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How “good” is bad News? Exploring Sentiments of Corporate Disclosures

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ABSTRACT

To satisfy legal requirements, listed companies are required to continuously publish a wide range of disclosures and reports. Regulatory authorities such as the SEC in the US or the FSA in the UK have developed a complex set of rules and regulations that aim at expanding transparency of capital markets. Therefore, corporations hire professional editorial teams, often being supported by financial service communication consultancies. While the regulatory objective is to increase transparency, the management has an inherent motivation to give the reports a positive spin. We aim to explore this conflict by analyzing the sentiment of corporate disclosures and to compare this tone with the price reactions following the disclosures' publication. On the basis of an empirical analysis of intraday stock price reactions and word lists which provide means to assess the tone of documents, our results provide evidence that corporates follow a strategy to positively adjust their external reporting.

Keywords

Transparency legislation, financial reporting, corporate disclosures, sentiment.

INTRODUCTION

Since the national regulators such as the SEC in the US or the FSA in the UK have the objective to maintain confidence in the financial systems, one central objective is market transparency. To comply with the corresponding regulatory legislation of the financial service industry, listed corporations have to report a wide range of financial transactions and reports or other relevant business events such as changes in the management board that have the potential to affect a firm's value. This paper explores such regulatory driven corporate disclosures with an analysis of sentiment, a field that has attracted much attention in the field of information systems research in recent years. The motivation of our research is based on the duality of motivation behind such disclosures: On the one hand side, the management needs to comply with regulations and therefore has to assure the report of all relevant cases. On the other hand, the management's major objective is to increase a firm' value, and therefore it will mitigate any effects that could negatively affect this value. Further, there exist a number of consultancy firms providing advice regarding financial service communication in this field. As the corporate disclosures have to cover both positive and negative facts, we assume that there exists a motivation to choose wordings that will make readers feel positive about the statements at first sight. We aim to explore these two facets of external reporting on business events in the following.

The remainder of our paper is as follows. In the next section, we provide a review on relevant literature regarding financial reporting, accounting information systems and the regulatory background. Further, we provide insights into the relevant literature on sentiment and its analysis. Then, we present our study setup, which comprises a description of our dataset and our research approach. In the subsequent section, we formulate our research hypotheses and present our empirical results. We finally conclude with a summary of our findings, the limitations of our research and potential future research directions.

LITERATURE REVIEW

Financial Reporting and Accounting Information Systems

The avoidance of information asymmetries represents an important issue in the financial sector. Especially capital markets are dependent on reliable information in order to be efficient. Key elements for information provision to the financial domain are corporate disclosures. With respect to corporate disclosures, which represent information that is publicly available, capital markets are tending to be semi-strong form efficient (Fama 1970), meaning all public information is reflected in securities prices. Financial reporting in general and especially corporate disclosures enable companies’ management to reduce information asymmetries between themselves and investors.

Healy and Palepu (2001) describe the role of disclosures in capital markets with respect to two issues which market participants have to deal with. Information disclosure helps to avoid breakdown of markets, as described by Akerlof (1970), because it can resolve adverse selection problems between investors and entrepreneurs. The existence of “information problems” does explain the important role of information and financial intermediaries, like rating agencies, financial analysts and banks, in order to overcome managers’ information advantage. They also argue that information disclosure is important for monitoring managers in a moral hazard setup, as described by Jensen and Meckling (1976), between investors and managers. Thus, the requirement for continuous revealing relevant information by managers to their investors is a solution to the “agency problem”.

Besides the need for information available to investors in order to achieve the above stated avoidance of information asymmetries, the relation between financial reporting and financial market reactions is addressed by capital market research. It is examined if the published information is relevant for investors. A variety of studies show that regulated financial reports provide pertinent information for market participants in order to predict future investor cash flows. An overall substantial review of the corresponding research topics is given by Kothari (2001).

Further, our study is associated with accounting information systems (AIS) research. AIS, as specialized subsystems of information systems (IS), emerged from the application of information and communication technology in the accounting domain (Sutton 1996). Therefore, the connection of the IS domain and accounting is established by AIS research (Poston and Grabski 2000). Samuels and Steinbart (2002) identified eight major research themes addressed by AIS research: organization and management of an IS; internal control and auditing; judgment and decision making; databases; expert systems, artificial intelligence, and decision aids; general AIS frameworks; the accounting and consulting profession; educational issues. These topics have been expanded by topics like the effects of decision aids on users, analysts’ forecasts and investments in information technology in recent years (Ferguson and Seow 2011). In general, the purpose of AIS is to process and report information with regard to the financial aspect of business events (Gelinas and Dull 2008). Since our study is associated with the reporting of such business events and the analyses of sentiments of related reporting (in our case corporate disclosures), we believe our study contributes to the understanding regarding the utilization of such reported information.

Regulatory Background

In almost all economies there exist financial regulating authority institutions with various jurisdictions. In the USA this is the Securities and Exchange Commission (SEC). SEC was established in 1934 and was given enforcement authority. In the UK, the Financial Service Authority (FSA) is an independent non-governmental financial supervisory authority. It has very broad statutory powers and sanctioning options (Busch 2002).

The FSA is responsible for maintaining market confidence in the UK financial system, the supervision of financial institutions and enforcement of regulatory rules. One of the main goals of the FSA is to identify market abuse and counteract financial crime (Busch 2002). A survey of Moneiro, Zaman, and Leiterstorf (2007) shows a significant reduction of insider trading from 19.6% to 2% for the FTSE 350 listed companies. From a perspective, the FSA is a non-profit society and is independent of the government supervisory body. It is empowered to make regulations and to set legally binding arrangements and sanctions.

The FSA regulated companies are required to meet the standards set out by the FSA in order to monitor and regulate their business. Companies are required to publish all inside information relevant to the market in a timely manner (EU directive 2003/6/EC). Inside information is any information which can be used by investors for investment decisions, and which would have an effect on security prices (Financial Services Authority 2011).

Sentiment Analysis

Sentiments in general represent opinions, ideas or beliefs based on emotions. They can also describe a shared belief or opinion among a group of individuals.

In the financial context, sentiment refers to general beliefs among investors or financial analysts on the behavior of capital markets with respect to external factors. In this sense, sentiments are also known as market sentiments. Market sentiment represents a general consensus of a group of investors whether markets are either bullish or bearish. This prevailing attitude can give an indication to the anticipated price movements in financial markets.

In this paper, we follow a definition of Pang and Lee (2008) and Pang, Lee and Vaithyanathan (2002), who state that sentiment analysis aims to determine the tone and the underlying information in source materials. Extracting sentiment from textual documents is a severe semantic problem. Recent studies tried to measure the mood of certain groups of individuals or investors in the financial domain with a variety of technical and statistical methods.

A relatively new subject to this topic is the extraction of sentiments from Web sources, like message boards, blogs and all kinds of user generated contents, in order to grasp the opinion of communities about a certain subject. Antweiler and Frank (2004) investigated the influence of financial message boards (in this case Yahoo! Finance and Raging Bull) on the movement of stock markets (concerning companies in the Dow Jones Industrial Average and Dow Jones Internet Index). They were able to provide evidence that internet message boards can give an indication for predicting market volatility and overall stock market movements. Further Studies were also able to analyze sentiments expressed on the internet and link them to stock market reactions. Bollen, Mao and Zeng (2011) investigated if collective mood states of the public are linked to development of the economy. In fact, they were able to find a correlation between the public mood, derived from a collection of tweets posted on twitter.com, and the following Dow Jones Industrial Average index values three to four days later. Besides analyzing sentiment of text documents or messages of virtual communities, the community network themselves are also in the focus of recent studies, evaluating the quality of investor communities (Gu, Konana, Rajagopalan and Chen 2007). Another study also examined the automated extraction of sentiment from stock message boards and compared the performance of several classifiers for the classification task (Das and Chen 2007). The classification task is to identify the sentiment (buy, hold, sell) of the messages posted by the authors or investors to the respective stock. From a methodological perspective, they applied additional databases for improving classification algorithms. An English dictionary and a hand-picked collection of words of the finance domain were applied. Because messages on internet stock message boards are highly ambiguous, meaning the classification cannot be easily conducted, the authors aimed at reducing the noise of their sample. They used the General Inquirer, a computer-assisted word categorization from Harvard University (categorized word lists are also available in the Harvard Psychosociological Dictionary), in order count the optimistic and pessimistic words in their sample of messages. By determining an optimism score for each message, they filtered messages by ambiguity which drastically improved classifiers' performance. In addition, using their developed methodology they generated a sentiment index by accumulating sentiment from board messages of tech-sector stocks and examined its relationship to the Morgan Stanley High-Tech Index. Their findings provide evidence that the stock index is related to the lagged sentiment value, but only a weak relationship was detected.

STUDY SETUP

Dataset Description

In the following, we make use of three different kinds of data sources. First, we have collected a sample of corporate disclosures that have been published in the UK. Second, in order to positively or negatively label these disclosures, we collected stock price series that provide a basis to assess capital market reactions following their publication. Third, we make use of two word lists that provide guidance with regard to assessing the tone of the disclosures.

Corporate disclosures

In this study, we focus on FTSE-100 corporate disclosures, which were published via Regulatory News Services (RNS). RNS is a financial communication channel for regulatory news announcements in the UK. Our collected sample of corporate disclosures were published between November 2007 and November 2009 during trading hours of the London Stock Exchange.

In total, our dataset comprises 4360 disclosures. Company disclosures published via RNS have the following data structure: company name, TIDM (company ID), headline, publication date and the text of the concrete disclosures.

Stock Price Series

In order to label corporate disclosures according to their price effect, required intraday price series of the corresponding stocks have been collected. The dataset shows the following formal setup relevant for our experiments: Instrument identifier, time stamps and stock prices exact to the second.

Word Lists

Besides corporate disclosures and the corresponding stock returns we make use of two word lists. All lists contain words which are considered as negative and positive in different terms. These lists provide word classifications for gauging tone or sentiments in textual documents.

The first word list consists of the TAGNeg list (see http://www.webuse.umd.edu:9090/tags/TAGNeg.html), containing words with a general negative meaning, and the TAGPos list (see http://www.webuse.umd.edu:9090/tags/TAGPos.html), containing words with a general positive meaning. These two lists are part of the Harvard Psychosociological Dictionary (H4-4), representing sentiments of words and goes back to Stone and Hunt (1963). The Harvard Psychosociological Dictionary consists of several word lists classified in categories of meaning in a more general psychsociological manner. The TAGNeg list used in our analysis contains 2006 words and the TAGPos list contains 1636 words.

Our second word list (FIN) was derived from Loughran and McDonald (2011). They created a dictionary of words in order to create alternative word lists which reflect more accurately the tone in the financial context compared to the Harvard word lists. Loughran and McDonald's derived word lists through textual analysis on a sample of Form 10-Ks (annual reports) published between 1994 and 2008. They used a word categorization method ("bag of words") in order to create the respective vectors of words and word counts. Along their analysis they created six word lists for different word classifications in financial text: negative, positive, uncertainty, litigious, strong modal and weak modal. For our analysis we consider the negative and positive word lists only (FIN-Neg and FIN-Pos). The FIN-Neg word list (words which have a negative meaning in the financial domain) contains 2337 words and the FIN-Pos word list (words which have a positive meaning in the financial domain) contains 353 words. Both lists are considered to better reflect tone in financial text. The authors were able to provide evidence that the FIN-Neg is more related to excess returns following the Form 10-K filing date compared to the Harvard word lists.

Research Approach

Most responses to published corporate disclosure usually take place within the first 15 minutes subsequent to its release (Patell and Wolfson 1981). Furthermore, Gosnell, Keown and Pinkerton (1996) determined a rapid change of stock prices within 15 minutes after the release of positive disclosure. In addition Muntermann and Güttler (2007) detected significant abnormal price effects within 15 to 30 minutes following the publication dates. Further, they found that the market adjusts more quickly to positive disclosures than to negative disclosures.

To assess the impact of corporate disclosures, we first labeled the disclosures positive or negative according to the price effect of the stock price 15 minutes subsequent to the publication date. Therefore, we used the stock price p_0 at the publication date of the disclosure and price p_1, which has been observed 15 minutes later.

The publication date of disclosures was given in a format exact to the minute (hh:mm) and price data was given in a form exact to the second (hh:mm:ss). For each disclosure we then calculated discrete returns as:

$$r = \frac{p_0 - p_1}{p_0}$$

Given the return measure, a company disclosure is labeled as

- positive if $r > 0$

  or

- negative if $r < 0$

Figure 1 shows the return distribution of the calculated stock returns and the labeling of our dataset.

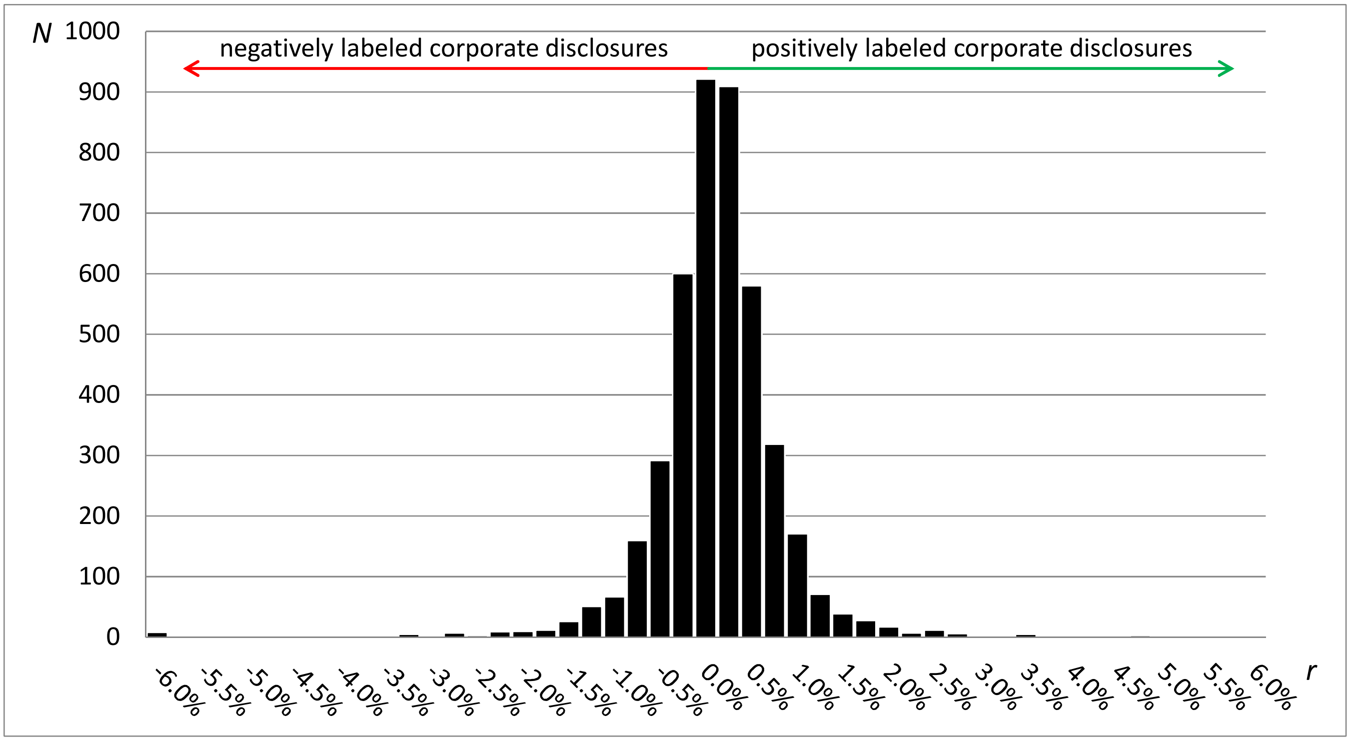

Figure 1. Histogram of stock returns

Our labeling approach provides 2183 positive labeled corporate disclosures and 2177 negative labeled disclosures.

RESEARCH HYPOTHESES AND EMPIRICAL RESULTS

In our research, we explore sentiments of corporate disclosures given the reaction of the capital market to their provided information content. Given the positive or negative price reaction of the corresponding stocks, we aim to analyze the role of subjective information that can be observed in regulatory-driven disclosures that should objectively report on business events in order to comply with market transparency legislation and the corresponding regulatory obligations. Since the analyzed RNS disclosures report on market-relevant events such as operational updates, financial statements and corporate actions that all can result in positive or negative market reactions, we hypothesize that positive (negative) price effects are driven by positive (negative) sentiment of the corporate disclosure. We derive this hypothesis from the word lists used in our study that for example list words such as “achievement”, “gain” and “improvement” in the positive category, while words such as ”bankruptcy”, “losses” and “penalty” are listed in the negative category. If a disclosure contains more (less) such positive words (#pos) than negative words (#neg), we refer to a positive (negative) sentiment in the following.

Given the labeling of corporate disclosures being based on the price reaction of the capital markets, we first explore positively labeled disclosures, i.e. those for which we observed a positive price reaction on the capital market. We consequently formulate our first research hypothesis that aims at exploring the sentiment of disclosures that resulted in positive price reactions.

H1*: *Positively labeled corporate disclosures show a positive sentiment.

Statistically, H1 is explored by the following null hypotheses $H1_0$, using the Harvard (H4-4) and Financial (FIN) word lists**,** which we aim to reject in the following. Since the word lists have a different ratio of positive and negative words (H4-4: 1:1.23; FIN 1:6.62), this test is rather ambitious. We therefore further adjusted our observation numbers by these factors (see negative (adj.)).

$\mathbf{H1_0}\ \mu(\#neg;\ poslabeled) \geq \mu(\#pos;\ poslabeled)$ *vs.* $\mathbf{H1_A}\ \mu(\#neg;\ poslabeled) < \mu(\#pos;\ poslabeled)$

Sample characteristics and test results are given in the following Table 1:

	Number of words from H4-4 list			Number of words from FIN list		
Words	Mean	Median	Std. dev.	Mean	Median	Std. dev.
#neg (adj.)	7.74 (6.31)	6	10.73 (8.75)	2.90 (0.44)	2	9.86 (1.49)
#pos	20.47	18	26.23	1.38	0	7.02
t-Value (*F*-Value)		23.93***	(8.97***)		6.13***	(22.20***)

**** indicates1% level of significance*

Table 1. Positively labeled disclosures sentiment (N = 2183)

For the hypotheses test, we applied an unequal variances *t*-test for comparing the means of two independent samples since the corresponding *F*-tests on the equality of the two sample variances have been rejected (Weiers 2005). The results presented above corroborate hypothesis H1, since the test statistics provide strong evidence to infer that positively labeled disclosures contain more positive tone words than negative words, i.e. the show a positive sentiment. We also detected statistical significance for the non-adjusted sample on a 1% level of significance.

After exploring the sentiment of positively labeled disclosures, we explore the sample of negatively labeled disclosures. Given the argument that negatively labeled disclosures should have a negative tone, we formulate the corresponding hypothesis H2:

H2: Negatively labeled corporate disclosures show a negative sentiment.

Statistically, H2 is explored by the following null hypotheses**,** which we again aim to reject in the following.

$H2_0$ μ*(#neg; neglabeled)* $\leq$ μ*(#pos; neglabeled)* *vs.* **$H2_A$** μ*(#neg; neglabeled)* > μ*(#pos; neglabeled)*

The following Table 2 shows descriptive sample characteristics and the statistical test result.

	Number of words from H4-4 list			Number of words from FIN list		
Words	Mean	Median	Std. dev.	Mean	Median	Std. dev.
#neg (adj.)	7.98 (6.50)	6	12.64 (10.31)	2.83 (0.42)	2	7.21 (1.09)
#pos	20.52	18	25.66	1.27	0	6.44
t-Value (*F*-Value)		23.63***	(6.19***)		6.06***	(34.95***)

**** indicates1% level of significance*

Table 2. Negatively labeled disclosures sentiment (N = 2177)

As the analysis is biased by the ratio of positive and positive word within the word lists (Harvard H4: 1:1.23; FIN list 1:6.62), we also adjusted the observations by these factors (negative (adj.)). High statistical significance has been found by an unequal variances *t*-test, but in contrast to H2, we detect strong evidence that also negatively labeled disclosures show a positive sentiment. This is remarkable as disclosures resulting in a negative market reaction come with a positive tone authored by the corporates of the disclosures.

Finally, we aim to compare the sentiment of negatively and positively labeled disclosures. To do so, we first calculated the ratio of negative / positive words (using the H4-4 and FIN lists) for each disclosure. Ratios have also been adjusted by the ratios of positive and negative words in the word list and calculated only if #pos and #neg were unequal zero.

Given the argument that negatively labeled disclosures should have a negative tone, we formulate the corresponding hypothesis H2:

H3: The sentiment of negatively labeled disclosures is worse than the sentiment of positively labeled disclosures.

H3 is addressed by the following null hypotheses:

$H3_0$ μ*(neg/pos ratio; neglabeled)* $\leq$ μ*(neg/pos ratio;poslabeled)* *vs.*

$H3_A$ μ*(neg/pos ratio; neglabeled)* > μ*(neg/pos ratio;poslabeled)*

The following Table 3 shows sample characteristics and our statistical test results.

	#neg/#pos ratio from H4-4 list				#neg/#pos ratio from FIN list			
Labeling	Mean	Median	Std. dev.	N	Mean	Median	Std. dev.	N
Negative	0.34	0,27	0.25	2175	0.36	0.18	0.42	255
Positive	0.33	0.27	0.23	2181	0.37	0.16	0.48	292
t-Value (*F*-Value)		0.82	(1.14***)			0.41	(1.36**)	

**** indicates1% level of significance*

Table 3. Sentiment comparison of negatively and positively labeled disclosures

The number of observations (N) differs from the total number of disclosures since not all texts contained one positive and one negative word from the two H4-4 and FIN word lists. This becomes especially relevant for the FIN list ratio, because it’s total word count is much smaller compared to the H4-4 list.

While the observed means and medians are much smaller than 1 (which would indicate a balance of positive and negative words), the actual number provide some evidence that all samples contain more positive than negative words of the word lists. One first surprising finding is that for both samples (i.e. for both the H4-4 and the FIN word lists), we observed quite similar sample characteristics. Given these findings and the test statistics we calculated test statistics for comparing the means of the two samples. We do not find any evidence that sentiment of negatively labeled disclosures is worse than the sentiment of positively labeled disclosures.

SUMMARY AND CONCLUSION

In this paper we have explored the sentiment of corporate disclosures that have been published by listed companies due to regulatory legislation. Our analysis covers a period of more than two years between November 2007 and November 2009 and is based on a unique dataset that contains 4360 corporate disclosures published via the Regulatory News Service (RNS) in the UK. In order to label these disclosures regarding their impact on the capital market, we have collected intraday price series of the corresponding stocks. Since financial research has shown that significant price effects can be expected for a period of 15 minutes following the publication of corporate disclosures, we calculated return measures for this period and labeled the documents according to these returns (i.e. positive and negative). As we are interested in the sentiment of the corporate disclosures, we then compared the disclosures’ contents with word lists that provide insights into the tone of a given document. We applied the well-known Harvard Psychosociological Dictionary H4-4 and a word list that has recently been developed for the financial domain (derived from Form 10-K reports) and applied a word count approach in order to explore the tone of the documents. Given the labeling of the disclosures based on their market impact, we hypothesized that positively (negatively) labeled disclosures are expected to show a positive (negative) sentiment. We were able to reject the statistical hypotheses that the mean word counts differ, but not as we have expected: According to our measures, all disclosures show a significant positive sentiment and there is no significant difference between positively and negatively labeled disclosures. We interpret this finding given the area of conflict the management faces. One the one hand side, given the regulatory legislation, corporates need to report all kinds of relevant business events that have the potential to (positively or negatively) affect the firm’s value, i.e. the value of the corporate shares. On the other hand, the management has a general motivation to increase the firm’s value and so, to mitigate the effects of negative fact being reported. Our results provide strong evidence that the management of publicly listed corporations put significant effort into the disclosures contents with the objective to give the reports a positive spin.

LIMITATIONS AND FURTHER RESEARCH

Our analysis is based on a statistical analysis of the tone of corporate disclosures. While the results provide first empirical insights into their sentiment, our research provides diverse motivation for future research directions in this field.

Our results are based on simple word count measures and statistical test procedures that we aim to refine in future research. First, we aim to refine our approach to compare the similarity of the given corporate disclosures and the wordlists and aim to apply document similarity measures that can be calculated by utilizing text mining techniques (Cios, Pedrycz, Swiniarski and Kurgan 2007). Another second stream of future research is domain-specific word lists. While our analysis is based on one generic psychsociological dictionary (H4-4) and one word list that has been developed for the financial domain (FIN), creating and evaluating own word lists could be subject of future research. Such word lists could be developed by applying an Support Vector Machine (SVM) approach to our sample of RNS disclosures by analyzing the vectors obtained from such an analysis (Witten and Frank 2005). Third, and after developing such specific word lists, text mining techniques could also provide means to develop forecasting models that could contribute to the explanation of price effects that have been observed by a wide range of empirical analyses that have explored intraday price effects following the publication of regulatory-driven corporate disclosures (Carter and Soo 1999; Muntermann and Güttler 2007; Patell and Wolfson 1984).

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