Decision Support Systems And Unfiltered Information: Evidence From Conference Calls

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Numerous financial decision support systems have been proposed in the literature that analyze corporate disclosures or financial news. However, these sources of corporate information are likely to be filtered before being published, either by investor relations departments or journalists. This bears the risk that the language is adapted to bias a decision support systems’ evaluations. Thus, unfiltered verbal communication should be a useful input for financial decision support systems since it is harder to manipulate. Using a sample of 200 earnings conference calls of German DAX firms, we analyze the relation of linguistic aspects of verbal management communication and the capital market reactions during the conference call. The results suggest that language aspects in the form of both sentiment and certainty assessments expressed by management influence the consequent capital market reaction. Our results show that unfiltered information released during conference calls is informative to the market and should therefore be considered as an input in decision support systems. As a consequence, these systems may profit from an increased robustness against impression management and from the possibility to react faster to new corporate information.

Keywords: Financial Decision Support Systems, Unfiltered Information, Corporate Communication, Earnings Conference Calls.
1 Introduction

Accounting numbers, textual corporate disclosures and related financial news have been used as input for information systems supporting investment decisions (Schumaker and Chen, 2009), going concern predictions (Martens et al., 2008) or fraud detection (Glancy and Yadav, 2011). All these sources are subject to an editing process before the corresponding information is published. Investor relations departments ensure that a clean language is used and a positive light is shed on the company (Fiol, 1995). In addition, newspaper articles are mostly edited and proof-read before they are distributed (Ihator, 2001). Thus, most of the information released by companies is filtered before it is published.

Previous financial decision support systems focus on these sources of filtered information which bears the risk that recommendations based on these systems are biased: once the main drivers of the system get known, investor relations departments may avoid or, in contrast, use certain words that are important for a system’s classification decisions (Goodman et al., 2007; Biggio et al., 2011). Focusing on unfiltered communication, e.g. verbal communication between managers on the one hand and security analysts or journalists on the other hand may improve existing solutions by reducing the risk of manipulations since verbal communication occurs more spontaneously (Chafe and Tannen, 1987; Chalfonte et al., 1991). This study analyzes whether unfiltered information released by companies is informative to market participants and therefore a useful input to financial decision support systems.

One source of unfiltered communication that might be appropriate within financial decision support systems are earnings conference calls which are held several hours after corporations release their earnings. During these calls, corporate representatives, i.e. the chief-executive officer (CEO), the chief-financial officer (CFO) or members of the investor relations department present details on the corporate performance in a formal presentation. Afterwards, participants are given the opportunity to ask questions to corporate representatives (Frankel et al., 1999). Previous research has shown that these conference calls are informative both for analysts and investors. This is evidenced in changes of analyst evaluations after conference calls (Bowen et al., 2002) and intra-day capital market reactions, indicating that investors make use of the information provided during the call (Frankel et al., 1999). Thereby, investors seem to value the discussion session more than the presentation session (Matsumoto et al., 2011).

Financial decision support systems might automatically analyze this unfiltered communication on a short-term basis to alert market participants when information potentially causing capital market reactions is released. One promising avenue in this respect is linguistic analysis, since previous research has outlined the importance of language aspects like sentiment (Das and Chen, 2007; Tetlock et al., 2008). However, to the best of our knowledge, previous studies analyzing the market impact of conference calls neglect the short-term impact of linguistic aspects during the call (Price et al., 2012). Nevertheless, an understanding of this short-term impact is especially valuable for the configuration of financial decision support systems, which have to cope with rapidly changing financial markets requiring quick decisions (Dhar and Stein, 1997). Furthermore, the different aspects of the discussion session have not been analyzed separately, although this could provide evidence on which parts of the discussions are most important.

Our research aims at closing this gap by investigating which aspects of unfiltered information affect market reactions on conference calls and should thus be considered in financial decision support systems. Therefore, we analyze a sample of 200 earnings conference calls held by constituents of the German blue chip stock index DAX. We calculate the market reaction during these conference calls and perform an automated content analysis, focusing on sentiment and certainty. Thus, our research contributes to the financial decision support system literature and to the literature on conference calls.

The remainder of this paper is structured as follows. Section 2 presents previous research related to financial decision support systems, conference calls and our research hypotheses. Section 3 summarizes the research methodology. In section 4, we present the results and conclude in section 5.
2 Background and Research Hypotheses

2.1 Decision support systems and corporate communication

Diverse financial decision support systems have been proposed utilizing data published by corporations: Thereby, aspects of corporate disclosures or reports have been taken into account to provide support for investment decisions (Mittermayer, 2004), risk management (Groth and Muntermann, 2011) or fraud detection (Glancy and Yadav, 2011). Furthermore, since information published within these sources is also reported in the media, several studies also account for financial news articles as input data (Schumaker and Chen, 2009).

Because of the well-known capital market impact of corporate news (Patell and Wolfson, 1984; Woodruff and Senchack, 1988), corporations are aware of the consequences of publishing new information. Previous studies have focused on whether corporations pursue “impression management” to appear in a positive light: a comparison of internal and external corporate communication showed that corporate evaluations differ in their positivity or negativity – depending on whether they are released to the public or kept within the corporation (Fiol, 1995). Prior research has also found that bad news are timed (Kothari et al., 2009) and that earnings releases are used for promotional aspects besides their informational aspect (Clarke and Murray, 2000; Henry, 2008). In addition, the amount of information published is determined by a company’s performance: better performing companies publish more detailed information than comparably worse performing ones (Williams, 2008). In effect, we can assume that corporate communications may be affected by impression management and that this risk is particularly high for written communication that was edited by corporate representatives (Fiol, 1995). If this information is taken up by the financial press, it is subject to a further editing process. As a result of these various rounds of “shaping”, the information might be seriously affected until it finally reaches the targeted audience – the investors (Ihator, 2001).

Hence, decision support systems relying on these sources of filtered information also bear the risk of being affected by impression management. To reduce this risk and to include information that is not filtered by investor relations departments and journalists, verbal communication by management can be a valuable input for decision support systems since it occurs more spontaneously than written communication and is thus less probable to be adjusted (Chafe and Tannen, 1987; Chalfonte et al., 1991). However, to the best of our knowledge, financial decision support systems have neglected such verbal unfiltered communication up to now.

2.2 Corporate communication in earnings conference calls

One primary source of verbal unfiltered communication are earnings conference calls, which are often held in conjunction with earnings releases to offer analysts and investors the possibility to directly communicate with company executives. Usually, corporations release their earnings in the morning before stock markets open in order to inform their shareholders about the current company performance. When the market opens, the new information of the earnings announcement is processed and incorporated into stock prices. Afterwards, a conference call takes place in the afternoon to provide the possibility to interact with the management and to answer remaining questions about issues discussed in the earnings release (Frankel et al., 1999).

Typically, a conference call starts with a presentation session, where the company’s CEO or CFO talks about 30 minutes to the audience. Afterwards, the participants are allowed to ask questions to the company executives, which usually takes 30-60 minutes (Matsumoto et al., 2011). Especially the discussion session can be assumed to contain unfiltered information which has a lower risk of being affected by impression management since the representatives answer spontaneously to the participants. Although we also expect spontaneous comments during the presentation, it is easier to prepare this session in advance which makes it more likely to be prone to impression management.
In previous research, it has been found that the accuracy of analysts’ forecasts increases after an earnings conference call has been held and that mainly analysts with weak prior performance profit from the call (Bowen et al., 2002). An increased market reaction during the call, i.e. in form of abnormal volume and unusually high volatility has also been observed, indicating that earnings conference calls are informative to investors (Frankel et al., 1999). Analyzing the presentation and the discussion sessions of the call separately shows that both are informative to the market but that the discussion is associated with a stronger capital market reaction (Matsumoto et al., 2011).

Recent studies have already investigated whether linguistic or verbal aspects of earnings conference calls like the sentiment articulated contain information valuable to investors: the tone expressed in the call is found to be related to long-term market reactions (Price et al., 2012) and higher linguistic complexity is found to decrease the capital market reaction (Brochet et al., 2012). Furthermore, linguistic aspects can also be used to draw conclusions about a firm’s financial future (Mayew and Venkatachalam, 2012) and to identify deceptive discussions (Larcker and Zakolyukina, 2012).

Although these studies provide first evidence that linguistic aspects expressed in conference calls are of relevance, they do not focus on the intraday market reaction during the conference call. Instead, they focus on long-term aspects. However, in the case of financial decision support systems, especially short-term predictions are valuable for users in order to cope with rapidly changing financial markets requiring quick decisions (Dhar and Stein, 1997) since capital markets react on new information within minutes rather than days (Muntermann and Guettler, 2007). Thereby, the presentation and especially the discussion can be assumed to be important sources for unfiltered corporate communication that merits further analysis in the decision support system context.

2.3 The impact of conference calls’ language aspects on market reactions

In order to investigate whether unfiltered corporate communication and especially linguistic aspects should be analyzed automatically and considered as an appropriate input for decision support systems, we examine whether linguistic aspects of the earnings conference calls’ contents influence the concurrent capital market reactions. If these linguistic aspects are related to the capital market reaction, they can be considered within decision support systems as well. As follows, we focus on two main linguistic aspects of corporate communications: the sentiment expressed during the call as well as the question whether the management gives an indication of how certain it is about the statements discussed. Both aspects are important since on the one hand, previous research focusing on other communication channels has already outlined the importance of sentiment expressed (Tetlock et al., 2008). On the other hand, the question of whether the management reports (un)certainly about his statements could also influence market reactions (Zhang, 2006).

In the following, we focus on the presentation session as well as on the managements’ answers during the discussion session because in these parts, managers present their views on the company’s prospects. Furthermore, the language aspects of the participants’ questions are included as control variables within our subsequent analyses.

2.3.1 Sentiment

Sentiment covers opinions, expectations or beliefs of market participants towards certain companies or financial instruments (Brown and Cliff, 2004). Recent research has provided evidence that sentiment expressed via different sources has an impact on investors’ decision-making activities and affects financial variables. For instance, media sentiment has been shown to influence market prices (Tetlock, 2007; Tetlock et al., 2008). In the field of social media, a disagreement within message board postings leads to an increase in trading volumes (Antweiler and Frank, 2004) and an index based on message board sentiment can have explanatory power for the corresponding stock index (Das and Chen, 2007). Other studies focus on publications that can be directly influenced by firms, for example by analyzing the sentiment of corporate disclosures (Loughran and McDonald, 2011). It is found that the sentiment in quarterly earnings press releases has an impact on the consequent market reaction (Henry, 2008;
Sadique et al., 2008). Turning to information that is less filtered than written communication, conference call tone has already been shown to have a long-term impact on financial markets (Price et al., 2012).

Thus, since the presentation and the discussion session are used by the management to inform investors about their views on the company’s performance and on its future prospects, positive and negative sentiment provides an indication on whether a manager assesses the company’s performance and prospects as good or bad and can thus lead to capital market reactions. Therefore, we hypothesize: The sentiment expressed within the presentation session has an impact on the consequent capital market reaction (H1a) and the sentiment expressed within the management’s answers during the discussion session has an impact on the consequent capital market reaction (H1b).

2.3.2 Degree of certainty

In general, (un)certainty can be defined as “the degree to which an individual is [not] confident that his or her attitude toward an object is correct” (Krosnick et al., 1993). This is relevant for investors who want to take an investment decision and consider the management’s statements (Howard and Sheth, 1969). The (un)certainty expressed by the management might then translate into investors’ own assessments and thus potentially in capital market reactions (Zhang, 2006).

For investors and analysts evaluating the discussions within conference calls, it is important to know how certain the management is regarding its statements. Since missing information is often interpreted as negative and leads to a decline in market prices (Hollander et al., 2010), it is essential for market participants to get any assessment, regardless of whether certainty or uncertainty is expressed. However, if a manager does not include such indications in his answers, market participants will not be sure whether a given information is valuable or not. This might lead to different expectations and to increased trading activity. Consequently, we hypothesize: The certainty assessments included in the managers’ statements during the presentation have an impact on the consequent capital market reaction (H2a) and the certainty assessments included in the managers’ answers during the discussion session have an impact on the consequent capital market reaction (H2b).

3 Research Methodology

3.1 Dataset acquisition

We focus on earnings conference calls of constituents of the German blue chip index DAX held in English. We focus on DAX firms because these are the most liquid German stocks and are rather comparable in terms of their overall information environment. This homogeneous setting allows us to assess the effect of sentiment and certainty on abnormal returns without fearing to measure spurious effects. The conference calls’ text is taken from transcripts obtained from Thomson Reuters Street Events which document the related presentations as well as the questions and answers during the discussion session. We selected those transcripts where the participants’ affiliations are given in order to distinguish between corporate participants as well as analysts and investors. Furthermore, we only consider those conference calls taking place during trading hours, so we are able to match them to intraday stock prices obtained from Thomson Reuters Tick History. Our sample covers 200 conference calls held by 26 different companies in the period from 2004 to 2007. We selected this time period in order to abstract from effects of the financial crisis, because we are interested in the overall benefit corporate communication during conference calls can exert on decision support systems.

3.2 Event study methodology

The information content of a conference call is measured by the abnormal market reaction during the call, determined by means of event study methodology (MacKinlay, 1997). Therefore, the market reactions during the event window (i.e. the conference call) and the estimation window (representing
The “normal” market reaction expected without the event taking place) are calculated. The difference between these two market reactions forms the abnormal market reaction.

The market reaction during the event window is determined by the return measure depicted in equation 1. Therefore, the prices of stock \( i \) at the beginning \( (P_{i0}) \) and at the end of the conference call \( (P_{i1}) \) are considered. The starting time of the conference call is directly taken from the transcripts. Unfortunately, the transcripts do not provide the length or the ending time of the call. Thus, we consider Matsumoto et al. (2011) who evaluate how many words per minute are usually spoken during conference calls. To check whether this measure is appropriate for the firms in our sample, we called the firms’ investor relations departments and asked for the typical length of the calls. Based on these evaluations, we consider it as appropriate to calculate the length of each conference call separately by applying an amount of 160 words spoken per minute (Matsumoto et al., 2011).

\[
R_i = \frac{P_{i1} - P_{i0}}{P_{i0}} \quad (1) \quad R_t = \alpha_t + \beta_t R_m + \varepsilon_t \quad (2) \quad AR_t = R_t - (\hat{\alpha}_t + \hat{\beta}_t R_m) \quad (3)
\]

The normal return is calculated using the market model (MacKinlay, 1997) that controls for general market movements. We first estimate the relation of the market return \( (R_m) \) to the firm-specific return \( (R_t) \) during a thirty-day estimation window that starts one day before the conference call and covers the same time period during the day as the conference call takes place (equation 2). The two parameters \( \alpha_t \) and \( \beta_t \) denote firm-specific coefficients estimated from regression analysis, while \( \varepsilon_t \) is an error term. The market portfolio is approximated using the DAX index. Having established the “normal” link between the firm and the market return through the estimated parameters \( \hat{\alpha}_t \) and \( \hat{\beta}_t \), it is now possible to come up with a “normal” return measure for the event window that is independent of any firm-specific event. Finally, this normal return measure is subtracted from the actual observed return to obtain the abnormal return \( AR_t \) (equation 3). This abnormal return measure is calculated for each firm separately. Since we want to investigate the general market impact of earnings conference calls, we are not concerned about whether the calls lead to positive or negative abnormal returns. Therefore, we take absolute values of \( AR_t \) subsequently.

### 3.3 Content analysis

To investigate the relation between the linguistic aspects of conference calls and the subsequent market reaction, we perform a content analysis of the conference calls to determine a sentiment and a certainty measure. In the course of content analysis, textual material is classified and reduced to more relevant and manageable bits of data (Weber, 1983), which can be done manually or by means of automated approaches. The advantage of automated content analysis is its independence of the coders’ judgments. As the dictionaries are commonly available, this type of analysis produces reliable results that can easily be reproduced (Krippendorff, 2013). Furthermore, it is possible to analyze large numbers of texts in short time intervals as the process only depends on computing power and not on the time consuming manual coding by individuals.

Automated content analysis is mainly based on dictionaries that classify words into pre-defined categories. In our study, we apply the dictionary of the General Inquirer (GI) (Stone et al., 1962). It is one of the most widely used dictionaries and has already been applied in a number of accounting and finance studies (Tetlock et al., 2008; Price et al., 2012). This is advantageous in comparison with supervised machine learning-based approaches, since no classifier training is necessary and thus, no manual document labeling is required.

The linguistic measures applied within this study are depicted in equation 4-7. We determine sentiment measures for positivity and negativity as the ratio of positive \( (pos) \) and negative \( (neg) \) words (GI categories “positiv” and “negativ”) to the number of total words \( (n) \) in a text. Furthermore, our sentiment polarity measure is based on both positive and negative terms and thus gives an overall impression of the sentiment of a text (Tetlock et al., 2008). Subsequently, we measure certainty expressed in a text as the ratio of words indicating certainty or uncertainty \( (kn) \) to the total number of
words \((n)\). Thus, it is measured whether it is declared how certain the statements made are. Therefore, the GI category “know” is applied.

\[
\text{positivity} = \frac{\text{pos}}{n} \quad (4) \quad \text{negativity} = \frac{\text{neg}}{n} \quad (5) \quad \text{polarity} = \frac{\text{pos} - \text{neg}}{\text{pos} + \text{neg}} \quad (6) \quad \text{know} = \frac{\text{kn}}{n} \quad (7)
\]

These measures are calculated for the conference call as a whole as well as for each section of the conference call separately, based on all statements of the corresponding section.

### 3.4 Regression analysis

We run 4 linear ordinary least squares (OLS) regressions on a conference call basis to provide evidence on the influence of language aspects (sentiment and certainty) as well as several control variables on the absolute abnormal market return. In model 1, we only include the control variables in order to obtain the baseline performance. In model 2, we include the linguistic aspects calculated for the whole call. In subsequent analyses, we split the variables into the presentation session and the managers’ answers to exploit the different types of unfiltered information provided during conference calls (model 3). We do not expect the questions of analysts to have a significant impact on the abnormal return, however, we include them as control variables. Finally, we divide the sentiment polarity variable into positivity and negativity to disentangle the effect of positive and negative tone on the abnormal market reaction (model 4).

As control variables, we include the number of corporate participants, the number of analysts, the number of words of the call (model 1 and 2) and the number of words of the different sections (model 3 and 4) to control for conference call length. Furthermore, the number of trades as well as the price deviation during the conference call are considered as important determinants of returns. We control for week-day patterns by including day-of-week dummy variables. To account for heteroscedasticity, all standard errors are clustered on the firm-level. Reported coefficients are standardized.

### 4 Empirical Study

#### 4.1 Descriptive statistics

For the conference calls in our sample, a mean absolute abnormal market return \((\text{ar}_\text{market})\) of 0.45 \% is observed. This confirms the results of previous studies (e.g. Matsumoto et al. (2011)) that conference calls are informative for market participants. During the call, it is mostly corporate representatives that talk. On average, only 2,221 words of the 10,196 words that are spoken during conference calls are spoken by analysts that ask questions. The remaining 7,975 words apply to the management’s answers (4,046) and the presentation session (3,929). The average conference call is attended by 4 corporate participants (e.g. CEO, CFO or investor relations managers) and 11 analysts.

Table 1 shows the descriptive statistics for the main independent variables of our study. We analyze the presentation \((\_p)\) and answer \((\_a)\) parts individually as well as the conference call as a whole \((\_t)\). The sentiment polarity expressed within the presentation is more positive than within the managers’ answers which might indicate that the presentation is used to shed a positive light on the company. This finding is corroborated when positivity and negativity are considered separately.

In the second linguistic content category of certainty assessments \((\text{know})\), we find that the amount of certainty related words is greater within the manager’s answers than within the presentation session. This indicates that such assessments by the manager are rather expected during the discussion session and might also be caused due to the more spontaneous conversations within this session. Considering the correlations, we observe the highest correlation between sentiment polarity expressed within the presentation and the managers’ answers (0.3288). All other correlations between different sentiment measures are inferior. Considering the know category, there are only correlations lower than 0.1377. Interestingly, there is a negative correlation between the number of words of the questions and the number of words of the answers (-0.2366). This might suggest that longer questions are oftentimes
closed questions that can be answered with short statements (e.g. “yes” or “no”), while short questions could be more open and thus the answers are more detailed (e.g. questions related to future prospects).

<table>
<thead>
<tr>
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<th>SD</th>
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<th>Mean</th>
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Table 1. Means and standard deviations (SD) of the main independent variables and the absolute abnormal market return.

### 4.2 Event study results

Table 2 shows the results of the 4 regressions explaining the absolute abnormal returns measured during the conference call. First of all, we present the results of the basic model containing the control variables only (1). Subsequently, we report the results of the model including linguistic variables related to the overall content of the call (2). The next regression (3) accounts for the linguistic aspects of the presentation and discussion sessions separately. Finally, regression (4) splits the sentiment measure into single measures for positivity and negativity.

The results of model (2) show that the linguistic aspects (sentiment as well as certainty) of the earnings conference call as a whole do not exert a significant influence on the abnormal market return. In model (3), we analyze the different parts of the call separately. There, we find that linguistic aspects influence the absolute abnormal returns during the conference call depending on whether they refer to the presentation or the discussion session. Considering the sentiment expressed in the conference call, we observe a negative influence of the sentiment polarity prevailing in the presentation, which is significant at the 5% level. Thus, if the management expresses a positive sentiment, this reduces absolute abnormal returns. On the other hand, if the management talks about negative aspects (negative values of polarity_p), the subsequent absolute abnormal return increases. This may be attributed to the fact that market participants view positive sentiment as impression management and thus only concentrate on negative aspects revealed by the management. Such an explanation is further corroborated by the results of model (4), where positivity and negativity are taken into account separately. Here, we confirm that negative sentiment, measured by negativity, increases the absolute abnormal return, which is significant at the 1% level, whereas positive sentiment has no significant influence. As follows, we can accept H1a. In contrast, we do not observe any significant influence of the sentiment expressed in the management’s answers during the discussion session and thus have to reject H1b. Since the polarity of the presentation session and the management’s answers are correlated, an explanation for this finding would be that the sentiment of the corporate answers has only a reduced impact on the abnormal market reaction.

Furthermore, we find that the management’s certainty assessments have an impact on the stock market reaction. As model (3) and (4) suggest, there is a negative influence of such statements included in the management’s answers, which is significant at the 5% level, so H2b can be accepted. Thus, if answers contain more assessments of how certain the management is, the abnormal market return is lower. In contrast, as hypothesized, if the management does not provide related assessments, the absolute abnormal returns during the earnings conference call rise. This may be explained by the fact that the market participants’ uncertainty increases, which leads to different expectations and thus to increased market reactions. In contrast, there is no significant influence of statements expressing certainty within the presentation session. Thus, H2a has to be rejected. This indicates that market participants wait for the discussion session in case that there were news released that need to be clarified. Considering the
control variables covering the linguistic aspects of the analysts’ questions, we find no significant influence.

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</table>

Table 2. OLS regression results explaining the absolute abnormal return during the conference call (n = 200 conference calls). Standard errors are clustered by stock, coefficients are standardized. _p denotes the presentation session, _a denotes the management’s answers, _t denotes the whole conference call. * p < 10%; ** p < 5%; *** p < 1%.

Taking into account the goodness of the results, it can be noted that all regressions lead to reliable results. In this context, already the lowest F-Score of the basic model of 3.80 indicates that the null hypothesis that no independent variable has an influence on the dependent variable can be rejected at the 1% level of significance. Furthermore, we detect no multicollinearity when calculating variance inflation factors since the highest score of 2.41 is below the threshold of 4 (O’Brien, 2007). If the contribution of the linguistic variables is assessed, we first take into account model (1) to evaluate the explanatory power of the linguistic variables by comparing model (1) with model (2) to model (4). In this case, the basic model explains 16.8% of the variance. If the linguistic variables are added, an adjusted R² of 21.2% is obtained which indicates an increase by 4.4 percentage points. This shows that linguistic aspects expressed in the presentation as well as in the question and answers session of conference calls have an influence on the subsequent market reactions and should therefore be considered by financial decision support systems.

4.3 Discussion

Our results confirm that linguistic aspects of unfiltered corporate communication during earnings conference calls have an impact on the instantaneous capital market reaction and should thus be considered as a valuable input for financial decision support systems. Furthermore, we show that it is useful to look at the different parts of the call because they seem to contain different information content. On the one hand, linguistic aspects of the discussion session containing spontaneous, unfiltered communication between corporate representatives and financial analysts as well as investors are shown to have an influence on the subsequent market reaction. On the other hand, the linguistic
aspects of the presentation session also explain the absolute abnormal return, although the presentation may be prepared and edited in advance.

Accounting for this source of unfiltered information within financial decision support systems also offers the possibility to react quicker to the information released during the conference call, i.e. before journalists have communicated these within news articles. In the specific case of earnings conference calls which are held verbally, waiting until a transcript is available for analysis would diminish the temporal advantage of such an automated analysis. Consequently, speech recognition technologies might be applied in a first step before an analysis to transform speech in real time to text in order to then perform automated content analysis as applied in this study. Although speech recognition is still evolving, current technology has reached a level of maturity so that it is even able to perform real time translations (Technet, 2012). Within this study, we did not evaluate this first step of such a real-time analysis as we did not have access to the voice recordings of the conference calls analyzed. Nevertheless, it seems feasible that a decision support system analyzes such a call. Related decision support systems might build upon unfiltered communication in order to alert users about discussions potentially causing capital market reactions.

While relying on linguistic aspects is still linked to the risk that managers adjust their speeches in order to influence a decision support system’s evaluations, a system considering unfiltered information can be assumed to be more robust against this kind of manipulation. In comparison to decision support systems considering filtered information, this unfiltered information is communicated more spontaneously and is therefore less vulnerable to such forms of impression management. Nevertheless, the speed advantage resulting from focusing on unfiltered information within financial decision support systems may decrease when every market participant applies related technologies. In this case, not analyzing unfiltered information might even be a comparative disadvantage in relation to other market participants.

5 Conclusion

Previous decision support systems have mainly used filtered information for supporting users and are thus faced with the risk of being influenced by impression management or by journalistic editing processes. In this study, we show that focusing on unfiltered information seems to be promising in order to enhance the robustness of related systems and to shorten the time until a system can provide a recommendation.

We contribute to the literature on financial decision support systems as well as corporate communications in earnings conference calls. We provide evidence that unfiltered information can be a valuable input for decision support systems. With respect to automated content analysis, we show that decision support systems may be improved by incorporating linguistic aspects related to sentiment and certainty. Thus, users are enabled to react faster to new information and corresponding systems are more robust against speech adaption since spoken language is more spontaneous than written (filtered) communication. Additionally, we contribute to the literature on earnings conference calls since we identify and explain why sentiment as well as statements expressing the degree of (un)certainty have an impact on the market reaction during earnings conference calls. Thereby, we are among the first investigating the intraday effects of conference calls and analyzing presentations, questions and answers separately.

From a practical perspective, we provide design recommendations for financial decision support systems that potentially improve these systems. In order to analyze earnings conference calls, related systems could first be enhanced with speech recognition technology in order to transform speech into text. Afterwards, related systems might incorporate the proposed content analysis procedure to examine the spoken text and to give recommendations. Here, the input variables of this study could be used to evaluate different configurations. Furthermore, our results are relevant for corporations hosting conference calls. We find that conference calls are informative for investors and that managers should be aware that their statements are evaluated thoroughly by capital market participants.
In future research, we plan to enlarge our sample by smaller firms that are confronted with reduced investor attention and analyst coverage which might influence the impact of earnings conference calls. Furthermore, we plan to analyze audio recordings of earnings conference calls. This offers the opportunity to take other factors into account, e.g. high or low voice or the speed of speech. Finally, information filtering by journalists or other intermediaries may also add value due to their thorough evaluations. In follow-up research, it would be worthwhile to compare which aspects of conference calls are filtered or explained in subsequent financial news articles.

References


