0.58	0.65
impulsive	0.50	0.01	0.43	0.49	0.50	0.52	0.61
independent	0.57	0.01	0.54	0.56	0.57	0.58	0.61
intellectual	0.55	0.02	0.46	0.53	0.55	0.58	0.65
motivating	0.54	0.02	0.46	0.51	0.54	0.57	0.65
optimistic	0.58	0.02	0.49	0.55	0.58	0.61	0.68
philosophical	0.53	0.01	0.45	0.51	0.53	0.54	0.59
positive	0.54	0.02	0.42	0.52	0.54	0.57	0.66
reliable	0.66	0.02	0.56	0.64	0.66	0.68	0.73
self_confident	0.48	0.01	0.43	0.46	0.48	0.49	0.55
structured	0.62	0.01	0.52	0.60	0.62	0.64	0.70
supportive	0.57	0.02	0.50	0.55	0.57	0.60	0.66
unconventional	0.50	0.02	0.43	0.48	0.50	0.52	0.60
visionary	0.56	0.03	0.45	0.53	0.56	0.59	0.68

This table presents descriptive statistics on the dimensions of communication identified by the Precire software before winsorizing. Refer to Appendix 1 for definitions of the dimensions.

Table 2 – Matrix of Correlations for Precire dimensions

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX	XXI	XXII
I	aggressive	1.00																					
II	authoritative	0.21	1.00																				
III	composed	-0.06	0.67	1.00																			
IV	dramatic	0.34	0.09	0.25	1.00																		
V	empathic	0.04	0.45	0.33	-0.16	1.00																	
VI	formal	-0.25	0.71	0.44	0.12	0.09	1.00																
VII	friendly	-0.34	0.33	0.50	-0.02	0.77	0.17	1.00															
VIII	goal_oriented	-0.27	0.74	0.85	0.03	0.29	0.69	0.46	1.00														
IX	impressive	0.26	0.76	0.75	0.49	0.43	0.57	0.46	0.62	1.00													
X	impulsive	0.89	0.02	-0.15	0.31	0.21	-0.46	-0.19	-0.41	0.14	1.00												
XI	independent	-0.19	-0.30	-0.25	-0.22	-0.28	-0.08	-0.30	-0.17	-0.30	-0.12	1.00											
XII	intellectual	0.09	0.85	0.57	0.33	0.30	0.87	0.28	0.65	0.84	-0.11	-0.29	1.00										
XIII	motivating	0.01	0.55	0.80	0.38	0.44	0.36	0.70	0.65	0.84	-0.05	-0.31	0.58	1.00									
XIV	optimistic	-0.16	0.53	0.74	0.29	0.39	0.47	0.72	0.70	0.76	-0.25	-0.28	0.60	0.96	1.00								
XV	philosophical	0.53	0.57	0.40	0.39	0.52	0.29	0.33	0.24	0.81	0.44	-0.39	0.67	0.60	0.48	1.00							
XVI	positive	-0.38	0.39	0.69	0.22	0.41	0.40	0.81	0.67	0.62	-0.40	-0.21	0.46	0.89	0.95	0.29	1.00						
XVII	reliable	-0.05	0.87	0.60	0.15	0.41	0.87	0.44	0.77	0.76	-0.21	-0.34	0.92	0.61	0.68	0.55	0.56	1.00					
XVIII	self_confident	-0.15	0.65	0.89	0.26	0.17	0.54	0.42	0.86	0.71	-0.32	-0.12	0.61	0.80	0.81	0.28	0.77	0.64	1.00				
XIX	structured	0.00	0.90	0.69	0.20	0.37	0.86	0.36	0.81	0.80	-0.17	-0.30	0.93	0.57	0.59	0.56	0.47	0.93	0.67	1.00			
XX	supportive	-0.17	0.59	0.65	0.06	0.69	0.41	0.86	0.66	0.68	-0.18	-0.31	0.56	0.87	0.91	0.51	0.89	0.69	0.67	0.57	1.00		
XXI	unconventional	0.60	0.48	0.34	0.52	0.22	0.25	0.09	0.09	0.75	0.46	-0.23	0.62	0.50	0.35	0.87	0.14	0.39	0.25	0.44	0.29	1.00	
XXII	visionary	-0.04	0.62	0.69	0.26	0.44	0.53	0.68	0.67	0.81	-0.14	-0.25	0.69	0.94	0.97	0.60	0.87	0.75	0.75	0.64	0.91	0.47	1.00

This table presents pairwise Pearson correlations for the dimensions of communication identified by Precire. All variables are winsorized one percent in each tail. Refer to Appendix 1 for definitions of the dimensions. * denotes significance at the 1 % level.

Table 3 – Factor Analysis

	Eigenvalue	Difference	Proportion	Cumulative
Factor1	11.6393	8.0826	0.5521	0.5521
Factor2	3.5567	1.2992	0.1687	0.7209
Factor3	2.2575	0.8071	0.1071	0.8279
Factor4	1.4505	0.6338	0.0688	0.8967
Factor5	0.8167	0.1697	0.0387	0.9355
Factor6	0.6470	0.2903	0.0307	0.9662
Factor7	0.3567	0.0814	0.0169	0.9831
Factor8	0.2754	0.1926	0.0131	0.9962
Factor9	0.0828	0.0372	0.0039	1.0001
Factor10	0.0456	0.0123	0.0022	1.0023
Factor11	0.0333	0.0169	0.0016	1.0038
Factor12	0.0164	0.0060	0.0008	1.0046
Factor13	0.0104	0.0115	0.0005	1.0051
Factor14	-0.0011	0.0008	-0.0001	1.0051
Factor15	-0.0019	0.0026	-0.0001	1.0050
Factor16	-0.0045	0.0041	-0.0002	1.0048
Factor17	-0.0086	0.0030	-0.0004	1.0043
Factor18	-0.0115	0.0024	-0.0005	1.0038
Factor19	-0.0139	0.0021	-0.0007	1.0031
Factor20	-0.0160	0.0042	-0.0008	1.0024
Factor21	-0.0202	0.0098	-0.0010	1.0014
Factor22	-0.0300	.	-0.0014	1.0000

This table presents the results of a Common Factor Analysis using the 22 dimensions of communication identified by Precire for 92,166 conference call transcripts. All dimensions are winsorized one percent in each tail. Refer to Appendix 1 for definitions of the dimensions.

Table 4 – Rotated factors loadings

Variable	Factor1	Factor2	Factor3	Factor4
aggressive	-0.2161	-0.0069	0.8953	-0.0424
authoritative	0.2537	0.8479	0.2210	0.2210
composed	0.7033	0.4786	0.0533	-0.0132
dramatic	0.3555	0.0533	0.5412	-0.4719
empathic	0.3021	0.1592	0.1821	0.8746
formal	0.1721	0.9150	-0.1746	-0.0845
friendly	0.7179	0.0617	-0.1149	0.6265
goal_oriented	0.5449	0.6930	-0.2467	0.0481
impressive	0.6096	0.5951	0.4747	0.0446
impulsive	-0.2117	-0.2413	0.8623	0.1403
independent	-0.2004	-0.1647	-0.2848	-0.2705
intellectual	0.3115	0.8870	0.2475	0.0211
motivating	0.9194	0.2791	0.2253	0.0992
optimistic	0.9177	0.3323	0.0309	0.0964
philosophical	0.3206	0.3927	0.7429	0.2620
positive	0.9388	0.2049	-0.1766	0.1444
reliable	0.3704	0.8693	0.0540	0.2025
self_confident	0.7437	0.5142	-0.0816	-0.1762
structured	0.3071	0.9158	0.1005	0.1096
supportive	0.7936	0.3250	0.0042	0.4721
unconventional	0.2384	0.3416	0.8034	-0.0508
visionary	0.8236	0.4232	0.1441	0.1618

This table presents the rotated factor loadings from a Common Factor Analysis for 92,166 conference call transcripts. The factors are rotated using the Varimax method. All dimensions are winsorized one percent in each tail. Refer to Appendix 1 for definitions of the dimensions.

Table- 5 Variables Definitions

Variable	Definition
$Charisma_{i,t}$	Measure of how charismatic the managerial communication in the Q&A section of the conference call is perceived. See Section 4.1 and 5 for details.
$Agitated_{i,t}$	Measure of how agitated the managerial communication in the Q&A section of the conference call is perceived. See Section 4.2 and 5 for details.
$CAR(0,1)_{i,t}$	Cumulative abnormal return over an event window starting on the day of the conference call and ending on the next trading day. See Section 5 for details.
$RC(0,1)_{i,t}$	Difference in the mean analyst recommendation between the trading day before the conference call and two trading days after the conference call, where the recommendation scale from 1 to 5 is inverted.
$CAV(0,1)_{i,t}$	Cumulative abnormal trading volume over an event window starting on the day of the conference call and ending on the next trading day. See Section 5 for details.
$DiscAcc_{i,t}$	Discretionary accruals in quarter t based on the model by Kothari et al. (2005). See Section 5 for details.
$EPSsurprise_{i,t}$	(Actual earnings per share for quarter *t* – last average earnings per share estimate prior to the respective earnings announcement) / stock price two days before the earnings announcement
$PreBHR_{i,t}$	Buy-and-hold return over the 60 trading days before the conference calls of quarter *t*.
$PreVola_{i,t}$	Standard deviation of the daily stock return returns over a time window ranging from 11 to 100 trading days before the conference call of quarter *t* (see Price et al. 2012).
$PreAlpha_{i,t}$	The intercept from regression model (3). See Section 5 for details.
$PreRMSE_{i,t}$	The root-mean-square error from regression model (3). See Section 5 for details.
$ROA_{i,t}$	Net income before taxes of quarter *t* / Total assets reported for quarter *t*
$\Delta ROA_{i,t}$	(Net income before taxes of quarter *t* – Net income before taxes of quarter *t-1*) / Total assets reported for quarter *t-1*
$StdROA_{i,t}$	Standard deviation of $ROA_{i,t}$ over quarters *t* to *t-4*, requiring that at least three quarters of ROA are available over this period.
$Loss_{i,t}$	Dummy variable which equals one if the net income before taxes of quarter t is negative
$Size_{i,t}$	Natural logarithm of the market value of all common stocks at the end of quarter *t*.
$Age_{i,t}$	Natural logarithm of (1 + (Date of Foundation – End of quarter *t* date) / 365)
$MTB_{i,t}$	(Market value of all common stocks at the end of quarter *t* + Interest bearing debt reported for quarter *t*) / Total assets reported for quarter *t*
$EPSforecast_{i,t}$	Mean earnings per share forecast for quarter *t+1* at the earnings press release date of quarter t / stock price on the day of the earnings press release of quarter *t*
$PresLM_{i,t}$	(Number of positive words – number of negative words) / (number of positive words + number of negative words) in the presentation part of the conference call corresponding to quarter t based on the Loughran and McDonald (2011) dictionary. See Section 5 for details.
$Q\&ALM_{i,t}$	(Number of positive words – number of negative words) / (number of positive words + number of negative words) in the Q&A part of the conference call corresponding to quarter *t* based on the Loughran and McDonald (2011) dictionary. See Section 5 for details.
$Q\&AHIV_{i,t}$	(number of positive words – number of negative words) / (number of positive words + number of negative words) in the Q&A part of the conference call corresponding to quarter *t* based on the Harvard IV dictionary. See Section 5 for details.
$ln(words_{i,t})$	Natural logarithm of the total number of words contained in the Q&A part of the conference call corresponding to quarter *t*

This table provides definitions of all variables employed in our regression analyses.

Table 6 – Descriptive Statistics

Variable	N	Mean	Standard Deviation	Minimum	10 % Quantile	Median	90 % Quantile	Maximum
$Charisma_{i,t}$	71,483	-0.02	0.99	-3.22	-1.28	-0.06	1.30	3.45
$Agitated_{i,t}$	71,483	0.08	0.99	-3.85	-1.18	0.05	1.39	4.02
$CAR(0,1)_{i,t}$	71,414	0.00	0.08	-1.09	-0.09	0.00	0.09	1.49
$RC(0,1)_{i,t}$	71,306	0.00	0.11	-2.00	-0.05	0.00	0.01	2.00
$CAV(0,1)_{i,t}$	70,322	4.59	3.83	0.00	1.81	3.74	8.09	254.99
$DiscAcc_{i,t}$	34,102	0.00	0.03	-0.19	-0.03	0.00	0.03	0.19
$EPSsurprise_{i,t}$	71,483	-0.07	44.77	-8,647.87	0.00	0.00	0.01	6,400.92
$PreBHR_{i,t}$	71,483	0.03	0.20	-0.92	-0.17	0.03	0.22	8.01
$PreVola_{i,t}$	71,483	0.02	0.02	0.00	0.01	0.02	0.04	0.35
$PreAlpha_{i,t}$	71,483	0.00	0.00	-0.01	0.00	0.00	0.00	0.24
$PreRMSE_{i,t}$	71,483	0.02	0.03	0.00	0.01	0.02	0.03	5.11
$ROA_{i,t}$	71,483	0.01	0.06	-3.74	-0.03	0.01	0.05	2.05
$\Delta ROA_{i,t}$	71,483	0.00	0.05	-2.17	-0.02	0.00	0.02	2.66
$StdROA_{i,t}$	71,483	0.02	0.04	0.00	0.00	0.01	0.04	1.77
$Loss_{i,t}$	71,483	0.23	0.42	0.00	0.00	0.00	1.00	1.00
$Size_{i,t}$	71,483	21.36	1.67	14.70	19.31	21.28	23.56	27.70
$Age_{i,t}$	71,483	2.90	0.89	-5.21	1.79	2.93	4.00	5.12
$MTB_{i,t}$	71,483	1.73	1.76	0.02	0.48	1.23	3.45	81.19
$EPSforecast_{i,t}$	71,483	-6.72	314.30	-24,889.38	-0.01	0.01	0.03	269.52
$PresLM_{i,t}$	71,483	0.29	0.26	-1.00	-0.05	0.31	0.60	1.00
$Q\&ALM_{i,t}$	71,483	0.35	0.27	-1.00	-0.02	0.38	0.68	1.00
$Q\&AHIV_{i,t}$	71,483	0.40	0.12	-0.38	0.25	0.40	0.56	0.96
$ln(words_{i,t})$	71,483	7.82	0.52	6.21	7.07	7.90	8.42	9.62

This table presents descriptive statistics on all variables employed in our tabulated analyses before winsorizing. For variable definitions, refer to Table 5.

Table 7 – Matrix of Correlations

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX	XXI	XXII	XXIII
I	*$Charisma_{i,t}$*	1																						
II	*$Agitated_{i,t}$*	-0.01*	1																					
III	*$CAR(0,1)_{i,t}$*	0.1*	0.03*	1																				
IV	*$RC(0,1)_{i,t}$*	0.04*	0.01	0.23*	1																			
V	*$CAV(0,1)_{i,t}$*	0.11*	0	0.06*	-0.02*	1																		
VI	*$DiscAcc_{i,t}$*	-0.03*	0.03*	-0.07*	-0.01	-0.01	1																	
VII	*$EPSsurprise_{i,t}$*	0.03*	0	0.13*	0.04*	0.05*	0.04*	1																
VIII	*$PreBHR_{i,t}$*	0.08*	0.01*	-0.02*	-0.01*	0.22*	0	0.05*	1															
IX	*$PreVola_{i,t}$*	-0.08*	0	0	-0.01	-0.07*	0	-0.11*	-0.04*	1														
X	*$PreAlpha_{i,t}$*	0.07*	0.04*	-0.04*	0.02*	0.23*	0.01	0.05*	0.39*	0.04*	1													
XI	*$PreRMSE_{i,t}$*	-0.02*	-0.01	-0.01	0	-0.01	0	-0.1*	0.01*	0.85*	0.1*	1												
XII	*$ROA_{i,t}$*	0	0.05*	0.09*	0.02*	0.14*	0.03*	0.17*	0.05*	-0.37*	0.11*	-0.42*	1											
XIII	*$\Delta ROA_{i,t}$*	0.02*	0.01	0.09*	0.02*	0.02*	0.04*	0.12*	0.03*	0.01*	0.01*	0.03*	0.28*	1										
XIV	*$StdROA_{i,t}$*	0.04*	-0.03*	-0.02*	0	-0.02*	-0.01	-0.05*	0	0.32*	0	0.38*	-0.33*	0.06*	1									
XV	*$Loss_{i,t}$*	0.04*	-0.05*	-0.1*	-0.01*	-0.07*	-0.04*	-0.15*	-0.04*	0.39*	-0.08*	0.45*	-0.64*	-0.14*	0.28*	1								
XVI	*$Size_{i,t}$*	0.07*	-0.09*	-0.01	0.01*	0.01*	-0.01	0.07*	0.03*	-0.47*	0.05*	-0.56*	0.32*	-0.01*	-0.2*	-0.31*	1							
XVII	*$Age_{i,t}$*	-0.02*	-0.01	0	0.01	-0.01*	0.01	0.02*	0	-0.16*	-0.03*	-0.21*	0.12*	0	-0.07*	-0.14*	0.18*	1						
XVIII	*$MTB_{i,t}$*	0.2*	-0.04*	-0.02*	-0.01	0.18*	-0.01	0.01	0.09*	0.05*	0.24*	0.11*	0	0	0.16*	0.09*	0.12*	-0.07*	1					
XIX	*$EPSforecast_{i,t}$*	-0.02*	0.03*	0.03*	0.01	0.07*	0	0.16*	0.06*	-0.27*	0.09*	-0.31*	0.37*	0	-0.19*	-0.27*	0.21*	0.05*	-0.05*	1				
XX	*$PresLM_{i,t}$*	0.44*	0	0.12*	0.04*	0.14*	0.01	0.08*	0.1*	-0.2*	0.13*	-0.15*	0.16*	0.04*	-0.05*	-0.15*	0.15*	-0.01*	0.19*	0.05*	1			
XXI	*$Q\&ALM_{i,t}$*	0.64*	-0.03*	0.1*	0.03*	0.09*	-0.01*	0.06*	0.09*	-0.13*	0.06*	-0.08*	0.05*	0.02*	-0.01*	-0.03*	0.08*	-0.01	0.13*	0.02*	0.46*	1		
XXII	*$Q\&AHIV_{i,t}$*	0.44*	-0.02*	0.06*	0.02*	0.03*	-0.03*	0.01*	0.04*	0	0.05*	0.05*	-0.03*	0.02*	0.05*	0.05*	-0.05*	-0.05*	0.14*	-0.03*	0.22*	0.41*	1	
XXIII	*$ln(words_{i,t})$*	0.01*	-0.01	-0.01*	-0.01	0.09*	0	0.02*	-0.01	-0.14*	-0.01*	-0.19*	0.14*	-0.01	-0.09*	-0.12*	0.44*	0.05*	0.07*	0.1*	0.08*	0.02*	-0.14*	1

This table presents pairwise Pearson correlations for the variables employed in our tabulated analyses. All variables are winsorized one percent in each tail. For variable definitions, refer to Table 5. * denotes significance at the 1 % level.

Table 8 – The effect of charismatic communication on stock returns

	(1) $CAR(0,1)_{i,t}$	(2) $CAR(0,1)_{i,t}$	(3) $CAR(0,1)_{i,t}$	(4) $CAR(0,1)_{i,t}$	(5) $CAR(0,1)_{i,t}$
$Charisma_{i,t}$	0.136***	0.101***	0.085***		0.084***
	(27.397)	(19.621)	(14.355)		(13.741)
$PresLM_{i,t}$		0.100***	0.094***	0.105***	0.094***
		(19.454)	(18.212)	(20.354)	(18.207)
$Q\&ALM_{i,t}$			0.028***	0.064***	0.027***
			(5.392)	(13.265)	(5.035)
$Q\&AHIV_{i,t}$				0.021***	0.005
				(4.683)	(1.167)
$EPSsurprise_{i,t}$	0.116***	0.113***	0.113***	0.113***	0.113***
	(15.542)	(15.402)	(15.362)	(15.291)	(15.363)
$PreBHR_{i,t}$	-0.018***	-0.020***	-0.021***	-0.020***	-0.021***
	(-3.272)	(-3.673)	(-3.785)	(-3.693)	(-3.782)
$PreVola_{i,t}$	0.048***	0.055***	0.056***	0.054***	0.056***
	(4.297)	(4.921)	(4.965)	(4.814)	(4.960)
$PreAlpha_{i,t}$	-0.064***	-0.073***	-0.073***	-0.072***	-0.073***
	(-11.440)	(-12.976)	(-13.018)	(-12.838)	(-13.007)
$PreRMSE_{i,t}$	0.007	0.007	0.008	0.010	0.008
	(0.599)	(0.607)	(0.662)	(0.813)	(0.643)
$ROA_{i,t}$	0.054***	0.051***	0.052***	0.051***	0.051***
	(6.777)	(6.441)	(6.466)	(6.414)	(6.459)
$\Delta ROA_{i,t}$	0.046***	0.046***	0.046***	0.046***	0.045***
	(6.008)	(6.038)	(6.031)	(6.052)	(6.024)
$StdROA_{i,t}$	-0.003	-0.002	-0.001	-0.000	-0.001
	(-0.437)	(-0.275)	(-0.226)	(-0.083)	(-0.230)
$Loss_{i,t}$	-0.080***	-0.068***	-0.068***	-0.064***	-0.068***
	(-13.135)	(-11.243)	(-11.175)	(-10.636)	(-11.177)
$Size_{i,t}$	-0.024***	-0.025***	-0.025***	-0.021***	-0.025***
	(-4.200)	(-4.213)	(-4.126)	(-3.621)	(-4.131)
$Age_{i,t}$	-0.005	-0.002	-0.003	-0.004	-0.003
	(-1.209)	(-0.539)	(-0.557)	(-0.809)	(-0.564)
$MTB_{i,t}$	-0.012**	-0.015**	-0.015**	-0.013**	-0.015**
	(-2.059)	(-2.472)	(-2.428)	(-2.268)	(-2.461)
$EPSforecast_{i,t}$	-0.001	0.001	0.001	-0.000	0.001
	(-0.234)	(0.149)	(0.162)	(-0.014)	(0.150)
$ln(words_{i,t})$	-0.014***	-0.018***	-0.018***	-0.017***	-0.017***
	(-3.091)	(-3.907)	(-3.934)	(-3.724)	(-3.760)
Observations	71,414	71,414	71,414	71,414	71,414
R-squared	0.052	0.059	0.060	0.056	0.060

This table presents the results of an OLS regression evaluating the effect of charismatic managerial communication in conference calls on short-term stock returns. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standardized beta coefficients and t-statistics clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Table 9 – The effect of charismatic communication on analyst recommendations

	(1) $RC(0,1)_{i,t}$	(2) $RC(0,1)_{i,t}$	(3) $RC(0,1)_{i,t}$	(4) $RC(0,1)_{i,t}$	(5) $RC(0,1)_{i,t}$
$Charisma_{i,t}$	0.048***	0.039***	0.034***		0.033***
	(10.622)	(8.120)	(6.007)		(5.666)
$PresLM_{i,t}$		0.026***	0.024***	0.028***	0.024***
		(5.596)	(5.051)	(5.997)	(5.043)
$Q\&ALM_{i,t}$			0.010*	0.023***	0.009
			(1.699)	(4.620)	(1.533)
$Q\&AHIV_{i,t}$				0.010**	0.004
				(2.248)	(0.842)
$EPSsurprise_{i,t}$	0.033***	0.032***	0.032***	0.032***	0.032***
	(6.012)	(5.883)	(5.855)	(5.834)	(5.858)
$PreBHR_{i,t}$	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***
	(-5.199)	(-5.299)	(-5.339)	(-5.312)	(-5.340)
$PreVola_{i,t}$	-0.004	-0.002	-0.002	-0.003	-0.002
	(-0.396)	(-0.226)	(-0.210)	(-0.267)	(-0.213)
$PreAlpha_{i,t}$	0.028***	0.025***	0.025***	0.026***	0.025***
	(5.535)	(5.036)	(5.026)	(5.152)	(5.034)
$PreRMSE_{i,t}$	0.026**	0.026**	0.026**	0.027**	0.026**
	(2.248)	(2.246)	(2.267)	(2.316)	(2.250)
$ROA_{i,t}$	0.021***	0.020***	0.021***	0.020***	0.021***
	(3.182)	(3.063)	(3.078)	(3.061)	(3.075)
$\Delta ROA_{i,t}$	0.012***	0.012***	0.012***	0.012***	0.012***
	(3.152)	(3.133)	(3.131)	(3.197)	(3.125)
$StdROA_{i,t}$	0.002	0.002	0.002	0.003	0.002
	(0.528)	(0.591)	(0.616)	(0.697)	(0.611)
$Loss_{i,t}$	0.004	0.007	0.007	0.009	0.007
	(0.705)	(1.216)	(1.245)	(1.473)	(1.243)
$Size_{i,t}$	0.016***	0.016***	0.016***	0.017***	0.016***
	(3.095)	(3.019)	(3.058)	(3.341)	(3.053)
$Age_{i,t}$	0.007*	0.008**	0.008**	0.008*	0.008**
	(1.848)	(2.020)	(2.013)	(1.924)	(2.006)
$MTB_{i,t}$	-0.017***	-0.018***	-0.018***	-0.017***	-0.018***
	(-3.711)	(-3.832)	(-3.816)	(-3.767)	(-3.833)
$EPSforecast_{i,t}$	-0.003	-0.002	-0.002	-0.003	-0.002
	(-0.553)	(-0.430)	(-0.424)	(-0.510)	(-0.433)
$ln(words_{i,t})$	-0.010**	-0.011**	-0.011**	-0.011**	-0.011**
	(-2.112)	(-2.316)	(-2.329)	(-2.186)	(-2.197)
Observations	71,306	71,306	71,306	71,306	71,306
R-squared	0.009	0.010	0.010	0.009	0.010

This table presents the results of an OLS regression evaluating the effect of charismatic managerial communication in conference calls on changes in analyst recommendations. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standardized beta coefficients and t-statistics clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Table 10 – The effect of charismatic communication on trading volumes

	(1) *CAV(0,1)i,t*	(2) *CAV(0,1)i,t*	(3) *CAV(0,1)i,t*	(4) *CAV(0,1)i,t*	(5) *CAV(0,1)i,t*
$Abs(Charisma_{i,t})$	0.027***	0.027***	0.026***		0.026***
	(5.877)	(5.706)	(5.623)		(5.632)
$Abs(PresLM_{i,t})$		0.052***	0.051***	0.050***	0.051***
		(9.412)	(9.088)	(8.948)	(9.086)
$Abs(Q\&ALM_{i,t})$			0.005	0.009*	0.006
			(1.037)	(1.864)	(1.195)
$Abs(Q\&AHIV_{i,t})$				-0.002	-0.003
				(-0.458)	(-0.524)
$Abs(EPSsurprise_{i,t})$	-0.011	-0.010	-0.010	-0.010	-0.010
	(-1.355)	(-1.259)	(-1.265)	(-1.246)	(-1.266)
$Abs(PreBHR_{i,t})$	0.134***	0.134***	0.134***	0.134***	0.134***
	(24.625)	(24.701)	(24.711)	(24.666)	(24.712)
$Abs(PreVola_{i,t})$	-0.103***	-0.099***	-0.098***	-0.096***	-0.098***
	(-9.705)	(-9.352)	(-9.337)	(-9.153)	(-9.339)
$Abs(PreAlpha_{i,t})$	0.121***	0.120***	0.120***	0.121***	0.120***
	(18.529)	(18.516)	(18.512)	(18.547)	(18.513)
$Abs(PreRMSE_{i,t})$	-0.000	-0.003	-0.003	-0.003	-0.003
	(-0.015)	(-0.202)	(-0.207)	(-0.235)	(-0.198)
$Abs(ROA_{i,t})$	-0.080***	-0.079***	-0.079***	-0.080***	-0.079***
	(-10.350)	(-10.407)	(-10.391)	(-10.444)	(-10.391)
$Abs(\Delta ROA_{i,t})$	0.057***	0.057***	0.057***	0.057***	0.057***
	(8.998)	(9.142)	(9.135)	(9.169)	(9.136)
$Abs(StdROA_{i,t})$	-0.032***	-0.031***	-0.031***	-0.031***	-0.031***
	(-4.211)	(-4.110)	(-4.112)	(-4.148)	(-4.112)
$Abs(Loss_{i,t})$	-0.076***	-0.070***	-0.070***	-0.069***	-0.070***
	(-12.085)	(-11.238)	(-11.240)	(-11.030)	(-11.236)
$Abs(Size_{i,t})$	-0.065***	-0.069***	-0.069***	-0.067***	-0.069***
	(-7.480)	(-7.870)	(-7.880)	(-7.640)	(-7.878)
$Abs(Age_{i,t})$	-0.029***	-0.028***	-0.028***	-0.028***	-0.028***
	(-4.365)	(-4.219)	(-4.217)	(-4.250)	(-4.219)
$Abs(MTB_{i,t})$	0.170***	0.165***	0.165***	0.166***	0.165***
	(18.065)	(17.764)	(17.760)	(17.766)	(17.754)
$Abs(EPSforecast_{i,t})$	-0.039***	-0.040***	-0.040***	-0.040***	-0.040***
	(-4.523)	(-4.786)	(-4.801)	(-4.734)	(-4.793)
$Abs(ln(words_{i,t}))$	0.086***	0.084***	0.085***	0.082***	0.085***
	(14.870)	(14.716)	(14.841)	(14.356)	(14.721)
Observations	70,322	70,322	70,322	70,322	70,322
R-squared	0.172	0.174	0.174	0.173	0.174

This table presents the results of an OLS regression evaluating the effect of charismatic managerial communication in conference calls on short-term trading volume. All independent variables are included absolute values. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standardized beta coefficients and t-statistics clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Table 11 – The relationship between charismatic communication and future operating performance

	(1) $ROA_{i,t+4}$	(2) $ROA_{i,t+4}$	(3) $ROA_{i,t+4}$	(4) $ROA_{i,t+4}$
$Charisma_{i,t}$	-0.004	-0.004	-0.005	-0.002
	(-0.628)	(-0.617)	(-0.605)	(-0.206)
$PresLM_{i,t}$		0.000	-0.000	-0.000
		(0.006)	(-0.033)	(-0.010)
$Q\&ALM_{i,t}$			0.001	0.004
			(0.174)	(0.529)
$Q\&AHIV_{i,t}$				-0.011*
				(-1.830)
$Discacc_{i,t}$	-0.034***	-0.034***	-0.034***	-0.034***
	(-5.455)	(-5.454)	(-5.452)	(-5.466)
$EPSsurprise_{i,t}$	0.002	0.002	0.002	0.002
	(0.137)	(0.137)	(0.136)	(0.145)
$PreBHR_{i,t}$	0.037***	0.037***	0.037***	0.037***
	(5.303)	(5.301)	(5.301)	(5.297)
$PreVola_{i,t}$	0.013	0.013	0.013	0.013
	(0.863)	(0.863)	(0.865)	(0.856)
$PreAlpha_{i,t}$	0.036***	0.036***	0.036***	0.036***
	(4.609)	(4.554)	(4.550)	(4.550)
$PreRMSE_{i,t}$	-0.116***	-0.116***	-0.116***	-0.116***
	(-7.143)	(-7.142)	(-7.138)	(-7.137)
$ROA_{i,t}$	0.555***	0.555***	0.555***	0.555***
	(21.658)	(21.640)	(21.639)	(21.660)
$\Delta ROA_{i,t}$	-0.116***	-0.116***	-0.116***	-0.116***
	(-5.933)	(-5.934)	(-5.934)	(-5.920)
$StdROA_{i,t}$	0.032	0.032	0.032	0.032
	(1.386)	(1.386)	(1.386)	(1.388)
$Loss_{i,t}$	-0.023**	-0.023**	-0.023**	-0.023**
	(-2.335)	(-2.350)	(-2.350)	(-2.365)
$Size_{i,t}$	0.056***	0.056***	0.056***	0.056***
	(5.226)	(5.226)	(5.232)	(5.214)
$Age_{i,t}$	0.023***	0.023***	0.023***	0.023***
	(3.411)	(3.409)	(3.409)	(3.435)
$MTB_{i,t}$	0.054***	0.054***	0.054***	0.054***
	(3.965)	(3.966)	(3.967)	(4.008)
$EPSforecast_{i,t}$	0.066***	0.066***	0.066***	0.066***
	(4.541)	(4.541)	(4.541)	(4.575)
$ln(words_{i,t})$	-0.011*	-0.011*	-0.011*	-0.013*
	(-1.721)	(-1.720)	(-1.721)	(-1.961)
Observations	27,693	27,693	27,693	27,693
R-squared	0.482	0.482	0.482	0.482

This table presents the results of an OLS regression evaluating the relationship between charismatic managerial communication in conference calls and the firm's future operating performance. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standardized beta coefficients and t-statistics clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Table 12 – The effect of charismatic communication on stock returns before, during and, after financial crisis.

	(1) $CAR(0,1)_{i,t}$	(2) $CAR(0,1)_{i,t}$	(3) $CAR(0,1)_{i,t}$
$Charisma_{i,t}$	0.008***	0.003**	0.007***
	(0.001)	(0.002)	(0.001)
$PresLM_{i,t}$	0.026***	0.032***	0.028***
	(0.004)	(0.005)	(0.002)
$Q\&ALM_{i,t}$	0.005	0.017***	0.008***
	(0.004)	(0.005)	(0.002)
$Q\&AHIV_{i,t}$	0.006	-0.009	0.004
	(0.008)	(0.010)	(0.003)
$EPSsurprise_{i,t}$	0.179***	0.237***	0.288***
	(0.027)	(0.029)	(0.021)
$PreBHR_{i,t}$	-0.020***	-0.016***	-0.005*
	(0.007)	(0.006)	(0.003)
$PreVola_{i,t}$	0.496**	0.394***	0.202**
	(0.215)	(0.117)	(0.083)
$PreAlpha_{i,t}$	-4.706***	-6.677***	-3.882***
	(0.950)	(0.864)	(0.385)
$PreRMSE_{i,t}$	-0.249	0.281*	0.081
	(0.266)	(0.165)	(0.096)
$ROA_{i,t}$	0.143***	0.111***	0.076***
	(0.040)	(0.036)	(0.016)
$\Delta ROA_{i,t}$	0.066	0.067***	0.067***
	(0.042)	(0.021)	(0.014)
$StdROA_{i,t}$	0.023	0.024	-0.010
	(0.028)	(0.028)	(0.016)
$Loss_{i,t}$	-0.004	-0.013***	-0.014***
	(0.003)	(0.003)	(0.001)
$Size_{i,t}$	0.000	0.001*	-0.002***
	(0.001)	(0.001)	(0.000)
$Age_{i,t}$	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)
$MTB_{i,t}$	-0.002***	-0.003***	-0.000
	(0.001)	(0.001)	(0.000)
$EPSforecast_{i,t}$	-0.001	-0.003	0.000
	(0.006)	(0.006)	(0.003)
$ln(words_{i,t})$	-0.004**	-0.004*	-0.002***
	(0.002)	(0.002)	(0.001)
Observations	8,511	8,312	54,591
R-squared	0.063	0.074	0.061

This table presents the results of a seemingly unrelated estimation evaluating how the effect of charismatic managerial communication in conference calls on short-term stock returns differ between pre-crisis, crisis, and post-crisis years. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standard errors clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Table 13 – The relationship between agitated communication and earnings management

	(1) *Agitatedi,t*	(2) *Agitatedi,t*
$Discacc_{i,t}$	0.016***	0.016***
	(2.946)	(2.958)
$Charisma_{i,t}$		0.053***
		(2.871)
$PresLM_{i,t}$		-0.033**
		(-2.510)
$Q\&ALM_{i,t}$		0.010
		(0.703)
$Q\&AHIV_{i,t}$		-0.014
		(-1.148)
$EPSsurprise_{i,t}$	-0.007	-0.007
	(-0.907)	(-0.857)
$PreBHR_{i,t}$	-0.000	-0.001
	(-0.076)	(-0.125)
$PreVola_{i,t}$	-0.011	-0.009
	(-0.697)	(-0.577)
$PreAlpha_{i,t}$	0.052***	0.050
	(6.310)	(5.971)
$PreRMSE_{i,t}$	-0.066***	-0.067
	(-3.062)	(-3.138)
$ROA_{i,t}$	0.047***	0.047***
	(2.714)	(2.693)
$\Delta ROA_{i,t}$	-0.009	-0.009
	(-1.326)	(-1.360)
$StdROA_{i,t}$	0.008	0.007
	(0.625)	(0.608)
$Loss_{i,t}$	-0.020	-0.021
	(-1.555)	(-1.572)
$Size_{i,t}$	-0.219***	-0.223
	(-8.803)	(-8.972)
$Age_{i,t}$	0.020	0.021
	(1.057)	(1.090)
$MTB_{i,t}$	0.013	0.011
	(0.787)	(0.685)
$EPSforecast_{i,t}$	-0.002	0.000
	(-0.107)	(0.020)
$ln(words_{i,t})$	0.037**	0.035
	(2.347)	(2.295)
Observations	34,102	34,102
R-squared	0.082	0.084

This table presents the results of an OLS regression evaluating the relationship between of agitated managerial communication in conference calls and earnings management. Table 5 provides details on the variable definitions. All variables are winsorized one percent in each tail. Each regression includes industry fixed-effects based on the Fama-French 48-classification and quarter fixed-effects. We present standardized beta coefficients and t-statistics clustered on the firm-level in parentheses. ***, ** and * denote statistical significance at the (two-sided) 1 %, 5 % and 10 % level, respectively.

Appendix 1

Dimension	Definition	Perceived understanding
empathic	The empathic communication style conveys a high sensitivity for the feelings of other people. The communication is cautious, focuses on feelings and tries to understand other people's perspectives. It deals directly with the statements of others and reacts sensitively to their feelings. Empathic communication focuses intensively on feelings and conditions of others.	Empathic = To focus on other people and their feelings.
friendly	The friendly communication style expresses social closeness to others and is perceived as sympathetic and warm-hearted. It conveys a general feeling of goodwill and a willingness to compromise. People who communicate friendly, appear likeable, benevolent and warm-hearted.	Friendly = To communicate benevolently, likeable and warmheartedly
supportive	The supportive communication style involves encouraging others and helping them to develop further. The focus is not on the own well-being but on others. Those who communicate supportively encourage others and convey a great willingness to help. Appreciation for others is shown. Supportive communication requires willingness to help and a serious interest in the well-being of others.	Supportive = To show interest in the well-being of others, to encourage - and to help them
positive	The positive communication style describes a positive and cheerful charisma that causes a pleasant mood. Positive communication creates a pleasant atmosphere through a positive and cheerful charisma.	Positive = To create a pleasant atmosphere through a positive
optimistic	The optimistic communicative style conveys confidence. The result is a positive view of the future that draws positive conclusions even from negative experiences and expresses that anything is possible. The confident attitude also means that risks are assessed more positively and are more likely to be taken. Optimistic communication is confident, draws positive conclusions and talks about positive expectations.	Optimistic = To communicate confidently regarding past and future.
visionary	People with a visionary communication style often refer to a glorious future and make promising statements. It is often a question of how more can be achieved and what potential improvements look like. Visions are communicated that indicate positive expectations and a promising future. People communicate visionary by expressing their great strategies and a promising future.	Visionary = To talk about great plans and a promising future.
formal	The formal communicative style presents facts as objectively as possible. It often consists of numbers, data and facts, resulting in a rational, fact-oriented and down-to-earth effect. Formal communication is always rational and fact-based.	Formal = To communicate rationally and fact-based.

structured	In the structured communication style, the individual statements of a narrative build on each other. Communication follows a logical structure and has a common thread. This creates an organized effect. A common theme and a logical structure are signs of the structured communication style.	Structured = To follow a common theme and a logic structure.
goal-oriented	Clear and unambiguous statements are made in the goal-oriented communication style. The communication is as efficient and concise as possible with the aim of finding a pragmatic solution. Goal-oriented communication requires clear, concise statements.	Goal-oriented = To make clear and concise statements.
reliable	People who choose the reliable communication style convey a sense of commitment. It is clearly stated for what responsibility is taken and the interlocutor knows that the statements of the other person will still be equally valid the next day. Those who make binding statements and assume responsibility appear as reliable.	Reliable = To make binding statements and take responsibility.
intellectual	The intellectual communication style creates a well thought-out and deliberate effect. Its structure is precise and rather complex. Contents are described in detail. All in all, a high standard of performance is imparted. Intellectual communication is characterized by thought-out precision and high complexity.	Intellectual = To communicate with thought-out precision and complexity.
unconventional	Unconventional communication means adding unusual, imaginative ideas to conversations, opening up innovative or unusual perspectives and making generally surprising statements. Communication is unconventional due to innovative and surprising elements.	Unconventional = To make statements with surprising and innovative elements.
philosophical	Philosophical communicators talk about the theoretical background of their statements. They discuss philosophical and significant topics in depth. Significant and in-depth discussions let communication appear philosophical.	Philosophical = To discuss philosophical and significant topics in depth.
impulsive	The impulsive style of communication is impatient, stormy or unsteady. Often a sudden impulse or intuition is the trigger for communication rather than thinking about the consequences of one's own statements and reflecting them. This quickly gives rise to heated discussions. Communication has an implusive effect if it is stormy and heated, but consequences are not taken into full account.	Impulsive = To communicate stormy and heated without thinking about consequnces.
aggressive	The aggressive communication style is about quick-tempered, relentless communication that puts pressure on others and provokes the interlocutor or the person addressed. This often	Aggressive = To provoke rather than give in while discussing.

	provokes discussions. Aggressively communicating people are relentless and like to trigger discussions.	
authoritative	The authoritarian communication style determines the direction and the tone of a conversation. Authoritarian communication means to set the tone and to take control of a conversation.	Authoritative = To set the tone and take control.
self-confident	Self-confident communicators tend to place themselves at the centre of communication. They rarely hold back, seem unreserved and do not get easily discouraged. They don't shy away from confrontation either. People who communicate self-confidently, like to be in the spotlight and do not shy away from confrontation.	Self-confident = To be in the spotlight and not to avoid confrontation.
composed	Composed communication relaxes conversational situations rather than causing nervousness and excitement. Even in stressful situations, people are still able to express themselves appropriately. People who communicate composed seldom seem nervous and stressed, so that they can still choose their words well even in difficult situations.	Composed = To communicate with little nervousness and stress.
dramatic	Dramatic communication means to exaggerate, to embellish stories and to present events more interesting and exciting than they really were. Dramatic communication means the exaggerated embellishment of narratives.	Dramatic = To exaggerate and embellish stories.
motivating	The motivating communication style conveys enthusiasm and activity. This effect makes it easier to carry away and inspire listeners. Conversations or texts are more likely to be experienced as exciting. Motivating communication means to carry listeners away with enthusiasm and activity.	Motivating = To excite the audience with enthusiasm and activity.
impressive	The impressive communication style is captivating and leaves a lasting impression on other people. Impressing communication means to captivate and inspire listeners.	Impressive = To communicate captivatingly and leave a lasting impression.
independent	Independent communication means to make statements independent of common opinions and other people. Those who communicate independently do not ensure the acceptance of their statements from others. They do not allow themselves to be influenced in what they say by the predominant opinion or the supposed judgments of others. Independent communication means not to be influenced by others, but to emphasize one's point, even if it meets little approval.	Independent = To communicate independently from others, even if it meets little approval.