ISSN: 2688-9323

The Impact of Earning Press Releases Sentiment on Abnormal Stock Returns and Volatility

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Abstract

This dissertation investigates the impact of sentiment in earnings press releases on abnormal stock returns and volatility based on 150 countries from 1 January 2000 to 31 December 2016. Using Henry's dictionary method for sentiment analysis, the study finds a negative association between optimistic tones in press releases and abnormal stock returns, implying that highly positive sentiment may trigger lower market reactions. Additionally, the results indicate that positive sentiment in press releases leads to reduced abnormal volatility both immediately and consistently over a period of 5 days, 10 days, and 30 days. These findings remain robust even after accounting for the impact of the 2008 financial crisis. By addressing both short-term and long-term effects, this research contributes to the literature on enhancing the understanding of how effectively investors incorporate sentiment from press releases into their trading behaviours.

Keywords

Earning Press Releases; Tone; Stock Returns; Volatility; Event Study.

1. Introduction

Corporate disclosures contain critical information about a company that influences investors [1]. Amongst these disclosures, earning press releases are notable and informative communications that managers frequently issue instant announcement and report quarterly earnings to external stakeholders [2]. Over the years, earning press releases have expanded both in content and length, attributed to the inclusion of more quantitative and qualitative disclosures [3].

Disclosures are generally divided into mandatory and voluntary disclosures. Mandatory disclosures are regulated by law, with countries worldwide following specific regulatory frameworks [4]. For example, foreign firms listed and traded on U.S. capital markets must comply with the Securities and Exchange Commission (SEC) disclosure rules. However, earnings press releases, which disclose information besides mandatory requirements, are considered voluntary disclosures [5]. Since voluntary disclosures are not subject to any explicit regulations, managers often have more flexibility in how they present the information-leading to potential manipulation through impression management.

Impression management, where managers strategically manipulate the tone of their communications to present their firms in a more favorable light, has become a central concern in understanding these dynamics [6]. This technique can distort investor perceptions by selectively highlighting positive aspects while downplaying negative information, aiming to manage investor expectations and maintain favorable market evaluations [7,8]. However, some argue that investors may struggle to make rational and perfectly informed decisions because of the challenges in processing the vast amounts of unstructured data attained in various corporate disclosures [9]. Thus, this dissertation seeks to explore how effectively current market participants incorporate sentiment from earnings press releases into their trading behaviors. This paper extends the existing literature by investigating how the market reacts to sentiments in earning press releases, with a particular focus on cumulative abnormal stock returns and abnormal volatility. While much of previous studies primarily concentrate on the short-term effects of narrative tone [10], this paper also addresses the long-term effects. Moreover, the sample base of this work consists of diverse industry types, which enhances the comprehensiveness of narrative tone measurements.

To conduct this research, sentiment analysis is applied to earning press releases from 150 countries, spanning 17 years (2000-2016). The Henry dictionary method is used to decide the emotional or psychological traits of each release by calculating the proportion of positive words in total words based on Henry's 2008 wordlist. A higher frequency of positive words leads to a higher positive score, indicating a more optimistic sentiment. Conversely, a lower frequency or absence of positive words corresponds to a negative score. This study finds a negative association between the tone of earnings press releases and abnormal stock returns, as well as volatility across three time frames (5 days, 10 days, and 30 days).

The significance of this research lies in its ability to provide insights into how market participants react to sentiment in earnings press releases in an era where information environments have undergone substantial changes. Additionally, the development of digital media and advances in sentiment analysis techniques have also revolutionized how investors process and respond to corporate disclosures. This study highlights the importance of narrative tone as a factor that can drive market behavior.

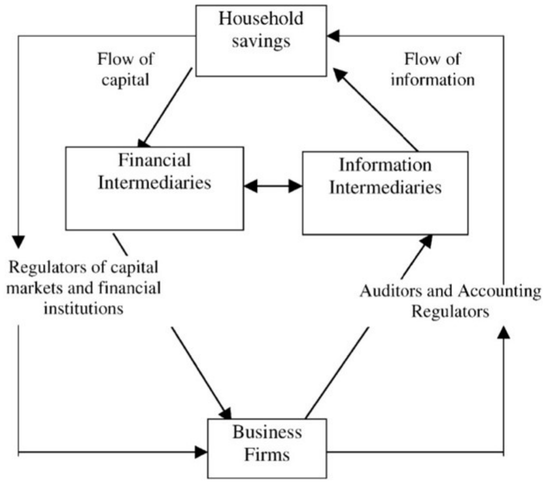
The remainder of this article is structured as follows. Section 2 provides a literature review, pointing to information asymmetry in today's information environment, reviewing current research on narrative disclosure sentiment, discussing advancements in sentiment analysis techniques, and covering relevant literature on tone and market reaction. Section 3 outlines the hypotheses guiding this research. Section 4 details the research design and methods, including sample data collection and regression models. Section 5 presents the research findings, followed by a robustness check in Section 6. Finally, Section 7 discusses the limitations of this study and offers suggestions for future research.

2. Literature Review

2.1. Information Asymmetry

In capital markets, business firms, financial intermediaries, and investors play key roles, and the relationships between them are interdependent. Paul and Krishna [4] present a model illustrating the interactions between firms, investors, and intermediaries (as shown in Table 1).

Table 1. Information environment in capital markets [4]



In this model, investors provide capital to firms either individually (e.g., through angel investors) or via financial intermediaries such as banks. In return, firms disclose information to investors, typically through financial reports, press releases, or communication channels involving financial analysts. Financial analysts, serving as information intermediaries, collect data from various sources, thereby reducing the information gap between firms and investors and enhancing market efficiency.

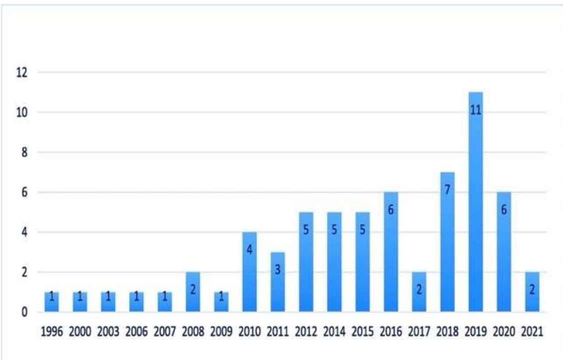
This information gap is closely tied to a common phenomenon in the financial market called information asymmetry. In the financial market, participants are typically divided into two groups: insiders with superior access to valuable information, and outsiders who are less informed. Information asymmetry describes the gap between these two parties. It can severely hinder the efficient allocation of resources in the capital market, making it difficult to direct savings toward profitable investment opportunities [4]. The misallocation of savings to unprofitable business ideas results in two major challenges: the information problem and the agency problem. The information problem arises when entrepreneurs possess more knowledge about their investment opportunities than investors, leading to the potential overvaluation of business ideas. If investors fail to recognize bad ideas, entrepreneurs can exploit this private information for personal gain. The agency problem occurs when self-interested entrepreneurs misuse investors' money after receiving the investment, leading to negative outcomes for investors.

Several solutions have been proposed to address information asymmetry and align the interests of insiders and outsiders. Financial analysts and rating agencies are essential in generating confidential information to expose any managerial mismanagement of company resources. Barth & Hutton [11] found that financial analysts help firms incorporate accruals and cash flow information more effectively. Additionally, regulations requiring full disclosure of private information by managers and investors help mitigate information asymmetry. This paper focuses primarily on earnings press releases as one solution to relieve information asymmetry.

2.2. Narrative Disclosure Tone Research

Table 2 presents that a growing body of research has focused on the textual analysis of narrative disclosures, particularly in regard to narrative tone. This reflects the growing recognition of the importance of tone analysis [10].

Table 2. Textual analysis of narrative disclosures [10]



Narrative disclosures involve the examination of written content within published communications between a company's management and external users, which may encompass diverse forms including the Management Discussion and Analysis (MD&A) While financial statements are commonly considered the foundation of accounting and their significance has been acknowledged by numerous researchers, narratives such as earning press releases also

ISSN: 2688-9323

provide worthy and crucial information to external users [3,12]. Given that quantitative information solely offers a partial view of a company's financial performance, the examinations of the narrative disclosure in earning press releases hold the utmost significance for investors seeking a comprehensive picture [13].

Earnings press releases are particularly significant because they provide valuable insights into a firm's financial performance and communicate this information to external parties. These reports, often accompanied by media coverage, contain both numerical data and textual descriptions of a company's past and projected financial activities. While the numbers convey information more exclusively, the accompanying narrative needs additional textual analysis techniques for information.

2.3. Applications of Sentiment Analysis in Finance

Conventional NLP methods, often referred to as the "dictionary approach," typically count positive and negative words using a predetermined sentiment dictionary [14]. By calculating the difference between positive and negative words in a particular text, and dividing by the total number of words, researchers can know the overall sentiment of the text. This method is widely employed to measure sentiment in financial contexts [15] due to its simplicity, ease of replication, and convenience in checking the contribution of individual words to the overall sentiment score [12,14]. However, the dictionary approach has notable limitations. For example, the method may treat phrases like "good performance" and "private good" as equally positive, even though their sentiment may differ. Additionally, all positive or negative words are assigned the same weight, which may not be appropriate in certain contexts. For example, "terrible" and "bad" are likely to be coded as the same weight though "terrible" probably has more negative sentiment in a case. Furthermore, negators and intensifiers ("not good" and "much worse"), synonyms and related words ("bad condition" and "disaster"), and idioms should be decided by researchers, especially when words and terms are not in the input dictionary.

Todd et al [16] indicate that domain-specific dictionaries may enhance the accuracy compared to the general dictionary method, but they may not capture the subtle differences or contexts of words outside of that specific field. Thus, misunderstandings are likely to arise when the text involves mixed fields or constantly evolving language patterns. They also have limitations in broader applications such as cross-industry or multilingual sentiment analysis since they are unable to summarize different contexts effectively. It is argued that applying advanced NLP mechanisms or combining manual and computer content analysis may be a more accurate measure of tone measurement [10]. By doing this, the measurement results derived will be closer to human assessment of the tone of a given text, that is, incorporating the context of the text rather than considering word frequency alone.

Machine Learning (ML) methods, such as Naive Bayes classifiers and more advanced models, have been shown to outperform traditional dictionary-based methods in classifying financial sentiment accurately [12]. Heitmann et al. [17] found that switching from dictionary methods to traditional ML methods (NB, SVM, and RF), increased sentiment classification accuracy by 9.13 percentage points, and a further switch to deep learning methods (CNN, RNN, and LSTM), led to an additional accuracy improvement of 4.56 percentage points.

Though ML-based sentiment measures offer advantages in contextual understanding, accuracy, and adaptability [12,16], they require more manual labor for coding and are harder to replicate compared to word-frequency measures [12]. Deep learning methods, while generally more accurate, also come with higher computational costs. For this reason, word-frequency approaches remain widely used in capital markets research on disclosure tone analysis.

Moreover, advancements in sentiment analysis techniques have continued to progress. Machine-learning architectures include support vector machines, boosting and bagging

ISSN: 2688-9323

algorithms, and random forests that decide the polarity of text tones by assigning sentiment scores to the categories of phrases in a sentence. Souma et al. [18] concluded that the sentiment of news articles can be linked to the average stock price returns within one minute of their release. In this study, Deep learning methods were utilized to examine the intraday Thomson Reuters News Archive and high-frequency DJIA 30 Index data between 2003 and 2013. Wan et al. [19] utilized convolutional neural networks and LSTM neural networks to analyze the emotion of news related to 87 companies covered by Reuters over seven years. They investigated how such sentiment propagates within company networks and assessed its impact on stock price fluctuations and volatility. Their findings revealed notable abnormal market returns and volatility on days when the level of sentiments is high. However, it is worth noting that the effectiveness of these sentiment variables may differ depending on their source.

2.4. Prior Literature on Sentiment Analysis

2.4.1. Overall Sentiment Analysis

Previous studies have extensively explored the association between managerial tone and management behaviors. Impression management refers to techniques used by managers to manipulate how their firm is perceived by third parties [6]. Managers can distort investors' expectations by selectively emphasizing positive information or presenting data in a favorable light. Negative tones in narratives have been linked to problematic behaviors, such as future fraudulent activities [15, 20]. Huang et al [7] find that firms that just beat the past earnings or analysts' forecasts tend to have a more positive abnormal positive tone, aiming to misinform investors.

Numerous works examine the signaling effect of the managerial tone on financial outcomes [1, 2, 21, 22, 23, 25, 26]. For instance, Price et al. [27] argue that the tone of conference calls can be a powerful predictor of abnormal returns. Wu et.al. [28] concluded that a more optimistic MD&A sentiment is associated with a higher firm value after surveying n4694 annual reports in the A-share markets of the Shanghai Stock Exchange from 2021 to 2017. Bian [29] found that in the Chinese stock market, a more optimistic managerial tone is associated with higher IPO first-day returns and post-IPO performance.

A smaller subset of studies focuses on the immediate stock market reactions to linguistic tone characteristics in management releases and MD&A [28, 30, 31], and earning press releases [2,15, 24, 25, 32]. Davis et al. [21] demonstrates that the three-day cumulative abnormal return around the earnings announcement is positively correlated with the tone of earnings press releases. However, Bonsall et al. [33] caution that this positive correlation only holds in the absence of clear quantitative earnings guidance.

2.4.2. Market Response to Press Releases Sentiment

Numerous studies have examined the relationship between the tone of earning press releases and abnormal stock returns. One branch argues that a positive tone in press releases tends to lead to abnormal positive returns [1, 2, 32, 34, 35]. For instance, Davis et al. [2] suggest that market participants interpret a positive tone as a signal of strong future performance and optimism from management, which boosts investor confidence and contributes to positive abnormal returns. However, several other papers indicate a negative relationship between tone and abnormal returns [1, 24, 35, 36]. These studies argue that investors may be skeptical about overly optimistic language, viewing it as an attempt to manipulate perceptions rather than reflect the true state of the company. Some research adopts a more neutral or mixed perspective toward the association between tone and abnormal stock returns. They note that the market's reaction to optimistic language depends on factors such as past firm performance, the credibility of the management, and overall market conditions [7, 37]. For example, Huang et al. [7] suggest that market responses to optimistic language are context-dependent, with

ISSN: 2688-9323

abnormal returns turning positive only if optimism in tone is consistent with the firm's past performance and industry conditions.

In terms of the impact of earning press releases tone on market volatility, some paper examines the immediate effect. They argue that press releases with a more uncertain or negative tone tend to trigger immediate spikes in volatility, while positive tones are associated with relatively muted immediate responses [30, 38, 39]. Other research observes the longer-term influence, suggesting that though positive or neutral tones may reduce volatility in the mid-term (weeks after the announcement), pessimistic tones generate persistently higher volatility as the market gradually adjusts to perceived risks and uncertainties [15, 40].

In summary, there is no consensus in the literature on the impact of tone in earnings press releases on abnormal stock returns and volatility. Moreover, some studies suggest that market participants may struggle to fully adjust to the influence of sentiment in these releases [41], while others indicate that investors may even overlook such language [2].Much of the literature also predates significant shifts in the information environment, including advancements in sentiment analysis techniques, which may affect how such information is interpreted and acted upon by market participants. Therefore, while the tone in earnings announcements provides critical signals about future firm performance, it remains unclear how effectively current market participants incorporate sentiment into their trading behavior. This dissertation seeks to address this gap by investigating the impact of sentiment in earnings press releases on abnormal stock returns, and on abnormal volatility over both short and mediate windows.

3. Hypothesis Development

3.1. Tone and Stock Returns

Prospect theory, proposed by Tversky & Kahneman [42], explains how people make decisions under conditions of risk and uncertainty. This theory challenges the traditional “expected utility theory”, which assumes that people are rational decision-makers. According to prospect theory, people do not always act rationally when making choices involving risk; instead, they evaluate potential outcomes relative to a reference point, often the status quo, and exhibit loss aversion.

The theory outlines two key stages in decision-making: editing and evaluation. During editing, individuals simplify their choices by organizing and framing them in a way that makes the decision easier to process. In the evaluation phase, they assess potential outcomes based on the perceived value. For example, consider a lottery game with two options: Option A offers a 50% chance of winning $1000 and a 50% chance of winning nothing, while Option B guarantees $400 with no risk. According to Prospect Theory, people tend to be more sensitive to losses than to gains. Thus, the potential disappointment of winning nothing in Option A may feel more significant than the pleasure of winning $1000. In contrast, Option B provides a smaller but guaranteed gain, which is often preferred because it avoids the risk of loss. Ultimately, Tversky & Kahneman [42] argue that this loss aversion influences decision-making under risk, causing people to favor safer choices even when riskier ones might offer greater rewards.

The concept “Attribute Framing Phenomenon” builds on Prospect Theory's insight into how presentation affects judgment. Attribute framing refers to how people perceive and evaluate an object or scenario more favorably when it is described in a positive frame compared to a negative one, even if the information is objectively equivalent. For instance, labeling a medical treatment as having a "90% survival rate" (positive frame) will generally lead to a more favorable and attractive perception than stating it has a "10% mortality rate" (negative frame), despite both descriptions conveying the same information. The underlying psychological mechanism is connected to loss aversion: people are more averse to negative framing because it triggers a stronger emotional reaction to potential losses. Thus, it can be logically thought

ISSN: 2688-9323

that more positive tones can impress investors positively and may further influence their behaviors and judgments positively. Based on this, the first hypothesize can be:

Hypothesis 1. Ceteris paribus, the tone of earnings press releases is positively associated with abnormal stock returns

3.2. Tone and Volatility

Disclosures are closely related to stock volatility because insufficient information implies higher risk [43]. Stock price volatility often arises from investors' lack of accurate information about a company [44]. Additionally, Veronesi [45] notes that investors' predictions about future earnings become more sensitive to new information released by the company, potentially increasing stock price volatility. Companies provide insights into past performance and future expectations through earnings press releases and related news coverage [44]. Therefore, it is reasonable to expect that the tone of earnings press releases may significantly impact stock price volatility. When companies use positive language in their reports, it is likely to alleviate uncertainty about their future performance. Consequently, positive reports may lead to decreased volatility, whereas negative reports can result in increased volatility. Based on this, the second hypothesis can be stated as:

Hypothesis 2. Ceteris paribus, the tone of earnings press releases is negatively associated with volatility

4. Research Design and Methodology

4.1. Data and Sample Collection

4.1.1. Tone and Abnormal Returns

This study examines a sample of 150 predominantly U.S.-based corporations, covering the period from January 1, 2000, to December 31, 2016. Earnings press releases for these companies were extracted from the Factiva database, and the frequency of daily press releases issued by each company was meticulously recorded. The sentiment of each release was analyzed using the Linguistic Inquiry and Word Count (LIWC) software, as described in the subsequent sections.

To study the impact of tone in corporate earnings press releases on abnormal returns, I constructed four key variables: standardized abnormal return, tone, firm size (ln_firm_size), and return on assets (roa). All data spans from January 1, 2000, to December 31, 2016. The "roa" variable was sourced from COMPUSTAT (North America version), while market returns were based on the S&P 500 Index, obtained from the Center for Research in Security Prices (CRSP) through the Wharton Research Data Services (WRDS) platform.

The market returns data, initially in simple returns format, were transformed into log returns and further standardized by subtracting the mean and dividing by the standard deviation. This transformation helps reduce skewness, making the data more normally distributed, which is suitable for statistical analysis. This also ensures more reliable and robust regression results.

Firm-specific returns were also extracted from the CRSP database, focusing on daily closing prices for each company over the same period. These closing prices were converted into log returns, allowing for a consistent measure of firm performance across time.

In the regressions, two control variables were included to capture firm-specific effects: the log of firm size (ln_firm_size) and return on assets (roa). These variables were selected due to their potential influence on pre-disclosure information and the details included in the press releases. Sadique et al. [44] argue that smaller companies tend to have more pre-disclosure information, which results in earnings announcements revealing less information, while larger companies exhibit the opposite behavior. The ln_firm_size variable was derived from the market value of

ISSN: 2688-9323

equity at the end of each fiscal quarter, downloaded from the CRSP database and then converted into logarithmic form.

Return on assets (roa) is another important control variable. According to Bushman et al. [46] roa is a critical indicator of firm financial performance and correlates with pre-disclosure information. Companies with higher ROA are more likely to have superior corporate governance structures and tend to disclose more information before earnings announcements, leading to less information being revealed at the time of the announcement. Conversely, companies with lower ROA tend to reveal more information during announcements. This comprehensive data collection process, including market returns, firm-specific returns, and control variables, ensures a solid foundation for analyzing the impact of tone in earnings press releases on abnormal returns.

4.1.2. Tone and Volatility

In analyzing the effect of tone on stock market volatility, I introduced an additional control variable: abnormal trading volume (ln_abnormal_volume), alongside ln_firm_size and roa. Sadique et al. [44] suggest that trading activity intensifies when new information is introduced to the market, as participants attempt to find a new equilibrium through increased buying and selling activity. Therefore, abnormal trading volume is a crucial factor in explaining market volatility.

Abnormal trading volume was calculated by dividing the daily trading volume by the average volume from the day prior to the release and the subsequent five days. The data for daily trading volumes during the period between January 1, 2000, and December 31, 2016, was sourced from the CRSP dataset.

4.2. Tone Analysis

The tone analysis process followed a series of structured and systematic steps. Initially, earnings press releases were downloaded from Factiva in RTF format for each company in the sample. These RTF files were then converted into smaller text files, each corresponding to a specific company's press releases.

Next, sentiment analysis was conducted using LIWC, a text analysis tool that categorizes words into various emotional, cognitive, and structural categories. LIWC provided metrics such as positive and negative emotion scores and other relevant linguistic features for each text file.

The initial output from LIWC (which consisted of files numbered 1-150) offered a preliminary view of the sentiment and tone present in the press releases. This data included detailed statistics about the frequency and intensity of various emotional and cognitive categories. To further refine the findings, I performed a secondary analysis that involved comparing the initial metrics with qualitative assessments to ensure accuracy and consistency. Additional checks were carried out to address any anomalies or inconsistencies.

According to Henry & Leons [12], domain-specific dictionaries provide more accurate measures of tone in explaining stock market reactions to earnings announcements. Thus, this dissertation employs Henry 2008 wordlist, a well-known automated wordlists designed specifically for financial and business contexts. It consists of 105 positive words and 85 negative words. Each press release text was analyzed using LIWC based on the Henry dictionary, and the net tone score for each text was calculated as follows:

TONE = (Positive Words – Negative Words) / (Positive Words + Negative Words)

This formula provided a standardized measure of tone for each company's press release, forming the basis for further analysis of its relationship with abnormal returns and market volatility.

ISSN: 2688-9323

4.3. Regression Models

4.3.1. Tone and Abnormal Return

Following Henry & Leone [12], this paper assumes that the financial market operates under semi-strong form market efficiency. According to Kothari & Warner [39], semi-strong market efficiency means that stock prices efficiently reflect all publicly accessible information. In line with prior research [1,12,21], this study employs a short-window event study methodology around the announcement period, specifically focusing on corporate press releases. This method is designed to capture the most relevant market reactions to earnings announcements.

The first model regresses the standardized cumulative abnormal return (CAR) on the tone of the press release, while controlling for firm size (measured as the natural log of firm size, ln_firm_size) and return on assets (ROA).

The short window spans from t = -2 to t = +2, with earnings announced at t = 0. Abnormal returns are calculated using the daily market model adjusted returns, defined as:

uit = Rit – (αi + βiRmt). Rit is the log return of firm i on day t, while Rmt is the return of the S&P500 Index on day t.

The market model parameters αi and βi for each firm are estimated by regressing the log return of the firm's stock on the log return of the S&P 500 Index. Using the estimated coefficients, the expected returns αi + βi Rmt are calculated. Abnormal returns, representing the deviation of actual returns from expected returns, are then determined. These abnormal returns are cumulated from t = -2 to t = +2 to derive the CAR. Finally, CAR is standardized by subtracting the mean and dividing by the standard deviation.

The tone variable measures the sentiment of the press release. The control variable ln_firm_size captures the effect of firm size on abnormal returns, calculated as the natural log of the firm's market value at the end of the day. ROA reflects firm-specific financial performance.

4.3.2. Tone and Volatility

To assess the impact of tone on stock return volatility, this paper uses realized volatility over different time spans 5 days, 10 days, and 30 days. Three separate models are constructed, each regressing the log of realized volatility on the tone of the press release and firm-specific control variables including firm size, return on assets, and abnormal trading volume.

Realized volatility is calculated for the 30 days leading up to the earnings announcement, using a combination of the simple moving average method and standard deviation. In addition to ln_firm_size and roa, ln (ABVOL) is included as a control variable in all models. ln (ABVOL) is the natural log of abnormal volume, measured as the difference in trading volume within a short window (one day before to five days after the earnings announcement) from its normal levels. All three control variables capture the impact of firm size, return on assets and abnormal trading volume on stock return volatility within the short window around the earnings announcement.

5. Empirical Results

5.1. Tone and Abnormal Return

5.1.1. Descriptive Statistics

Table 3. Descriptive table

Variable	Obs	Mean	Std. Dev.	Min	Max
CAR	7954	.058	.984	-4.902	4.066
tone	7954	.578	.389	-1	1
ln firm size	7954	15.915	1.158	10.686	19.474
roa	7943	.133	.086	-.341	.597

Table 3 presents that the average cumulative abnormal return (CAR) is 0.058, which is quite close to zero, suggesting that on average, firms do not experience large abnormal returns in the short window around earnings announcements. The substantial variation in CAR, with a standard deviation of 0.984, points to the fact that while the mean effect is small, there is considerable heterogeneity in how different firms experience abnormal returns.

The tone variable has a mean of 0.578 and a standard deviation of 0.389. This suggests that corporate press releases in the sample tend to have a generally positive sentiment, with relatively few companies releasing negative-toned announcements. This skew towards positivity is consistent with “impression management”, a corporate communication strategy in which firms may opt for more optimistic or positive language in their announcements to bolster market confidence as argued by Henry [1].

Firm size (log-transformed) has an average of 15.915, with values ranging from 10.686 to 19.474. This indicates that the sample consists primarily of medium to large firms, which is consistent with many event studies focusing on more established, publicly traded companies [47].

5.1.2. Correlation Table

Table 4. Correlation table

Variables	(1)	(2)	(3)	(4)
(1) CAR	1.000			
(2) tone	-0.085	1.000		
(3) ln_firm_size	-0.143	0.053	1.000	
(4) roa	-0.069	0.067	0.178	1.000

Table 4 provides insight into the relationships among the variables. The negative correlation between tone and CAR (-0.085) suggests that contrary to what one might intuitively expect, as hypothesis one demonstrates, more positive tones in press releases are associated with lower abnormal returns. This could align with findings in prior literature, such as that of Henry & Leone [15], where overly positive tones might signal overconfidence or bias, leading to market skepticism and resulting in lower returns. However, the correlation magnitude is modest, indicating that other factors beyond tone are likely contributing to the abnormal returns.

Firm size shows a stronger negative correlation with CAR (-0.143), which is consistent with a study indicated by Henry [1] that suggests larger firms, often subject to greater market scrutiny, tend to experience smaller abnormal returns due to less unexpected information being revealed.

5.1.3. The Association between CAR and Tone

Table 5. Linear regression

CAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.19	.028	-6.77	0	-.245	-.135	***
ln_firm_size	-.112	.01	-11.70	0	-.131	-.093	***
roa	-.457	.129	-3.55	0	-.709	-.205	***
Constant	2.013	.151	13.35	0	1.717	2.308	***

Mean dependent var	0.059	SD dependent var	0.984
R-squared	0.028	Number of obs	7943
F-test	76.084	Prob > F	0.000
Akaike crit. (AIC)	22059.630	Bayesian crit. (BIC)	22087.550

****** p<.01, ** p<.05, * p<.1*

ISSN: 2688-9323

Table 5 presents the relationship between CAR and tone. The coefficient for tone is -0.19 ($p < 0.01$), indicating that a more positive tone in press releases is associated with lower abnormal returns. This result could be interpreted in a few ways. First, it might suggest that markets react unfavorably to overly optimistic language, perhaps perceiving it as signaling management's attempt to mask underlying weaknesses. Alternatively, it could be that markets are more sensitive to understated or neutral tones, viewing them as more credible.

This negative relationship is consistent with certain strands of the literature [1, 2]. For instance, Loughran & McDonald [24] point out that investors may become skeptical of excessive positivity since overly positive sentiments are interpreted as warning signals by investors.

The coefficient for firm size is also negative and significant (-0.112, $p < 0.01$), reinforcing the notion that larger firms tend to experience smaller abnormal returns. This result is consistent with previous findings in the literature, such as those by Kothari & Warner [37], which suggest that the impact of earnings announcements is smaller for larger firms due to their greater visibility and the relatively lower amount of new information provided in their earnings reports.

ROA shows a significant negative association with CAR (-0.457, $p < 0.01$). This finding may appear counterintuitive at first glance—since better financial performance (higher ROA) is typically expected to result in positive market reactions. However, this result could be explained by the fact that firms with higher profitability may already have higher expectations baked into their stock prices. Thus, even relatively strong earnings announcements might not produce large positive abnormal returns if they are in line with or slightly below these high expectations. This is consistent with findings in Henry & Leone [12], where highly profitable firms are found to be subject to higher market expectations, resulting in smaller positive reactions to earnings announcements.

In terms of model fit, the R-squared value of 0.028 indicates that the model explains only a small portion of the CAR variation. While this may seem low, it is not unusual in financial market studies, where individual firm performance is influenced by a wide range of factors beyond the variables considered in this dissertation. The statistically significant F-test ($p < 0.01$) confirms that the model as a whole is meaningful.

5.2. Tone and Volatility

5.2.1. Descriptive Statistics

From the three different time windows (5 days, 10 days, and 30 days) in Table 6, the descriptive statistics show a decreasing trend in volatility as the window length increases. For the 5-day window, the mean volatility is -0.046 with a relatively high standard deviation of 1.124. This indicates that, within 5 days, the market experiences relatively larger short-term fluctuations in response to earnings press releases. Volatility decreases slightly, with a mean of -0.042 and a lower standard deviation of 0.815 in the 10-day window, suggesting that the market starts to stabilize after the initial response to earnings announcements. Volatility continues to decline to -0.037, with a much lower standard deviation of 0.535, reflecting the market becomes further constant as earnings information becomes fully incorporated into prices.

In contrast, the tone variable, with a mean of around 0.578, remains relatively stable across the three windows, indicating that the tone of press releases does not change substantially regardless of the three time periods. The other variables, including firm size, abnormal volume, and ROA, also remain stable, suggesting that firm-level characteristics being observed do not vary significantly over time.

This pattern is typical because abnormal volatility spikes tend to decay over time as markets adjust to new information. This finding is consistent with theories such as the Efficient Market Hypothesis, and mean reversion, along with empirical evidence from event studies, all point to a process where volatility increases in response to new information and then gradually declines

ISSN: 2688-9323

because that information is incorporated into prices. Fama [48] finds that prices tend to incorporate new information at first, but the market makes further adjustments, and thus abnormal fluctuations diminish during research on market efficiency. Event study literature also documents abnormal volatility typically peaks immediately in short windows around the corporate announcement, and this volatility diminishes over time when market participants digest the new information [49]. The conclusion is also in line with mean reversion.

Table 6. Descriptive table (5 days)

Variable	Obs	Mean	Std. Dev.	Min	Max
volatility	7435	-.046	1.124	-5.159	5.067
tone	7435	.579	.389	-1	1
ln firm size	7435	15.912	1.155	10.686	19.474
ln abnormal volume	7435	0	0	0	0
roa	7435	.133	.086	-.318	.597

Descriptive table (10 days)

Variable	Obs	Mean	Std. Dev.	Min	Max
volatility	7924	-.042	.815	-4.642	3.686
tone	7924	.578	.389	-1	1
ln firm size	7924	15.916	1.157	10.686	19.474
ln abnormal volume	7924	0	0	0	0
roa	7924	.133	.086	-.341	.597

Descriptive table (30 days)

Variable	Obs	Mean	Std. Dev.	Min	Max
volatility	7946	-.037	.535	-2.584	2.122
tone	7946	.578	.389	-1	1
ln firm size	7946	15.917	1.158	10.686	19.474
ln abnormal volume	7946	0	0	0	0
roa	7946	.133	.086	-.341	.597

5.2.2. Correlation Table

Table 7. Correlation table (5 days)

Variables	(1)	(2)	(3)	(4)	(5)
(1) volatility	1.000				
(2) tone	-0.027	1.000			
(3) ln_firm_size	-0.082	0.052	1.000		
(4) ln_abnormal_vo~e	-0.006	0.021	-0.096	1.000	
(5) roa	-0.047	0.066	0.171	-0.025	1.000

Correlation table (10 days)

Variables	(1)	(2)	(3)	(4)	(5)
(1) volatility	1.000				
(2) tone	-0.044	1.000			
(3) ln_firm_size	-0.119	0.052	1.000		
(4) ln_abnormal_vo~e	-0.020	0.015	-0.100	1.000	
(5) roa	-0.078	0.067	0.177	-0.037	1.000

Correlation table (30 days)

Variables	(1)	(2)	(3)	(4)	(5)
(1) volatility	1.000				
(2) tone	-0.073	1.000			
(3) ln_firm_size	-0.175	0.053	1.000		
(4) ln_abnormal_vo~e	-0.024	0.015	-0.100	1.000	
(5) roa	-0.109	0.067	0.178	-0.037	1.000

ISSN: 2688-9323

As shown in Table 7, the correlation between tone and volatility is negative and increases in magnitude as the time window lengthens: -0.027 for 5 days, -0.044 for 10 days, and -0.073 for 30 days. This suggests that as the market has more time to process the information, the negative association between positive tone and volatility becomes stronger. This could imply that optimistic tones may initially create uncertainty or doubt in the market, leading to higher volatility in the short term, but as time passes, the market begins to discount or adjust to this tone, leading to less volatility over longer windows.

5.2.3. The Association between Tone and Volatility

Table 8. Linear regression (5 days)

volatility	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.059	.033	-1.76	.078	-.125	.007	*
ln_firm_size	-.075	.011	-6.54	0	-.097	-.053	***
ln_abnormal_volume	-3252108.7	2762940.7	-1.18	.239	-8668255.2	2164037.8	
roa	-.434	.154	-2.82	.005	-.735	-.132	***
Constant	1.238	.181	6.85	0	.884	1.592	***

Mean dependent var	-0.046	SD dependent var	1.124
R-squared	0.009	Number of obs	7435
F-test	16.026	Prob > F	0.000
Akaike crit. (AIC)	22787.723	Bayesian crit. (BIC)	22822.292
*** p<.01, ** p<.05, * p<.1			

Linear regression (10 days)

volatility	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.071	.023	-3.03	.002	-.117	-.025	***
ln_firm_size	-.077	.008	-9.67	0	-.093	-.062	***
ln_abnormal_volume	-5512347.3	1912421.9	-2.88	.004	-9261198.3	-1763496.4	***
roa	-.546	.107	-5.10	0	-.756	-.336	***
Constant	1.301	.126	10.32	0	1.054	1.548	***

Mean dependent var	-0.042	SD dependent var	0.815
R-squared	0.020	Number of obs	7924
F-test	39.714	Prob > F	0.000
Akaike crit. (AIC)	19093.410	Bayesian crit. (BIC)	19128.299
*** p<.01, ** p<.05, * p<.1			

Linear regression (30 days)

volatility	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.08	.015	-5.28	0	-.11	-.05	***
ln_firm_size	-.075	.005	-14.49	0	-.085	-.065	***
ln_abnormal_volume	-4799315.9	1240718.3	-3.87	0	-7231449.8	-2367182.1	***
roa	-.482	.069	-6.95	0	-.618	-.346	***
Constant	1.268	.082	15.53	0	1.108	1.428	***

Mean dependent var	-0.037	SD dependent var	0.535
R-squared	0.042	Number of obs	7946
F-test	87.574	Prob > F	0.000
Akaike crit. (AIC)	12270.848	Bayesian crit. (BIC)	12305.751
*** p<.01, ** p<.05, * p<.1			

The regression results across the 5-day, 10-day, and 30-day windows in Table 8 demonstrate that the tone of earnings announcements consistently has an increasingly significant negative association with stock return volatility. This indicates that a more positive tone is associated with lower volatility, this relationship becomes stronger over longer windows. In the 5-day window, the tone coefficient is -0.059 (p = 0.078), which is statistically significant at the 10%

ISSN: 2688-9323

level. In the 10-day window, the tone coefficient becomes more significant, with a value of -0.071 (p = 0.002), significant at the 1% level. The 30-day window shows the strongest association, with the tone coefficient being -0.08 (p < 0.001), also significant at the 1% level.

This pattern suggests that while the tone of announcements immediately impacts volatility, the effect becomes more pronounced as more time passes, indicating that the market continues to respond to the sentiment of the earnings announcement for several weeks after the event. This result aligns with the findings of Davis et al. [2], which suggest that tone influences market perceptions and volatility in the medium term, rather than just immediately.

6. Further Analysis

6.1. Impact of the 2008 Financial Crisis

Increased level of uncertainty over periods of financial crisis causes firms to alter sentiments in their narrative disclosures [20]. In this case, this study considers how the financial crisis in 2008 affected both abnormal returns and volatility. The whole sample is divided into two parties: 2000-2007 is the pre-crisis period while 2008-2016 is the post-crisis period. Panel A and Panel B in Table 14 show the impact of tone on volatility over 30 days. Panel A and Panel B in Table 15 present the impact of tone on abnormal returns.

Table 9. Linear regression (Panel A: 2000-2007)

volatility	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.075	.022	-3.46	.001	-.117	-.032	***
ln_firm_size	-.067	.007	-8.99	0	-.082	-.053	***
ln_abnormal_volume	-4761542.4	1681999.6	-2.83	.005	-8059109.8	-1463975.1	***
roa	.016	.101	0.16	.872	-.182	.214	
Constant	1.069	.116	9.24	0	.842	1.296	***

Mean dependent var	-0.030	SD dependent var	0.547
R-squared	0.023	Number of obs	4397
F-test	26.049	Prob > F	0.000
Akaike crit. (AIC)	7073.782	Bayesian crit. (BIC)	7105.725

*** p<.01, ** p<.05, * p<.1

Linear regression (Panel B: 2008-2016)

volatility	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.097	.019	-5.03	0	-.135	-.059	***
ln_firm_size	-.085	.007	-12.62	0	-.098	-.072	***
ln_abnormal_volume	-3280250.3	1588968.7	-2.06	.039	-6395465.8	-165034.73	**
roa	-.964	.086	-11.17	0	-1.133	-.795	***
Constant	1.513	.108	14.03	0	1.302	1.725	***

Mean dependent var	-0.040	SD dependent var	0.519
R-squared	0.082	Number of obs	4222
F-test	94.429	Prob > F	0.000
Akaike crit. (AIC)	6085.742	Bayesian crit. (BIC)	6117.482

*** p<.01, ** p<.05, * p<.1

Tables 9 and 10 demonstrate that tone consistently has a significant negative relationship with both volatility and CAR across two time periods. This suggests that a more positive tone reduces both volatility and abnormal returns. The significance of tone is robust across all models, with p-values near zero and strong t-values. Similarly, firm size is consistently negatively associated with both volatility and CAR across both periods, indicating that larger firms tend to experience

ISSN: 2688-9323

lower volatility and cumulative abnormal returns. The consistency in the signs and significance of tone and firm size suggests that these variables maintain stable relationships with volatility and CAR over time.

Table 10. Linear regression (Panel A 2008-2016)

CAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.239	.037	-6.49	0	-.311	-.167	***
ln_firm_size	-.129	.013	-10.08	0	-.154	-.104	***
roa	-1.252	.164	-7.62	0	-1.574	-.93	***
Constant	2.422	.205	11.82	0	2.02	2.823	***

Mean dependent var	0.041	SD dependent var	0.973
R-squared	0.054	Number of obs	4222
F-test	80.370	Prob > F	0.000
Akaike crit. (AIC)	11526.447	Bayesian crit. (BIC)	11551.839
*** p<.01, ** p<.05, * p<.1			

Linear regression (Panel B 2000-2007)

CAR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
tone	-.165	.039	-4.20	0	-.241	-.088	***
ln_firm_size	-.101	.013	-7.51	0	-.128	-.075	***
roa	.355	.182	1.95	.052	-.002	.713	*
Constant	1.718	.208	8.25	0	1.31	2.127	***

Mean dependent var	0.078	SD dependent var	0.987
R-squared	0.018	Number of obs	4394
F-test	26.417	Prob > F	0.000
Akaike crit. (AIC)	12283.249	Bayesian crit. (BIC)	12308.801
*** p<.01, ** p<.05, * p<.1			

The coefficients for tone and firm size are slightly larger in absolute terms in the post-crisis period compared to the pre-crisis period, which may indicate that the effects of tone and firm size on volatility and CAR have intensified after 2008. This could reflect changes in market behavior or increased sensitivity among investors to tone during the post-crisis period, which is in line with the finding of Tetlock [35]. However, the impact of return on assets (ROA) on volatility and CAR differs notably between the two periods. In the post-crisis period, ROA has a significant negative impact on both volatility and CAR, suggesting that higher profitability is associated with lower risk and reduced abnormal returns. In contrast, ROA's impact on volatility is insignificant during the pre-crisis period.

7. Conclusion

This dissertation explores the effect of disclosure sentiment in earning press releases on abnormal stock returns and volatility. The findings reveal that the tone of press releases is negatively associated with abnormal stock returns and volatility. In alignment with prior literature such as Henry & Leone, the study argues that optimistic tones can trigger lower market reactions if investors perceive them as inflated. In addition, after examining three-time windows as 5 days, 10 days, and 30 days, it was found that positive sentiment in earning press releases leads to lower abnormal volatility, both immediately and consistently over time. This result further supports the arguments of Davis et al. These two findings are still robust when taking into account the financial crisis in the year of 2008.

This paper extended the existing literature by investigating how the market reacts to sentiments in earning press releases, with a particular focus on cumulative abnormal stock returns and abnormal volatility. While much of previous studies focus primarily on the short-term effects of narrative tone [10], this paper also addresses the long-term effects. Moreover, the sample base of this work consists of different industry types, which enhances the comprehensiveness of narrative tone measurement.

My article can be further expanded based on the following limitations, which offer potential direction for future research. First, besides extracting sentiment indices based on word frequency, advanced techniques such as natural language processing (NLP) mechanisms which have been mentioned in this document are suggested to enhance accuracy. Second, the inclusion of more macroeconomic and financial variables can provide more comprehensive implications for a wide array of control variables. Finally, while this paper mainly focuses on U.S. data, future research is likely to benefit from examining contexts outside the United States such as the European circumstance.

Acknowledgments

With many thanks to Professor Nikos Tsileponis, University of Bristol Business School.

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