UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

# Earnings Conference Calls and Stock Returns:

*The interplay between tone and information specificity*

Graduation School

Master thesis in Accounting and Financial Management, 30 credits.

University of Gothenburg School of Business, Economics and Law


**Supervisor**

Mari Paananen

**Author:**

Imelda Taraj


Spring 2019

## Abstract

After the adoption of RegFD, quarterly earnings conference calls (ECCs) have become an important channel for voluntary corporate disclosure. However, the extent to which the information content affects capital markets is little researched. Using Stanford NER algorithm and Loughran and McDonald (2011) wordlists on 2,639 conference calls transcripts, I examine the incremental informativeness of quarterly earnings conference calls in terms of *tone* and *specificity*, and the impact of their interplay in capital markets.

In this thesis, I perform a path analysis including analysts' tone and its impact on capital markets, measured in terms of cumulative abnormal returns in a two-day window (CAR 0,1). The mediating variable is *information specificity*, as a proxy for a quality characteristic of information driven by analysts' tone. I find that analysts' tone is a significant direct and indirect predictor of abnormal returns (CAR 0,1). While the direct path has been confirmed by prior literature, I document the importance of indirect paths of how analysts' tone affects CAR (0,1). Specifically, I document that a more negative analysts' tone during Q&A sessions affects positively *information specificity* disclosed by managers in their answers. Further, I document that *information specificity* is associated positively with CAR (0,1).

My findings are consistent with prior literature establishing the importance of Q&A session of ECCs in explaining post-earnings announcement drifts. Further, I contribute by documenting a significant mediating path in the analysis, *information specificity*. These findings are of interest to investors, analysts and regulators to better understand the analysts' role in shaping firms' information environment and quality.

Keywords: conference calls, disclosure, content analysis, textual analysis, word sentiment, information specificity, cumulative abnormal returns.

Data availability: All data used in this study are publicly available and are found in the sources indicated in the text.

## Acknowledgements

Firstly, I would like to thank my thesis supervisor Mari Paananen for her patience, continuous support and constructive discussions throughout the process of researching and writing this thesis. While consistently allowing this paper to be my own work, she steered me in the right direction and challenged my ideas whenever needed. During this period, not only did I become more passionate about research, but also, I enjoyed profoundly learning more about research, text analysis and the specific topic I studied.

I would also like to thank the expert involved in developing the Java application for this research project, Elis Taraj. Without his participation and input, the separation of the text from the ECCs narratives could not have been successfully conducted.

Finally, I want to express my gratitude and love to my parents, to my friends and to my boyfriend for always providing me with support and encouragement. My accomplishments would not have been possible without them. Thank you.

# Table of Contents

**List of Figures and Tables**

# 1 Introduction

Over the past decades, Earnings conference calls (ECCs) have become an important form of voluntary disclosures, turning into significant information events for the market (Bowen et al., 2002, Kimbrough 2005). This increased importance is mainly due to the adoption of Regulation Fair Disclosure (RegFD) issued by US Securities and Exchange Commission in August 2000. The RegFD requires public disclosure of all released nonpublic information from listed companies, including open and available ECCs webcasts and transcripts (Sec.gov, 2019). ECCs are held shortly after companies announce their earnings results and they provide an opportunity for management to further comment on firms' current and future performance. The conference calls typically begin with a prepared statement by management summarizing the press release, which is followed by an open question and answer session.

The impact ECCs have on capital markets has increased mainly due to the analysts' role as information intermediaries between companies and investors (Huang et al., 2018). With their questions during the ECCs and later with their stock recommendation reports, analysts play an important role in shaping the information environment in capital markets and decreasing information asymmetry. Until recently, research on ECCs impact on capital markets has focused on changes in equity market reactions during and after ECCs. However, there is little in-depth examination of ECCs narratives, which could potentially provide a direct evidence on how ECCs shape firms' information environment (Matsumoto et al., 2011).

ECCs are composed of two sessions: introduction and question and answers (Q&A). During the introduction session of ECCs, managers provide an overview of quarterly firm performance and any additional, voluntary disclosures not included in the earnings report released. During Q&A sessions, analysts' questions related to reported financial statements can uncover important information, incrementally informative over the press release (Matsumoto et al., 2011 and Price et al., 2012). Thus, both the tone and the content of the discussion between management and analysts could provide important private information for investors. Moreover, due to the spontaneous nature of the Q&A session, verbal cues may impact the volume of additional information disclosed during the discussion portion of the ECCs (Mayew et al., 2012 and Matsumoto et al., 2011).

In this study, I conduct an in-depth text analysis of ECCs transcripts for Q&A sessions and I identify the impact of financial analysts' tone on the specificity of information disclosed by management. Taking into consideration prior literature findings that managers' tone is significantly more optimistic compared to analysts' tone (Brockman et al., 2015), I expect that more challenges posed from analysts during the Q&A session may trigger additional, more detailed information from managers in order to support their optimistic views. Thus, I perform a path analysis and document that a more negative tone of participating analysts, triggers more specific and detailed information from representative managers. This, in turn, decreases information asymmetry and positively affects stock prices. I introduce the measure of *Specificity*, to quantify the level of details in information provided by managers when questioned by analysts. The *Specificity* measure is proxied as the ratio between the total volume of specific entity names used by managers when answering analysts' inquiries to the total volume of words of the answers during Q&A sessions.

The next section includes the introduction of the research question and the contributions of this study. Section 3 discusses a literature review on textual analysis of ECCs followed by Section 4 with hypotheses development. Section 5 discusses variable measures and methodology and Section 6 presents my empirical results. Section 7 presents findings from the sensitivity analysis and robustness checks and section 8 concludes.

# 2 Research Question and Contributions

The main aim of this study is to investigate the following research questions:

*RQ: Does analysts' tone affect management information specificity during ECCs and ultimately stock prices in capital markets?*

To address this research question, I perform a path analysis of the impact of the analysts' tone during the Q&A sessions of ECCs on capital markets. Firstly, I examine whether a more negative tone in analysts' questions is positively associated with the *specificity* of information disclosed by managers. Secondly, I examine whether *specificity* is positively associated with the stock market reactions to the additional, more specific disclosures. My study is built on in part by Price et al. (2012) who examine the incremental informativeness of quarterly ECCs and the corresponding market reaction. They find that the tone of Q&A portion of ECCs has significant explanatory power on concurrent abnormal stock returns (CARs) and trading volumes. Based on the suggested cause-effect association between tone and CARs by Price et al. (2012), my study aims to extend the literature by examining how tone affects stock prices.

This thesis makes several contributions to literature, analysts, investors and regulators. Firstly, it contributes to prior literature involved in text and sentiment analysis by adding an information quality characteristic to tone impacts, such as specificity of information provided during Q&A sessions. My thesis aims to examine how tone influences the level of information specificity provided to capital markets. The *specificity* measure used in this thesis captures a quality aspect of information disclosed during ECCs. Prior literature has examined tone impact on capital markets, however, to my knowledge, there are no studies incorporating the quality aspect of information disclosed as a function of tone.

Secondly, my study contributes to literature on disclosure quality. Prior studies rely on readability or size of filings as a qualitative measure of financial disclosures (Li, 2008; De Franco et al., 2015). My thesis suggests the specificity of information disclosed during the Q&A sessions of ECCs as an additional qualitative measure, which has an effect on analysts' forecasts and investors' decision-making (Hope et al., 2016).

Finally, to the best of my knowledge, only a few studies examine the interaction between participants in ECCs. Thus, studying the interplay between analysts' tone and the level of specificity of firms' disclosures gives further insights to investors and regulators regarding the role of analysts in improving the quality of information.

# 3 Literature Review

Prior literature on company disclosure focuses primarily on capital market implications of quantitative information disclosed in financial statements or earning releases, as the main channel of information disclosure by companies. Only recently, researchers begun exploring verbal communications, as an additional source through which information is channeled to capital markets. Verbal communications provide context to the financial figures released and add to investors' understanding of firm performance (Price et al., 2012).

ECCs became an important source of information for capital markets mainly after the adoption of RegFD. The scope of RegFD required public companies to end selective disclosure of important information to analysts and investors (Sec.gov, 2019). Instead, all disclosed nonpublic information should be accessible by capital markets' participants, at the same time decreasing trading costs and lowering firms' cost of capital (Brown et al., 2004). After the adoption of RegFD, several studies focused on examining whether value relevant information is provided during ECCs. Kohlbeck and Magilke (2002) document higher abnormal returns during earnings announcement periods accompanied by conference calls, while Bushee et al. (2001) note increased levels of trading activity and return volatility during conference calls. Further, studies have examined whether ECCs help in decreasing information asymmetry in capital markets (Venkataraman et al., 2001 and Brown et al., 2004). Research shows that ECCs help to mitigate potential information asymmetry between managers and investors (Frankel et al., 1999; Bowen et al., 2002; Kimbrough 2005).

In addition to research showing that ECCs improve the information environment in capital markets and reduce information asymmetry, several studies focus on the impact ECCs have on analysts' forecast properties. Bowen et al. (2002) document that the improvement in analyst forecast accuracy relating to earnings announcements is better when earnings reports releases are accompanied by conference calls. Moreover, Kimbrough (2005) notes that while there is mixed evidence regarding the increase of the total amount of information for currently reported earnings, ECCs provide useful forecasting information, resulting in timelier analyst and investor reactions for trading purposes. While monitoring price change during and after firm disclosures is the most common research approach, a few recent studies have also incorporated content analysis in order to examine the disclosure content. Davis et al. (2012) find that a positive tone in press releases is related to increased future return-on-assets. Further, using a sample in the telecommunications and computer industry, Henry (2008) shows that the tone of words in earning announcements affects

the initial market reaction to earnings reports. Sadique et al. (2008) extend these findings by including in their analysis the content of both earnings announcements and related press release. They find that a positive tone is related to increased returns and decreased volatility. Another study by Demers and Vega (2010) demonstrate that the managerial word choice is related to both abnormal returns and idiosyncratic volatility for up to 60 days following the announcement. Overall, these studies establish that information content of the word choice in communications related to earnings release are incrementally informative to capital markets.

Furthermore, a few recent studies carry out tone analysis of ECCs. Frankel et al. (2009) find a positive association between the stock returns generated during the conference calls and the participants' tone. Further, Price et al. (2012) find that the tone of ECCs has a significant explanatory power on the concurrent abnormal stock return and predictive power relating to post announcement abnormal stock return. Mayew et al. (2012) used vocal emotion analysis software to analyze conference call audio files. They find that managerial vocal cues contain useful information about a firm's fundamentals, incremental to both quantitative and qualitative information.

While the above-mentioned studies use text analysis to study the information content of ECCs, they do not distinguish between the tone of the opening remarks and the Q&A section of the call. Opening remarks are formal, structured and essentially reiterate the information disclosed in the earnings press release (Frankel et al., 1999; Kimbrough, 2005). On the other hand, the Q&A portion includes questions and statements from third-party intermediaries, thus providing more assurance about the quality of the overall Q&A tone signal (Price et al., 2012). Thus, separating the two components of ECCs in the analysis allows me to determine the contribution of the informal, unscripted discussion between management and analysts beyond the information in the earnings numbers and accompanying announcement (Price et al., 2012).

Brockman et al. (2015) complemented prior research by separately studying the managers' and analysts' tone in ECCs and their respective impact. They document that while the tone of both parties influences the capital market, analysts' tone is relatively more informative, and investors react more strongly to it compared to managers' tones. Milian et al. (2017) study the analyst feedback during ECCs and focus on analysts' praise of management. They document that the amount of praise by analysts on an earnings conference call is strongly associated with the earnings surprise and to a greater extent the earnings announcement stock return.

# 4 Hypotheses development

For this thesis, I develop two hypotheses. My first hypothesis relates to the specificity of information during the Q&A sessions as a function of analysts' tone. Disclosure theory establishes that managers are incentivized to postpone the disclosure of non-favorable news (Dye 1985). However, I propose that they are less able to avoid such disclosures when directly inquired by analysts. I expect that, in order for the management team to maintain their significantly more optimistic tone compared to analysts (Brockman et al., 2015), more challenges posed from analysts during the Q&A session, may trigger additional, more detailed information. Also, during the Q&A sessions, managers are more likely to disclose additional information, uncovered during the opening remarks due to time limit or non-relevance (Matsumoto et al., 2011).

Based on the above reasoning, I expect that a negative tone from analysts will challenge management team and generate more specific information. Thus, my first hypothesis is:

*$H_1$: A negative analysts' tone increases managers' information specificity during the Q&A session.*

My second hypothesis is related to the degree of specificity of information generated during ECCs and its impact on capital markets. As discussed above, there are a few recent studies on tone analysis and its impact on capital markets, but to my knowledge there is no research on the content of ECCs and its impact. I predict that the investors' reactions to analysts' tone is a result of both sentiment and more specific information provided during the Q&A session of ECCs. Thus, I perform a path analysis and expect that the increased specificity of information as a result of analysts' tone is one channel through which tone is associated with the observed change in stock price after ECCs. My second hypothesis is:

*$H_2$: The specificity of information disclosed by management during ECCs is associated with changes in stock prices during and after ECCs.*

# 5 Research Design

## 5.1 Sample and data

The adoption of RegFD required firms to make their ECCs available to the public, thus over time, electronic conference call transcripts and webcasts have become widely available. I use ECCs transcripts to construct a sample of 20 consecutive quarters for the period 2013-2017. I use the S&P Capital IQ database to extract the sample of transcripts. Furthermore, I implement the following additional filters to construct the final ECCs transcript sample following Price et al. (2012). First, I exclude all companies for which there is no sufficient market data available in Compustat or Center for Research in Security Prices (CRSP) databases. Further, I exclude financial firms with stock codes 10, 11 and 12 and other financials (SIC 6000-6999) and utilities (SIC 4900-4949) due to high regulation in their respective industries.

In order to ensure a pseudo-random sample, which includes companies with a variety of characteristics, I categorize the sample in terciles based on market capitalization (MV) and Book-to-Market (BM) values, following Price et al. (2012). BM is calculated as the Compustat average book value of two consecutive quarters divided by the market value at the end of the preceding quarter. Furthermore, I categorize size terciles based on NYSE market-capitalization breakpoints from Kenneth French's[1] website.

Based on portfolios created from size-BM combinations, I further separate companies into dividend and non-dividend paying, since I expect different characteristics in information disclosure when investors cash inflows are uncertain. Thus, in total, I construct 18 portfolios of companies for 20 consecutive quarters. From each portfolio, I select randomly ten companies for each quarter. Since the selection is random, some of the selected companies did not hold conference calls during the time period selected and several others did not hold conference calls every quarter. Thus, Table 1 shows the construction of the sample of companies for each portfolio. The total sample size for this study is 2,639 company-quarter observations.

[1] Since the file contains every fifth percentile of market capitalization breakpoints, I calculate the terciles as (p35 – p30)/5 × 3 = p33 and (p70 – p65)/5 × 2 = p67, where p = percentile.
Mba.tuck.dartmouth.edu. (2019). Kenneth R. French - Home Page. [online] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

***Table 1 Portfolio distribution of sample firms***

| Portfolios/ Selection | | MV | | | | | |
|---|---|---|---|---|---|---|---|
| | | 33% | | 67% | | 100% | |
| | | D | ND | D | ND | D | ND |
| BM | 33% | 8 | 10 | 8 | 10 | 9 | 10 |
| | 67% | 5 | 10 | 10 | 10 | 7 | 10 |
| | 100% | 8 | 10 | 7 | 7 | 6 | 7 |

Table 1 shows the distribution of companies selected as part of the pseudo random sample, based on market value (MV), book-to-market value (BM) terciles and dividend and non-dividend payers (D, ND).

## 5.2 Measuring Tone variable

In order to measure the tone, I use the Loughran and McDonald (2011) wordlist, as a suitable tool for tone measurement in a financial context. Prior research has documented better results on tone measurement in a financial context using Loughran and McDonald (2011) wordlist compared to the Harvard General Inquirer, Diction, or Henry (2008) dictionaries (Price et al., 2012; Milian et al., 2017). In order to study the impact of analysts' tone on managers' responses, I use the Q&A portion of the ECCs.

The sentiment algorithm generates eight categories: negative, positive, uncertainty, litigious, constraining, superfluous, interesting and modal. Appendix 1 shows a sample of the results obtained from the Python script measuring the sentiment for the analysts' questions. In order to create the analysts' tone (ANALYST TONE) variable, I follow Brockman et al. (2015) and calculate a ratio for each ECCs as (Positive -Negative)/ (Positive + Negative). Such variable can have values from -1 to +1, which shows the relative positivity of the analysts' tone. Thus, a higher ratio of ANALYST TONE indicates a more positive tone of the analyst and a lower ratio of ANALYST TONE indicates a more negative tone of the analyst. In this thesis, I am looking at how a more negative analysts' tone, thus a lower ANALYST TONE impacts the mediating variable *Specificity*.

### 5.3 Measuring Specificity variable

In order to construct the measure of *information specificity* of managers' answers (ANSWER SPEC) during Q&A sessions, I follow Hope et al. (2016) and define ANSWER SPEC, as the number of words revealing specific information, divided by the number of total words in the narrative. In order to identify the specific entity names during management's answers, I use the Stenford Named Entity Recognition (NER), which is a java implementation of NER, developed by the Stanford Natural Language Processing Group (Nlp.stanford.edu, 2019). Stenford NER identifies and extracts specific terms related to seven specific entity categories, including (1) names of persons, (2) names of locations, (3) names of organizations, (4) quantitative values in percentages, (5) money values in dollars, (6) times, and (7) dates. Prior research has shown that Stenford NER can extract entity names close to human performance (Hope et al., 2016). Shortcomings are noticed relating to information in different currency from USD, but since the sample of this study is based on North-American companies, it does not affect this study. Appendix 2 shows a sample of the results obtained from the Python script measuring the specificity of the managers' answers.

### 5.4 Measuring control variables

I include several control variables in my analysis which may affect equity markets. I include both control variables relating to firm performance and ECCs sentiment and content.

In order to control for impact of firms' performance on capital markets, I include variables suggested in the literature on short-window market reactions. Frankel et al. (1999) show that firm size, leverage and earnings are positively associated with voluntary managerial disclosures, while book to market value is associated negatively. Thus, I include the natural log of firms' market capitalization at the end of the quarter (SIZE), leverage (LEV) measured as total liabilities divided by total assets and BM calculated as the average book value of equity of two consecutive quarters divided by the market value at the end of the preceding quarter. Lastly, I include firm's return on assets (ROA) calculated as the ratio of net income to total asset.

Furthermore, Chen et al. (2002) find that in volatile environments, investors require, and managers disclose additional information. Therefore, I include variables to capture the volatility of environment such as stock return volatility (VOL), measured as the standard deviation of daily returns for the 90-day period ending 10 days prior to the conference call. Also, I calculate the unexpected earnings surprise (SURP) as the difference between current quarter earnings per share and earnings per share in the same quarter of the prior year, divided by the stock price at the close

of the latest quarter. Finally, I control for abnormal price changes in the period prior to the conference call by calculating CAR (-60,-2) (Arslan-Ayaydin; Boudt and Thewissen, 2016).

Additionally, I include four dummy variables to consider firms' characteristics such as dividend policy, losses, institutional ownership and special non-recurrent financial items. DIV is equal to one if the company has paid dividend during the quarter and otherwise DIV = 0. Price et al. (2012) show that the Q&A session becomes a more important information source when investors' cash inflows are uncertain compared to when they receive dividend. LOSS equals 0 if the company has incurred losses and 1 otherwise. I expect firms incurring losses will provide more information to decrease information asymmetry. OWN equals 1 when firms have shares owned by institutions and 0 otherwise. I expect that institutional ownership may serve as a potential driver of specificity due to recurring audits and other internal controls. Further, I have added the variable of special items (SPECIAL), defined from COMPUSTAT as 'unusual or nonrecurring items that include, among other things, restructuring charges, asset impairments, M&A charges, nonrecurring profits or losses on sale of assets, and investments divided by end-of-year total assets'. I have added this variable to the model since unusual items/events that impact financial statements may trigger the disclosure of more information from management due to the nature and circumstances of the event.

Lastly, CAR (0,1) can be affected by ECCs related variables, other than analysts' tone. Brockman et al., (2015) document that both the tone of managers during the introduction part of ECCs and the tone of managers during the Q&A session have a significant impact on the cumulative abnormal returns during and after ECCs. The tone of the introduction part of ECCs (INTRO TONE), can be used as a proxy for earnings release tone. Brockman et al. (2015) show that managers' tone (MANAGER TONE) during the Q&A session differs significantly from INTRO TONE due to analysts' interaction, therefore I control for its impact. I measure all tone variables with Loughran and McDonald (2011) wordlist, consistent with the ANALYST TONE measurement method.

Finally, I include a content control variable such as information specificity of introduction part of the ECCs (INTRO SPEC) as a proxy for the information specificity disclosed during earning release, since introduction is a reiteration of current earnings press releases. Similar to ANSWER SPEC, I use Stenford NER to measure specific entity categories of the introduction part of ECCs and calculate the ratio as total number of specific words revealing specific information, divided by the number of total words used in the introduction part.

## 5.5 Path model

For this thesis, I expect that cumulative abnormal returns will be affected by analysts' tone through a direct path and through an indirect path, mediated by information specificity as shown in Figure 1. The main dependent variable, CAR (0,1) is defined as the cumulative abnormal return from the date of the conference call, Day 0, to Day +1. I calculate the abnormal return for a company as the difference between the return for the company on day *t* and the mean return on day *t* for all companies in the same size decile. The basis for the path analysis lies in a hypothesized cause-effect relation between a source and an outcome variable, mediated by a third one (Bhattacharya et al., 2012). Theoretically, a direct path includes only one path coefficient, while an indirect path is composed of the path coefficient between the source variable and the mediating variable, as well as the path coefficient between the mediating variable and the outcome variable (DeFond et al, 2016). Thus, the final coefficient of the indirect path is the product of these two path coefficients. The path analysis automatically standardizes all variables in the model with a mean of 0 and a standard deviation of 1, allowing comparison of the magnitudes of the coefficients (DeFond et al, 2016). In Figure 1, the direct path predicts a positive association between ANALYST TONE and CAR (0,1). This path is supported by prior literature findings, showing that a more positive analysts' tone (an increase in ANALYST TONE) increases CAR (0,1) (Brockman et al., 2015). Further, the model shows two indirect paths. The first indirect path predicts that a more negative analysts' tone (thus, a decrease in ANALYST TONE) increases information specificity in managers' answers (ANSWER SPEC) during ECCs. The second indirect path predicts that ANSWER SPEC is positively associated with CAR (0,1).

***Figure 1 Path Model***

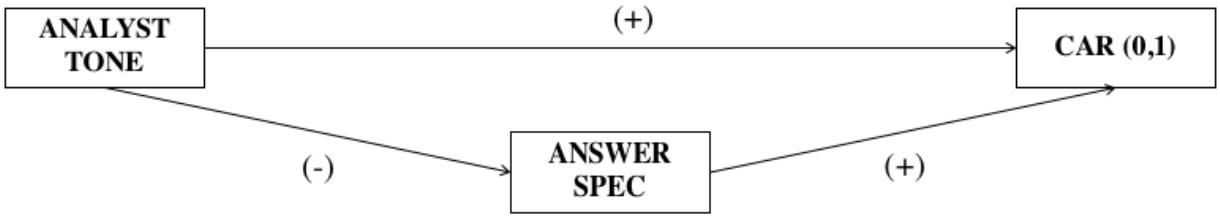



Figure 1 shows the direct and indirect paths through which ANALYST TONE impacts CAR (0,1). Since ANALYST TONE is measured as the ratio of words (Postive- Negative)/(Positive+Negative), a higher ANALYST TONE ratio means a more positive tone. Thus, I expect that a more positive tone will affect positively CAR (0,1), as established by prior literature. For the indirect path, I expect that a more positive (negative) ANALYST TONE is negatively (positively) related to ANSWER SPEC. Finally, a more specific information delivered by managers is expected to affect positively CAR (0,1).

# 6 Results and Analysis

## 6.1 Descriptive Statistics and correlations

Table 1 presents descriptive statistics for all dependent variables, treatment variables, and control variables. I report the statistics of means, median, maximums, minimums, standard deviations, and the number of observations for each variable over the five-year sample period from 2013 to 2017. The mean of the dependent variable, cumulative abnormal returns from Day 0 to Day +1—that is, CAR (0,1)—is 0.04% and the median is 0,18%. These results show that companies tend to experience slightly positive abnormal returns during the time around conference calls. The standard deviation of 9.5% reveals significant changes across the abnormal returns, with a minimum CAR (0,1) of –42.6% and a maximum CAR (0,1) of 65.77%.

As for the independent variables, Table 1 shows that ANALYST TONE tends to be more negative than positive, with a mean and median of -0.01. Compared to INTRO TONE and MANAGER TONE which tend to be more positive than negative tones, ANALYST TONE statistics are consistent with prior research showing analysts are generally more negative in tone compared to managers (Brockman et al., 2015). The standard deviation is 36,93%, and the range is from a minimum of –0.92 to a maximum of 0.91. Further, the ANSWER SPEC variable has a mean of 0.04 and a median of 0.03. Compared to INTRO SPEC which has a mean of 0.14 and median of 0.13, answers during Q&A session are less rich in information specificity compared to introduction. Since introduction part of ECCs is a prepared summary of earnings release, it is expected to provide more specific information compared to a spontaneous Q&A session. Additionally, standard deviation is 14.86% and the range of the minimum to 0.59% and maximum 11.95%. This shows for significant variations regarding the level of detail and specificity of information provided by companies.

Further, Table 2 presents the descriptive statistics for the company-level control variables. Some of the variables seem significantly skewed even after winsorizing at 1% from both tails, such as ROA, SIZE or BM. However, because the sample population used in this study is large, this does not affect the reliability of the models.

***Table 2 Descriptive Statistics***

| Variables | Mean | Median | Mini | Maxi | Standard Deviation | No. Of Observations |
|---|---|---|---|---|---|---|
| CAR (0,1) | 0.04% | 0.18% | -42.61% | 65.77% | 9.50% | 2 639 |
| | | | | | | |
| ANALYST TONE | -0.01 | -0.01 | -0.92 | 0.91 | 0.32 | 2 540 |
| ANSWER SPEC | 0.04 | 0.03 | 0.01 | 0.12 | 0.01 | 2 639 |
| MANAGER TONE | 0.29 | 0.31 | -0.75 | 0.94 | 0.27 | 2 613 |
| INTRO TONE | 0.36 | 0.39 | -0.70 | 0.96 | 0.28 | 2,568 |
| INTRO SPEC | 0.14 | 0.13 | 0.04 | 0.43 | 0.04 | 2,638 |
| BM | 0.52 | 0.35 | -0.95 | 32.32 | 0.92 | 2 635 |
| CAR(-60,-2) | 0.42% | 0.44% | -207.28% | 170.72% | 27.58% | 2 639 |
| SIZE | 2.89 | 2.86 | 0.86 | 5.24 | 0.88 | 2 635 |
| ROA | -0.19% | 2.23% | -269.86% | 274.45% | 18.36% | 2 639 |
| SURP | 0.12% | 0.07% | -252.38% | 289.17% | 13.45% | 2 635 |
| VOL | 2.45% | 2.08% | 0.50% | 20.76% | 2.45% | 2 638 |
| LEV | 46.25% | 44.14% | 1.94% | 290.59% | 46.25% | 2 639 |
| DIV | 0.42 | 0.00 | 0.00 | 1.00 | 0.49 | 2 635 |
| LOSS | 0.73 | 1.00 | 0.00 | 1.00 | 0.44 | 2,635 |
| OWN | 0.06 | 0.00 | 0.00 | 1.00 | 0.24 | 2,638 |

Table 2 shows the descriptive statistics for the variables included in the path models. The summary statistics presented are after the winsorization at 1% in both sides. All tests have been performed with unwisorized variables, and no significant changes have been noted.

Table 3 shows the correlations between control variables. Most of the correlations between the control variables are less than 0.2 which means that multicollinearity is not significant and does not imply issues for interpreting the regressions. However, there are a few exceptions with correlation above 0.2. Between ANSWER SPEC and INTRO SPEC, there is a significant correlation since managers include information from the introduction part of ECCs when answering to analysts' questions. Similarly, MANAGER TONE is correlated to INTRO TONE, since it is the same management team presenting during the introduction part and later answering the questions during the Q&A session. Further, Brockman et al., (2015) show that due to analysts' tone, managers' tone becomes less positive compared to introduction tone, hence the correlation between MANAGER TONE and ANALYST TONE.

Between SIZE, ROA, LOSS and OWN there are positive correlations since larger sized companies tend to have higher profits and returns on asset and often, have higher percentages of shares owned by institutions. Similarly, the correlation between DIV, ROA, VOL and LOSS can be explained due to less profitable companies implementing more conservative dividend policies, when stock returns suffer high volatility. Further, the correlation between BM and SURP is explained by abrupt investors reactions to new information in firms with lower market value

***Table 3 Correlations***

| Var | CAR01 | ANSWER SPEC | ANALYST TONE | INTRO TONE | INTRO SPEC | MANAGER TONE | BM | CAR602 | SIZE | DIV | LEV | ROA | SURP | VOL | LOSS | OWN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CAR01 | 1.00 | | | | | | | | | | | | | | | |
| ANSWER SPEC | 0.05** | 1.00 | | | | | | | | | | | | | | |
| ANALYST TONE | 0.18*** | -0.05** | 1.00 | | | | | | | | | | | | | |
| INTRO TONE | 0.15*** | -0.02 | 0.17*** | 1.00 | | | | | | | | | | | | |
| INTRO SPEC | 0.04* | 0.21*** | 0.01 | -0.16*** | 1.00 | | | | | | | | | | | |
| MANAGER TONE | 0.13*** | -0.13*** | 0.29*** | 0.36*** | -0.04** | 1.00 | | | | | | | | | | |
| BM | 0.05** | 0.02 | 0.01 | -0.13*** | -0.00 | -0.09*** | 1.00 | | | | | | | | | |
| CAR602 | -0.05** | -0.02 | 0.03 | -0.02 | -0.00 | 0.01 | -0.02 | 1.00 | | | | | | | | |
| SIZE | 0.06*** | -0.08*** | -0.02 | 0.21*** | -0.03 | 0.12*** | -0.29*** | -0.04** | 1.00 | | | | | | | |
| DIV | -0.01 | 0.17*** | -0.04** | -0.04* | 0.08*** | -0.04* | -0.05** | 0.01 | 0.09*** | 1.00 | | | | | | |
| LEV | 0.00 | 0.04* | -0.05** | -0.05** | -0.03* | 0.01 | 0.08*** | -0.04** | 0.11*** | 0.02 | 1.00 | | | | | |
| ROA | 0.08*** | 0.14*** | 0.02 | 0.13*** | 0.19*** | 0.03* | 0.18*** | -0.02 | 0.30*** | 0.21*** | -0.07*** | 1.00 | | | | |
| SURP | 0.11*** | 0.02 | 0.03 | -0.01 | 0.02 | 0.03 | 0.39*** | -0.01 | 0.02 | -0.01 | 0.11*** | 0.28*** | 1.00 | | | |
| VOL | -0.05** | -0.10*** | -0.01 | -0.17*** | -0.10*** | -0.07*** | 0.16*** | 0.08*** | -0.44*** | -0.31*** | 0.09*** | -0.47*** | -0.02 | 1.00 | | |
| LOSS | 0.10*** | 0.12*** | 0.01 | 0.19*** | 0.22*** | 0.08*** | -0.13*** | -0.05** | 0.39*** | 0.27*** | -0.01 | 0.5*** | 0.11*** | -0.45*** | 1.00 | |
| OWN | 0.01 | -0.03*** | -0.04** | -0.01 | -0.14*** | 0.05*** | -0.05*** | -0.00 | 0.31*** | 0.05** | 0.15*** | 0.06*** | 0.00 | -0.10*** | 0.03 | 1.00 |

This table provides correlations for the full sample of 2,639 company-quarter observations

## 6.2 Path analysis

As explained in Section 5, in order to understand how ANALYST TONE affects CAR (0,1) directly and through ANSWER SPEC, I construct a path model to identify the cause effect relations between the variables.

The direct path of the model studies cumulative abnormal returns (CAR 0,1) as a function of analysts' tone, managers' answers' specificity and other controls for company *j* and quarter *t*:

$$\text{CAR}(0,1)_{j,t} = \beta_0 + \beta_1 \text{ ANSWER SPEC}_{j,t} + \beta_2 \text{ ANALIST TONE}_{j,t} + \text{Controls}_{j,t} + \varepsilon_t . \quad (1)$$

Secondly, I model the indirect path model, which studies answers' specificity as a function of analysts' tone:

$$\text{ANSWER SPEC}_{j,t} = \alpha_0 + \alpha_1 \text{ ANALYST TONE}_{j,t} + \varepsilon_t . \quad (2)$$

The path coefficient $\beta_2$ is the magnitude of the direct path of how ANALYST TONE affects CAR (0,1) while the path coefficient $\alpha_1 * \beta_1$ is the magnitude of the indirect path from ANALYST TONE to CAR (0,1), mediated through ANSWER SPEC. Figure 2 presents the updated path diagram of direct and indirect (i.e., mediated) path shown in Figure 1, including the respective coefficients and predicted signs.

***Figure 2 Path Model with coefficients***

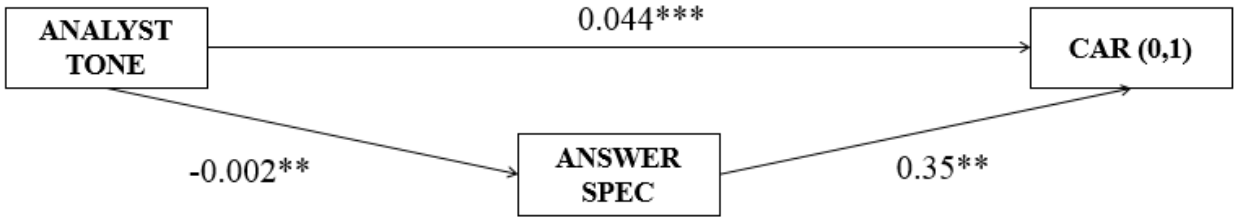



Figure 2 shows the direct and indirect paths through which ANALYST TONE impacts CAR (0,1). ANALYST TONE has a significant direct impact on CAR with a magnitude of 0.044. Further, it affects CAR (0,1) through ANSWER SPEC with a combined coefficient of 0.001** (-0.002*0.35).

Table 4 presents the path coefficients of the main variables. The direct path presents the results of the impact of ANALYST TONE on CAR (0,1). The direct path coefficient ($\beta_2$) between CAR (0,1) and ANALYST TONE is significant and positive at $p < 0.01$, consistent with prior research. The first indirect path presents the coefficient between ANALYST TONE and ANSWER SPEC ($\alpha_1$). The coefficient is significant and negative at $p < 0.05$, indicating that a more negative analysts' tone (so a decrease ANALYST TONE) increases the specificity of information disclosed by managers. The second indirect path presents the coefficient between ANSWER SPEC and CAR (0,1). The coefficient between ANSWER SPEC and CAR (0,1) ($\beta_1$) is significant and positive at $p < 0.05$, indicating that an increase in information specificity disclosed by managers affects positively CAR (0,1). The total mediated path for ANSWER SPEC [ *(ANALYST TONE, ANSWER SPEC) * (ANSWER SPEC, CAR (0,1)*] is significantly negative at $p < 0.05$, with a coefficient of -0.001. The coefficient implies that a one-standard deviation increase in ANALYST TONE results in a 0.001-standard-deviation decrease in CAR (0,1), mediated by ANSWER SPEC. Further, the proportion of the total effect (the sum of the direct and the mediated path coefficients) of ANALYST TONE on CAR (0,1) that is attributable to ANSWER SPEC is about 2.2 percent [0.001/(0.001+ 0.044)].

***Table 4 Path analysis with mediating variable answer specificity***

| CAR (0,1) | | Coefficient | t-Statistics |
|---|---|---|---|
| **Analyst Tone Test** | | | |
| *Direct Path* | | | |
| p (ANALYST TONE, CAR(0,1)) | ($\beta_2$) | 0.044*** | 9.23 |
| Mediated Path | | | |
| p (ANALYST TONE, ANSWER SPEC) | ($\alpha_1$) | -0.002** | -2.34 |
| p (ANSWER SPEC, CAR (0,1) | ($\beta_1$) | 0.35** | 2.51 |
| Total mediated path for CAR (0,1) | ($\alpha_1$*$\beta_1$) | -0.001** | -1.96 |
| Controls | | Yes | Yes |
| N | | 2 516 | |

Table 4 reports the results from path analysis that examines the effect of Analysts Tone (Managers Tone) on CAR (0,1). p ($Var_1$,$Var_2$) stands for the standartized path coefficient. The t-Statistics of the coefficients are presented in parentheses. *, **, *** denote the level of significance respectively at at 10%, 5% an 1%.

Overall, Table 4 suggests that the direct path of Analyst Tone has a higher magnitude on impacting CAR (0,1) compared to the indirect paths through Specificity. This means that one unit change in ANALYST TONE will directly affect CAR (0,1) more significantly than through ANSWER SPEC. However, this comparison in magnitude between direct and indirect paths is subject to limitations due to potential measurement errors in the empirical proxies used for the tone and specificity variable in this study. Further, there may be other potential important paths, not observed in my models. The direct path captures all the residual effects not explained by indirect paths, thus an underestimation/overestimation of the indirect path is possible as a result of potential measurement errors or omitted paths (Baron and Kenny, 1986).

It is important to note that these findings introduce a new dimension of analysts' role in shaping information environment in capital markets. Beside confirming prior research that shows that a more positive analyst tone is positively associated with cumulative abnormal returns, this thesis suggests that a more negative analysts' tone, mediated by information specificity, also affects positively the cumulative abnormal returns. Thus, when the tone of analysts is negative, its impact on CAR (0,1) is two-dimensional. Firstly, it directly impacts negatively CAR (0,1) since investors react strongly to analysts' tone. Secondly, it positively impacts specificity of information, which in turn impacts CAR (0,1) positively.

To understand the impact of positive and negative analysts' tone on CAR (0,1) and answer' specificity, I run the path analysis separately for companies and quarters with ANALYST TONE < 0 and the ones with ANALYST TONE > 0. Table 5 shows the results of the path regression separately for companies and quarters with negative analysts' tone (Panel A) and for the ones with positive analysts' tone (Panel B).

Panel A shows that the direct path between ANALYST TONE and CAR (0,1) remains significant and positive, thus a more negative analysts' tone impacts negatively CAR (0,1). Further, the first indirect path remains significant and negative, indicating that a more negative analysts' tone increases managers' answers' specificity. However, the second indirect path becomes only marginally significant compared to the original path model, at $p < 0.1$ instead of $p < 0.05$. These results indicate that in firms with negative analysts' tone, the significance of information content decreases in determining CAR (0,1). These findings are consistent with Brockman et al. (2015) suggesting that investors react more strongly to negative tones, thus decreasing the importance of information content.

Panel B shows the results for companies and quarters characterized by a positive analysts' tone. The results differ significantly compared to the original model and Panel A. The direct path is statistically insignificant, indicating that when the analysts' tone is positive, an increase in the positivity ratio does not impact CAR (0,1). Further, the first indirect path is also statistically not significant, suggesting that a positive tone of analysts does not trigger more specific information from managers. These results confirm again my first hypothesis that a negative analysts' tone plays an important role in increasing specificity, while a positive one does not have an impact. Lastly, the second indirect path between answers' specificity and CAR (0,1) shows to be not significant, thus indicating that when the analysts' tone is positive, an increase in information specificity does not impact CAR (0,1).

***Table 5 Path analysis with mediating variable answer specificity***

| CAR (0,1) | | Coefficient | t-Statistics |
|---|---|---|---|
| **Panel A: Negative Analyst Tone Test** | | | |
| *Direct Path* | | | |
| p (ANALYST TONE, CAR(0,1)) | ($\beta_2$) | 0.049*** | 3.42 |
| Mediated Path | | | |
| p (ANALYST TONE, ANSWER SPEC) | ($\alpha_1$) | -0.005** | -2.44 |
| p (ANSWER SPEC, CAR (0,1) | ($\beta_1$) | 0.361* | 1.78 |
| Total mediated path for CAR (0,1) ($\alpha_1$*$\beta_1$) | | -0.002* | -1.66 |
| **Panel B: Positive Analyst Tone Test** | | | |
| *Direct Path* | | | |
| p (ANALYST TONE, CAR(0,1)) | ($\beta_2$) | 0.02 | 1.55 |
| Mediated Path | | | |
| p (ANALYST TONE, ANSWER SPEC) | ($\alpha_1$) | 0.00 | 0.58 |
| p (ANSWER SPEC, CAR (0,1) | ($\beta_1$) | 0.27 | 1.85 |
| Total mediated path for CAR (0,1) ($\alpha_1$*$\beta_1$) | | 0.00 | 0.44 |
| Controls | | Yes | Yes |
| N | | 2 516 | |

# 7 Sensitivity Analysis

## 7.1 The direct impact of managers' answers specificity on CAR (0,1)

Prior research documents a variety of CAR determinants, relating to both firms' financial performance and ECCs sentiment (Matsumoto et al., 2011, Price et al., 2012). However, to my knowledge, the effect of specificity of answers provided by managers during ECCs on CAR has not been studied previously. The path model in Section 6 shows that the specificity of answers provided by managers' is a significant mediating path of how the tone of analysts affects market reactions in terms of CAR. In order to study the direct effect of the specificity of managers' answers on CAR, I run a regression of CAR (0,1) on ANSWER SPEC. I control for other determining factors of abnormal returns, suggested by prior literature and I use fixed effects for firms and quarters. Both the control variables and the fixed effects serve as a robustness check for the indirect path in Section 6.

Model 3 shows the direct regression between CAR (0,1) as a dependent variable and ANSWER SPEC as the main independent variable. Further, I control for firm level characteristics which prior literature suggests as determining the level of disclosure details and returns, such as ROA, SIZE, LEV, DIV, BM, VOL, CAR (-60,-2), SURP, OWN, LOSS ( Chen et al., 2002, Frankel et al., 1999, Matsumoto et al., 2011, Price et al., 2012). Also, I include ECCs' related variables that prior research has shown affecting CAR (0,1) such as MANAGER TONE and INTRO TONE (Brockman et al., 2015). Finally, I include the variable INTRO SPEC, as a proxy for the information specificity during the earnings press release. The regression model is as follows:

$$\text{CAR}(0,1)_{j,t} = \gamma_0 + \gamma_1 \text{ANSWER SPEC}_{j,t} + \gamma_2 \text{ANALYST TONE}_{j,t} + \text{Controls}_{j,t} + \varepsilon_t \quad . \quad (3)$$

Table 6 presents the results of regressing CAR (0,1) on ANSWER SPEC, controlling for other variables suggested in the literature on short-window market reactions. The coefficient on ANSWER SPEC is positive (0.44) and significant at $p < 0.05$ level. This means that after controlling for other determinants relating to firm performance and ECCs sentiment, the specificity of information provided by managers during the Q&A session adds value relevant information into capital markets.

Additionally, Table 6 suggests that other ECCs tone variables are statistically significant, such as ANALYST TONE, MANAGER TONE and INTRO TONE. While this is consistent with prior literature, it is important to note that based on the results, ANSWER SPEC has a stronger influence on CAR (0,1) compared to other significant variables. These results further support the path analysis results in Model (1) and (2), according to which, ANSWER SPEC is a significant mediating variable on how ANALYST TONE impacts CAR (0,1).

***Table 6 Regression analysis of CAR (0,1) on answer specificity and controls***

| Variable | Predicted Sign | Coefficient | t-Statistics |
|---|---|---|---|
| ANSWER SPEC | + | 0.44** | 2.50 |
| ANALYST TONE | + | 0.04*** | 7.00 |
| MANAGER TONE | + | 0.03*** | 3.83 |
| INTRO TONE | + | 0.06*** | 5.02 |
| INTRO SPEC | + | 0.19 | 1.64 |
| CAR (-60,-2) | - | 0.02*** | -2.70 |
| ROA | - | 0.03 | -1.05 |
| BM | - | 0.00 | -0.40 |
| LEV | - | 0.00 | -0.11 |
| DIV | - | 0.01 | -1.09 |
| SIZE | - | 0.07*** | -4.71 |
| VOL | + | 0.04 | 0.13 |
| SURP | + | 0.07*** | 4.70 |
| SPECIAL | + | 0.01** | 2.12 |
| OWN | - | 0.00 | -0.12 |
| LOSS | + | 0.00 | 0.30 |
| Constant | + | 0.14 | 2.73 |
| Firm FE | | yes | yes |
| Quarter FE | | yes | yes |
| N | 2.441 | | |
| Adjusted $R^2$ in % | 4.1 | | |

Table 6 reports coefficient estimates from the regression of CAR (0,1) on determinants for the full sample. All variables are explained in the Research Design section. Standard errors are clustered by firm. ***, **, * indicate significance at the 1, 5, and 10 % levels respectively (two-tailed).

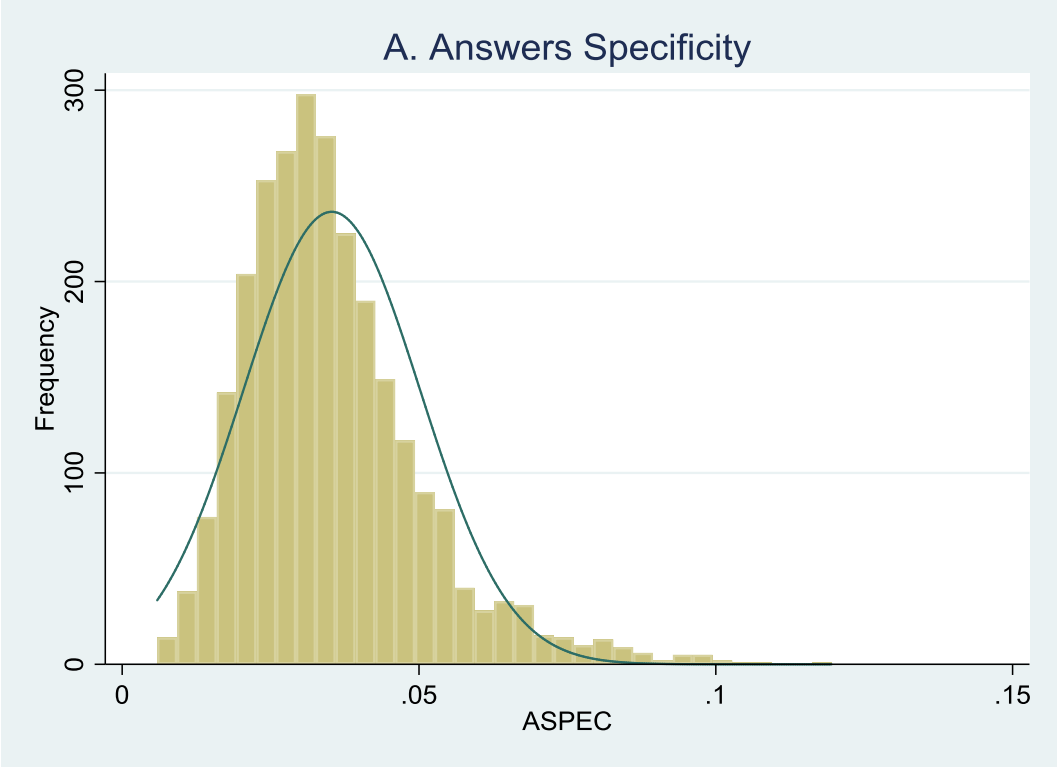
## 7.2 The direct impact of analysts' tone on information specificity

This section reports the robustness test for the mediating variable ANSWER SPEC and the first path of the analysis (ANALYST TONE, ANSWER SPEC). As described in the Introduction part of this thesis, ECCs are held shortly after companies announce their earnings results and they typically begin with an introduction of the prior quarter performance, followed by an open Q&A session. While in this study I focus on the specificity of information based on managers' answers during Q&A session (ANSWER SPEC), the information specificity of the ECCs introduction part (INTRO SPEC) may significantly affect the specificity of information delivered through managers' answers during the Q&A session. I visually inspected the specificity distributions for ANSWER SPEC and INTRO SPEC and reported them in Figure 3. Both distributions appear to be substantially skewed to the left, however due to the large number of observations in my sample, this does not adversely affect the reliability of the tests. Figure 3 shows that the distribution of ANSWER SPEC is roughly centered around 0.3 and INTRO SPEC around 1.3, which means that there is a significant difference between the variables, with INTRO SPEC being richer in information specificity.

Furthermore, Table 7 confirms the difference between ANSWER SPEC and INTRO SPEC distribution and shows that the difference is significant for the total use of specific words and across sub-categories. INTRO SPEC has a higher mean and it is more resourceful in information specificity due to the nature of the introduction part. Introduction part is a prepared script by management, which summarizes events occurred during the previous quarter, thus providing more specific information. On the contrary, Q&A sessions are more spontaneous and management cannot prepare for analysts' questions, thus the answers may contain less specific information compared to introduction part.

***Figure 3 Distribution of Intro and Answers Specificity measure***

*Panel A*




*Panel B*

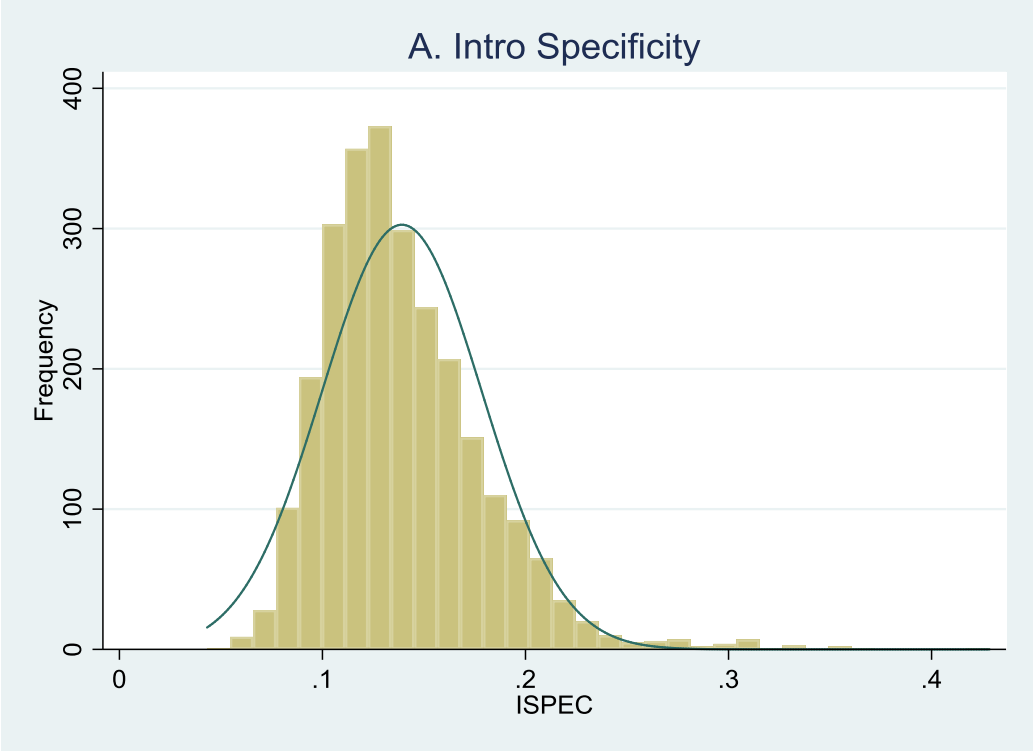



Figure 3 presents the distribution of Answer Specificity (Panel A) and Intro Specificity (Panel B).

***Table 7 Intro and Answer Specificity Differences***

| Categories | No. Of Obs. | INTRO SPEC (Mean) | ANSWER SPEC (Mean) | SPEC DIFF | p-Value | Wilcoxon test (z-score) |
|---|---|---|---|---|---|---|
| Total Specificity | 2 639 | 0.14 | 0.04 | 0.10 | -1.4e*** | -62.7*** |
| Specificity Categories | | | | | | |
| *Date* | 2 639 | 0.25 | 0.01 | 0.24 | -2.5** | -57.7*** |
| *Location* | 2 639 | 0.01 | 0.00 | 0.01 | -1.9** | -8.9*** |
| *Money* | 2 639 | 0.24 | 0.01 | 0.24 | -2.5** | -56.1*** |
| *Organization* | 2 639 | 0.17 | 0.01 | 0.16 | -2.7*** | -59.8*** |
| *Percent* | 2 639 | 0.05 | 0.00 | 0.05 | -2.4** | -46.7*** |
| *Person* | 2 639 | 0.06 | 0.00 | 0.06 | -2.5** | -45.9*** |
| *Time* | 2 639 | 0.00 | 0.00 | 0.00 | -1.3 | -14.1*** |

Table 7 shows the difference-in-means and medians tests between information specificity between the introduction session and managers' answers during the Q&A session of ECCs. The variable modifier SPEC DIFF indicates the difference between the two variables; p-values for mean test are in parentheses; Wilcoxon test shows the z-score and the significance for median test.

The analysis from the descriptive statistics results suggest that both median and mean of ANSWER SPEC and INTRO SPEC are significantly different. Further, for all categories, the mean and median of INTRO SPEC is higher compared to ANSWER SPEC and it indicates an overall higher ratio of specificity during the introduction part of ECCs. However, for both introduction part and Q&A session, the categories that seem to provide more specific information are Date, Money and Organization. Since both sessions follow similar trends in the categories of information disclosed, this may indicate that the specificity of information is driven by the managers' disclosure choice rather than analysts' tone. Strategic management literature suggests that individual influences can impact corporate disclosures. Further, Bamber et al., (2010) show that managers' unique disclosure style is a determining factor in their firms' voluntary financial disclosure choices.

A limitation of the path model in Section 6 is that it does not control for managers' unique disclosure style, therefore there is a risk that the results are driven by managers' disclosure style rather than analysts' tone. However, the management team presenting the firm's quarterly earnings during the introduction session is responsible for answering analysts' questions later in Q&A session, thus I expect that the managers' unique disclosure style impacts both the introduction and the Q&A session of the ECCs. Also, since introduction is held before Q&A session, I expect that there is no cause-effect relation between ANALYST TONE and INTRO SPEC, in contrast to the significant cause-effect relation between ANALYST TONE and ANSWERS SPEC shown in Model (2). Thus, I run a path analysis between ANALYST TONE and CAR (0,1), but this time the mediating variable is INTRO SPEC instead of ANSWER SPEC.

Table 8 shows the results for the later path analysis replacing the mediating variable ANSWER SPEC, with INTRO SPEC. The direct path between ANALYST TONE and CAR (0,1), shows similar results in significance and magnitude as the original model in Section 6. Furthermore, as predicted, the indirect path between ANALYST TONE and INTRO SPEC is not significant, suggesting that INTRO SPEC is not a significant mediating variable. Thus, while both INTRO SPEC and ANSWER SPEC are prone to managers' unique disclosure style, differently from INTRO SPEC, ANSWER SPEC has a statistically significant relation with ANALYST TONE. This suggests that ANSWER SPEC is not solely driven by managers' disclosure choice, but analysts' pressure affects managers' answers' specificity. This additional path analysis serves as a robustness tests for the original path analysis presented in Section 6, which shows that the variable ANSWER SPEC is a statistically significant mediating variable on how ANALYST TONE impacts CAR (0,1).

***Table 8 Path analysis with mediating variable Intro Specificity***

| | Path = Analyst Tone | |
|---|---|---|
| CAR (0,1) | Coefficient | t-Statistics |
| *Direct Path* | | |
| p(Analyst, CAR) | 0.044 | 7.18*** |
| Mediated Path | | |
| p(Analyst Tone, Intro Specificity) | 0.002 | 0.22 |
| p(Specificity, CAR (0,1) | 0.345 | 2.51** |
| Total mediated path for CAR (0,1) | 0.001 | |
| Controls | yes | yes |
| N | 2 539 | |

Table 7 reports the results from path analysis that examines the effect of Analysts Tone on CAR (0,1), with the mediating variable of Intro Tone. P ($VAR_1$, $VAR_2$) stands for the standartized path coefficient. The t-Statistics of the coefficients are presented in parentheses. *, **, *** denote the level of significance respectively at at 10%, 5% an 1%.

# 8 Conclusion

The main focus of this thesis was the dynamic interaction between the firms' management team and financial analysts on quarterly earnings conference calls. I perform a path analysis and study the direct and indirect relations between analysts' tone and cumulative abnormal returns. Consistently with prior research, I document that analysts' tone plays a significant role in predicting CAR (0,1). Furthermore, I document that the increased specificity in managers' answers as a result of analysts' tone is another channel through which tone is associated with the observed change in stock price after ECCs.

The results also show that specificity of managers' answers carry significantly more weight in determining CAR (0,1) compared to other tone and performance variables. While the market reacts to managers' tone, analysts' tone and introduction tone, investors base their decisions more heavily on the information specificity. The coefficient on managers' answers' specificity is larger in magnitude than the tone counterparts. This result is important because it demonstrates that investors place more value into information quality compared to tone.

Lastly, the results show that when in the sub category of companies with negative tone of analysts, a more negative tone affects positively answers' specificity, however, answers' specificity decreases in significance in affecting CAR (0,1). These results suggest that information quality becomes less important in investors' decision making in firms characterized by negative analysts' tone.

This study makes several contributions to literature and capital markets in understanding the role of analysts in shaping information environment in capital markets. Firstly, it adds to literature involved in text and sentiment analysis by studying an information quality characteristic, *information specificity,* as a function of tone. The results show that there is a significant negative relation between the analysts' tone and information specificity, thus a more negative tone increases information specificity. Secondly, it contributes to literature on disclosure quality by documenting that a higher specificity in disclosures during the Q&A session of ECCs has a significant impact and a large magnitude in affecting CAR (0,1). Lastly, this study contributes to investors' and regulators' understanding of analysts' role in increasing information quality in capital markets.

# References

Arslan-Ayaydin, Ö., Boudt, K. and Thewissen, J. (2016). Managers set the tone: Equity incentives and the tone of earnings press releases. Journal of Banking & Finance, 72, pp.S132-S147.

Bamber, L., Jiang, J. and Wang, I. (2010). What's My Style? The Influence of Top Managers on Voluntary Corporate Financial Disclosure. The Accounting Review, 85(4), pp.1131-1162.

Baron, R. M., and D. A. Kenny. 1986. The moderator-mediator variable distinction in social psychological research: Conceptual,strategic, and statistical considerations. Journal of Personality and Social Psychology 51: 1173–1182.

Bhattacharya, N., Ecker, F., Olsson, P. and Schipper, K. (2012). Direct and Mediated Associations among Earnings Quality, Information Asymmetry, and the Cost of Equity. The Accounting Review, 87(2), pp.449-482.

Bowen, R., Davis, A. and Matsumoto, D. (2002). Do Conference Calls Affect Analysts' Forecasts? The Accounting Review, 77(2), pp.285-316.

Brown, S., Hillegeist, S. and Lo, K. (2004). Conference calls and information asymmetry. Journal of Accounting and Economics, 37(3), pp.343-366.

Brockman, P., Li, X. and Price, S. (2015). Differences in Conference Call Tones: Managers vs. Analysts. Financial Analysts Journal, 71(4), pp.24-42.

Bushee, B., Matsumoto, D. and Miller, G. (2001). Open versus Closed Conference Calls: The Determinants and Effects of Broadening Access to Disclosure. SSRN Electronic Journal.

Chen, S., Defond, M., & Park, C. (2002). Voluntary disclosure of balance sheet information in quarterly earnings announcements. Journal of Accounting and Economics, 33, 229–251.

Davis, A., Piger, J. and Sedor, L. (2012). Beyond the Numbers: Measuring the Information Content of Earnings Press Release Language*. Contemporary Accounting Research, 29(3), pp.845-868.

Demers, E. and Vega, C. (2010). Soft Information in Earnings Announcements: News or Noise? SSRN Electronic Journal.

Dye, R. (1985). Disclosure of Nonproprietary Information. Journal of Accounting Research, 23(1), p.123.

Frankel, R., Johnson, M. and Skinner, D. (1999). An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium. Journal of Accounting Research, 37(1), p.133.

Frankel, R., Mayew, W. and Sun, Y. (2009). Do pennies matter? Investor relations consequences of small negative earnings surprises. Review of Accounting Studies, 15(1), pp.220-242.

Henry, E. (2008). Are Investors Influenced By How Earnings Press Releases Are Written? Journal of Business Communication, 45(4), pp.363-407.

De Franco, G., Hope, O.-K., Vyas, D., & Zhou, Y. (2015). Analyst report readability. Contemporary Accounting Research, 32(1), 76–104.

Huang, A., Lehavy, R., Zang, A. and Zheng, R. (2018). Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. Management Science, 64(6), pp.2833-2855.

Kimbrough, M. (2005). The Effect of Conference Calls on Analyst and Market Underreaction to Earnings Announcements. The Accounting Review, 80(1), pp.189-219.

Kohlbeck, M. and Magilke, M. (2002). The Impact of Concurrent Conference Calls on the Information Content of Earnings Announcements. SSRN Electronic Journal.

Loughran, T. and Mcdonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. The Journal of Finance, 66(1), pp.35-65.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. Journal of Accounting and Economics, 45(2), 221–247.

Matsumoto, D., Pronk, M. and Roelofsen, E. (2011). What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. The Accounting Review, 86(4), pp.1383-1414.

Mayew, W. and Venkatachalam, M. (2012). The Power of Voice: Managerial Affective States and Future Firm Performance. The Journal of Finance, 67(1), pp.1-43.

Mba.tuck.dartmouth.edu. (2019). Kenneth R. French - Home Page. [online] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french [Accessed 12 Jan. 2019].

Milian, J. and Smith, A. (2017). An Investigation of Analysts' Praise of Management During Earnings Conference Calls. Journal of Behavioral Finance, 18(1), pp.65-77.

Nlp.stanford.edu. (2019). The Stanford Natural Language Processing Group. [online] Available at: https://nlp.stanford.edu/software/CRF-NER.html [Accessed 11 May 2019].

Price, S., Doran, J., Peterson, D. and Bliss, B. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. Journal of Banking & Finance, 36(4), pp.992-1011.

Sadique, S., In, F. and Veeraraghavan, M. (2008). The Impact of Spin and Tone on Stock Returns and Volatility: Evidence from Firm-Issued Earnings Announcements and the Related Press Coverage. SSRN Electronic Journal.

Sec.gov. (2019). Selective Disclosure and Insider Trading. [online] Available at: https://www.sec.gov/rules/final/33-7881.htm [Accessed 23 May 2019].

Venkataraman, K., Thompson, R. and Eleswarapu, V. (2001). The Impact of Regulation Fair Disclosure: Trading Costs and Information Asymmetry. SSRN Electronic Journal

# Appendix 1

Tone measurement from analysts' questions

| | ISIN | year | All notes | Text | rate_d | rate_sentences | Negative | Positive | Uncertainty | Litigious | Constraining | Superfluous | Interesting | Modal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Q_Acacia Comm | | </Answe | </Answer: | {"and i wa | and i wast | 0,3 | 0,1 | 0,3 | 0,0 | - | - | - | 0,5 |
| 1 | Q_Acacia Comm | | </Answe | </Answer: | {'</questi | </questio | 0,2 | 0,2 | 0,1 | - | 0,1 | - | - | 0,5 |
| 2 | Q_Acacia Comm | | </Answe | </Answer: | {'could yo | could you | 0,3 | 0,2 | 0,3 | 0,0 | 0,1 | - | 0,0 | 0,5 |
| 3 | Q_Acacia Comm | | </Answe | </Answer: | {'and sort | and sort o | 0,3 | 0,1 | 0,4 | 0,0 | - | - | 0,0 | 0,4 |
| 4 | Q_Acacia Comm | | </Answe | </Answer: | {'and this | and this is | 0,5 | 0,2 | 0,4 | 0,0 | - | - | 0,0 | 0,6 |
| 5 | Q_Activision Bli | | </Answe | </Answer: | {"</answe | </answers | 0,3 | 0,1 | 0,3 | - | 0,0 | - | - | 0,4 |
| 6 | Q_Activision Bli | | </Answe | </Answer: | {'</answe | </answers | 0,1 | 0,2 | 0,5 | 0,0 | - | - | - | 0,7 |
| 7 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,1 | 0,2 | 0,2 | - | - | - | - | 0,3 |
| 8 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,2 | 0,4 | 0,3 | - | - | - | 0,0 | 0,4 |
| 9 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,1 | 0,2 | 0,2 | 0,1 | - | - | - | 0,3 |
| 10 | Q_Activision Bli | | </Answe | </Answer: | {'will ther | will there | 0,1 | 0,2 | 0,5 | - | 0,0 | - | - | 0,5 |
| 11 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,3 | 0,3 | 0,2 | - | 0,0 | - | - | 0,5 |
| 12 | Q_Activision Bli | | </Answe | </Answer: | {'</answe | </answers | 0,1 | 0,1 | 0,3 | - | - | - | - | 0,5 |
| 13 | Q_Activision Bli | | </Answe | </Answer: | {'the -- be | the -- befo | 0,1 | 0,3 | 0,3 | 0,0 | - | - | 0,0 | 0,3 |
| 14 | Q_Activision Bli | | </Answe | </Answer: | {"</answe | </answers | - | 0,3 | 0,3 | - | - | - | - | 0,4 |
| 15 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,1 | 0,1 | 0,2 | - | - | - | 0,0 | 0,3 |
| 16 | Q_Activision Bli | | </Answe | </Answer: | {'</questi | </questio | 0,1 | 0,3 | 0,3 | - | - | - | 0,0 | 0,5 |
| 17 | Q_Activision Bli | | </Answe | </Answer: | {"and\nth | andthen h | 0,1 | 0,3 | 0,4 | - | - | - | - | 0,6 |

# Appendix 2

Specificity measurement from managers' answers.

| | ISIN | LOCATION_COUNT | PERSON_COUNT | ORGANIZATION_COUNT | MONEY_COUNT | PERCENT_COUNT | DATE_COUN | TIME_COUNT | O_COUNT |
|---|---|---|---|---|---|---|---|---|---|
| 0 | A_Acacia Communicatio | 15 | 15 | 37 | 0 | 26 | 17 | 0 | 3561 |
| 1 | A_Acacia Communicatio | 22 | 35 | 37 | 12 | 40 | 28 | 0 | 4219 |
| 2 | A_Acacia Communicatio | 30 | 18 | 22 | 9 | 14 | 47 | 0 | 4157 |
| 3 | A_Acacia Communicatio | 17 | 22 | 34 | 0 | 28 | 33 | 0 | 3325 |
| 4 | A_Acacia Communicatio | 19 | 21 | 29 | 0 | 36 | 36 | 0 | 3510 |
| 5 | A_Activision Blizzard, Inc | 9 | 9 | 25 | 16 | 0 | 17 | 0 | 1938 |
| 6 | A_Activision Blizzard, Inc | 0 | 7 | 26 | 2 | 6 | 7 | 0 | 2118 |
| 7 | A_Activision Blizzard, Inc | 2 | 4 | 37 | 8 | 4 | 17 | 0 | 2178 |
| 8 | A_Activision Blizzard, Inc | 1 | 7 | 28 | 0 | 2 | 7 | 0 | 1457 |
| 9 | A_Activision Blizzard, Inc | 6 | 14 | 60 | 0 | 4 | 19 | 0 | 2415 |
| 10 | A_Activision Blizzard, Inc | 8 | 10 | 46 | 3 | 2 | 14 | 0 | 2424 |
| 11 | A_Activision Blizzard, Inc | 12 | 5 | 52 | 0 | 2 | 16 | 0 | 3123 |
| 12 | A_Activision Blizzard, Inc | 7 | 3 | 44 | 4 | 10 | 13 | 0 | 2248 |
| 13 | A_Activision Blizzard, Inc | 1 | 15 | 43 | 3 | 4 | 11 | 0 | 2107 |
| 14 | A_Activision Blizzard, Inc | 2 | 15 | 45 | 0 | 0 | 10 | 2 | 3330 |
| 15 | A_Activision Blizzard, Inc | 0 | 5 | 30 | 0 | 0 | 9 | 0 | 1446 |
| 16 | A_Activision Blizzard, Inc | 11 | 9 | 37 | 5 | 12 | 12 | 3 | 3039 |
| 17 | A_Activision Blizzard, Inc | 4 | 10 | 27 | 9 | 6 | 10 | 3 | 2380 |
| 18 | A_Activision Blizzard, Inc | 3 | 12 | 23 | 0 | 2 | 20 | 0 | 2208 |
| 19 | A_Activision Blizzard, Inc | 8 | 11 | 47 | 4 | 10 | 18 | 2 | 3227 |
| 20 | A_Activision Blizzard, Inc | 5 | 4 | 45 | 4 | 0 | 5 | 0 | 2176 |
| 21 | A_Activision Blizzard, Inc | 4 | 7 | 45 | 5 | 2 | 7 | 0 | 1923 |
| 22 | A_Activision Blizzard, Inc | 3 | 7 | 36 | 10 | 0 | 14 | 0 | 2153 |
| 23 | A_Activision Blizzard, Inc | 5 | 12 | 14 | 6 | 8 | 10 | 0 | 2257 |
| 24 | A_Activision Blizzard, Inc | 0 | 17 | 51 | 3 | 0 | 14 | 0 | 2808 |
| 25 | A_ADDvantage Technol | 10 | 44 | 36 | 20 | 8 | 15 | 0 | 5694 |
| 26 | A_ADDvantage Technol | 3 | 12 | 15 | 14 | 0 | 14 | 0 | 1922 |
| 27 | A_ADDvantage Technol | 4 | 26 | 17 | 3 | 2 | 22 | 0 | 3424 |
| 28 | A_ADDvantage Technol | 22 | 27 | 18 | 48 | 2 | 12 | 0 | 3236 |