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Earnings Call Tone and Abnormal Returns: Evidence from the Swedish Market

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Abstract

This thesis examines how managerial sentiment in quarterly earnings conference calls is associated with the short-window stock price reaction of Swedish listed companies. While extensive evidence on the informational role of managerial tone exists in the U.S. setting, evidence from non-U.S. contexts remains scarce. Using a sample of 4,041 firm-quarter observations from 195 firms listed on Nasdaq Stockholm between 2015 and 2025, we employ a bag-of-words textual analysis method based on the Loughran and McDonald (2011) dictionary to quantify positive and negative tone in the earnings call transcripts. We separate the presentation and Q&A sections of the call to isolate scripted from spontaneous communication. We regress the cumulative abnormal return (CAR) in a three-day event window around the call on our tone measures and control variables using OLS with firm and year-quarter fixed effects and standard errors clustered by firm and quarter. We find that the net tone in the conference call is positively and significantly associated with CAR in both the presentation and Q&A section. However, we do not find support for an asymmetric effect where negative words have a stronger association with CAR than positive words. Overall, our analysis provides evidence that abnormal returns are associated not only with *what* managers report, but also with *how* they say it.

Keywords: Textual analysis, Earnings conference calls, Tone, Market reactions, Event study

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1. Introduction

1.1 Background

If financial markets were perfectly efficient, the tone of managerial communication should not significantly alter market outcomes. Yet an increasing body of literature finds sentiment expressed in media, corporate filings and earnings conference calls to be a predictor of abnormal returns and trading volume (Tetlock, 2007; Loughran & McDonald, 2011; Price et al., 2012). This suggests that not only financial results matter, but also the manner in which they are communicated and framed. There are several disclosure channels through which firms communicate their current and expected future earnings to investors, including periodic financial reports, earnings press releases and earnings conference calls (Frankel et al., 1999; Bushee et al., 2003). The main role of such public disclosures is to bridge the information gap between managers and external capital providers. As managers are generally assumed to possess superior information about the firm's future prospects (Healy & Palepu, 2001), investors rely heavily on their communication when making trading decisions.

Understanding how capital market participants process and react to new information has long been a central topic in accounting and finance research. Early research has focused mainly on the role of quantitative financial information in shaping stock price movements (Williams, 1956; Gordon, 1959; Miller & Modigliani, 1961), but later studies recognise the importance of qualitative information. Shiller (1981) and Cutler et al. (1989) were among the first to demonstrate that conventional quantitative measures of firm fundamentals are insufficient in fully explaining large stock price movements. Subsequent researchers have examined the informativeness of sentiment in various corporate filings, media content and earnings conference calls (Huang et al., 2014; Tetlock et al., 2008; Price et al., 2012). These studies document varying relationships between managerial sentiment and market reactions but consistently find that tone significantly impacts market outcomes.

We examine managerial sentiment in the context of earnings conference calls. Earnings calls take place quarterly, accompanying firms' quarterly earnings announcements, and enable managers to voluntarily disclose additional information to the market (Brown et al., 2004). There are several reasons for the choice of studying earnings conference calls. First, conference calls constitute a major channel of investor communication in which managers can supplement information contained in regulatory filings (Frankel et al., 1999). Second, the calls are released in connection with earnings announcements during periods known to exhibit heightened market attention and have been established as significant information events to the market (Kimbrough, 2005). Third, the spoken nature of the calls enables managers to express information in a less constrained manner which has implications for informativeness (Matsumoto et al., 2011). Lastly, the high availability and largely standardised format of the call transcripts enable us to systematically extract sentiment from a large sample of corporate disclosures. The impact of conference calls on capital markets is also well documented in empirical literature and has been found to significantly explain stock market movements (Frankel et al., 1999; Matsumoto et al., 2011; Price et al., 2012; Jiang et al., 2019).

1.2 Purpose and Contribution

While there exists a substantial body of empirical research on managerial sentiment, its exploration outside the U.S. context remains limited. A small number of studies extend the literature to Chinese markets (Wu et al., 2021; Chang et al., 2023; Qin & Cui, 2024), but evidence from European settings is sparse, and to our knowledge no prior study examines the Swedish market.

This gap is meaningful because Sweden differs from the U.S. along several dimensions that are theoretically relevant for the relationship between managerial communication and market reactions. The Scandinavian institutional environment is characterised by concentrated ownership, lower litigation risk, and weaker formal shareholder protection mechanisms despite strong enforcement quality (La Porta et al., 1998; La Porta et al., 2008). These features alter the incentives managers face when communicating with investors and may shape how the market interprets that communication. Further, cultural differences may shape managerial communication styles as Scandinavian managers are generally found to emphasise cooperation and consensus in their communication (Grenness, 2003). Finally, the calls themselves are held in English, while most Swedish managers and market participants are non-native speakers, which is a linguistic feature that may influence both the production and interpretation of sentiment. Together, these institutional, cultural and linguistic differences make it an open empirical question whether findings established in the U.S. extend to the Swedish setting.

This thesis contributes to the literature by providing evidence on the relationship between earnings conference call sentiment and stock market reactions in Sweden, a setting with materially different institutional and linguistic conditions from the markets that dominate the existing literature. Against this background, we examine the following research question:

How does the sentiment in quarterly earnings conference calls affect stock price movements around the call on the Swedish stock market?

Drawing on theories of information asymmetry and signalling and on behavioural finance evidence of tone-driven market reactions, we expect managerial sentiment to be positively associated with cumulative abnormal returns. We further expect this relationship to be asymmetric. Motivated by Tversky and Kahneman's (1979) loss aversion and the negativity bias documented in the empirical literature (Tetlock, 2007; Tetlock et al., 2008; Loughran & McDonald, 2011), we expect that negative tone has a stronger association with cumulative abnormal returns than positive tone.

1.3 Scope

To address our research question and hypotheses, we draw on a sample of 4,041 firm-quarter observations from Swedish listed firms between 2015 and 2025. We exclude firms with a market capitalization below 2,000 MSEK, which removes small and micro-cap stocks that may suffer from liquidity issues, do not hold earnings conference calls, or lack sufficient analyst coverage. To quantify managerial sentiment, we apply a bag-of-words approach using the dictionary developed by Loughran and McDonald (2011) to classify positive and negative words in each transcript. The resulting net sentiment, positive proportion and negative proportion measures serve as our main independent variables. We further split each transcript into the managerial presentation and Q&A section of the earnings call, motivated by empirical research arguing that the two sections exhibit different characteristics and levels of informativeness (Matsumoto et al., 2011; Price et al., 2012). Our dependent variable, cumulative abnormal returns (CAR), is calculated using a short-window event study following Price et al. (2012) and captures the market reaction immediately around the call. We regress CAR on our measures of conference call tone using OLS with firm and year-quarter fixed effects, employing standard firm-level controls throughout.

1.4 Results

We find that net tone is positively and significantly associated with cumulative abnormal returns around the earnings call. A one standard deviation increase in net tone is associated with an increase in the three-day cumulative abnormal return of approximately 1.08% in the presentation section and 1.23% in the Q&A section. The result is robust to alternative tone definitions, the use of the Henry (2008) dictionary, and alternative event window specifications. The evidence from our analysis supports H1, that the qualitative content of managerial communication is associated with abnormal returns beyond the quantitative earnings information conveyed in the call.

The evidence for our second hypothesis is more nuanced. We do not find conclusive evidence that negative words have a stronger absolute association with the cumulative abnormal returns than positive words. In the presentation section, we cannot significantly distinguish the magnitudes of the positive- and negative-word effects, meaning we cannot conclude any asymmetric effect. In the Q&A section, we find evidence of the opposite asymmetry. When comparing the differences in the standard-deviation scaled effect, the positive-word coefficient is significantly larger in absolute magnitude than the negative-word coefficient.

2. Literature Review and Theory

This section presents the theoretical frameworks and empirical literature underpinning our study. The theoretical part covers capital markets efficiency, pricing, information asymmetry, agency problems and behavioural finance. The literature review assesses empirical work on qualitative information content, textual and sentiment analysis, corporate disclosure channels, and earnings conference calls. The section concludes with developing our hypotheses.

2.1 Theoretical Frameworks

2.1.1 Information Efficiency and Capital Market Reactions

Under the efficient market hypothesis (EMH), security prices fully reflect all available information (Fama, 1970). The EMH distinguishes between weak, semi-strong and strong forms of efficiency. Assuming a semi-strong form, in which prices adjust immediately to publicly available information, sentiment-based trading should not systematically generate abnormal returns after fundamental information, such as earnings surprises, is controlled for. However, empirical evidence challenges this prediction. Linguistic tone in media, corporate filings and earnings conference calls has been shown to predict abnormal returns and trading volume (Tetlock, 2007; Loughran & McDonald, 2011; Price et al., 2012). Two interpretations are consistent with this evidence. Either narrative tone contains informational content that investors rationally price into securities, in which case the EMH still holds, or behavioural frictions cause investors to incorporate tone irrationally, producing systematic return patterns. The theoretical frameworks outlined below develop both interpretations.

2.1.2 Information Asymmetry and Signalling

Information asymmetry and the separation of ownership and control create a demand for accounting information by external parties (Beyer et al., 2010). Because external capital providers lack the information that managers have regarding the firm's expected returns, they struggle to evaluate the firm's future prospects and may consequently misprice firms, over-pricing firms with low profitability and under-pricing firms with high profitability. This increases the managerial incentive to voluntarily disclose additional information, to reduce information asymmetry and avoid mispricing of the firm. Earnings conference calls, held quarterly following the release of a firm's financial results, are one of several channels enabling managers to disclose additional information to investors. Brown et al. (2004) find that firms holding regular conference calls experience sustained reductions in information asymmetry and achieve subsequent lower costs of capital, consistent with Beyer et al. (2010).

From this perspective, managerial tone itself may act as a signal of private knowledge, where an optimistic tone conveys credible private information about favourable prospects, while a pessimistic tone reveals adverse future outcomes. If managers use sentiment to genuinely inform investors of future prospects, then under the EMH, tone should predict returns and investors are rational in incorporating it into prices. This view is consistent with signalling theory, in which managers voluntarily disclose private information to influence investors' beliefs about firm performance (Verrecchia, 2001). This perspective implies that managerial tone could predict abnormal returns as it contains information beyond what is captured by quantitative numbers, with stronger effects when information asymmetry is greater. For instance, when public disclosures around the earnings announcements are low (Verrecchia, 2001), or when analyst coverage is insufficient (Healy & Palepu, 2001).

2.1.3 Managerial Incentives, Agency and Strategic Disclosures

The separation of ownership and control in large publicly traded firms also creates agency problems, described by Jensen and Meckling (1976) as cases in which the agent (manager) does not act in the best interest of the principal (external investors). In contrast to managers voluntarily disclosing private information to reduce mispricing, agency theory suggests that managers have incentives to manipulate investors for their own private benefit (Jensen & Meckling, 1976). For instance, by being deceptive about earnings to keep the cost of capital low, preserve firm reputation, or influence their own compensation (Hope & Wang, 2018).

From this perspective, tone may be used to strategically conceal bad news and inflate perceived and expected performance, rather than to disclose private information.

A related explanation comes from Davis et al. (2015), who find evidence that sentiment in earnings calls largely reflects idiosyncratic, manager-specific communication styles, rather than private knowledge or strategic intent. Both perspectives imply that the observed tone could result from either strategic manipulation or manager-specific tendencies, rather than it carrying credible information of firm fundamentals. Under this view, sentiment should not be incorporated into stock prices by rational investors, who correctly interpret the information and disregard emotional or speculative elements when making decisions to maximise their own utility (Szyszka, 2013). As rational investors filter out strategic or idiosyncratic sentiment, they leave tone with no predictive power for returns. Further explanations for the persistence of sentiment-driven return patterns in the empirical literature points toward behavioural mechanisms developed in the next section.

2.1.4 Behavioural Finance Theories

Behavioural finance theories relax the assumption of perfectly rational investors and provide explanations for why managerial tone shapes market reactions even when it carries no incremental information. Prospect theory, salience effects and the affect heuristic are particularly relevant.

First, prospect theory holds that individuals evaluate outcomes relative to a reference point and respond differently depending on whether they are framed as positive or negative (Tversky & Kahneman, 1981). These "framing effects" capture psychological factors affecting individuals' decision-making and are relevant in explaining the seemingly irrational behaviour of pricing in sentiment. A feature of prospect theory is loss aversion, the principle that an outcome is perceived as worse when framed as a loss rather than as a gain (Tversky & Kahneman, 1979). In the context of managerial disclosures, this implies that negatively framed statements should trigger stronger investor reactions than positively framed ones.

Second, investors exhibit limited attention and processing capacity, suggesting that information presented in the most salient and easily processed form is better absorbed (Hirshleifer & Teoh, 2003), and that the market favours attention-grabbing information rather than a full information set with all options (Barber & Odean, 2008). Emotionally salient language in earnings calls may therefore have a disproportionately large effect on shaping investors' reactions relative to the underlying quantitative information.

Third, the affect heuristic argues that emotional reactions guide how people evaluate risk, probabilities and new information (Slovic et al., 2007). When managers frame information in a positive or negative light, investors form an immediate emotional response that shapes their subsequent processing and judgment of the information, regardless of whether the tone reflects private information or not. Together, these three mechanisms suggest that managerial tone may predict abnormal returns through psychological channels rather than informational ones, with negative framing potentially carrying disproportionate weight.

2.2 Literature Review

2.2.1 Limitations of Quantitative Accounting Measures

Understanding how capital markets process new information has long been a central topic in accounting and finance research, with early work focusing almost exclusively on quantitative financial measures. Williams (1956) and Gordon (1959) argued that a stock's value should be determined by the present value of expected future cash flows, measured by dividends, earnings, or coupon payments. Miller and Modigliani (1961) reject the importance of payout policy, arguing that in efficient markets firm value is determined by investment policy and earnings power rather than the dividend payout ratio. Shareholder wealth therefore remains unchanged regardless of whether earnings are distributed or retained. While influential, these frameworks proved insufficient on their own to explain large stock price movements (Feldman et al., 2010). Shiller (1981) and Cutler et al. (1989) provided early evidence that conventional quantitative measures of firm fundamentals could not adequately explain large stock price fluctuations, encouraging a growing body of research exploring qualitative complements to financial information.

2.2.2 Qualitative Information and Textual Analysis

The indication that quantitative information cannot fully explain stock price movements has motivated a body of literature exploring the qualitative side of corporate disclosure and communication. Loughran and McDonald (2016), in their survey of textual analysis in accounting and finance, note that textual analysis extends across many disciplines under various labels, including computational linguistics, natural language processing, information retrieval and content analysis. In accounting and finance, it has become a central tool for quantifying qualitative information in corporate disclosures. Before an analysis can be conducted, text must be represented as numerical input. Bochkay et al. (2023) distinguish between two general approaches to text representation, the bag-of-words (BOW) approach, which represents documents as vectors of word counts, and the word-embedding approach, which captures semantic relations among words.

The BOW approach relies on a dictionary, a predefined wordlist used as a baseline of recognising, classifying and counting words. Loughran and McDonald (2011) make a foundational contribution by showing that general-purpose dictionaries are poorly suited for the financial context and develop a finance-specific dictionary based on the appearance of sentiment-bearing words in 10-K filings, which is better at reflecting the true tone in financial texts. They document that negative words appear more often than positive words in the Management Discussion and Analysis (MD&A) sections, and that tone measured with their dictionary is significantly associated with firm performance and market reactions. Much of the subsequent textual analysis literature, including this thesis, adopts their dictionary within a BOW approach.

2.2.3 Sentiment in Media and Corporate Filings

Two early applications of textual analysis examined how media sentiment shapes capital market outcomes. Tetlock (2007) investigates the interaction between sentiment in news stories and stock market reactions and finds that pessimistic media content predicts immediate downward pressure on stock prices, which partially reverses over the following days. He argues that this pattern is inconsistent with media content acting as a simple proxy for new fundamentals or as pure noise but appears to genuinely impact investor behaviour. Tetlock et al. (2008) extend the analysis to the firm level and show that pessimistic sentiment in news stories about specific firms predicts subsequent low earnings and stock returns. Together, these studies provide early evidence that textual tone captures qualitative information that affects investors, a theme later studies extend to firms' own disclosure channels.

Subsequent literature shifted attention from media coverage to corporate filings, where managers themselves shape the narrative around their firm. Feldman et al. (2010) examine year-over-year tone changes in the MD&A section of U.S. 10-K filings, finding that tone shifts are associated with stock returns around the filing date, even after controlling for accrual-based earnings surprises. Li (2008) takes a complementary angle, examining the readability of 10-Ks rather than their tone. Using the Fog index, which combines word counts, complex word frequency and sentence length to quantify readability, Li (2008) finds that firms with weaker and less persistent earnings tend to file reports that are longer and harder to read. In a later paper, Li (2010) narrows the focus to forward-looking statements within the MD&A and finds that the tone managers use when discussing the future is positively associated with future performance.

2.2.4 Earnings Press Releases and Conference Calls

A parallel line of research turned from corporate filings to earnings press releases and conference calls. Henry (2008) examines whether the tone of earnings press releases affects investor reactions and is among the first to establish a relationship between press release tone and abnormal stock returns, after controlling for financial performance. She interprets these results through prospect theory, arguing that press releases serve a dual purpose of both informing investors about firm's financial results, and promoting the firm by framing those results in a favourable light. Davis and Tama-Sweet (2012) provide direct support for this interpretation. Comparing pessimistic language in the same firm-quarter across two channels, they find that managers use pessimistic language more carefully in the earnings press release compared to the MD&A section of their 10-K. This pattern is consistent with the promotional role of press releases, because the 10-K is formally filed and heavily regulated, managers are forced to deviate less from the underlying financial reality (Davis & Tama-Sweet, 2012).

A distinct feature of Henry (2008) is the emphasis on both positive and negative words, whereas earlier studies of media and corporate filings mainly focused on negative words (Tetlock, 2007; Tetlock et al., 2008; Loughran & McDonald, 2011; Davis & Tama-Sweet, 2012). Price et al. (2012) build on this two-sided approach and extend it to earnings conference calls, finding that tone is a significant predictor of abnormal returns and trading volume around the call, with the Q&A section carrying incremental explanatory power beyond the managerial presentation.

Later research builds on Price et al. (2012) and examines the strategic and stylistic characteristics of conference call tone. Huang et al. (2014) examine how managers strategically manage tone in earnings press releases and find that abnormally positive tone predicts worse future performance, even though it triggers an immediate positive market reaction that later reverses. They argue that managers use tone strategically and partially mislead investors about firm fundamentals. Jiang et al. (2019) build on the idea that managers strategically adapt their tone and construct a monthly manager-specific sentiment index, finding that higher managerial sentiment is associated with lower subsequent stock performance and earnings surprises. Bochkay et al. (2020) add nuance to the simple positive-negative dichotomy and evaluate the extremity of language by ranking words from strongly negative to strongly positive. They show that the use of extreme language amplifies trading volume and price reactions.

Collectively, studies on earnings conference calls provide recurring evidence that tone carries incremental information beyond quantitative fundamentals. It is not only *what* managers say when they talk about past and future performance that matters, but also *how* they say it. This motivates the closer examination of how conference calls operate as an information channel.

2.2.5 Earnings Conference Calls as an Information Channel

Earnings conference calls are particularly interesting among corporate disclosure channels as they are not bound by formal accounting rules, allowing managers more flexibility in their expressions and a less scripted style than written filings. Held quarterly alongside the earnings release, they enable managers to voluntarily disclose additional information beyond what the press release contains (Frankel et al., 1999; Brown et al., 2004).

The impact of conference calls on capital markets is well documented, with implications for information asymmetry, stock market movements and analyst forecasts. Brown et al. (2004) find that firms holding conference calls regularly experience reductions in information asymmetry among investors. Frankel et al. (1999) show that calls are associated with return variance and trading volume beyond what is explained by the accompanying press release, suggesting that price reactions reflect more than quantitative information alone. Conference calls also provide information to analysts, reducing initial underreaction (Kimbrough, 2005), and improving the accuracy of subsequent earnings forecasts (Bowen et al., 2005).

The spoken form of conference calls, in contrast to the written format of press releases, has further implications for their informativeness. Matsumoto et al. (2011) examine the management presentation and subsequent Q&A section separately and find that both sections carry incremental information beyond the accompanying press release. They suggest that analysts' questions may push managers to reveal information they otherwise would not have disclosed, with the spontaneous nature of the Q&A driving its incremental informativeness. Mayew and Venkatachalam (2012) extend the analysis beyond word content to managerial vocal cues, which signal positive or negative managerial affective states during the call. They find that these cues contain useful information about firm fundamentals and are incorporated into stock prices, with reactions being more pronounced when managers face more extensive scrutiny and questioning.

2.2.6 The Swedish Market Context

While prior research has documented robust relationships between managerial tone and market reactions, the evidence base remains heavily concentrated in the U.S. context, with a smaller body of work in China (Wu et al., 2021; Chang et al., 2023; Qin & Cui, 2024) and limited evidence from European markets. This is a meaningful gap, as institutional differences across countries shape both disclosure practices and market structures. Sweden offers a particularly interesting setting as its institutional environment differs from the U.S. along dimensions directly relevant to how sentiment in earnings calls is produced and processed by the market.

The most salient of these dimensions concern shareholder protection (La Porta et al., 1998) and the role of litigation in corporate governance (La Porta et al., 2008). In the U.S., strong shareholder protection and litigation-based governance shape both firms' access to external financing and capital market outcomes. In contrast, the Scandinavian institutional environment exhibits weaker shareholder protection mechanisms and strong enforcement quality (La Porta et al., 1998). La Porta et al. (1998) argue that civil-law countries with weaker investor protection tend to develop equity markets dominated by concentrated ownership structures, including family ownership, controlling shareholders and dominant blockholders, an effect found to be more pronounced in the Swedish market relative to the U.S. market. Concentrated ownership may mitigate manager-shareholder agency conflicts by enabling controlling owners to monitor management directly (Cieslak et al., 2021), thereby reducing the reliance on public disclosure. However, minority investors in Sweden lack the same access to private information as the controlling owners and are less protected by the Swedish civil-law system than the American common-law system. Consequently, they remain highly dependent on public disclosures to assess firm performance.

A second institutional feature relevant to earnings call communication is the lower litigation risk faced by Swedish managers compared to their U.S. counterparts. La Porta et al. (2008) emphasise the market-supporting features of common-law countries, relying more heavily on private enforcement through courts and enabling investors to use litigation to address self-dealing managers, whereas civil-law systems rely more on regulation and public enforcement.

Lower litigation exposure in Sweden may give managers more flexibility to express sentiment during conference calls, potentially leading to more candid statements sending signals that more closely reflect their true underlying views. Lastly, Scandinavian business culture may also shape the tone and style of managerial communication. Scandinavian managers have been found to consciously adapt their communication to cultural norms emphasising cooperation and consensus (Grenness, 2003), and modesty and equality (Smith et al., 2003). While these cultural patterns are not the focus of our analysis, they highlight the setting that systematically differs from the U.S. context where prior evidence has been generated.

2.3 Hypothesis Development

We develop two hypotheses, grounded in the theoretical frameworks and empirical literature presented above. The first is mainly grounded in information asymmetry, signalling and affect heuristics, and the second in prospect theory, loss aversion and the negativity bias.

Our first hypothesis examines the relationship between sentiment in earnings conference calls and cumulative abnormal returns (CAR), where we expect a positive association. From a signalling perspective, managerial tone reduces information asymmetry by conveying credible private knowledge about firm prospects (Brown et al., 2004). Positive tone would thus signal favourable expectations, and negative tone would signal adverse ones, leading rational investors to update their valuations accordingly. From a behavioural perspective, the affect heuristic (Slovic et al., 2007) predicts the same directional effect through a different mechanism. Positive managerial tone triggers a positive emotional reaction among investors, inducing trading behaviour that drives the stock price up. Both perspectives therefore predict net sentiment to be positively associated with the CAR around the earnings call.

Our second hypothesis tests for asymmetry in this relationship, where we expect negative words to have a stronger association with CAR than positive words. While studies on earnings conference calls typically examine the aggregate interaction between positive and negative words (Henry, 2008; Price et al., 2012; Jiang et al., 2019; Bochkay et al., 2020), evidence from media and corporate filings points to a negativity bias where negative words carry disproportionate weight (Tetlock, 2007; Tetlock et al., 2008; Loughran & McDonald, 2011). Prospect theory provides a theoretical foundation for this asymmetry. Tversky and Kahneman (1979) suggest that the psychological pain of a loss is magnified relative to the pleasure of an equivalent gain, and investors’ loss aversion should therefore translate into stronger market reactions to negative framing than positive framing.

Our hypotheses are stated as:

H1: The net sentiment of Swedish earnings calls is positively associated with cumulative abnormal returns (CAR) around the event window.

H2: Negative words in earnings conference calls have a stronger association with cumulative abnormal returns than positive words.

3. Method

This section presents our research design, which combines textual analysis with an event study methodology. We then develop our regression models and define dependent, independent and control variables. Finally, we describe the sample selection and data collection process.

3.1 Research Design

3.1.1 Textual Analysis

Our analysis builds on textual analysis using a bag-of-words (BOW) approach with a defined dictionary of tonal words. The BOW method has been criticised in previous literature for ignoring word context and assigning equal weight to all words (Bochkay et al., 2023). In response, several scholars advocate for machine learning methods. Deep learning models specifically trained on financial text can outperform commonly used sentiment quantifiers in terms of accuracy (Huang et al., 2022), and Gentzkow et al. (2019) argue that machine learning methods should only be avoided when access to training data is limited.

Despite this superiority in accuracy, scholars are not in agreement on the use of machine learning models. In critique of Gentzkow et al. (2019), Loughran and McDonald (2020) express a less optimistic perspective, arguing that dictionary methods are much less likely to capture data artefacts. A machine learning model will likely outperform a dictionary method on accuracy, but not necessarily for the right reasons. When applying machine learning, researchers lose the ability to verify whether the model is genuinely capturing sentiment or merely exploiting incidental artefacts in the data that happen to predict the desired outcome (Loughran & McDonald, 2020). This lack of transparency is a documented challenge in machine learning, and Huang et al. (2022) highlight the model's "black box" nature, arguing that its limited interpretability poses difficulties for researchers whose objective is theory testing.

Given this discussion, our analysis implements a BOW dictionary approach. While it may not be the most sophisticated method available, it offers a solid foundation with high interpretability and replicability and remains widely used to measure sentiment (Loughran & McDonald, 2020). This approach allows us to remain in control of the theoretical aspects and rely on previous literature, rather than a "black box" algorithm, as the arbiter of tone.

3.1.2 Event Study

An event study methodology is employed to examine the effect of earnings call tone on stock prices. Following the common structure in previous literature, we regress abnormal stock returns as the dependent variable (Henry, 2008). We limit our analysis to a short-window event study covering one day before, the day of, and one day after the earnings conference call. This window captures the immediate capital market response while avoiding documented biases that arise when calculating abnormal returns over longer horizons (Barber & Lyon, 1997; Kothari & Warner, 1997).

A consequence of this choice is that we ignore the post-earnings-announcement drift (PEAD), the phenomenon where cumulative abnormal returns continue to move up (down) for firms with good (bad) news for up to 60 days after the announcement (Ball & Brown, 1968). Bernard and Thomas (1989) argue that PEAD reflects the delayed incorporation of earnings information, which could in principle be relevant for our study. However, studying PEAD in connection with sentiment analysis is not common practice in previous literature (Henry, 2008; Henry & Leone, 2016; Bochkay et al., 2020). We therefore set PEAD aside and focus on the immediate market reaction.

3.1.3 Regression Model

To investigate the relationship between conference call tone and capital market reactions we run a series of ordinary least squares (OLS) regression models. To test our hypotheses, we apply two different regression models, using the same logic but slightly modified.

3.1.3.1 Hypothesis 1

To test our hypothesis that a higher positive net tone is associated with a higher cumulative abnormal return around the event window, we run the following regression:

$$CAR = \alpha_0 + \beta_1 UE + \beta_2 NetTONE + \beta_3 CONTROLS + \varepsilon$$

The regression uses the Cumulative Abnormal Return (*CAR*) as the dependent variable. *UE* is the unexpected earnings, *NetTONE* is our measure of conference call tone, and *CONTROLS* include our list of control variables, including fixed effects. Following the rationale from our hypothesis, we expect that β_2 is positive and significant, indicating that there is a positive association between net tone and *CAR*, when controlling for other explanatory variables.

3.1.3.2 Hypothesis 2

To test the difference in magnitude between the usage of more positive and negative words, we run a second variation of our model with new measures as the key independent variables. We run the following model:

$$CAR = \alpha_0 + \beta_1 UE + \beta_2 POSTONE + \beta_3 NEGTONE + \beta_4 CONTROLS + \varepsilon$$

where *POSTONE* and *NEGTONE* are the relative proportions of positive and negative words to the total number of words in the call. We expect β_2 to be positive and significant while we expect β_3 to be negative and significant, when controlling for other explanatory variables. We perform Wald tests of the hypothesis about difference in magnitudes, given the estimated coefficients, their standard errors and covariance.

3.2 Variables

In this section we outline our conceptualisation and measurements for our independent, dependent and control variables. We also discuss our use of fixed effects and highlight statistical considerations. Table 1 shows a detailed variable definition summary of all variables used in later tabulated regressions.

3.2.1 Independent Variables

3.2.1.1 Presentation vs Q&A

Prior research shows that earnings announcements themselves, separate from the earnings call, have a significant impact on abnormal returns (Henry, 2008; Davis et al., 2008). This raises an identification concern: an observed correlation between conference call tone and stock market returns could simply reflect the market's reaction to the earnings press release rather than the tone of the call itself. A call with a positive tone may, for instance, merely reflect a strong result in the given quarter, which would in turn drive the abnormal return. To address this concern, we follow previous literature (Kimbrough, 2005; Matsumoto et al., 2011; Price et al., 2012) and separate each call into a presentation and a Q&A section. Since the presentation section largely restates information already available in the press release, we treat its tone as a potential proxy for quarter-specific earnings quality, allowing us to isolate the incremental effect of the Q&A tone. See Section 3.3.3 and Appendix B: *Split presentation and Q&A section* for details on the splitting procedure.

3.2.1.2 Dictionary Choice

The dictionary determines which words are extracted and classified, making it a foundational choice in our methodology. Four dictionaries dominate the textual analysis literature on corporate financial disclosure: the Harvard IV-4 General inquirer, Diction, Henry (2008) and Loughran and McDonald (2011) as discussed by Luo and Zhou (2020).

The Harvard and Diction dictionaries are widely used (Feldman et al., 2010; Henry & Leone, 2016; Tetlock, 2007; Tetlock et al., 2008) but do not classify words from a financial perspective. The Henry (2008) dictionary was developed from earnings press releases and is applied in papers similar to ours (Price et al., 2012; Davis et al., 2015; Henry & Leone, 2016), but its main limitation is its size, with only 85 negative and 105 positive words.

The Loughran and McDonald (2011) dictionary was constructed from common sentiment words in U.S. 10-K and 10-Q filings and has been continuously updated through February 2024. It is considerably more exhaustive than Henry (2008), containing 2,355 negative and 354 positive words. The roughly 7:1 skew towards negative words is a deliberate choice by the authors. Loughran and McDonald (2011) find that financial language is more precise about negative outcomes, while positive language is often boilerplate and heavily dominated by a few words such as “strong” and “growth”. The dictionary has been overwhelmingly preferred in recent papers on the usefulness and determinants of tone in financial disclosures (Feldman et al., 2010; Huang et al., 2014; Blau et al., 2015; Davis et al., 2015) and is used to construct the sentiment data in the WRDS SEC Analytics Suite (Luo & Zhou, 2020).

Our main analysis uses the Loughran and McDonald (2011) dictionary, given its finance-specific construction and exhaustive word list. As a robustness check, we replicate the analysis with the Henry (2008) dictionary. The opposite positive/negative skew offers a further safeguard against our results being driven by dictionary construction. An excerpt of words from each dictionary can be found in Appendix A.

3.2.1.3 Measure of Sentiment

The dictionary of positive and negative words is used in a BOW approach to count the number of words classified as each for all our transcripts. Using our raw counts of classified words, we calculate a measure of net tone in the earnings conference call transcripts. The measure is:

$$NetTONE = \frac{Positive - Negative}{Positive + Negative}$$

where Positive is the number of positive words classified by the dictionary and Negative is the number of negative words classified by the dictionary. Our *NetTONE* measure is a widely used definition in earlier papers (Henry, 2008; Price et al., 2012; Henry & Leone, 2016) as well as more recent studies outside the U.S. context (Chang et al., 2023). We calculate two more measures for the relative proportions of negative and positive words using the raw counts for classified words. The measures are:

$$POSTONE = \frac{Positive}{Total}$$

$$NEGTONE = \frac{Negative}{Total}$$

where Positive is the number of positive words classified by the dictionary, Negative is the number of negative words classified by the dictionary, and Total is the total number of words in the transcript. As mentioned in 3.2.1.1, we measure the tone separately in the presentation and Q&A sections. The variable *NetTONE_PRES* is constructed as the *NetTONE* measure described above but is limited to the manager's introductory presentation in the call. Similarly, *NetTONE_QA* is constructed as the *NetTONE* measure but is limited to only the Q&A portion of the call. Lastly, the measures *POSTONE* and *NEGTONE* are used to calculate variables for the presentation and Q&A section. We end up with six different variables for tone, where each variable captures either the presentation or Q&A section of the call. For H1, we create the net tone measures: *NetTONE_PRES* and *NetTONE_QA*. For H2: we create the positive or negative proportion measures: *POSTONE_PRES*, *NEGTONE_PRES* and *POSTONE_QA*, *NEGTONE_QA*.

3.2.2 Dependent Variable

To measure the market reaction around the earnings conference call event window, we use the cumulative abnormal return (CAR) to represent stock price movements. The abnormal return

(AR) is defined as the difference between the raw return of stock *i* on day *t* and the daily return of the OMXSPI index on day *t*. We use the OMXSPI index as it is a value-weighted index including all traded stocks on the Nasdaq Stockholm exchange and gives a fairer reference point than the limited OMXS30 index.

We cumulate abnormal returns over a short event window, days minus one through one, where day zero is the day of the quarterly earnings conference call, in line with Price et al. (2012). By using CAR, we isolate abnormal stock returns relative to expected returns and capture the investor reaction. Our main CAR measure associated with conference call *i* becomes:

$$CAR[-1:1]_i = \sum_{t=-1}^{1} AR_{i,t}$$

where: $AR_{i,t}$ is the abnormal return, calculated as the actual return of stock *i* minus the return of the OMXSPI index during day *t*.

3.2.3 Control Variables

The key variable *UE* controls for unexpected earnings. We use a seasonal random walk model, in accordance with Price et al. (2012) and calculate *UE* as the difference between the earnings-per-share and the earnings-per-share in the same quarter of the previous year, scaled by the stock price at the end of the lagged quarter. Our formula becomes:

$$UE_{i,q} = \frac{EPS_{i,q} - EPS_{i,q-4}}{StockPrice_{i,q-4}}$$

where:
$EPS_{i,q}$ denotes earnings-per-share for firm *i* in quarter *q,*
$EPS_{i,q-4}$ denotes earnings-per-share for firm *i* in quarter q of the previous year,
$StockPrice_{i,q-4}$ is the stock price for firm *i* at the end of quarter q of the previous year.

Previous research, such as Bochkay et al. (2020), uses a measure of the difference in actual and analyst forecasted earnings scaled by the stock price to estimate unexpected earnings. Price et al. (2012) argue that the seasonal random walk measure is most appropriate as the earnings in the same quarter of the previous year are the most important benchmark for managers and investors. In line with arguments provided by Price et al. (2012), we follow their definition of the variable. Controlling for unexpected earnings ensures that price reaction is not falsely attributed to tone. We expect *UE* to have a positive effect on CAR as higher unexpected earnings are associated with increases in the stock price, based on the results of previous literature (Henry, 2008; Price et al., 2012).

SIZE is used to control for firm size and is estimated using the natural logarithm of firm market capitalization at the end of the previous quarter, following previous literature (Price et al., 2012; Henry & Leone, 2016; Bochkay et al., 2020). Smaller firms have been found to exhibit greater sensitivity to shifts in investor sentiment (Baker & Wurgler, 2006), and we use the variable to control for differences in return sensitivity across sizes. The expectation of the effect of size is ambiguous. While Price et al. (2012) find a small but positive effect of size, one could argue that larger firms have more information already priced in, making the reaction smaller. We expect a positive effect, following the results of previous literature.

BTM denotes the book-to-market ratio of equity per share. This variable picks up and controls for disclosure differences between firms based on their growth opportunities (Price et al., 2012). Fama and French (1992) find that firms' book-to-market ratios capture cross-sectional variations in stock market returns. Following the findings of both Henry (2008) and Price et al. (2012), we expect a positive association between *BTM* and CAR.

ROA is used to include a baseline profitability measure that captures differences in levels of profitability across firms, following Price et al. (2012) and Bochkay et al. (2020). We expect *ROA* to have a positive association with CAR in line with previous studies.

LEV measures the financial leverage of firms. Baker and Wurgler (2006) find that firms with high leverage or high financial distress are more sensitive to managerial sentiment-driven mispricing. Price et al. (2012) find a positive association between leverage and CAR. However, firms with higher leverage could create stronger reactions to negative news and thus amplify the effect. We expect the leverage to have a positive effect.

ANALYST controls for analyst coverage, capturing differences in monitoring levels, information asymmetry and firm visibility between firms and is included following Price et al. (2012) and Bochkay et al. (2020). There are no consistent findings in previous literature of the association between analysts and CAR. More analysts could entail a higher degree of sensitivity to sentiment, creating a positive effect, but could also mean that more information is already priced in, creating a dampened effect. We expect a small but positive effect.

VOL captures return volatility over the 90-day trading period ending ten days before the earnings call, controlling for investor-perceived uncertainty that may affect market reactions to unexpected earnings or tone (Price et al., 2012). We expect a positive sign, as higher prior volatility may amplify price reactions when new information arrives.

PCOUNT and *QCOUNT* control for call length in the presentation and Q&A sections respectively. Following Price et al. (2012), they proxy for information quantity and are calculated as total word counts (in thousands) in the respective section. We expect positive signs for both, as more disclosure can trigger a stronger reaction.

LOSS is an indicator variable that equals 1 if actual earnings per share is lower than 0 in the quarter of that earnings call. Following reasoning from Henry and Leone (2016) and Bochkay et al. (2020), we control for differences in stock market reactions to earnings announcements with profits and losses. We expect *LOSS* to have a negative association with CAR.

Table 1 – Variable Definitions

Variable	*Definition*	*Source*	*Sign (exp.)*
Dependent & Independent Variables			
CAR[-1:1]	The accumulated abnormal return in percentage of stock i during one day before, the day of, and one day after the earnings conference call. The abnormal return is calculated as the daily difference between the raw returns of stock i and the OMXSPI index return the same day. Winsorized at the 1st and 99th percentiles.	LSEG (Stock Returns) and Capital IQ Pro (Index Returns)	
NetTONE_QA	The number of positive minus the number of negative words divided by the sum of the number of positive and negative words in the Q&A section according to the Loughran & McDonald (2011) dictionary.	Transcripts from Capital IQ Pro	+
NetTONE_PRES	The number of positive minus the number of negative words divided by the sum of the number of positive and negative words in the presentation section according to the Loughran & McDonald (2011) dictionary.	Transcripts from Capital IQ Pro	+
POSTONE_QA	The number of positive words classified by Loughran & McDonald (2011) divided by total number of words in the Q&A section, rescaled to percentage terms.	Transcripts from Capital IQ Pro	+
NEGTONE_QA	The number of negative words classified by Loughran & McDonald (2011) divided by total number of words in the Q&A section, rescaled to percentage terms.	Transcripts from Capital IQ Pro	-
POSTONE_PRES	The number of positive words classified by Loughran & McDonald (2011) divided by total number of words in the presentation section, rescaled to percentage terms.	Transcripts from Capital IQ Pro	+
NEGTONE_PRES	The number of negative words classified by Loughran & McDonald (2011) divided by total number of words in the presentation section, rescaled to percentage terms.	Transcripts from Capital IQ Pro	-

Table 1 – Variable Definitions (*Continued*)

Variable	***Definition***	***Source***	***Sign (exp.)***
Control Variables			
UE	EPS from the latest FQ minus EPS from the latest FQ lagged by one year divided by the closing price of the latest FQ lagged by one year, rescaled to percentage terms. The EPS is calculated as the income available to common equity including extraordinary items divided by basic weighted average shares. Winsorized at the 1st and 99th percentiles.	LSEG	+
SIZE	The natural logarithm of all relevant issue level share types multiplied by the latest closing price at the date of the conference call in MSEK. Winsorized at the 1st and 99th percentiles.	LSEG	+
ANALYST	The natural logarithm of the number of sell-side analysts covering the security during the last FQ. We treat the variable as 0 if not available.	LSEG	+
ROA	Income after tax for the fiscal quarter divided by the average total assets over the year, expressed in percentage. Winsorized at the 1st and 99th percentiles.	LSEG	+
VOL	The standard deviation of daily stock returns for the 90-day trading period ending 10 days before the earnings call rescaled to percentage terms. Winsorized at the 1st and 99th percentiles.	LSEG	+
LEV	The ratio of long-term debt (sum of long-term debt and capital lease obligations) to total assets (total assets of the company) during the last FQ in MSEK. Winsorized at the 1st and 99th percentiles.	LSEG	+
BTM	The book to market ratio is calculated on a per share basis as the inverse of the price to book value per share which is calculated by dividing the company's latest closing price by its book value per share (total equity from the latest fiscal period divided by current total shares outstanding). Winsorized at the 1st and 99th percentiles.	LSEG	+
PCOUNT	The total word count in thousands for the presentation section of the transcript. Winsorized at the 1st and 99th percentiles.	Transcripts from Capital IQ Pro	+
QCOUNT	The total word count in thousands for the Q&A section of the transcript. Winsorized at the 1st and 99th percentiles.	Transcripts from Capital IQ Pro	+
LOSS	A binary indicator variable that equals 1 if the actual earnings per share is lower than 0 during the last FQ. The actual earnings per share is defined as the company's actual value normalized to reflect the I/B/E/S default currency and corporate actions (e.g. stock splits).	LSEG	-

This table shows the variable definition, source and expected signs for all variables used in later analysis. Transcripts and OMXSPI index returns from Capital IQ Pro were collected on 2026-02-26. Data from LSEG Workspace was collected on 2026-03-04.

3.2.4 Fixed Effects

Firm fixed effects absorb time-invariant firm traits such as communication style or industry positioning, helping ensure unbiased estimates. Their inclusion is further motivated by our panel structure, which contains repeated observations from the same firms across multiple quarters. Henry (2008) similarly applies firm fixed effects to address firm idiosyncrasies when studying the effect of conference call tone on stock markets.

Year-quarter fixed effects remove macroeconomic shocks specific to each quarter, allowing us to isolate the variables of interest. This is particularly relevant given that our sample period from 2015 to 2025 encompasses several market-wide events, such as the Covid-19 pandemic and inflation spikes, which affect returns and sentiment broadly. Following Bochkay et al. (2020), we use year-quarter rather than year fixed effects, since most of our variables relate to quarterly events.

3.2.5 Statistical Considerations

Panel data with firm-quarter observations introduces statistical issues such as outliers, heteroscedasticity, and cross-sectional or time-series dependence, which may bias estimates or lead to unreliable inference. We implement several adjustments commonly used in related empirical research.

Several of our continuous variables, including *BTM, LEV, VOL* and *UE*, may exhibit highly skewed distributions or contain extreme observations due to distressed firms, accounting adjustments or data processing issues. If left untreated, such outliers can disproportionately influence OLS estimates and bias the resulting coefficients. Following Bochkay et al. (2020) and Huang et al. (2020), we winsorize continuous variables in our study (*CAR[-1:1], UE, SIZE, BTM, ROA, VOL, LEV, QCOUNT, PCOUNT*), at the 1st and 99th percentiles. Inherently bounded variables, including our tone measures, the analyst measure and the binary *LOSS* indicator, are not winsorized.

Residuals in our firm-level panel may also exhibit heteroscedasticity and correlation across observations, violating OLS assumptions of constant error variance and independent observations. Observations from the same firm can be correlated over time, while firms reporting earnings in the same period may be exposed to common macroeconomic or market shocks. Such shocks can be captured in our abnormal return measure, creating cross-sectional dependence across firms. Ignoring these issues understates standard errors and overstates statistical significance. Consistent with Price et al. (2012) and Bochkay et al. (2020) and following the two-way clustering methodology of Petersen (2009), we compute heteroscedasticity-robust standard errors clustered at both the firm and quarter levels. This approach allows residuals to be correlated within firms over time and across firms within the same quarter, producing more reliable inference.

3.3 Sample Selection

3.3.1 Sample Creation

Our initial sample consists of all 408 stocks listed on the Nasdaq Stockholm Main Market as of February 2026, retrieved from Avanza. We exclude firms with a market capitalization below 2,000 MSEK. This threshold is chosen with reference to the European classification of small cap companies, defined as companies with a market capitalization below MEUR 150, corresponding to approximately 1,650 MSEK. To account for exchange-rate fluctuations and potential date-specific conversion effects, we select a slightly higher and rounded threshold of 2,000 MSEK. This excludes small and micro-cap stocks, which may suffer from illiquidity, do not hold earnings conference calls, or lack sufficient analyst coverage. Since the initial list consists of stocks rather than companies, we retain only one share class per company (the most liquid), reducing the sample to 244 companies.

From these 244 companies, we are able to collect 5,478 quarterly earnings conference call transcripts in English between 2015 and 2025, covering 195 companies. The 10-year window is chosen in light of the relatively limited number of Swedish listed firms compared to prior literature. By extending the period, we ensure an adequate number of observations.

In our sample we do not consider delisted companies for two main reasons, which introduces a potential survivorship bias. First, a comprehensive list of delisted companies is difficult to obtain. Second, well-known delistings that we can manually inspect during our sample period have largely been driven by M&A activity rather than bankruptcies or financial distress.

Among the collected transcripts, we remove those with a .txt file size smaller than 1KB to exclude incomplete or corrupted files. Further, we require each transcript to include both a presentation and Q&A section and remove transcripts that have fewer than 500 words in one section (*PCOUNT* or *QCOUNT* below 0.5), which ensures sufficient text for a meaningful tone measure. Next, we remove observations for the periods subject to M&A activity to avoid mixing pre- and post-restructuring periods (see Appendix B for details). Finally, we inspect observations with missing values and find no systematic bias towards particular firm types (e.g. smaller firms). We consequently choose to drop all observations with missing values for any of our variables. Our sample creation is summarised in Table 2.

Table 2 – Sample creation

Criteria	**Adjustments**	**Observations**
Collected transcripts		5,478
File size below 1 KB	-21	5,457
Missing presentation or Q&A section	-241	5,216
PCOUNT & QCOUNT below 0.5	-199	5,017
M&A complications	-11	5,006
Missing values in panel data	-965	4,041
Final sample size		4,041

This table shows our sample creation and cleaning process. The sample size in models including fixed effects is 4,038 due to the automatic removal of 3 singleton observations, because they have too little within-firm variation left after the firm fixed effects were absorbed.

3.3.2 Data Collection

Quarterly earnings conference call transcripts are manually collected from Capital IQ Pro. The daily index return of the OMXSPI was collected from Capital IQ Pro. All data from Capital IQ Pro was collected on 2026-02-26. The data used to calculate our variables *SIZE*, *LEV*, *LOSS*, *ANALYST*, *BTM* was collected as panel data as of the date the earnings conference call was held. The data used to calculate our variables *CAR*[-1:1] and *VOL* was collected as a time series of stock returns and later matched with the date of the earnings conference call. The data used to calculate *UE* was collected on a quarterly basis for each company and later matched with the date of the earnings conference call. All data from LSEG Workspace was collected on 2026-03-04.

3.3.3 Data Cleaning

The conference call transcripts are collected in .pdf format and need to be parsed into .txt files that can be used to quantify the sentiment according to the dictionary. We remove specific strings of text associated with our data collected from Capital IQ, for example disclaimers and recurring strings. These disclaimers include words that could bias our results, like “loss” or “expense”, and other boilerplate text that could influence our variables including total word counts. We perform a general cleaning, standardisation and tokenisation in accordance with previous literature on textual analysis methods (Loughran & McDonald, 2011; Loughran & McDonald, 2016; Bochkay et al., 2023). We split the transcripts into a presentation and Q&A section to measure the sentiment separately, as previously outlined. We are able to split 4,968 transcripts with high confidence. The rest of the transcripts are split either under assumptions or manually. A detailed description of our parsing, cleaning, splitting and aggregation process can be found in Appendix B. We measure the sentiment on a total of 10,736 transcripts divided by presentation and Q&A using the February 2024 version of Loughran and McDonald's Master Dictionary available on their website. In the last step we aggregate the results to be used in later regressions.

3.3.4 Data Considerations

The Q&A section of each transcript is analysed in its entirety rather than separating analyst questions and manager responses. Reliably distinguishing questions from answers is challenging due to substantial variation in the Q&A structure across firms and reporting periods. Q&A responses are not always consistently formatted, and answers frequently involve multiple managers contributing sequentially to answer the question. Attempting to remove analyst questions would therefore risk introducing classification errors and overall inconsistencies across transcripts. Analysing the full Q&A section ensures a consistent and replicable measurement of tone across all observations.

A common issue with financial disclosures is that managers often use positive words in a negative statement to neutralise the negativity (Loughran & McDonald, 2016; Loughran & McDonald, 2011). For example, the words "best" and "increasing" in sentences like "not the best" and "not increasing" would incorrectly be classified as positive. Following the methodology outlined in Loughran and McDonald (2011), we account for simple negation by identifying one of six common negation words (no, not, none, neither, never, nobody) occurring within three words preceding a positive word and flip the count towards a negative if one of the words is found. We do not consider negation of negative words, following the outlined methodology in previous literature.

Using AI, we take the negation handling one step further and identify common false-positive patterns such as "not only", "not least" and "no" used in conversations like "no, we are happy with the result". We create a negation list that ignores common misclassifications in our sample. Details can be found in Appendix B.

4. Findings and Analysis

This section presents descriptive statistics for our variables, followed by a discussion of correlations and OLS assumptions. We then proceed to our hypothesis tests and report the results from our regression models.

4.1 Description of Data

4.1.1 Descriptive Statistics

Table 3 – Descriptive Statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Panel A. Dependent variable								
CAR[-1:1]	4,041	0.425	8.025	-20.698	-4.387	0.399	5.116	22.390
Panel B. Independent variables								
NetTONE_QA	4,041	-0.007	0.227	-0.867	-0.157	0.000	0.153	0.700
NetTONE_PRES	4,041	0.441	0.223	-0.833	0.305	0.462	0.600	0.970
POSTONE_QA	4,041	1.375	0.459	0.141	1.056	1.334	1.641	3.879
POSTONE_PRES	4,041	2.298	0.709	0.137	1.813	2.229	2.713	5.322
NEGTONE_QA	4,041	1.370	0.378	0.388	1.109	1.327	1.586	3.511
NEGTONE_PRES	4,041	0.885	0.414	0.060	0.582	0.828	1.121	3.042
Panel C. Control variables								
UE	4,041	0.090	2.756	-14.458	-0.258	0.055	0.442	13.835
SIZE	4,041	10.115	1.443	7.336	9.002	9.962	11.108	13.563
ANALYST	4,041	1.784	0.874	0.000	1.099	1.609	2.398	3.497
ROA	4,041	1.357	1.944	-6.659	0.464	1.202	2.090	9.251
VOL	4,041	2.190	0.848	0.928	1.586	2.010	2.595	5.347
LEV	4,041	0.208	0.144	0.000	0.098	0.194	0.292	0.636
BTM	4,041	0.551	0.507	0.027	0.218	0.413	0.722	2.936
PCOUNT	4,041	2.919	1.018	1.044	2.192	2.811	3.486	6.073
QCOUNT	4,041	3.268	1.619	0.650	1.956	3.084	4.355	7.999
LOSS	4,041	0.076	0.265	0.000	0.000	0.000	0.000	1.000

This table presents summary statistics for 4,041 firm-quarter observations of Stockholm-listed firms between 2015-2025. CAR[-1:1] is the 3-day cumulative abnormal return around the conference calls (raw returns less OMXSPI return), in percent. NetTONE_PRES (NetTONE_QA) is (positive − negative)/(positive + negative) Loughran and McDonald (2011) words in the presentation (Q&A). POSTONE_PRES, NEGTONE_PRES (POSTONE_QA, NEGTONE_QA) are the positive and negative Loughran and McDonald (2011) word counts as a percentage of total words in the presentation (Q&A). UE is the unexpected earnings calculated as (EPSq −EPSq−4)/Price (end of q-4), in percent. SIZE is the log of firm market capitalization from the previous quarter. ANALYST is the log of sell side analysts covering the firm in the previous quarter. ROA is the return on assets, calculated as income after tax divided by the average total assets, expressed in percentage. VOL is the volatility in percentage and calculated as the standard deviation of daily returns for the 90 trading-day period ending 10 days prior to the call. LEV is the leverage, calculated as the ratio of long-term debt to total assets. BTM is the book-to-market ratio per share. PCOUNT (QCOUNT) is the total word count in thousands in the presentation (Q&A). LOSS is a binary indicator, 1 if actual EPS is below zero, else 0. CAR[-1:1], UE, SIZE, BTM, ROA, VOL, LEV, QCOUNT, PCOUNT are winsorized at the 1st and 99th percentiles.

Summary statistics for our main variables are found in Table 3. *CAR[-1:1]* has a standard deviation of 8.025 and ranges between -20.7% to +22.4%, suggesting meaningful positive and negative variation of market reactions around the event window. The *NetTONE_PRES* variable has a mean (0.441) that differs largely from the *NetTONE_QA* variable mean (-0.007). Similar statistics are found in *POSTONE_QA* and *NEGTONE_QA* that both have a mean around 1.37, while the mean for *POSTONE_PRES* (2.298) exceeds *NEGTONE_PRES* (0.885). This descriptive evidence highlights a systematically lower use of negative words in the presentation section and supports our decision to separate the two and measure the sentiment separately.

Our findings are in line with Price et al. (2012) and Bochkay et al. (2020) who find descriptive evidence suggesting that managers tend to use more positive than negative words in the presentation section of the earnings conference calls. These findings are in contradiction with word usage in 10-K filings that are studied by Loughran and McDonald (2011), who find that the majority of tonal words are negative.

UE is centred around 0 with a peaked centre, as 2,385 observations lie between -0.5 and 0.5. This behaviour is expected as our sample includes mainly large and mature companies where the earnings are predictable quarter-over-quarter and is in line with the findings in Price et al. (2012). Further, the *LOSS* variable is heavily skewed as most of the observations have a positive actual EPS and thus coded as 0. Out of the 4,041 observations, 308 are coded as 1 which limits the explanatory power. In untabulated results, we test a different measure using the quarterly reported EPS from the previous FQ and find no significant improvement in the skewness and choose to keep the definition in line with previous literature.

4.1.2 Correlation

A correlation table for our variables can be found in Appendix D. Net tone variables (*NetTONE_QA* & *NetTONE_PRES*) are both positively and significantly correlated with *CAR[-1:1],* providing initial univariate support for H1. For H2, positive measures (*POSTONE_PRES* & *POSTONE_QA*) show positive and significant while negative measures (*NEGTONE_QA* & *NEGTONE_PRES*) show negative and significant correlation to *CAR[-1:1].* A correlation of 0.432 between *NetTONE_QA* and *NetTONE_PRES* supports the descriptive evidence in relation to the two measures carrying overlapping but distinct information. Other key variables such as *NetTONE_QA* & *NEGTONE_QA* (r = -0.686), *NetTONE_QA* & *POSTONE_QA* (r = 0.796) and *NetTONE_PRES* & *NEGTONE_PRES* (r = -0.816) are highly correlated as they are constructed from the same positive and negative word counts. This is not an inherent issue as these variables are tested separately in the two different hypotheses and never included in the same regression model. Most correlations between control variables do not raise immediate concerns. The high correlations between *SIZE* & *ANALYST* (r = 0.785), *SIZE* & *QCOUNT* (r = 0.590), and *ANALYST* & *QCOUNT* (r = 0.633) reflect an intuitive pattern of larger firms having higher analyst coverage and thus generating longer Q&A sessions. Regarding potential multicollinearity, this is tested below in Section 4.1.3.3.

4.1.3 Assumptions

We assess the Gauss-Markov assumptions of linearity, normality, homoscedasticity and autocorrelation, alongside multicollinearity and outliers. The tests reported below are based on Model 5 (Section 4.2.1, Table 4), the fully specified regression with firm and quarter fixed effects for H1. In untabulated results, we replicate the same tests on Model 10 (Section 4.2.2, Table 5), the fully specified model for H2, and find no material deviations from the results presented here. Complementary plots and tables are provided in Appendix D.

4.1.3.1 Linearity

A residual plot (Figure 1) shows residuals centred approximately around zero, but a visible curvature in the smoothed trend line suggests mild nonlinearity. Partial residual plots indicate that this nonlinearity is concentrated in *UE*, *NetTONE_PRES* and *NetTONE_QA* (Figures 2-4). For *UE*, which is highly centred around zero (see Section 4.1.1), a zoomed-in plot (Figure 5) shows an approximately linear relationship in the densest part of the distribution. For *NetTONE_PRES* and *NetTONE_QA,* the linear approximation holds well in the centre but breaks down at the tails, with a particular downward curve at the high positive tone values. Worth noting is the sparse number of observations at the edges of the distribution that may further destabilise the estimated linear fit. To test whether this nonlinearity affects our results, we re-estimate the main regressions including quadratic terms for *UE*, *NetTONE_PRES* and *NetTONE_QA*. These terms are neither statistically significant nor do they improve overall model fit. Taken together, the linear specification is kept. Our findings suggest that the linear specification is broadly appropriate with mild nonlinearity present. No single variable appears solely responsible, and the deviations are observed at the sparsely populated tails.

4.1.3.2 Homoscedasticity

A Breusch-Pagan test rejects the null hypothesis of homoscedasticity (BP = 70.802, $p < 0.001$), indicating potential issues with heteroscedasticity. Visual inspection of the residual vs. fitted plot (Figure 1) shows a pattern that is largely flat and centred around zero, with slight curvature at the extreme tails. Overall, homoscedasticity cannot be fully satisfied. To ensure valid statistical inference under heteroscedasticity and cross-sectional dependence, all our regressions use two-way clustered standard errors following Petersen (2009).

4.1.3.3 Remaining Diagnostics

For normality, we plot the distribution of the residuals alongside a Q-Q plot and conclude that the assumption is largely satisfied and unlikely to materially bias inference. To assess autocorrelation, we run a Durbin-Watson test together with an AR(1) regression of the residuals, which regresses this period's residuals on last period's residuals. Both indicate mild negative serial correlation. The magnitude is economically small and is further absorbed by our clustered standard errors.

For multicollinearity, we calculate the Variance Inflation Factors (VIF) for our main variables of interest and find a maximum of 2.179 and mean of 1.354, indicating no major issues. All VIF values are reported in Table 9 in Appendix D.

Finally, to address outliers, we winsorize continuous variables prone to extreme values to limit their influence on the regression (see Section 3.2.5 for details). Additionally, we calculate Cook's Distance and find that the most influential observation has a value of 0.019, below the rule-of-thumb thresholds of 0.5 and 1. About 7% (288 observations) exceed the 4/n threshold. Re-estimating the regression on samples that exclude the 20, 50, 100 and 288 observations with the highest Cook's Distance yields similar results in terms of sign, magnitude and significance across all iterations.

4.2 Hypothesis Testing

4.2.1 Hypothesis 1

Table 4 reports the regression results for H1. In Model 1, *UE* is positive and significant at the 5% level. Model 2 estimates the *NetTONE* measures without *UE* and shows that both the presentation and Q&A tone are positive and significant. When *UE* and the *NetTONE* measures are included jointly in Model 3, *UE* loses significance, and this pattern persists after adding controls in Model 4 and firm and quarter fixed effects in Model 5. In the fully specified model, both *NetTONE* variables remain positive and significant at the 0.1% level, indicating a robust positive association with *CAR[-1:1]*, while *UE* remains insignificant. Among the control variables, *VOL* and *ROA* are positive and significant in both Models 4 and

5. The estimated coefficients imply that a one standard deviation increase in *NetTONE_PRES* and *NetTONE_QA* is associated with an increase in CAR over the three-day window of approximately 1.08% and 1.23% respectively.

Table 4 – Hypothesis 1 model regression results

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dependent Variable	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]
Constant	0.407* (0.188)	-1.363* (0.566)	-1.282* (0.561)	-5.045** (1.810)	
UE	0.192* (0.081)		0.133 (0.074)	0.072 (0.071)	0.026 (0.063)
NetTONE_PRES		4.106*** (0.994)	3.894*** (0.982)	3.503*** (0.872)	5.507*** (0.842)
NetTONE_QA		3.322*** (0.753)	3.309*** (0.752)	3.415*** (0.775)	4.783*** (0.959)
SIZE				0.266 (0.199)	0.597 (0.612)
ANALYST				-0.105 (0.297)	-0.009 (0.554)
ROA				0.286* (0.109)	0.566*** (0.153)
VOL				0.661* (0.275)	0.792* (0.378)
LEV				1.222 (0.910)	-0.767 (1.730)
BTM				-0.524 (0.436)	-0.311 (0.750)
PCOUNT				-0.003 (0.099)	-0.058 (0.215)
QCOUNT				-0.088 (0.119)	-0.138 (0.163)
LOSS				-0.885 (0.765)	0.124 (0.758)
Firm & Quarter FE	No	No	No	No	Yes
S.E. Clustered by:	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter
Observations	4,041	4,041	4,041	4,041	4,037
Adj. R2	0.004	0.031	0.032	0.043	0.069
Within R2					0.062

The table presents results from OLS regressions of CAR[-1:1] on UE, net tone (NetTONE_PRES, NetTONE_QA) and controls. Standard errors, clustered at firm and quarter are shown in parentheses. Model 1-3 are without controls, Model 4 adds controls, Model 5 adds firm and quarter fixed effects. CAR[-1:1] is the 3-day cumulative abnormal return around the conference calls (raw returns less OMXSPI return), in percent. NetTONE_PRES (NetTONE_QA) is (positive − negative)/(positive + negative) Loughran and McDonald (2011) words in the presentation (Q&A). UE is the unexpected earnings calculated as (EPSq −EPSq−4)/Price (end of q-4), in percent. SIZE is the log of firm market capitalization from the previous quarter. ANALYST is the log of sell side analysts covering the firm in the previous quarter. ROA is the return on assets, calculated as income after tax divided by the average total assets, expressed in percentage. VOL is the volatility in percentage and calculated as the standard deviation of daily returns for the 90 trading-day period ending 10 days prior to the call. LEV is the leverage, calculated as the ratio of long-term debt to total assets. BTM is the book-to-market ratio per share. PCOUNT (QCOUNT) is the total word count in thousands in the presentation (Q&A). LOSS is a binary indicator, 1 if actual EPS is below zero, else 0. CAR[-1:1], UE, SIZE, BTM, ROA, VOL, LEV, QCOUNT, PCOUNT are winsorized at the 1st and 99th percentiles. Significant codes: *p<0.05; **p<0.01; ***p<0.001

As robustness checks, we re-estimate Model 5 using alternative tone definitions, the Henry (2008) dictionary, and alternative event windows (*CAR[0:2*] and *CAR[-3:3]*). The estimated coefficients on the tone measures remain positive and highly significant across all specifications, supporting the stability of our results. Overall, the evidence supports H1 and indicates that net tone in both the presentation and Q&A sections is positively associated with CAR.

4.2.2 Hypothesis 2

Table 5 – Hypothesis 2 model regression results

	Model 6	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Dependent Variable	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]	CAR[-1:1]
Constant	-0.504 (0.617)	-0.695 (0.463)	-0.983 (0.684)	-5.253** (1.780)	
UE	0.166* (0.078)	0.134 (0.076)	0.134 (0.075)	0.069 (0.072)	0.021 (0.065)
POSTONE_QA	2.118*** (0.344)		1.507*** (0.365)	1.592*** (0.347)	2.123*** (0.375)
NEGTONE_QA	-1.459*** (0.343)		-0.876* (0.326)	-0.821* (0.313)	-1.298** (0.426)
POSTONE_PRES		1.252*** (0.200)	0.815*** (0.203)	0.814*** (0.202)	1.371*** (0.312)
NEGTONE_PRES		-2.000*** (0.466)	-1.523** (0.484)	-1.288** (0.437)	-1.802*** (0.382)
SIZE				0.227 (0.205)	0.570 (0.616)
ANALYST				-0.101 (0.298)	-0.119 (0.553)
ROA				0.313** (0.113)	0.586*** (0.152)
VOL				0.686* (0.273)	0.806* (0.374)
LEV				1.036 (0.936)	-0.952 (1.710)
BTM				-0.538 (0.439)	-0.469 (0.783)
PCOUNT				0.060 (0.102)	0.039 (0.212)
QCOUNT				-0.060 (0.110)	-0.088 (0.153)
LOSS				-0.830 (0.764)	0.147 (0.762)
Firm & Quarter FE	No	No	No	No	Yes
S.E. Clustered by:	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter
Observations	4,041	4,041	4,041	4,041	4,037
Adj. R2	0.026	0.027	0.034	0.045	0.072
Within R2					0.066

The table presents results from OLS regressions of CAR[-1:1] on UE, tone proportions (POSTONE_PRES, NEGTONE_PRES, POSTONE_QA, NEGTONE_QA) and controls. Standard errors, clustered at firm and quarter are shown in parentheses. Model 6-8 are without controls, Model 9 adds controls, Model 10 adds firm and quarter fixed effects. CAR[-1:1] is the 3-day cumulative abnormal return around the conference calls (raw returns less OMXSPI return), in percent. POSTONE_PRES, NEGTONE_PRES (POSTONE_QA, NEGTONE_QA) are the positive and negative Loughran and McDonald (2011) word counts as a percentage of total words in the presentation (Q&A). UE is the unexpected earnings calculated as (EPSq −EPSq−4)/Price (end of q-4), in percent. SIZE is the log of firm market capitalization from the previous quarter. ANALYST is the log of sell side analysts covering the firm in the previous quarter. ROA is the return on assets, calculated as income after tax divided by the average total assets, expressed in percentage. VOL is the volatility in percentage and calculated as the standard deviation of daily returns for the 90 trading-day period ending 10 days prior to the call. LEV is the leverage, calculated as the ratio of long-term debt to total assets. BTM is the book-to-market ratio per share. PCOUNT (QCOUNT) is the total word count in thousands in the presentation (Q&A). LOSS is a binary indicator, 1 if actual EPS is below zero, else 0. CAR[-1:1], UE, SIZE, BTM, ROA, VOL, LEV, QCOUNT and PCOUNT are winsorized at the 1st and 99th percentiles. Significant codes: *p<0.05; **p<0.01; ***p<0.001

Table 5 presents the regression results for H2. Models 6 and 7 estimate the positive and negative word proportions separately for the Q&A and presentation sections respectively, while Model 8 includes both jointly. In all three specifications, the tone proportions are statistically significant. *UE* is positive and significant at the 5% level in Model 6 but becomes insignificant in the more developed specifications. Adding controls in Model 9 and firm and quarter fixed effects in Model 10 leaves the significance of the tone proportions intact. As expected, the coefficients on negative proportions are negative in both sections, while the coefficients on positive proportions are positive, indicating that more negative words are associated with lower CAR and more positive words with higher CAR. The control variables behave similarly to the H1 regressions.

To formally assess the differences in estimated coefficient magnitudes, we conduct six Wald tests, reported in Table 6. Four are the within-section tests of the equality of the positive and negative coefficients, two for the presentation and two for the Q&A. In each case one version using the raw coefficients and one version scaled by the standard deviation of the underlying tone measure to account for differences in variation. The remaining two compare the within section differences across sections, again using raw and scaled estimates. In each test, the null hypothesis is that the positive and negative coefficients are equal in absolute magnitude, meaning that their sum equals zero given the opposite signs.

Table 6 – Linear Hypothesis test

Null hypothesis	χ^2	**Estimate**	**P-value**
Presentation section			
POSTONE_PRES + NEGTONE_PRES = 0	0.779	-0.431	0.377
SD x POSTONE_PRES + SD x NEGTONE_PRES = 0	0.698	0.225	0.403
Q&A section			
POSTONE_QA + NEGTONE_QA = 0	2.815	0.825	0.093
SD x POSTONE_QA + SD x NEGTONE_QA = 0	5.595	0.483	0.018*
Cross-section			
POSTONE_PRES + NEGTONE_PRES - POSTONE_QA - NEGTONE_QA = 0	2.846	-1.257	0.091
SD x POSTONE_PRES + SD x NEGTONE_PRES - SD x POSTONE_QA - SD x NEGTONE_QA = 0	0.498	-0.257	0.480

This table shows Wald tests of the equality in absolute magnitude of the positive- and negative-word proportion coefficients estimated in Model 10 (Table 5). Each null hypothesis sets the listed linear combination of coefficients to zero. Standard deviation (SD) scaled tests weigh each coefficient by the SD of the underlying tone measure. POSTONE_PRES, NEGTONE_PRES (POSTONE_QA, NEGTONE_QA) are the positive and negative Loughran and McDonald (2011) word counts as a percentage of total words in the presentation (Q&A). Significant codes: *p<0.05; **p<0.01; ***p<0.001

For the presentation section, we cannot reject the null in either the raw or scaled test (p = 0.38 and 0.40), meaning we cannot reliably distinguish the absolute magnitude of the positive and negative word effects, given our data. For the Q&A section, the raw comparison provides only marginal evidence of a statistical difference (p = 0.09), but the scaled test rejects the null at the 5% level (p = 0.018). The estimated linear combination in the scaled Q&A test is positive (+0.483), implying that a one standard-deviation change in the positive-word proportion is associated with a larger absolute change in *CAR[-1:1]* than a one standard-deviation change in the negative-word proportion. This is the opposite asymmetry to what H2 predicts. The cross-section comparison shows marginal significance in the raw tests but no significance in the scaled one. This means we cannot conclude that the asymmetries between positive and negative words differ significantly across the presentation and Q&A sections.

As robustness tests, we re-estimate Model 10 using the Henry (2008) dictionary and alternative CAR windows. The results are similar across these specifications, supporting the stability of our findings.

4.3 Summary of Results

Our results provide support for H1 but not for H2. For H1, tone in both the presentation and Q&A sections is positively and significantly associated with CAR, and these results remain robust across alternative measures and event windows. For H2, we do not find support for the prediction that negative words have a stronger association with CAR than positive words. Contrary to the expected asymmetry, the evidence in the Q&A section suggests that positive words have a stronger association with CAR than negative words, while no statistically significant conclusion can be drawn for the presentation section.

The within R-Squared of our fully specified models (Models 5 and 10) are 6.2% and 6.6% respectively. We do not consider this problematic. Both constituent parts of our CAR measure, firm raw returns and market index returns, are inherently noisy, and this noise carries through to the three-day cumulative abnormal return. Comparable studies report within R-Squared and R-Squared values in the same range, between 1 and 11% (Henry, 2008; Feldman et al., 2010; Price et al., 2012; Huang et al., 2014; Bochkay et al., 2020). Our objective is not to maximise the explanatory part of CAR over the event window, but to investigate the association between tone and market reactions. Thus, the within R-Squared values we obtain are consistent with this objective and with prior literature.

5. Discussion

In this section, we analyse and discuss our results in light of the theoretical frameworks and prior literature presented in Section 2. We first discuss the findings for H1 and H2 individually, before situating them within the Swedish context and considering how the two hypotheses relate to each other. Throughout, we position our results in relation to existing literature and theory.

5.1 Tone as an Informative Signal

The results from the H1 tests suggest that the net tone in Swedish quarterly earnings conference calls is, on average, informative and is positively reflected in stock prices. This finding aligns with the body of US-based evidence that tone in managerial disclosures conveys incremental qualitative information (Henry, 2008; Feldman et al., 2010; Loughran & McDonald, 2011; Price et al., 2012), and extends the evidence by showing that the informational role of qualitative disclosure is not confined to the U.S. setting but also applies in Sweden.

As outlined in Section 3.2.1.1, presentation tone can be viewed as a proxy for quarter-specific earnings quality. The fact that Q&A net tone remains positive and highly significant once presentation net tone and our control variables are included provides evidence that tone is independently associated with abnormal returns. Put differently, the language managers use is associated with stock price reactions beyond the reported figures and investors appear to respond not only to *what* managers report but also to *how* they say it. This is consistent with H1 and the reasoning of prior literature (Price et al., 2012; Bochkay et al., 2020).

From a signalling perspective (Verrecchia, 2001; Brown et al., 2004), our results are consistent with the mechanism by which tone conveys credible information to the market. Optimistic language is interpreted as a signal of positive prospects and is associated with higher abnormal returns, while pessimistic language signals negative prospects and is associated with lower abnormal returns. From a behavioural perspective, the results are also broadly consistent with the mechanisms underlying framing effects and the affect heuristic (Tversky & Kahneman, 1979, 1981; Slovic et al., 2007), where positively framed information shapes investors' initial reactions and contributes to higher abnormal returns, even when the tone itself conveys no new information.

5.2 Asymmetry Between Positive and Negative Language

We do not find support for H2 in our sample. In the presentation section, our inability to reject the equality of absolute effects makes it difficult to draw any meaningful conclusions in connection to H2. We thus remain inconclusive about consistency with prospect theory and negativity bias. In the Q&A section, the standard-deviation-scaled comparison shows that positive words have a stronger association with CAR than negative words, which is opposite to what H2 predicts. While the point estimates thus suggest an asymmetry within the Q&A

section, the cross-section comparison does not allow us to conclude that this asymmetry differs significantly from the one in the presentation.

Although we cannot claim a section-dependent pattern, the direction of the point estimate is nonetheless noteworthy. One interpretation centres on the different functions of the two sections, building on Matsumoto et al. (2011) and Mayew and Venkatachalam (2012). The presentation section is carefully prepared, scripted and reviewed by management, and there are strong incentives to project optimism and manage the tone strategically (Huang et al., 2014; Hope & Wang, 2018). Positive language is therefore expected in this section of the call, while negative language tends to appear only when absolutely necessary, which can make it a stronger signal of adverse conditions when it does appear. This pattern is reflected in our descriptive statistics, where the use of negative words in the presentation (mean = 0.88) is far less common than the use of positive words (mean = 2.28).

The Q&A section operates under different conditions. As argued by Matsumoto et al. (2011), the less formal and more spontaneous nature of analyst questioning limits managers' ability to strategically adapt their language in real time. Analyst questions often concern issues or bad news, making some degree of negative tone the norm in any Q&A section. If positive words, on the other hand, can survive the tough analyst scrutiny, they may stand out as a stronger signal. This interpretation is difficult to reconcile with the mechanism underlying prospect theory but is plausible under the mechanisms of salience effects theory (Hirshleifer & Teoh, 2003) and signalling (Verrecchia, 2001; Brown et al., 2004). In a context where negative tone is expected, positive language becomes the more salient and informative signal and is therefore associated with a larger market reaction than negative language. We treat this interpretation as suggestive rather than conclusive, given that the cross-section comparison does not establish a significant difference between the two sections.

5.3 Results in the Swedish Market Context

A result that stands out compared to prior literature is the insignificance of the unexpected earnings (UE) measure once tone variables are added. We see two non-mutually exclusive interpretations. First, our UE measure may capture less market-relevant information in the Swedish context. Investors may place greater weight on EPS surprises relative to analyst expectations rather than beating last year's earnings, which is what is captured in our measure (current EPS minus EPS four quarters earlier). Second, our presentation tone measures may proxy for elements of earnings quality that investors price in, but that UE itself fails to capture, consistent with the reasoning by Price et al. (2012). The Swedish institutional setting also offers a further mechanism that supports both interpretations. As discussed in the literature review, the concentrated ownership structure of Swedish firms means that large shareholders can obtain private information without relying primarily on public managerial disclosures (La Porta et al., 1998). If dominant blockholders have access to earnings information prior to the call and adjust their expectations beforehand, the “unexpected” component of our UE measure mostly reflects the reaction of minority holders, creating a potentially attenuated effect relative to the U.S.

Ownership concentration also offers a possible interpretation for the absence of a clear negativity bias. If informed blockholders already possess private information about the firm, negative prospects are likely reflected in the market expectations before being expressed in the earnings call, dampening the market response to negative tone within the event window. The lower litigation risk in Sweden compared to the U.S. (La Porta et al., 2008) may further grant Swedish managers greater flexibility in their disclosures. In a litigation-prone environment, overly positive statements expose managers to legal risks if those statements deviate from the underlying fundamentals, making the careful balancing of positive and negative words a strategic necessity. In Sweden, managers face less of this constraint and are freer to frame their results as they wish, which may blur the distinction between the market's response to positive and negative language. This does not align with loss aversion but is consistent with our finding that net tone has a strong association with CAR while the individual positive and negative effects are difficult to distinguish.

A final consideration regarding the Swedish context is that we use a dictionary developed in the U.S. setting to quantify sentiment, while most participants in the analysed earnings calls are non-native English speakers. Non-native speakers generally rely on a more limited and standardised vocabulary than native speakers. On the one hand, this linguistic consistency may improve the accuracy of our bag-of-words method, since standardised vocabulary is more likely to be captured by the dictionary. On the other hand, inherent differences in how native and non-native speakers use expressions, and how those are interpreted by an audience that is itself often non-native, may introduce more subtle linguistic nuances that our method cannot capture.

5.4 Connecting the Two Hypotheses

Together, our results provide a more coherent understanding of how qualitative information in Swedish quarterly earnings calls is incorporated into stock prices. While our analysis cannot attribute the results to a single underlying mechanism, the evidence from H1 is broadly consistent with both signalling and behavioural explanations operating in parallel. However, the evidence from H2 is not consistent with the mechanisms underlying loss aversion or negativity bias, and in the Q&A section it even points in the opposite direction. The most plausible reading of our findings is that tone operates as neither a pure signal of private information (Verrecchia, 2001), nor a pure behavioural response (Slovic et al., 2007; Tversky & Kahneman, 1979), but rather as a joint product of both mechanisms. Disentangling their relative contributions remains open for future research.

6. Conclusions

We investigate managerial tone in quarterly earnings conference calls of Swedish companies and how the qualitative information conveyed through positive and negative words is associated with investor reactions. Our data suggests that the net tone of positive and negative words is positively and significantly associated with the cumulative abnormal returns in a three-day event window around the earnings call, even after controlling for quantitative earnings. We find no support for the prediction that negative words carry greater weight than positive words in the association with the cumulative abnormal returns. In the Q&A section we instead find evidence of the opposite asymmetry with positive words carrying greater weight, although we remain cautious about drawing section-dependent conclusions.

We contribute to existing literature by extending the analysis of qualitative information in earnings conference calls to a new research context. Our findings extend the empirical evidence on tone beyond the heavily studied U.S. setting and show that net tone is associated with abnormal returns in Sweden, a smaller Nordic market characterised by low litigation risks, concentrated ownership structures and a consensus-oriented communication style. The presence of this association in an environment dominated by non-native English speakers and shaped by different cultural norms further suggests that the findings of prior literature are not contingent on specific U.S. communication styles or institutional contexts.

Our study is subject to several limitations. First, the findings are inherently correlational. While we apply firm and quarter fixed effects and control for other explanatory variables, our event window regressions identify associations rather than causal effects. Second, the bag-of-words approach used to quantify tone relies on a predefined dictionary, which bounds what the method can capture and does not account for context, introducing a potential measurement error we are unable to quantify. Finally, both dictionaries used in our analysis were developed in the U.S. context for native English speakers, whereas our sample is dominated by non-native speakers. Linguistic differences in expressions may therefore not be fully captured, potentially biasing our tone measures.

The limitations of our study point to several avenues for future research. A natural step would be to refine the measurement of tone, for example by developing a specific Swedish sentiment dictionary or adopting a more sophisticated word-embedding method that can better capture nuanced language and the linguistic characteristics of non-native English speakers. A second area would be to extend the analysis from association to causal identification, for instance by exploiting managerial turnover and the resulting variation in tone across managers. Finally, the reverse asymmetry observed in the Q&A section warrants further exploration, both within Sweden and in other Nordic and European contexts. Such work could clarify whether the pattern reflects the Scandinavian institutional setting, the structural differences between the presentation and Q&A sections discussed in Section 5.2, or some other underlying mechanism.

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8. Appendix

Appendix A: Example of words

Table 7 shows 10 randomly drawn words classified as positive and negative from the Loughran & McDonald Master Dictionary and the Henry (2008) dictionary.

Table 7 – Extracted Words from Dictionaries

Loughran & McDonald		Henry	
Positive	Negative	Positive	Negative
SURPASSES	CORRECTING	RISE	UNCERTAINTY
BREAKTHROUGHS	PRECLUDES	BEATING	DECREASES
ACHIEVEMENT	ASSAULT	ACCOMPLISHES	WEAKENED
EXCELLENCE	ARGUMENTS	STRONGER	RISKS
ENHANCED	CRIMINALLY	EXCELLENT	CHALLENGING
EMPOWERING	ENCUMBERING	EXCEED	CHALLENGES
COMPLEMENTED	EXCULPATE	ENJOYED	WORSENS
BOOM	TRAGEDY	BETTER	DROP
WORTHY	ANNULMENT	BEAT	DROPPING
REVOLUTIONIZES	VOIDED	SOLID	SMALLER

Appendix B: Methodology Notes

Handling M&As: A few companies in our sample were involved in M&As during the sample period. Since we extract data prior to the earnings conference call to calculate our variables, this is something we need to address. We identify three cases of company restructuring in our sample worth noting. First, Africa Oil Corp changed its name to Meren Energy in May of 2025, following the acquisition of Prime Oil & Gas. Second, ÅF merged with Pöyry in February of 2019. Third, Tieto and EVRY merged on December 5 of 2019, creating TietoEVRY. We remove four firm-quarter observations following the acquisition for these companies, ensuring that all data being used reflects the correct company structure.

File format: The data collected in .pdf format from Capital IQ is found in two different formats, pre and post Q2 2018. The transcripts after Q2 2018 include a front page with summary statistics. To remove this, we create a Python script that searches for the string "S&P Global Market Intelligence Estimates", found on the first page of post Q2 2018 versions. If found, that page is removed. When all transcripts have a consistent format, they are converted into .txt files.

Sample specific cleaning: The .txt files contain unwanted strings that we remove before the next step. The following strings are removed: "*S&P Global Market Intelligence*", "a *division* *of S&P Global Inc.*", "*All Rights reserved.*", "*All rights reserved.*", "*spglobal.com/marketintelligence*", "*EARNINGS CALL*". Furthermore, the files include a disclaimer at the end with words like "*lost*", "*loss*", "*expense*" and "*incident*" that would bias our word counts. We use two different strings of text and truncate the transcript from: "*The information in the transcripts ("Content") are provided*" and "*These materials have been prepared solely for information purposes*" which removes the disclaimers. Additionally, we remove all text inside square brackets which include: "[Technical Difficulty]" and "[Operator Instructions]". Lastly, we remove all appearances of the company name to avoid issues with names being counted as sentiment or skewing the total number of words.

General cleaning: In the last step of our cleaning we make all text lowercase, remove punctuation and tokenise words in accordance with previous literature. We do not take lemmatisation (e.g. increase, increasing, increased) into consideration as this is considered by the dictionary.

Split presentation and Q&A section: To distinguish between words used in the presentation and Q&A section, we perform a split on the cleaned .txt files at the occurrence of the string: "question and answer", which is the header of the Q&A section. If the string is found twice, we perform the split on the second occurrence as we find a pattern that it is often used in the presentation section of the call. If the string is found more than twice, we split manually. If the string is not found at all, we remove the transcript. Out of the 5,478 transcripts we attempt to split, we are able to split 4,968 with only one occurrence of the string. 313 transcripts are split under the assumption that the second occurrence is the correct split. 42 transcripts are split manually. As a quality check, we ensure that the file size is above 10 KB. Files below 10 KB are double checked, and we perform 7 more manual splits after unwanted results from the assumption of second occurrence.

Handling negation exceptions: We log all flipped cases from our negator rule, i.e. count as a negative if one of six common negation words (*no, not, none, neither, never, nobody*) occurs within three words preceding a positive word. Using our log file, we ask OpenAI's GPT-5.4 to "identify common misclassification cases and suggest how we should implement exceptions in our parsing code". The result yields exception cases provided in Table 8. If any negator is immediately followed by an exception, we do not flip the word to negative.

Using this method, we identify common falsely classified negators, but edge cases and general ambiguity in classifying the words as negative or positive remain. We acknowledge potential issues with having an AI classify exception cases. However, after we do manual inspection of flipped cases and confirm the exception cases generated by AI as feasible, we argue that the potential error lies within us missing exception cases, not that the ones generated are incorrect. Any missed exception cases would have been missed regardless of using AI or not. Lastly, the negation rule (prior to negation exception cases) concerns 7,970 flipped cases and we classify a total of 578,535 positive words across the entire sample, making the potential error arising from the use of AI small.

Table 8 – Negation Exception Cases

Negator	Exception	Example
NOT	ONLY; JUST; NECESSARILY; LEAST	"we did not only increase, but"
NEVER	BEEN	"never been stronger/better"
NO	THAT; OKAY; YES; SO, THANKS; IT	"no, that is good" (conversational)

Appendix C: Use of AI

Coding: Our method relies on Python code to move from plain pdf files of quarterly earnings conference calls transcripts into quantifiable sentiment measures in panel data. The entire process from data cleaning to regression analysis is performed in R. We used three large language models (OpenAI ChatGPT 5.2, ChatGPT 5.3 & ChatGPT 5.4, Anthropic Claude Sonnet 4.6 and Claude Opus 4.7) to assist in generating code. We manually inspect all of the generated code, perform test runs on limited samples and finally do manual checks on the generated output before the outputs are used for further analysis.

Grammar: We mainly used three large language models (OpenAI ChatGPT 5.4, Anthropic Claude Opus 4.7 and Google Gemini 3) to improve the grammar, flow and structure of specific sentences. The AI tools did not support in generating large bodies of text, fact-check nor formulate arguments.

Links: ChatGPT, Claude, Gemini

Coding tools were used continuously in 2026 January through May. Grammar tools were used 2026 April through May.

Appendix D: Complementary Tables and Figures

Figure 1 – Residuals vs Fitted (Model 5)

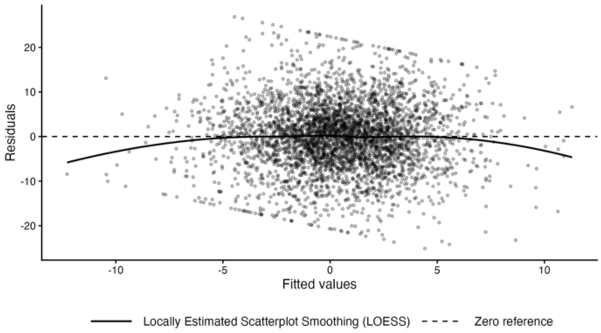

Figure 2 – Partial Residual Plot (UE)

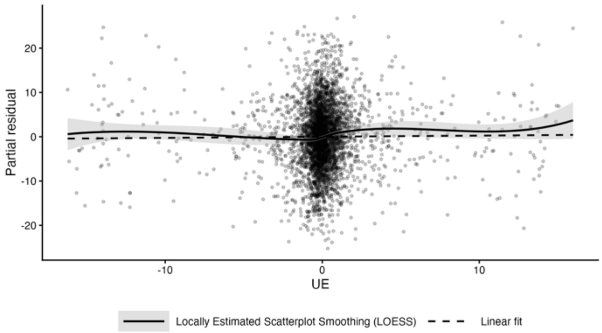

Figure 3 – Partial Residual Plot (NetTONE_PRES)

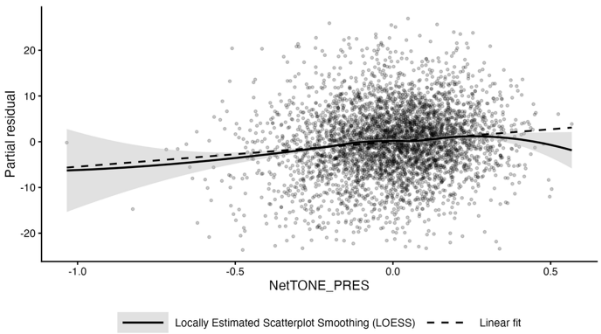

Figure 4 – Partial Residual Plot (NetTONE_QA)

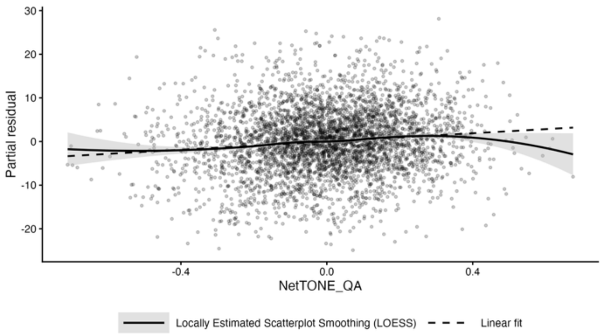

Figure 5 – CAR[-1:1] & UE Linearity (Zoomed)

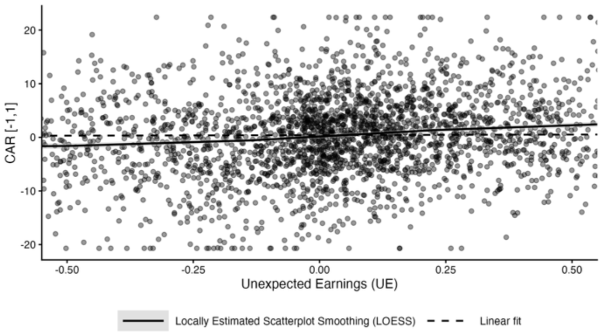

Table 9 – Variance Inflation Factors (VIF)

UE	NetTONE_QA	NetTONE_PRES	SIZE	ANALYST	ROA	VOL	LEV	BTM	PCOUNT	QCOUNT	LOSS
1.170	1.162	1.239	2.179	1.655	1.516	1.170	1.049	1.622	1.029	1.142	1.310

This table shows the variance inflation factors (VIF) from the fully specified OLS estimation of CAR[-1:1], on UE, net tone variables (NetTONE_PRES, NetTONE_QA) and controls (Model 5 in Table 4). The VIF of variable i is calculated as $VIF_i = \frac{1}{1-R_i^2}$ where R_i^2 is the coefficient of determination from a regression of variable i regressed on all other predictors.

Table 10 – Pearson Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) CAR [-1:1]	1.000																
(2) UE	0.066***	1.000															
(3) NetTONE_QA	0.143***	0.063***	1.000														
(4) NetTONE_PRES	0.155***	0.132***	0.432***	1.000													
(5) POSTONE_QA	0.135***	0.048***	0.796***	0.319***	1.000												
(6) POSTONE_PRES	0.117***	0.096***	0.341***	0.538***	0.426***	1.000											
(7) NEGTONE_QA	-0.091***	-0.047***	-0.686***	-0.338***	-0.158***	-0.060***	1.000										
(8) NEGTONE_PRES	-0.109***	-0.090***	-0.300***	-0.816***	-0.116***	-0.018	0.371***	1.000									
(9) SIZE	0.006	0.021	-0.088***	-0.097***	-0.103***	0.076***	0.030*	0.167***	1.000								
(10) ANALYST	-0.031**	0.003	-0.114***	-0.145***	-0.123***	0.041***	0.045***	0.203***	0.785***	1.000							
(11) ROA	0.117***	0.273***	0.054***	0.164***	-0.001	0.046***	-0.075***	-0.156***	0.128***	-0.056***	1.000						
(12) VOL	0.018	-0.081***	-0.039**	-0.084***	-0.052***	-0.156***	0.011	-0.002	-0.366***	-0.286***	-0.126***	1.000					
(13) LEV	-0.010	-0.008	0.011	0.002	0.047***	0.063***	0.020	0.027*	-0.071***	0.077***	-0.266***	-0.044***	1.000				
(14) BTM	-0.089***	-0.128***	-0.131***	-0.177***	-0.078***	-0.112***	0.128***	0.129***	-0.231***	0.031**	-0.399***	0.249***	0.199***	1.000			
(15) PCOUNT	0.000	-0.024	0.023	-0.026*	-0.035**	-0.139***	-0.061***	-0.040**	0.195***	0.174***	-0.036**	0.038**	-0.029*	0.033**	1.000		
(16) QCOUNT	-0.017	-0.005	-0.007	-0.096***	-0.102***	0.016	-0.107***	0.130***	0.590***	0.633***	-0.053***	-0.132***	0.005	-0.035**	0.198***	1.000	
(17) LOSS	-0.068***	-0.129***	-0.010	-0.077***	-0.009	-0.068***	0.002	0.051***	-0.208***	-0.087***	-0.458***	0.275***	0.021	0.226***	0.028*	-0.057***	1.000

This table presents the Pearson correlation for our variables included in our regressions. CAR[-1:1] is the 3-day cumulative abnormal return around the conference calls (raw returns less OMXSPI return), in percent. NetTONE_PRES (NetTONE_QA) is (positive − negative)/(positive + negative) Loughran & McDonald (2011) words in the presentation (Q&A). POSTONE_PRES, NEGTONE_PRES (POSTONE_QA, NEGTONE_QA) are the positive and negative Loughran & McDonald (2011) word counts as a percentage of total words in the presentation (Q&A). UE is the unexpected earnings calculated as (EPSq −EPSq−4)/Price (end of q-4), in percent. SIZE is the log of firm market capitalization from the previous quarter. ANALYST is the log of sell side analysts covering the firm in the previous quarter. ROA is the return on assets, calculated as income after tax divided by the average total assets, expressed in percentage. VOL is the volatility in percentage and calculated as the standard deviation of daily returns for the 90 trading-day period ending 10 days prior to the call. LEV is the leverage, calculated as the ratio of long-term debt to total assets. BTM is the book-to-market ratio per share. PCOUNT (QCOUNT) is the total word count in thousands in the presentation (Q&A). LOSS is a binary indicator, 1 if actual EPS is below zero, else 0. CAR[-1:1], UE, SIZE, BTM, ROA, VOL, LEV, QCOUNT and PCOUNT are winsorized at the 1st/99th percentiles. *Significant codes: *p<0.05; **p<0.01; ***p<0.001*