

Evidence on the Information Content of Text in Analyst Reports

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ABSTRACT: We document that textual discussions in a sample of 363,952 analyst reports provide information to investors beyond that in the contemporaneously released earnings forecasts, stock recommendations, and target prices, and also assist investors in interpreting these signals. Cross-sectionally, we find that investors react more strongly to negative than to positive text, suggesting that analysts are especially important in propagating bad news. Additional evidence indicates that analyst report text is more useful when it places more emphasis on nonfinancial topics, is written more assertively and concisely, and when the perceived validity of other information signals in the same report is low. Finally, analyst report text is shown to have predictive value for future earnings growth in the subsequent five years.

Keywords: *analyst report; naïve Bayes; textual analysis; information content.*

I. INTRODUCTION

Analyst reports are a useful source of information for both institutional and individual investors (SRI International 1987). An analyst report typically provides several quantitative summary measures, including a stock recommendation, an earnings forecast, and sometimes a target price;¹ it also provides a detailed, mostly textual analysis of the company.

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¹ In this paper, we refer to the earnings forecast, stock recommendation, and target price released in the same analyst report as the quantitative summary measures.

This textual analysis is an important component of the report; at an average of 7.7 pages in our sample, it constitutes the main body of a report and covers a wide range of topics, such as the company's recent financial performance, business strategies, competitive position within the industry, risk exposure, and the effectiveness of its management.

In this study, we employ a naïve Bayes machine learning approach to extract textual opinions from a large sample of analyst reports.² Doing so provides the basis for testing the information content of report text. Specifically, we investigate the following issues: (1) Does analyst report text provide incremental information beyond the quantitative summary measures released contemporaneously? (2) Does it provide value by assisting investors in interpreting the quantitative signals? (3) Under what circumstances do investors find text particularly useful? The extant literature has not provided answers to these questions.

Investors may perceive text as being the most important research output in an analyst report because it contains analysts' research ideas useful for investors to form their own investment decisions.³ Survey evidence supports this perception. Since 1998, investors consistently rank written reports as a far more important attribute of analysts than stock selections or earnings estimates, according to *Institutional Investor* (II) magazine's annual survey of nearly 3,500 institutional investors.⁴ Moreover, investors spend millions of dollars annually to purchase the full content of analyst reports, even though they could subscribe to databases, such as I/B/E/S and Bloomberg, that provide only analysts' quantitative outputs.

However, whether text is incrementally useful to investors is still an open empirical question. Text might not provide independent information if analysts use it merely to support or justify the contemporaneously issued quantitative summary measures (Francis and Soffer 1997). Furthermore, investors may find text difficult to use because, in contrast to quantitative signals, textual discussion in analyst reports, such as product quality and management effectiveness, may not be verifiable *ex post*, comparable across different reports, or easily converted into numerical inputs that investors can use in their quantitative investing models.

Despite the apparent importance of analyst report text, the extant literature largely overlooks it and focuses almost exclusively on analysts' quantitative research outputs (Ramnath, Rock, and Shane 2008; Bradshaw 2011). This imbalance in the research effort might prevent the literature from developing a comprehensive understanding of the analysts' information role (Bradshaw 2011). For example, if analyst report text is informative, then it is possible that part of the documented market reaction to the quantitative signals is attributable to its correlation with the textual information. Moreover, the recent debate in the literature about whether analysts are an important information intermediary is inconclusive (Altinkılıç and Hansen 2009; Altinkılıç, Balashov, and Hansen 2013; Bradley, Clarke, Lee, and Ormthanalai 2014), perhaps because these studies do not take into account the information role of analyst report text.

To investigate the information content of analyst report text, we use the naïve Bayes machine learning approach to extract textual opinions from 363,952 analyst reports issued for the S&P 500 firms during the 1995–2008 period. Specifically, our trained naïve Bayes algorithm classifies more than 27 million sentences in our sample reports into either positive, negative, or neutral

² This approach is a computational linguistic algorithm that applies Bayes' theorem with a "naïve" assumption that words are conditionally independent. See Section IV for details.

³ This idea is conveyed in the following quotation from A. M. (Toni) Sacconaghi, a 13-time "All-Star" analyst by *Institutional Investor*: "As an analyst, the goal should be to deliver outstanding research that your clients can depend upon and use to make their own decisions—whether or not their ultimate conclusion agrees with yours" (*Institutional Investor* 2011).

⁴ In 2010 and 2011, for example, written reports rank 5th, considerably higher than earnings estimates (12th); stock selection is not in the top-12 list. This survey does not include target price as a candidate.

opinion categories.⁵ We then aggregate the sentence-level opinions for each report to determine an overall report opinion. Our validity tests show that the naïve Bayes approach outperforms dictionary-based approaches based on both the general dictionaries and financial dictionaries.⁶

We begin the empirical analyses with a description of the textual opinions in our sample analyst reports. On average, an analyst report comprises 53 percent neutral sentences, 33 percent positive sentences, and 14 percent negative sentences. We plot the temporal variation of analyst reports' overall textual opinions during 1996–2008 and show that they co-move with the stock market's boom and bust, and have become less optimistic after 2001.

Our first set of empirical tests indicates that the market reaction to textual opinions, conditional on the contemporaneously released quantitative summary measures, is statistically and economically significant. Specifically, we find that a one standard deviation increase in the favorableness of the textual opinion measure results in an additional two-day abnormal return of 41 basis points. In addition, we find that the market reacts to the favorable (unfavorable) quantitative summary measures in a report more intensely when the accompanying textual opinion is more positive (negative). These results indicate that analyst report text provides information on a stand-alone basis, as well as helping investors to interpret other signals in the report.

To further understand the information content of analyst report text, we investigate the determinants of the cross-sectional variation in its information content. First, we compare the relative weights investors attach to positive and negative text. Prior studies document a greater market reaction to recommendation downgrades compared to upgrades (Ivkovic and Jegadeesh 2004; Asquith, Mikhail, and Au 2005). We find that, on average, investors similarly attach more than twice the weight to negative as they do to positive text in analyst reports. This result suggests that analysts are especially important in propagating bad news.

Next, we explore the effect of different characteristics of analyst reports on the information content of report text. After controlling for factors previously shown to explain analyst forecasting performance (brokerage size, II Star status, experience, and Regulation Fair Disclosure [Reg FD]), we find that investors react to analyst report text more intensely when it places greater emphasis on nonfinancial topics, when it is written more assertively or concisely, and when the report contains bold or conflicting quantitative summary signals.

Finally, as a non-market-based test of the information content, we examine whether analyst report text can predict future earnings growth. We find that text predicts future earnings growth in the subsequent five years, and that it provides greater predictive power economically and predicts earnings growth over a longer horizon than do quantitative summary measures. These results are intuitive because analysts provide detailed fundamental analyses in report text, many of which, such as analysts' evaluation of companies' management quality, strategic alliances, and capital investments, have implications for long-term earnings. Moreover, we find that negative text is almost twice as informative as positive text in predicting earnings growth, consistent with investors' stronger reaction to negative text.

Overall, our study complements the existing analyst literature that focuses on quantitative signals by providing a more comprehensive understanding of the value of analyst research to investors. We do so by documenting the first large-sample evidence on the information content of analyst report

⁵ We classify opinions at the sentence level because the sentence is a natural unit in language for expressing an opinion (Ivers 1991).

⁶ The naïve Bayes approach achieves a classification accuracy of 80.9 percent in the in-sample validation and 76.9 percent in the out-of-sample validation, which is substantially higher than that achieved using dictionary-based content analysis approaches based on the general dictionaries (48.4 percent for General Inquirer [GI]; 51.7 percent for Linguistic Inquiry and Word Count [LIWC]; 54.9 percent for Diction), and on financial dictionaries recently developed by Loughran and McDonald (2011) (62.0 percent) and Henry (2006) (65.4 percent).

text. Our study offers a more definitive answer to the value of analyst report text than previous studies (Asquith et al. 2005; Twedt and Rees 2012) for several reasons. First, our sample provides greater confidence in the generalizability of our results.⁷ Second, our use of the naïve Bayes machine learning approach produces a more accurate classification of the textual opinions. Third, we conduct both market- and non-market-based tests of the incremental informativeness of report text, document its economic significance, and show its value in helping investors to interpret the quantitative summary measures. Furthermore, our study is the first to explore cross-sectional variation in text's information content. The insight that text's informativeness is determined by its topics, writing style, and features of other signals in the reports has important implications for both investors and analysts.

Section II discusses relevant prior studies; Section III develops hypotheses; Section IV describes the naïve Bayes machine learning approach; Section V presents the sample selection and variable descriptions; Section VI discusses the empirical results; Section VII provides an additional test; and Section VIII concludes.

II. PRIOR STUDIES

Our paper relates to prior research on financial analysts and to research that applies the naïve Bayes algorithm to classify textual information. Previous research on financial analysts focuses mostly on analysts' quantitative research outputs, including stock recommendations, earnings forecasts, target prices, and forecasts of some elements in financial statements, such as cash flows and revenues. Overall, the findings of these studies suggest analyst quantitative outputs are informative (Womack 1996; Givoly and Lakonishok 1979; Lys and Sohn 1990; Brav and Lehavy 2003; Asquith et al. 2005; Givoly, Hayn, and Lehavy 2009; Call, Chen, and Tong 2013; Ertimur, Livnat, and Martikainen 2003).

By contrast, only a few studies examine the qualitative content of analysts' written reports.⁸ Of these studies, Asquith et al. (2005) manually catalog the content of 1,126 reports issued by 56 II All-American "First Team" analysts during the 1997–1999 period. They construct a variable called the "strength-of-arguments" for analyst reports as the number of categories with positive remarks less the number of categories with negative remarks for 14 categories. Asquith et al. (2005) find that, conditional on revisions of recommendations, earnings forecasts, and target prices, the strength of arguments is marginally significant in explaining five-day abnormal returns surrounding the report date. While Asquith et al. (2005) provide insight into the role of written reports, their study uses a small and non-random sample. Their small regression sample of 193 observations may explain their unintuitive result that the market reacts negatively to the strength of arguments for upgrade reports. Furthermore, because their sample contains only top-ranked analysts who likely receive greater attention from the market, no more than three SELL reports in their main test, and reports issued only in the boom years of 1997–1999, it is not clear whether their results are generalizable.

⁷ Two prior studies that examine analyst report text use small and non-random samples. Asquith et al. (2005) manually catalog a small number of reports issued by 56 II All-American "First Team" analysts during the 1997–1999 period. Because these celebrity analysts have greater impacts on the market (Gleason and Lee 2003; Stickel 1992), their results may not be generalizable to reports issued by non-star analysts. Twedt and Rees (2012) study initiation reports issued by analysts in 2006. An initiation report is the first report issued by an analyst when she decides to cover a company; hence, their results could be partially explained by analysts' coverage decisions (McNichols and O'Brien 1997). Initiation reports are also much longer and more favorable than regular analyst reports. Therefore, it is not clear whether the results in these papers can be generalized to regular analyst reports.

⁸ Hirst, Koonce, and Simko (1995) conduct an experiment with 291 graduate students and find that their subjects' judgment about a stock is influenced by the strength of arguments contained in an analyst report only when the analyst report is unfavorable. De Franco, Hope, Vyas, and Zhou (2014) study the readability of analyst reports and find that it correlates with analyst ability and stock trading volume. Huang, Lehavy, Zang, and Zheng (2014) compare the thematic content of analyst report text with that of the earnings conference call transcripts and find that analysts serve as both the information interpretation role and the information discovery role immediately after the conference calls.

Twedt and Rees (2012) use a dictionary approach to assess the tone of 2,057 initiation reports issued in 2006. They find that, conditional on earnings forecasts and stock recommendations, the market reacts positively to the textual tone of initiation reports. However, one potential limitation of their study is their use of initiation reports, which tend to be much longer and more favorable than regular analyst reports.⁹ Hence, it is not clear whether their results can apply to regular analyst reports.

By employing the naïve Bayes algorithm to extract opinions in analyst written reports, our study adds to the burgeoning literature that applies computational methods to analyze textual information. The naïve Bayes algorithm is one of the most successful classification techniques in the information retrieval and computational linguistics literature (Lewis 1998). It has been used to extract opinion in a wide variety of text domains, including manager opinions in financial statements (Li 2010), investor sentiments in Internet stock message boards (Das and Chen 2007; Antweiler and Frank 2004), and editorial opinions in *Wall Street Journal* articles (Yu and Hatzivassiloglou 2003). This study extends our understanding of the naïve Bayes learning method by showing its superior performance relative to the dictionary-based methods, based on both the general and financial dictionaries for the context of analysts' written reports.

III. HYPOTHESES DEVELOPMENT

Information Content of Analyst Report Text

Analyst report text can provide incremental information beyond quantitative summary measures by supplying detailed information about many aspects of the company, and thus allowing every investor to use it according to her unique set of private information. For example, certain elements in the text might provide an investor with new information or confirm her private signals. She might also place different weights on the various information signals discussed in the text, based on the precision of her private signals. In contrast, quantitative summary measures provide only aggregations of analysts' information. For example, prior research shows that many analysts generate target prices based on price-multiple heuristics, such as price-earning-to-growth (PEG) (Bradshaw 2002; Asquith et al. 2005). An investor who does not agree with such valuation models can still make use of analysts' comments on the companies' expected growth in forming her own target price. Furthermore, text is not subject to the same restrictions that limit the information content of earnings forecasts and stock recommendations. Earnings forecasts are restricted to information about short-term earnings, and a stock recommendation is a discrete signal with only five levels: strong buy, buy, hold, sell, and strong sell.

However, there are two reasons to believe that analyst report text might not provide information beyond quantitative summary measures. First, text could be provided merely to support or justify the quantitative summary measures issued contemporaneously. Second, processing analyst written reports demands not only a sophisticated understanding of language, but also a significant amount of financial and industry knowledge. Therefore, it might be difficult for investors to convert text into numerical inputs that they can use in their investing models. Given the above discussion, we hypothesize that:

H1a: Investors react to the information in analyst report text conditional on the report's quantitative summary measures that are released contemporaneously.

H1a predicts that analyst report text provides information content that is independent of the contemporaneously issued quantitative summary measures. Another way that analyst report text

⁹ Their sample initiation reports have an average length of more than 18 pages, longer than the average length of 7.7 pages of our sample reports.

might provide value to investors is by helping them interpret quantitative summary measures. Specifically, investors may perceive quantitative summary measures as more credible if textual analyses support or justify these measures. This leads to the following hypothesis:

H1b: Investor reactions to favorable (unfavorable) quantitative summary measures are stronger when the overall textual opinion of the analyst report is more positive (negative).

Cross-Sectional Determinants of the Information Content of Analyst Report Text

This section identifies several analyst report characteristics that may influence the usefulness of analyst report text to investors.

Direction of Textual Opinions

There are several reasons that investors may react more strongly to negative than to positive report text. First, [Hong, Lim, and Stein \(2000\)](#) propose that analysts are especially important in propagating bad news because managers push out good news as fast as possible, but are less forthcoming with bad news ([Miller 2002](#); [Kothari, Shu, and Wysocki 2009](#)). This asymmetric disclosure by managers implies that the market is more likely to have advance knowledge of favorable than unfavorable content in analyst reports, resulting in a stronger market reaction to negative than to positive report text. Second, prior research shows that analysts are optimistically biased because of incentives to generate underwriting business ([Lin and McNichols 1998](#)), increase trading commissions ([Irvine 2001](#)), and retain access to management ([Das, Levine, and Sivaramakrishnan 1998](#)). Recognizing analysts' incentives, investors might consider analysts' unfavorable comments to be more credible. Finally, [Epstein, and Echnieder \(2008\)](#) argue that investors treat textual information as ambiguous signals because its information quality is difficult to judge. Their theory suggests that ambiguity-averse investors make a worst-case assessment of quality when interpreting textual information by assuming that good news is unreliable and bad news is very reliable. As a result, investors react more strongly to bad news than to good news. Collectively, these intuitions lead to the following hypothesis:

H2a: Investors react more strongly to negative than to positive text in analyst reports.

Emphasis on Nonfinancial Topics

We also examine whether the inclusion of nonfinancial information impacts the influence of analyst written reports on investor decision making. Nonfinancial information is information not yet recognized by the financial reporting system ([Stocken and Verrecchia 2004](#)). It is well documented that nonfinancial measures, such as customer satisfaction, brand recognition, and corporate social responsibility, are key drivers of firm value ([Ittner and Larcker 1998](#); [Barth, Clement, Foster, and Kasznik 1998](#); [Dhaliwal, Li, Tsang, and Yang 2011](#)). Prior research also shows that analysts are a source of nonfinancial information on a firm ([Bradshaw 2002, 2009](#); [Previts, Bricker, Robinson, and Young 1994](#)).

There is cross-sectional variation among analyst reports in their emphasis on nonfinancial topics. Analyst reports that emphasize nonfinancial topics more may be perceived as more informative for several reasons. First, managers might be less willing to disclose nonfinancial information due to proprietary cost ([Verrecchia 1983](#)); thus, analyst research on nonfinancial information could be more valuable to investors. Second, since nonfinancial information is voluntarily disclosed and hard to verify *ex post*, investors may perceive analysts' discussion of nonfinancial information to be more credible than that disclosed by managers. Last, since nonfinancial information on topics such as the synergy of a merger or an industry's competitive landscape is challenging for investors to process,

investors may rely more on analysts' opinions due to analysts' superior industry knowledge and analytical skills. The above discussion leads to our next hypothesis:

H2b: Investors react more strongly to analyst report text that places a greater emphasis on nonfinancial information.

Assertiveness of Text

We expect analysts to use a more assertive writing style to convey information signals with greater precision. It is also well documented in the psychology literature that people use a confidence heuristic; that is, they assume a more confident communicator to be more accurate, competent, and credible (Zarnoth and Sniezek 1997; Sniezek and Van Swol 2001; Price and Stone 2004). Therefore, investors likely perceive a more assertively written analyst report as reflecting higher information quality, and thus react more strongly to it. Based on this idea, we predict:

H2c: Investors react more strongly to analyst report text when it is written more assertively.

Conciseness of Text

Extensive finance and economics literatures document the limited attention of even sophisticated investors, which in turn affects security pricing (Hirshleifer and Teoh 2003; Daniel, Hirshleifer, and Teoh 2002). Prior research (Li 2008; Lehavy, Li, and Merkley 2011) shows that longer annual reports are less readable and harder to process. Therefore, it is reasonable to assume that a more concise report is easier to process and likely to receive more attention than a longer report, resulting in a greater price reaction. Hence, we hypothesize the following:

H2d: Investors react more strongly to analyst report text when it is written more concisely.

Perceived Validity of Headlines

In a typical analyst report, quantitative summary measures are presented at the top of the first page, often in italics or in a larger headline font. The psychology literature suggests that when a communicator's message disconfirms the recipient's prior expectation, the recipient will find it more difficult to judge the validity of the message and will seek information from the communicator's message arguments (Hirst et al. 1995; Mercer 2004). In the context of the analyst report, a headline may disconfirm investors' prior expectation if it contains bold signals that deviate substantially from investors' prior expectations or inconsistent signals reflecting a mix of good and bad news. In either case, investors would question the validity of the headlines and thus place more weight on the report text (Koehler 1993), leading to the following two hypotheses:

H2e: When headlines in analyst reports contain bold signals, investors react more strongly to the text.

H2f: When headlines in analyst reports contain inconsistent signals, investors react more strongly to the text.

IV. THE NAÏVE BAYES MACHINE LEARNING APPROACH AND MEASUREMENT OF TEXTUAL OPINION

Naïve Bayes Classification

The naïve Bayes classification is a statistical learning method that assigns the textual document to the most likely category based on the statistical relation between words and categories learned

from a training dataset. Formally, the approach assigns a document d , containing m words, $\{w_1, w_2, \dots, w_m\}$, to one of k categories, $c^* \in \{c_1, c_2, \dots, c_k\}$, by maximizing the conditional probability that the document belongs to a particular category, $P(c|d)$:

$$c^* = \operatorname{argmax}_{c \in \{c_1, c_2, \dots, c_k\}} P(c|d).$$

Applying Bayes rule based on the “naïve” assumption that, given a document’s category, w_i ’s are conditionally independent yields the following:

$$c^* = \operatorname{argmax}_{c \in \{c_1, c_2, \dots, c_k\}} P(c) \prod_{j=1}^m P(w_j|c). \quad (1)$$

The assumption ignores the internal structure of words in a document, such as the sequence of words. Hence, the approach is also referred to as the “bag of words” approach. Prior research shows that applying this assumption yields a classification of text as effective as that of other approaches that incorporate the internal structures of documents (Lewis 1998; Manning and Schütze 1999).

The naïve Bayes classification can be viewed as a prediction model, with the words in the document as the input variables and the probability of the opinion categories as the predicted value. The parameters of this prediction model, the conditional probabilities of word occurrence given a category, are learned from a training dataset that represents the specific domain being examined, which, in our study, is analyst reports.

The specificity of the analyst domain is one of the advantages of the naïve Bayes machine learning approach. By adapting to the words that appear in a specific domain and their probabilistic relation to a certain opinion category, this approach leads to increased classification accuracy for the specific analyst context compared to dictionary-based approaches. This feature is important because, as Pang and Lee (2008) discuss, opinions are highly domain-dependent, in terms of both vocabulary and the conditional probabilities of the opinion categories given the domain vocabulary.

Implementation of the Naïve Bayes Machine Learning Approach and Its Performance

To classify the opinions in analyst reports, we begin with the set of all reports in the Investext database issued for S&P 500 firms during the 1995–2008 period. This yields a set of 488,494 reports. We next partition each report into sentences, and delete sentences that fall under the category of “brokerage disclosure.”¹⁰ After cleaning the data of such statements, we end up with a final classification sample consisting of 27,231,727 sentences.

First, to construct a training dataset for the naïve Bayes machine learning approach, we randomly select 10,000 sentences from our sample and manually classify each sentence into one of three categories: positive, negative, and neutral.¹¹ This classification yields a total of 3,580 positive, 1,830 negative, and 4,590 neutral sentences in the training dataset. The higher percentage of positive versus negative sentences is consistent with findings that show an optimistic bias in analyst forecasts and recommendations (Ramnath et al. 2008). Next, the naïve Bayes algorithm “learns” the parameters of the prediction model from the training dataset by solving the maximum likelihood

¹⁰ The category of brokerage disclosure includes explanations of stock-rating systems, disclosures regarding conflicts of interest, analyst certifications, and other disclosures required by regulations, as well as disclaimers, glossaries, and descriptions of the brokerage or research firm. It does not contain analyst opinions about the companies covered. We manually identify these disclosure sections for each brokerage and research firm and then remove them from our sample.

¹¹ We conduct the classification. To avoid unnecessary influences on the opinion assignment, we are given only the sentences, without any other information from the analyst reports. Following Li (2010), to keep a neutral prior in classifying the sentences, we ignore any prior knowledge about the topic mentioned in the sentence.

problem specified in Equation (1). Last, we use our “trained” naïve Bayes classifier to assign each sentence in our sample to the category with the highest predicted probability.

Because the power of the empirical tests depends crucially on the classification effectiveness, we evaluate the performance of the naïve Bayes approach. Such an evaluation is also important because this is the first study to use the naïve Bayes approach on analyst reports; whether it can outperform dictionary approaches is unknown.

To gauge the accuracy of the naïve Bayes algorithm, we follow Li (2010) and use both in-sample validation and out-of-sample ten-fold cross validation. Our in-sample validation uses the same set of data to both train and test the naïve Bayes classifier, providing an upper bound for the classifier’s performance. Our out-of-sample validation uses different data at the training and testing stages to provide a more realistic measure of performance. Accuracy is measured as a percentage determined by the number of correct classifications of sentences divided by the number of sentences in the dataset.

The results in Table 1 show that the naïve Bayes classifier achieves accuracy of 80.89 percent in the in-sample validation and 76.91 percent in the ten-fold cross validation. These accuracy rates are greater than the accuracy rate of 62.02 percent and 65.44 percent obtained from the financial dictionaries of Loughran and McDonald (2011) and Henry (2006), respectively, in classifying analyst reports. These rates are also greater than those obtained from general dictionaries in classifying analyst reports, which are 48.40 percent, 51.74 percent, and 54.93 percent, for General Inquirer (GI), Linguistic Inquiry and Word Count (LIWC), and Diction, respectively. Finding that the naïve Bayes approach outperforms both financial and general dictionaries in classifying analyst reports suggests that analyst reports constitute a unique domain and that learning the probabilistic relation between words and a certain opinion category results in improved accuracy.

Measurement of Opinions at the Report Level

The naïve Bayesian learning approach yields the number of positive (N_POS), negative (N_NEG), and neutral sentences (N_NEU) for each report. The length ($LENGTH$) of a given report is the sum of these three numbers. Report length excludes the brokerage disclosure sentences removed from the beginning sample set (see footnote 10).

To measure the overall opinion in an analyst report, we use the following metric:

$$OPN = \frac{N_POS - N_NEG}{LENGTH} = PCT_POS - PCT_NEG,$$

where PCT_POS (PCT_NEG) is the percentage of positive (negative) sentences in a report.¹² Here, OPN decreases with N_NEU to capture the effect that a greater number of neutral statements will dilute the overall strength of the opinion statements.

V. SAMPLE SELECTION AND VARIABLE DESCRIPTIONS

Selection of Sample Analyst Reports

We extract report date, report title, analyst name, name of the institution issuing the report, and full report content from every downloaded analyst report. From the initial sample of 488,494

¹² We also examine two other measures, where $OPN' = (N_POS - N_NEG)/(N_POS + N_NEG)$ depends on only the ratio of positive to negative sentences, ignoring sentences classified as neutral. The second measure is $OPN'' = \ln[(1 + N_POS)/(1 + N_NEG)] \approx \{(N_POS - N_NEG)/(N_POS + N_NEG)\} \ln(1 + N_POS + N_NEG)$, and increases with both the ratio of positive to negative sentences and the overall percentage of opinionated statements (i.e., $N_POS + N_NEG$). The empirical results based on these two alternative measures are very similar.

TABLE 1

Accuracy of the Naïve Bayes Machine Learning Approach versus Financial Dictionary and General Dictionary Approaches

	Accuracy (%)	False Positive (%)	False Negative (%)	False Neutral (%)
Naïve Bayes (in-sample validation)	80.89	6.07	2.31	10.73
Naïve Bayes (ten-fold cross validation)	76.91	7.79	3.04	12.26
Financial Dictionaries:				
Loughran and McDonald (2011) word list	62.02	4.65	7.93	25.40
Henry (2006) word list	65.44	12.70	5.23	16.63
General Dictionaries:				
General Inquirer	48.40	23.74	8.94	18.92
Linguistic Inquiry and Word Count	51.74	13.14	2.92	32.20
Diction	54.93	10.33	6.65	28.09

This table reports the results for the naïve Bayes classifier from the in-sample and the ten-fold cross validation tests, as well as the prediction results using the word lists developed by Loughran and McDonald (2011), Henry (2006), General Inquirer (GI), Linguistic Inquiry and Word Count (LIWC), and Diction. For the in-sample test for the naïve Bayes classifier, we use 10,000 manually coded sentences to train the classifier and test it with the same sample. In the ten-fold cross validation, the sample of 10,000 sentences is randomly and evenly split into ten subsets (folds) and the classifier is trained and tested ten times. Each time, nine folds of data (out of the ten) are selected as the training data, and the remaining one fold is used to test the classifier; the reported accuracy is the average of the ten tests. For the Loughran and McDonald (2011) word list, the Henry (2006) word list, GI, LIWC, and Diction, the sentence is classified as positive if the percentage of positive words is greater than that of negative words, negative if the percentage of negative words is greater than that of positive words, and neutral if the percentage of positive words equals that of negative words. For the Loughran and McDonald (2011) word list, the percentage of positive (negative) words is the percentage of words in Loughran and McDonald's Fin-Pos (Fin-Neg) word lists. For the Henry (2006) word list, the percentage of positive (negative) words is the percentage of words in Henry's "positivity" ("negativity") word lists. For GI, the percentage of positive (negative) words is the percentage of positive (negative) words classified by GI's "Positiv" and "Negativ" word lists. For LIWC, the percentage of positive (negative) words is the percentage of positive (negative) emotion words classified by the LIWC software. For Diction, the percentages of positive (negative) words is the percentage of words in Diction's "praise," "satisfaction," and "inspiration" ("blame," "hardship," and "denial") categories. Accuracy is measured as the number of correct classifications divided by the number of sentences in the test sample. The false positive (false negative, false neutral) rate is defined as the number of sentences incorrectly predicted to be positive (negative, neutral), divided by the total number of sentences in the test sample.

reports, we delete 25,313 reports that cover multiple stocks, as indicated by the report titles, because we cannot discern company-specific opinions from these reports. We next match the reports in our sample with I/B/E/S to obtain stock recommendations, earnings forecasts, and target prices. The overlap between Investext and I/B/E/S provides the sample for our main analyses. As described in detail in Appendix A, we match 363,952 reports to I/B/E/S, including 321,533 with valid stock recommendations, 320,094 with valid earnings forecasts, and 254,387 with valid target prices.

Descriptions of Textual Opinions

Panel A of Table 2 provides the descriptive statistics for our key variables. Overall, we find that the average length of the reports in our sample is 57 sentences, of which 31 sentences are neutral, 19 are positive, and 7 are negative. The textual opinion measure (*OPN*), which captures the percentage difference in positive versus negative sentences, has a mean value of 18.7 percent, consistent with analysts' well-known optimism.

TABLE 2
Descriptive Statistics of Textual Opinions and the Quantitative Summary Measures in Analyst Reports

Panel A: Summary Statistics

	<u># of Obs.</u>	<u>Mean</u>	<u>Median</u>	<u>Std. Dev.</u>	<u>25%</u>	<u>75%</u>
<i>LENGTH</i>	343,099	56.784	40.000	73.467	21.000	68.000
<i>OPN</i>	343,099	0.187	0.188	0.199	0.062	0.316
<i>PCT_POS</i>	343,099	0.326	0.321	0.156	0.217	0.429
<i>PCT_NEG</i>	343,099	0.140	0.120	0.106	0.063	0.200
<i>REC</i>	321,533	3.674	4.000	0.878	3.000	4.000
<i>REC_REV</i>	314,703	0.000	0.000	0.319	0.000	0.000
<i>EF</i>	319,818	0.056	0.054	0.038	0.038	0.072
<i>EF_REV</i>	287,018	0.000	0.000	0.004	0.000	0.000
<i>TP</i>	254,203	1.251	1.173	0.481	1.046	1.318
<i>TP_REV</i>	248,174	0.000	0.000	0.091	0.000	0.000
<i>CAR</i>	363,747	0.000	0.000	0.051	-0.019	0.020
<i>PRIOR_CAR</i>	363,695	0.000	0.000	0.076	-0.033	0.034
<i>SIZE</i>	363,786	9.589	9.480	1.212	8.746	10.366
<i>BM</i>	363,786	0.381	0.324	0.389	0.199	0.503

Panel B: Textual Opinions by Report Type

<u>Report Type by Recommendation</u>	<u># Obs.</u>	<u>Avg. OPN</u>	<u>Avg. PCT_POS (%)</u>	<u>Avg. PCT_NEG (%)</u>	<u>Avg. PCT_NEU (%)</u>	<u>Avg. LENGTH</u>
BUY	177,883	0.231	34.864	11.784	53.352	59.105
HOLD	123,304	0.138	30.162	16.394	53.444	54.093
SELL	20,346	0.089	27.544	18.655	53.801	53.468
Upgrade	8,588	0.229	35.281	12.420	52.300	68.002
Reiteration	297,274	0.186	32.612	13.986	53.402	53.531
Downgrade	8,841	0.101	28.917	18.792	52.291	57.219

This table reports the descriptive statistics for the 363,952 sample reports.

Variable Definitions:

LENGTH = total number of sentences in the analyst report;

PCT_POS = percentage of sentences in the analyst report that are classified as positive by the naïve Bayes approach;

PCT_NEG = percentage of sentences in the analyst report that are classified as negative by the naïve Bayes approach;

PCT_NEU = percentage of sentences in the analyst report that are classified as neutral by the naïve Bayes approach;

OPN = textual opinion, calculated as $PCT_POS - PCT_NEG$;

REC = recommendation from I/B/E/S, reordered such that a higher value indicates a more positive recommendation (1: Sell; 2: Underperform; 3: Hold; 4: Buy; 5: Strong Buy);

REC_REV = recommendation revision, calculated as the current report's *REC* minus the last *REC* in I/B/E/S issued by the same analyst for the same firm;

EF = earnings forecast from I/B/E/S scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

EF_REV = earnings forecast revision, calculated as the current report's *EF* minus the last *EF* in I/B/E/S issued by the same analyst for the same firm's same fiscal year, winsorized at the top and bottom 1 percent;

TP = target price from I/B/E/S scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

(continued on next page)

TABLE 2 (continued)

TP_REV = target price revision, calculated as the current report's *TP* minus the last *TP* in I/B/E/S issued by the same analyst for the same firm, winsorized at the top and bottom 1 percent;

CAR = cumulative two-day abnormal returns starting from the current report date, where abnormal returns are calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

PRIOR_CAR = cumulative ten-day abnormal returns ending before the current report date, where abnormal returns are calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

SIZE = logarithm of the firm's market value of equity; and

BM = firm's book value of equity to its market value of equity.

Figure 1 plots the results for our textual opinion classifications and report length over time. First, the results show that analyst report length decreases over our sample period from around 65–70 sentences during 1996–1999 to around 50 sentences during 2006–2008. This decrease is accompanied by an increase in report frequency. On average, an analyst issues 10.5 reports for our sample firms in 1998, and that number increases gradually to 33 by 2008. Second, the results show that textual opinion reflects stock-market cycles. Specifically, we find that report opinions are most optimistic during the boom market in the late 1990s, reaching their peak at the same time as the S&P 500 index in early 2000 with an average *OPN* of 0.264. However, the favorableness of report opinions drops by 41 percent during the market crash of 2001 to 0.155 in late 2001. Similarly, during 2002–2006, textual opinion becomes increasingly optimistic as the average *OPN* increases from 0.148 to 0.202, reflecting another market boom period. Favorableness then decreases dramatically by nearly 78 percent during the 2008 financial crisis from 0.195 in 2007 to 0.043 in the fourth quarter of 2008. This co-movement with stock market boom and bust provides validation for our textual opinion measure. Finally, the results in Figure 1 show that textual opinions generally become less optimistic after 2001, consistent with the impact of regulatory changes, including the enactment of Reg FD in 2000 and the Global Settlement reached in 2003, on the financial analyst industry.

Association between Textual Opinions and the Quantitative Summary Measures

Table 2, Panel B describes textual opinions by report type. Specifically, our average *OPN* decreases by 40 percent from 0.231 to 0.138 from a BUY to a HOLD recommendation and by a further 36 percent from 0.138 to 0.089 from a HOLD to a SELL. Although the literature often combines HOLD and SELL as sell recommendations, our finding here suggests that analysts are considerably more negative in the text of a SELL report than a HOLD report. We also note that even in SELL reports, we find more positive than negative sentences.

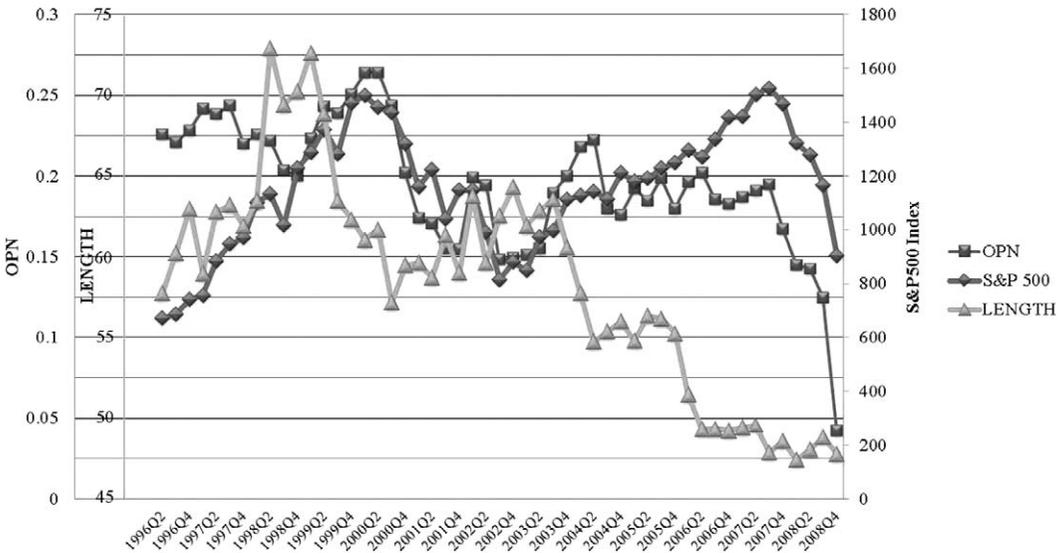
Furthermore, the results in Panel B of Table 2 show that average *OPN* drops by 19 percent from 0.229 to 0.186 from an upgrade to a reiteration (i.e., a report that contains the same stock recommendation level as in the last report issued by the same analyst), and by more than 46 percent from 0.186 to 0.101 from a reiteration to a downgrade, suggesting that the *level* of *OPN* reflects *revisions* in the recommendations. This finding is consistent with analysts discussing what has changed at the company since their last report and providing detailed explanations for the revisions of the quantitative summary measures.

VI. EMPIRICAL RESULTS

Information Content of Analyst Report Text

Table 3, Panel A reports the market reaction (*CAR*) across *OPN* quintiles by recommendation level. The top and bottom quintiles contain reports with the most and least favorable textual opinions,

FIGURE 1
Overall Textual Opinion in Analyst Reports



respectively. We measure *CAR* using abnormal returns over days [0, +1] relative to the report date, where abnormal return is the difference between a firm’s buy-and-hold return and the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index, denoted as *CAR*.¹³

The results in Panel A of Table 3 indicate that, for each recommendation level, *CAR* increases monotonically with *OPN* quintile rankings, suggesting that textual opinions provide incremental information beyond the recommendation level. The results further show that market reactions for firms with analyst textual opinions in the bottom two quintiles are negative even when the overall recommendation is BUY; likewise, market reactions for firms with textual opinions in the top three quintiles are positive, even when the overall recommendation is SELL. This latter result is particularly surprising, because SELL is a rare recommendation, which is often considered highly credible because of analysts’ incentives to issue optimistically biased reports. Our result, however, indicates that when a SELL recommendation is accompanied by favorable textual opinions, investors react to the latter and ignore the recommendation.

The results in Table 3, Panel A also show that the differences in *CARs* between BUY and SELL reports within an opinion quintile are all less than 0.64 percent, which is economically small and at times statistically insignificant. These results suggest that given the textual opinions conveyed in the written report, whether the report concludes with BUY or SELL makes little difference to investors. In contrast, within BUY, HOLD, and SELL report categories, the differences in *CARs* between the top and bottom *OPN* quintiles are 1.77 percent, 2.13 percent and 2.50 percent, respectively, all of which are significant at the 0.01 level, and indicate the economically significant value of reading beyond the “headlines.” Finally, similar to the results in Table 3, Panel A, our results in Table 3, Panel B show that *CARs* increase monotonically with *OPN* quintile rankings within each revision type.

¹³ Empirical results based on three- and five-day abnormal returns surrounding the report date are similar.

TABLE 3

Cumulative Abnormal Returns (CARs) around Report Issuance by Textual Opinions and Recommendation Levels and Revisions

Panel A: Abnormal Returns by Textual Opinions and Recommendation Levels

<i>OPN</i>	BUY		HOLD		SELL		All <i>REC</i> Levels	BUY – SELL
	<i>CAR</i>	# of Obs.	<i>CAR</i>	# of Obs.	<i>CAR</i>	# of Obs.		
5 (Top Quintile)	0.92%	42,847	0.89%	16,268	1.01%	1,631	0.91%	-0.09%
4	0.45%	38,300	0.35%	20,458	0.26%	2,610	0.41%	0.19%*
3	0.22%	34,320	0.01%	23,264	0.07%	3,806	0.13%	0.15%
2	-0.08%	29,153	-0.30%	25,896	-0.54%	4,940	-0.21%	0.47%***
1 (Bottom Quintile)	-0.85%	22,383	-1.24%	31,614	-1.49%	6,902	-1.12%	0.64%***
All <i>OPN</i> Quintiles	0.26%		-0.21%		-0.52%			
Top – Bottom	1.77%***		2.13%***		2.50%***			

Panel B: Abnormal Returns by Textual Opinions and Recommendation Revisions

<i>OPN</i>	Upgrade		Reiteration		Downgrade		All <i>REC</i> Revisions	Upgrade – Downgrade
	<i>CAR</i>	# of Obs.	<i>CAR</i>	# of Obs.	<i>CAR</i>	# of Obs.		
5 (Top Quintile)	2.89%	2,023	0.89%	56,826	-1.42%	883	0.92%	4.31%***
4	2.31%	1,944	0.39%	56,480	-1.44%	1,199	0.42%	3.75%***
3	2.07%	1,781	0.12%	56,134	-1.85%	1,535	0.13%	3.92%***
2	2.04%	1,366	-0.18%	55,489	-2.66%	1,927	-0.21%	4.70%***
1 (Bottom Quintile)	1.33%	981	-0.97%	56,508	-4.96%	2,813	-1.12%	6.29%***
All <i>OPN</i> Quintiles	2.24%		0.05%		-2.98%			
Top – Bottom	1.56%***		1.86%***		3.54%***			

*, ***, Indicates $p < 0.1$ and $p < 0.01$, respectively.

This table reports the market reaction to analyst reports across the quintiles of *OPN* for each level of recommendation. *OPN*: the textual opinion, calculated as the percentage of positive sentences minus the percentage of negative sentences in the report as classified by the naïve Bayes approach; *OPN* is ranked into quintiles in each month; *CAR*: the cumulative two-day abnormal returns starting from the current report date, with abnormal returns calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index.

To examine how much abnormal returns can be triggered by per-unit variation in textual opinions beyond the impact of the quantitative summary measures, we estimate the following multivariate regression:

$$CAR = \alpha_0 + \beta OPN + \gamma_1 REC_REV + \gamma_2 EF_REV + \gamma_3 TP_REV + \sum_j \delta_j \cdot Controls_j + \varepsilon. \quad (2)$$

We include in Equation (2) the revisions of the recommendation, earnings forecast, and target price because previous research shows that revisions of these signals are informative to investors (Jegadeesh, Kim, Krische, and Lee 2004; Barber, Lehavy, and Trueman 2010).¹⁴ In Equation (2),

¹⁴ In an alternative specification, we include both the levels and revisions of the quantitative summary measures and find similar results.

REC represents the five-level recommendation values, where *REC* equals 1 for Sell; 2 for Underperform; 3 for Hold; 4 for Buy; and 5 for Strong Buy; *EF* and *TP* are defined as the annual earnings forecast and target price scaled by the stock price 50 days before the report date, respectively; *REC_REV* is the recommendation revision, measured as the current report's *REC* minus the analyst's last *REC* in I/B/E/S for the same stock; and earnings forecast revision (*EF_REV*) and target price revision (*TP_REV*) are defined similarly. Following [Brav and Lehavy \(2003\)](#), we winsorize *EF_REV* and *TP_REV* at the top and bottom 1 percent to reduce the influence of outliers.

The regression also includes several control variables. To address the concern that analysts may piggyback on recent news or events, we include abnormal returns during the ten trading days prior to the report date (*PRIOR_CAR*) to control for any potential short-term momentum or reversal in stock price. To control for investor reactions due to firm characteristics and industry- and market-wide conditions, we include firm size (*SIZE*), measured as the logarithm of the market value of equity, book-to-market ratio (*BM*), and industry and year fixed-effects in Equation (2). Because multiple analysts can follow the same firm, and one analyst can cover multiple firms, standard errors in all empirical tests are estimated with a two-way cluster control at the firm and analyst levels. Finally, if an earnings announcement or a management forecast is issued during the *CAR* window, then we delete the observation to mitigate the concern that such events might affect both market reactions and analyst opinions.¹⁵ Our final sample for estimating Equation (2) contains 112,304 observations.

Table 4, Panel A presents the estimated results for Equation (2). Column (1) reports the results without the opinion variables, while column (2) reports the results including *OPN*. Comparing column (2) with column (1), we find two pieces of evidence consistent with H1a, which states that textual opinions provide information beyond quantitative summary measures. First, the adjusted R^2 increases 21 percent from 3.37 percent to 4.09 percent after including *OPN* in the regression, suggesting that textual opinions account for some variation in the abnormal returns beyond that provided by the quantitative summary measures or control variables. Second, the estimated coefficient of 0.0208 on *OPN* is not only statistically significant ($p < 0.01$ level), but also economically significant. On average, a one standard deviation increase in *OPN* increases the two-day abnormal returns by 41 basis points.^{16,17} This is comparable to the magnitude of the abnormal

¹⁵ We remove 59,713 observations because the companies issue earnings announcements during the *CAR* window, and an additional 8,037 observations for management forecasts. We obtain the earnings announcement dates from the Compustat database and the management forecast dates from the First Call database. Our results are qualitatively similar if we do not remove these observations.

¹⁶ Recent studies have developed dictionaries specifically for financial contexts ([Loughran and McDonald 2011](#); [Henry 2006](#)). However, these word lists are based on 10-Ks and earnings releases rather than on analyst reports. In an untabulated test, we estimate Equation (2) using the textual opinions measured with dictionary-based methods. We find that while the estimated coefficients of textual opinion remain statistically significant, their economic significance decreases considerably. Specifically, the word list developed by [Loughran and McDonald \(2011\)](#) produces the largest economic significance (33 basis points) among all the dictionaries examined, which is still 20 percent lower than that of the naïve Bayes method. Other dictionary methods (GI, LIWC, Diction, and the word list developed by [Henry \[2006\]](#)) understate the economic significance by up to 41 percent. This is consistent with the findings in Section IV that the naïve Bayes method classifies the textual opinions in analyst reports more accurately than dictionary-based methods.

¹⁷ As a robustness test, we replicate Equation (2) using the market reaction during a 40-minute announcement window, centered on the analyst report announcement time, to alleviate the concern that the market's documented reaction is caused by concurrent events. We use stock transaction data from the TAQ database and the announcement time from I/B/E/S. Market reaction is measured as $(PRC_{post}/PRC_{pre} - 1)$, where PRC_{post} is the mean transaction price in the last ten minutes of the announcement window or the previous ten minutes if there is no transaction in the last ten minutes. PRC_{pre} is the mean transaction price in the first ten minutes of the announcement window or the next ten minutes if there is no transaction in the first ten minutes. The untabulated result shows that the estimated coefficient on *OPN* is significant at the $p < 0.01$ level, indicating that our main results are not driven by concurrent events.

TABLE 4
Information Content of Analyst Report Text

Panel A: Estimation Results of Equation (2)

	(1) Coefficients (t-stats)	(2) Coefficients (t-stats)	(3) Coefficients (t-stats)
<i>OPN</i>		0.0208*** (19.69)	
<i>PCT_POS</i>			0.0129*** (11.89)
<i>PCT_NEG</i>			-0.0364*** (-15.19)
<i>REC_REV</i>	0.0122*** (12.31)	0.0116*** (11.77)	0.0115*** (11.68)
<i>EF_REV</i>	1.1415*** (9.31)	0.9919*** (8.27)	0.9687*** (8.14)
<i>TP_REV</i>	0.0492*** (12.11)	0.0442*** (10.99)	0.0432*** (10.79)
<i>PRIOR_CAR</i>	-0.0217** (-2.30)	-0.0260*** (-2.76)	-0.0267*** (-2.82)
<i>SIZE</i>	-0.0008*** (-3.11)	-0.0008*** (-3.20)	-0.0009*** (-3.48)
<i>BM</i>	0.0009** (2.05)	0.0017*** (3.88)	0.0016*** (3.69)
Intercept	0.0122*** (5.15)	0.0093*** (3.82)	0.0133*** (5.55)
# of Obs.	112,304	112,304	112,304
Adj. R ²	3.37%	4.09%	4.25%

*, **, *** Indicates $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A reports the estimation results of Equation (2): $CAR = \alpha_0 + \beta_k OPINION_k + \gamma_1 REC_REV + \gamma_2 EF_REV + \gamma_3 TP_REV + \Sigma_i \delta_i \bullet Controls_i + \varepsilon$. All regressions include industry and year fixed-effects; standard errors are estimated with a two-way cluster control at the firm and analyst levels.

Variable Definitions:

CAR = dependent variable, which is the cumulative two-day abnormal returns starting from the current report date, with abnormal returns calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

PCT_POS = percentage of sentences in the analyst report that are classified as positive by the naïve Bayes approach;

PCT_NEG = percentage of sentences in the analyst report that are classified as negative by the naïve Bayes approach;

OPN = textual opinion, calculated as $PCT_POS - PCT_NEG$;

REC_REV = recommendation revision, calculated as the current report's *REC* minus the last *REC* in I/B/E/S issued by the same analyst for the same firm;

EF_REV = earnings forecast revision, calculated as the current report's earnings forecast minus the last earnings forecast in I/B/E/S issued by the same analyst for the same firm's same fiscal year, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

TP_REV = target price revision, calculated as the current report's target price minus the last target price in I/B/E/S issued by the same analyst for the same firm, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

PRIOR_CAR = cumulative ten-day abnormal returns ending the day before the current report date, where abnormal returns are calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

SIZE = logarithm of the firm's market value of equity; and

BM = firm's book value of equity to its market value of equity.

(continued on next page)

TABLE 4 (continued)

Panel B: Estimation Results of Equation (3)

	Predicted Sign	Coefficients	(t-stats)
<i>OPN</i>	+	0.0171***	(14.91)
<i>OPN</i> × <i>REC_REV</i> × <i>REC_DIR</i>	+	0.0093**	(2.09)
<i>OPN</i> × <i>EF_REV</i> × <i>EF_DIR</i>	+	1.2928***	(2.79)
<i>OPN</i> × <i>TP_REV</i> × <i>TP_DIR</i>	+	0.0293*	(1.71)
<i>REC_REV</i>	+	0.0066***	(4.78)
<i>REC_DIR</i>	+	0.0061***	(4.43)
<i>REC_DIR</i> × <i>REC_REV</i>	−	−0.0068***	(−3.87)
<i>EF_REV</i>	+	0.4617***	(4.59)
<i>EF_DIR</i>	+	0.0019***	(7.07)
<i>EF_DIR</i> × <i>EF_REV</i>	−	−0.6095***	(−5.14)
<i>TP_REV</i>	+	0.0344***	(6.80)
<i>TP_DIR</i>	+	0.0010***	(2.60)
<i>TP_DIR</i> × <i>TP_REV</i>	−	−0.0146***	(−2.61)
<i>PRIOR_CAR</i>		−0.0263***	(−2.79)
<i>SIZE</i>		−0.0009***	(−3.50)
<i>BM</i>		0.0019***	(4.14)
Intercept		0.0200***	(6.99)
# of Obs.		112,304	
Adj. R ²		4.29%	

*, **, *** Indicates $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

Panel B reports the estimation results of Equation (3): $CAR = \alpha + \beta_0 OPN + \beta_1 OPN \times REC_REV \times REC_DIR + \beta_2 OPN \times EF_REV \times EF_DIR + \beta_3 OPN \times TP_REV \times TP_DIR + \gamma_1 REC_REV + \gamma_2 REC_DIR + \gamma_3 REC_DIR \times REC_REV + \gamma_4 EF_REV + \gamma_5 EF_DIR + \gamma_6 EF_DIR \times EF_REV + \gamma_7 TP_REV + \gamma_8 TP_DIR + \gamma_9 TP_DIR \times TP_REV + \sum \theta_j \bullet Controls_j + \varepsilon$. All regressions include industry and year fixed-effects; standard errors are estimated with a two-way cluster control at the firm and analyst levels.

Variable Definitions:

CAR = dependent variable, which is the cumulative two-day abnormal returns starting from the current report date, with abnormal returns calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

OPN = textual opinions, calculated as the percentage of positive sentences minus the percentage of negative sentences in the report as classified by the naïve Bayes approach;

REC_REV = recommendation revision, calculated as the current report’s *REC* minus the last *REC* in I/B/E/S issued by the same analyst for the same firm;

REC_DIR = 1 if *REC_REV* is larger than 0, −1 if *REC_REV* is smaller than 0, and 0 if *REC_REV* equals 0;

EF_REV = earnings forecast revision, calculated as the current report’s earnings forecast minus the last earnings forecast in I/B/E/S issued by the same analyst for the same firm’s same fiscal year, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

EF_DIR = 1 if *EF_REV* is larger than 0, −1 if *EF_REV* is smaller than 0, and 0 if *EF_REV* equals 0;

TP_REV = target price revision, calculated as the current report’s target price minus the last target price in I/B/E/S issued by the same analyst for the same firm, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

TP_DIR = 1 if *TP_REV* is larger than 0, −1 if *TP_REV* is smaller than 0, and 0 if *TP_REV* equals 0;

PRIOR_CAR = cumulative ten-day abnormal returns ending before the current report date, where abnormal returns are calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

SIZE = logarithm of the firm’s market value of equity; and

BM = firm’s book value of equity to its market value of equity.

returns induced by a one standard deviation increase in EF_REV and TP_REV , both of which are 40 basis points.¹⁸

We also estimate Equation (2) using a subsample of analyst reports that reiterate all the quantitative summary measures. Since their revisions are all zero, we include their levels in the regression instead. There are 67,123 such reports, making up 59.8 percent of the sample used in Table 4. The untabulated results show that the coefficient on OPN remains highly significant at the 0.01 level and that the adjusted R^2 increases from 0.05 percent to 0.92 percent after including OPN in the regression, suggesting that the information in the reiteration reports comes mostly from the text rather than the quantitative summary measures. We further find that the economic magnitude of OPN , measured as a one standard deviation increase of it results in an additional two-day abnormal return of 29 basis points, is smaller than the 41 basis points of the overall sample, consistent with the explanation that text is perceived as more informative in revision versus reiteration reports.¹⁹

To test H1b, we modify Equation (2) by including the interaction of OPN with each of the three quantitative summary measures, REC_REV , EF_REV , and TP_REV , as well as the variable indicating the corresponding measure's revision direction, REC_DIR , EF_DIR , or TP_DIR . The revision direction of recommendations, REC_DIR , equals 1 if REC_REV is positive, -1 if REC_REV is negative, and 0 otherwise. EF_DIR and TP_DIR are defined similarly:

$$\begin{aligned} CAR = & \alpha + \beta_0 OPN + \beta_1 OPN \times REC_REV \times REC_DIR + \beta_2 OPN \times EF_REV \times EF_DIR \\ & + \beta_3 OPN \times TP_REV \times TP_DIR + \gamma_1 REC_REV + \gamma_2 REC_DIR \\ & + \gamma_3 REC_DIR \times REC_REV + \gamma_4 EF_REV + \gamma_5 EF_DIR + \gamma_6 EF_DIR \times EF_REV \\ & + \gamma_7 TP_REV + \gamma_8 TP_DIR + \gamma_9 TP_DIR \times TP_REV + \sum_j \theta_j \cdot Controls_j + \varepsilon. \end{aligned} \quad (3)$$

According to H1b, the intensity of the market reaction to the favorable quantitative summary measures is higher when OPN is *higher*; the intensity of the market reaction to the unfavorable quantitative summary measures is higher when OPN is *lower*. That is, the effect of textual opinions on the intensity of the market reaction to the quantitative summary signals depends on the direction of the quantitative summary signals. We include the revision direction variables, REC_DIR , EF_DIR , or TP_DIR , so that the predicted sign of β_1 , β_2 , and β_3 , respectively, is positive regardless of the direction of the quantitative summary measures.²⁰

¹⁸ In an untabulated test, we replace OPN with the change in OPN from the last to the current report (ΔOPN) and re-estimate Equation (2). We find that the adjusted R^2 decreases from 4.09 percent to 3.76 percent and that the economic magnitude of ΔOPN , where a one standard deviation increase in ΔOPN increases the two-day abnormal returns by 27 basis points, is one-third smaller than that of OPN , indicating that OPN provides greater explanatory power for market reactions than does ΔOPN . This is probably because analysts describe in their text how the company has changed since their last reports, so that the level measure, OPN , captures what is new. In an alternative specification, we define $\Delta OPN'$ as the current report's OPN minus the consensus OPN (the average OPN of the reports issued by all other analysts for the same firm during the last 90 days), and our results are qualitatively the same. That is, the results support H1a, but the statistical and economic significance of $\Delta OPN'$ and the adjusted R^2 of the regression are lower than those based on OPN .

¹⁹ As a sensitivity test, we estimate Equation (2) using the subsample of 45,181 analyst reports that revise any of the quantitative summary measures and find results similar to those reported in column (2) of Table 1. Specifically, OPN is positive and significant at the 1 percent level. The economic significance of OPN in revision reports is much higher (a one standard deviation increase adds 78 basis points to the two-day abnormal return) than that in the overall sample.

²⁰ When the quantitative summary measure is favorable, such as an upward revision, the intensity of the market reaction is higher when OPN is higher. For example, the intensity of the market reaction to an upward earnings forecast revision is $\partial CAR / \partial EF_REV = \beta_2 OPN + \gamma_4 + \gamma_6$. When the quantitative summary measure is unfavorable, such as a downward revision, the intensity of the market reaction is higher when OPN is lower. For example, the intensity of market reaction to a downward earnings forecast revision is $\partial CAR / \partial EF_REV = -\beta_2 OPN + \gamma_4 - \gamma_6$. Therefore, the predicted sign of β_1 , β_2 , and β_3 stays positive.

Table 4, Panel B reports the results for Equation (3). We find that the estimated coefficients on β_1 , β_2 , and β_3 are positive and significant or marginally significant ($p < 0.05$, 0.01 , and 0.1 , respectively), consistent with H1b. The coefficient on *OPN* is positive and significant ($p < 0.01$), consistent with H1a. The combined evidence in this section suggests that analyst report text provides both information on a “stand-alone” basis and also assists investors in interpreting the quantitative summary measures.

Cross-Sectional Determinants of the Information Content of Analyst Report Text

H2a predicts that the market will exhibit asymmetric reactions to positive versus negative opinions in analyst reports. To test this prediction, we replace *OPN* with both *PCT_POS* and *PCT_NEG* in estimating Equation (2). The results, reported in column (3) of Table 4, Panel A, show significant coefficients of 0.0129 and -0.0364 on *PCT_POS* and *PCT_NEG*, respectively ($p < 0.01$). These results indicate that investors place more than twice as much weight on negative versus positive comments in analyst reports (an F-test confirms that the difference between the magnitude of the two coefficients is significant at the 0.01 level). As discussed in Section III, several theories could explain this result: (1) the market has less foreknowledge of the unfavorable content in analyst reports because of managers’ incentives to delay bad news; (2) investors recognize analysts’ conflicts of interest and consider their unfavorable comments more credible; or (3) investors treat textual information as ambiguous because it is difficult to judge its information quality, and, thus, they assume good news is unreliable and bad news is very reliable.

H2b–H2f hypothesize five factors that might influence how investors use analyst report text: (1) emphasis on nonfinancial topics (*NONFIN*) is measured as the percentage of sentences in the report text that do not contain “\$” or “%,” because analysts tend to discuss financial information with dollar denomination or percentage changes;²¹ (2) assertiveness of text (*ASSERTIVE*) is measured as the percentage of sentences in the report text that contain any of the words in the strong modal word list developed by Loughran and McDonald (2011) to capture confident expressions in financial text; (3) conciseness of text (*CONCISE*) is measured as -1 times the estimated residual from regressing report length (*LENGTH*) on firm size (*SIZE*), book-to-market ratio (*BM*), and the recent return of the firm (*PRIOR_CAR*), all of which control for the normal length of the text;²² (4) bold signals in the headline (*BOLD*) are measured as an indicator variable that equals 1 if the report contains an earnings forecast deviating from the consensus by at least two standard deviations, and 0 otherwise; and (5) inconsistency in the headline (*INCON*) is measured as an indicator variable that equals 1 if the report’s recommendation and earnings forecast are revised in different directions (i.e., they are not both upgraded, downgraded, or reiterated), and 0 otherwise.

To test H2b–H2f, we expand Equation (2) to include the economic factors that we identify and their interaction terms with textual opinions:

²¹ To validate this measure, we randomly select 500 sentences that contain “\$” or “%” and find that 81.4 percent of them are related to financial topics; we also randomly select 500 sentences that do not contain “\$” or “%” and find that 85.6 percent of them are related to nonfinancial topics. Using sentences containing a number other than those denoting a quarter or year as an alternative measure yields qualitatively similar results.

²² Following Li (2008), we use -1 times *LENGTH* as an alternative measure for textual conciseness and find similar results.

$$\begin{aligned}
 CAR = & \alpha_0 + \alpha_1 OPN + \beta_1 OPN \times NONFIN + \beta_2 OPN \times ASSERTIVE + \beta_3 OPN \times CONCISE \\
 & + \beta_4 OPN \times BOLD + \beta_5 OPN \times INCON + \beta_6 OPN \times BROKERSIZE \\
 & + \beta_7 OPN \times STAR + \beta_8 OPN \times EXPR + \beta_9 OPN \times POSTFD + \alpha_2 REC_REV \\
 & + \alpha_3 EF_REV + \alpha_4 TP_REV + \gamma_1 NONFIN + \gamma_2 ASSERTIVE + \gamma_3 CONCISE + \gamma_4 BOLD \\
 & + \gamma_5 INCON + \gamma_6 BROKERSIZE + \gamma_7 STAR + \gamma_8 EXPR + \gamma_9 POSTFD \\
 & + \gamma_{10} PRIOR_CAR + \gamma_{11} SIZE + \gamma_{12} BM + \varepsilon.
 \end{aligned}
 \tag{4}$$

In Equation (4), we also control for the variables that may contribute to analyst forecast performance and interact them with *OPN*. For example, [Clement \(1999\)](#) and [Jacob, Lys, and Neale \(1999\)](#) suggest that larger brokerage houses provide more research support to analysts, which leads to better forecasting performance. We measure broker size as the number of analysts issuing earnings forecasts from this brokerage house (*BROKERSIZE*). Another factor that may impact earnings forecast accuracy is the analyst's star ranking. Prior research yields mixed results ([Stickel 1992](#); [Emery and Li 2009](#)). To control for analyst ranking, we include an indicator variable, *STAR*, that equals 1 if the analyst is ranked as an II All-Star in the current year, and 0 otherwise. Several prior studies show that forecasting performance is related to experience ([Mikhail, Walther, and Willis 1997](#); [Clement 1999](#)). We control for experience and measure it as the number of quarters an analyst has been forecasting earnings (*EXPR*). Finally, we consider the effect of Reg FD, the regulation that prohibits private communications between managers and analysts, on analysts' forecast performance. Prior studies found mixed evidence on whether the informativeness of analysts' earnings forecasts and stock recommendations has changed since the enactment of Reg FD ([Francis, Nanda, and Wang 2006](#); [Heflin, Subramanyam, and Zhang 2003](#)). We include an indicator variable that equals 1 if the report was issued in 2001 when Reg FD became effective or later, and 0 otherwise (*POSTFD*).

Table 5, Panel A provides the summary statistics for our report characteristic and control variables included in Equation (4). On average, 64.7 percent of analyst report text is about nonfinancial topics; 10 percent of text contains at least one word from [Loughran and McDonald's \(2011\)](#) strong modal list; 13.4 percent of the sample reports contain bold forecasts; 32.8 percent contain inconsistent revisions in recommendations and earnings forecasts; 33 percent are issued by star analysts; and 88.5 percent are announced post-Reg FD. The average broker size (95) suggests that a large number of our sample reports are from large brokerage houses. The average analyst in our sample has a forecasting experience of 31 quarters.

Table 5, Panel B reports the estimation results for Equation (4). The coefficients of interest are those on the interaction terms. We find a positive and significant coefficient on *OPN* × *NONFIN* ($p < 0.01$), consistent with H2b that investors find text that places more emphasis on nonfinancial topics to be more informative. The positive and significant coefficients on *OPN* × *ASSERTIVE* and *OPN* × *CONCISE* (both $p < 0.1$) are consistent with H2c and H2d, respectively; that is, investors react more strongly to more assertive and more concise text. The positive and significant coefficients on *OPN* × *BOLD* and *OPN* × *INCON* (both $p < 0.01$) indicate that investors place more weight on the text when the headlines contain bold or inconsistent signals, thus supporting H2e and H2f, respectively. We also find a significant and positive coefficient on *OPN* × *BROKERSIZE* ($p < 0.01$), indicating that analysts who work for larger brokerage houses provide more informative report text. Finally, the coefficients on *OPN* × *STAR*, *OPN* × *EXPR*, and *OPN* × *POSTFD* are statistically insignificant, indicating that the market does not react differently to text written by star analysts or more experienced analysts, or text written after Reg FD.

Overall, our findings support H2a-H2f and suggest that analyst report text is more useful when it conveys bad news, when it emphasizes nonfinancial topics more, when it is more assertive and concise, and when the perceived validity of the report headlines is low.

TABLE 5

Cross-Sectional Variation in the Information Content of Analyst Report Text

Panel A: Summary Statistics

	<u># of Obs.</u>	<u>Mean</u>	<u>Median</u>	<u>Std. Dev.</u>	<u>25%</u>	<u>75%</u>
<i>NONFIN</i>	91,438	0.647	0.657	0.168	0.538	0.768
<i>ASSERTIVE</i>	91,438	0.103	0.086	0.089	0.040	0.147
<i>CONCISE</i>	91,438	-0.400	16.972	70.908	-10.146	32.697
<i>BOLD</i>	91,438	0.134	0.000	0.341	0.000	0.000
<i>INCON</i>	91,438	0.328	0.000	0.470	0.000	1.000
<i>BROKERSIZE</i>	91,438	94.786	107.000	57.882	48.000	134.000
<i>STAR</i>	91,438	0.330	0.000	0.470	0.000	1.000
<i>EXPR</i>	91,438	30.922	26.000	20.344	16.000	42.000
<i>POSTFD</i>	91,438	0.885	1.000	0.319	1.000	1.000
<i>PRIOR_CAR</i>	91,438	-0.002	0.000	0.080	-0.035	0.035
<i>SIZE</i>	91,438	9.796	9.709	1.193	8.928	10.649
<i>BM</i>	91,438	0.404	0.332	0.321	0.207	0.516

Panel B: Estimation Results of Equation (4)

	<u>Coefficients</u>	<u>(t-stats)</u>
<i>OPN</i>	0.0038	(0.71)
<i>OPN</i> × <i>NONFIN</i>	0.0142***	(3.34)
<i>OPN</i> × <i>ASSERTIVE</i>	0.0203*	(1.84)
<i>OPN</i> × <i>CONCISE</i>	0.0388*	(1.89)
<i>OPN</i> × <i>BOLD</i>	0.0157***	(5.07)
<i>OPN</i> × <i>INCON</i>	0.0082***	(3.66)
<i>OPN</i> × <i>BROKERSIZE</i>	0.0060***	(3.04)
<i>OPN</i> × <i>STAR</i>	-0.0023	(-0.89)
<i>OPN</i> × <i>EXPR</i>	-0.0000	(-0.74)
<i>OPN</i> × <i>POSTFD</i>	-0.0041	(-1.07)
<i>REC_REV</i>	0.0110***	(9.91)
<i>EF_REV</i>	0.8373***	(6.84)
<i>TP_REV</i>	0.0438***	(10.01)
<i>NONFIN</i>	-0.0048***	(-3.49)
<i>ASSERTIVE</i>	-0.0004	(-0.15)
<i>CONCISE</i>	-0.0067	(-1.47)
<i>BOLD</i>	-0.0040***	(-4.23)
<i>INCON</i>	-0.0024***	(-3.72)
<i>BROKERSIZE</i>	-0.0000**	(-1.98)
<i>STAR</i>	0.0005	(0.68)
<i>EXPR</i>	0.0000	(0.27)
<i>POSTFD</i>	-0.0020	(-0.79)
<i>PRIOR_CAR</i>	-0.0270**	(-2.50)
<i>SIZE</i>	-0.0009***	(-3.31)
<i>BM</i>	0.0016***	(3.18)
Intercept	0.0146***	(4.52)
# of Obs.	91,438	
Adj. R ²	4.04%	

(continued on next page)

TABLE 5 (continued)

*, **, *** Indicates $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

This table reports the estimation results of Equation (4): $CAR = \alpha_0 + \alpha_1 OPN + \beta_1 OPN \times NONFIN + \beta_2 OPN \times ASSERTIVE + \beta_3 OPN \times CONCISE + \beta_4 OPN \times BOLD + \beta_5 OPN \times INCON + \beta_6 OPN \times BROKERSIZE + \beta_7 OPN \times STAR + \beta_8 OPN \times EXPR + \beta_9 OPN \times POSTFD + \alpha_2 REC_REV + \alpha_3 EF_REV + \alpha_4 TP_REV + \gamma_1 NONFIN + \gamma_2 ASSERTIVE + \gamma_3 CONCISE + \gamma_4 BOLD + \gamma_5 INCON + \gamma_6 BROKERSIZE + \gamma_7 STAR + \gamma_8 EXPR + \gamma_9 POSTFD + \gamma_{10} PRIOR_CAR + \gamma_{11} SIZE + \gamma_{12} BM + \varepsilon$.

All regressions include industry and year fixed-effects; standard errors are estimated with a two-way cluster control at the firm and analyst levels. The dependent variable is *CAR*, which is the cumulative two-day abnormal returns starting from the current report date, with abnormal returns calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index.

Variable Definitions:

OPN = textual opinions, calculated as the percentage of positive sentences minus the percentage of negative sentences in the report as classified by the naïve Bayes approach;

REC_REV = recommendation revision, calculated as the current report's *REC* minus the last *REC* in I/B/E/S issued by the same analyst for the same firm;

EF_REV = earnings forecast revision, calculated as the current report's earnings forecast minus the last earnings forecast in I/B/E/S issued by the same analyst for the same firm's same fiscal year, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

TP_REV = target price revision, calculated as the current report's target price minus the last target price in I/B/E/S issued by the same analyst for the same firm, scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

NONFIN = the percentage of sentences in reports that do not contain "\$" or "%";

ASSERTIVE = the percentage of sentences in reports that contain any of the word in the strong modal word list from Loughran and McDonald (2011);

CONCISE = -1 times the residual from regressing report length (*LENGTH*) on firm size (*SIZE*), book-to-market ratio (*BM*), and the recent return of the firm (*PRIOR_CAR*), the one used in Panel B is scaled by 1,000 to facilitate interpretation;

BOLD = an indicator variable that equals 1 if the report's earnings forecast is at least two standard deviations away from the 30-day consensus, and 0 otherwise;

INCON = an indicator variable that equals 1 if the report's recommendation and earnings forecast are revised in different directions, and 0 otherwise;

BROKERSIZE = number of analysts issuing earnings forecasts from this brokerage house, the one used in Panel B is scaled by 100 to facilitate interpretation;

STAR = an indicator variable that equals 1 if the analyst is an *Institutional Investor* All-Star analyst in the current year, and 0 otherwise;

EXPR = number of quarters the analyst has been forecasting earnings according to I/B/E/S;

POSTFD = an indicator variable that equals 1 if the report is issued in 2001 or later;

PRIOR_CAR = cumulative ten-day abnormal returns ending before the current report date, where abnormal returns are calculated as the raw return minus the buy-and-hold return on the NYSE/AMEX/NASDAQ value-weighted market index;

SIZE = logarithm of the firm's market value of equity; and

BM = firm's book value of equity to its market value of equity.

VII. AN ADDITIONAL TEST

In our final set of analyses, we conduct a non-market-based test for the information content of analyst report text by examining text's ability to predict earnings growth (Penman 1992; Abarbanell and Bushee 1997). Because a substantial amount of text is based on fundamental analysis, we expect it to contain discussions about the value-drivers that analysts are likely to use in their security valuation, including those about long-term fundamentals (Lev and Thiagarajan 1993; Lev

and Nissim 2004).²³ Therefore, we regress future earnings growth over the subsequent five years on textual opinion and the quantitative summary measures:

$$GROWTH_{t+n} = \alpha + \beta_1 OPN_t + \beta_2 REC_t + \beta_3 EF_t + \beta_4 TP_t + \beta_5 ROA_t + \beta_6 SIZE_t + \beta_7 BM_t + \varepsilon, \quad (5)$$

where $GROWTH_{t+n}$ is measured as operating income from year $t+n$ minus operating income in year t , scaled by total assets in year t (Lev and Nissim 2004). In addition to the quantitative summary measures, we include earnings performance in the previous year (ROA_t) to control for mean-reversion in profitability. We also control for firm size ($SIZE_t$) and book-to-market ratio (BM_t) because these characteristics are likely to be associated with future earnings growth. The regression is estimated with industry and year fixed-effects to control for industry- and economy-wide factors that affect firms' fundamental performance.

Table 6 reports the results based on Equation (5). It shows that OPN is significantly associated with future earnings growth in the subsequent five years ($p < 0.01$), suggesting that analyst report text has predictive power for both short- and long-term fundamentals beyond other information signals included in the regression. This result corroborates the finding of the informativeness of text inferred from investors' reaction as described in Section VI. From Table 6, we also see that the result of text stands in contrast to the results of earnings forecasts and target prices. The coefficients on EF are insignificant or even significantly negative, indicating that the information contained in earnings forecasts is very short-term.²⁴ Furthermore, we find that the coefficients on TP are all negative and mostly significant, suggesting that target price is a poor indicator of future earnings growth. Similar to our findings for OPN , the results show that recommendation levels are significantly and positively related to future earnings growth. However, this effect holds only until the fourth year. In terms of economic significance, a one standard deviation increase in OPN predicts an earnings increase of 3.40 percent of total assets in the subsequent five years, which is considerably larger than the economic significance of recommendations: an increase of 1 in REC (for example, from SELL to HOLD or from HOLD to BUY) predicts a total earnings increase of 1.45 percent of total assets in the subsequent five years.

To find out whether positive and negative text has asymmetric predictive power for future earnings growth, we replace OPN with PCT_POS and PCT_NEG and report the results in Table 6. The result shows that both variables are correlated with future earnings growth in the expected direction ($p < 0.01$). The total amount of earnings decreases in the subsequent five years predicted by negative text is 99 percent larger than that of earnings increases predicted by the same amount of positive text, which explains investors' stronger reaction to negative than to positive text, documented in Section VI.

Overall, the results in Table 6 reveal that text is the most useful component of analyst reports in terms of the economic magnitude of earnings' predictive power and the ability to predict earnings growth over a longer horizon. These findings from our non-market-based test reveal the economic

²³ Some examples of analyst reports' analyses of long-term fundamentals include: "We believe Nucor's unique combination of low-cost production of steel and steel products, innovative technology, creative labor and management practices, vertical integration, and tremendous financial strength have positioned the company to continue to gain market share over the next five to 10 years" (report on Nucor, issued by G. S. Lucas from Wells Fargo on 8/16/2000). "We believe that this transaction assures solid growth for Ecolab for the next 5–10 years through market share gain opportunities in the underpenetrated European market, and rollout of numerous U.S. products into Europe" (report on Ecolab, issued by G. Yang from Citigroup on 12/11/2000). "We believe slower population growth in Tenet's two most important states over the next 10 years could have a negative impact on the company's growth" (report on Tenet Healthcare, issued by G. Lieberman from Morgan Stanley on 3/5/2002).

²⁴ In an untabulated test, we find that EF is positively associated with future earnings growth only in the subsequent two quarters (significant at the 0.01 level) and not beyond.

TABLE 6
Predictive Value of Analyst Report Text for Future Earnings Growth

	$GROWTH_{t+1}$	$GROWTH_{t+2}$	$GROWTH_{t+3}$	$GROWTH_{t+4}$	$GROWTH_{t+5}$	$GROWTH_{t+1}$	$GROWTH_{t+2}$	$GROWTH_{t+3}$	$GROWTH_{t+4}$	$GROWTH_{t+5}$
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)	(t-stats)
<i>OPN</i>	0.0256*** (13.14)	0.0359*** (11.20)	0.0390*** (9.95)	0.0357*** (7.60)	0.0346*** (6.10)	0.0218*** (8.82)	0.0275*** (6.28)	0.0281*** (4.99)	0.0258*** (3.70)	0.0251*** (2.88)
<i>PCT_POS</i>						-0.0331*** (-8.69)	-0.0525*** (-7.44)	-0.0605*** (-6.14)	-0.0555*** (-4.53)	-0.0536*** (-3.78)
<i>PCT_NEG</i>						0.0015*** (3.21)	0.0027*** (2.95)	0.0034*** (2.62)	0.0034*** (2.10)	0.0025 (1.31)
<i>REC</i>	0.0016*** (3.34)	0.0029*** (3.06)	0.0037*** (2.70)	0.0036** (2.16)	0.0027 (1.37)	0.0003 (1.14)	-0.0007 (-1.48)	-0.0013* (-1.73)	-0.0020* (-1.92)	-0.0020 (-1.55)
<i>EF</i>	0.0003 (1.15)	-0.0007 (-1.47)	-0.0013* (-1.73)	-0.0020* (-1.91)	-0.0020 (-1.55)	-0.0000*** (-3.35)	-0.0000*** (-4.83)	-0.0000*** (-4.03)	-0.0000 (-1.52)	-0.0000* (-1.77)
<i>TP</i>	-0.0000*** (-3.35)	-0.0000*** (-4.87)	-0.0000*** (-4.02)	-0.0000 (-1.46)	-0.0000* (-1.73)	-0.0000*** (-3.34)	-0.0000*** (-4.83)	-0.0000*** (-4.752***)	-0.0000 (-1.52)	-0.0000* (-1.77)
<i>ROA_t</i>	-0.3366*** (-17.24)	-0.4493*** (-10.68)	-0.4761*** (-7.87)	-0.4112*** (-5.40)	-0.3543*** (-4.09)	-0.3363*** (-17.22)	-0.4486*** (-10.67)	-0.4752*** (-7.85)	-0.4104*** (-5.38)	-0.3535*** (-4.07)
<i>SIZE</i>	0.0005 (0.39)	-0.0006 (-0.31)	-0.0019 (-0.71)	-0.0043 (-1.29)	-0.0070* (-1.79)	0.0004 (0.38)	-0.0007 (-0.33)	-0.0020 (-0.73)	-0.0043 (-1.31)	-0.0070* (-1.80)
<i>BM</i>	-0.0285*** (-13.13)	-0.0420*** (-11.05)	-0.0481*** (-10.77)	-0.0535*** (-9.81)	-0.0597*** (-8.81)	-0.0285*** (-13.13)	-0.0420*** (-11.06)	-0.0481*** (-10.78)	-0.0536*** (-9.82)	-0.0598*** (-8.81)
Intercept	0.0012 (0.11)	-0.0068 (-0.38)	0.0109 (0.48)	0.0828*** (2.99)	0.1510*** (4.64)	0.0036 (0.33)	-0.0015 (-0.08)	0.0174 (0.76)	0.0890*** (3.19)	0.1568*** (4.76)
# of Obs.	199,178	193,912	188,588	183,970	177,630	199,178	193,912	188,588	183,970	177,630
Adj. R ²	30.97%	27.35%	23.05%	18.75%	17.26%	31.00%	27.40%	23.11%	18.79%	17.29%

(continued on next page)

TABLE 6 (continued)

*, **, *** Indicates $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

This table reports the regression results of Equation (5): $GROWTH_{t+h} = \alpha + \beta_1 OPN_t + \beta_2 REC_t + \beta_3 EF_t + \beta_4 TP_t + \beta_5 ROA_t + \beta_6 SIZE_t + \beta_7 BM_t + \epsilon$. All regressions include industry and year fixed-effects; standard errors are estimated with a two-way cluster control at the firm and analyst levels. The dependent variable is $GROWTH_{t+h}$, defined as the operating income in year $t+h$ minus the operating income in year t , scaled by the total assets in year t .

Variable Definitions:

PCT_POS = percentage of sentences in the analyst report that are classified as positive by the naïve Bayes approach;

PCT_NEG = percentage of sentences in the analyst report that are classified as negative by the naïve Bayes approach;

OPN = textual opinion, calculated as $PCT_POS - PCT_NEG$;

REC = recommendation from I/B/E/S, reordered such that a higher value indicates a more positive recommendation (1: Sell; 2: Underperform; 3: Hold; 4: Buy; 5: Strong Buy);

EF = earnings forecast from I/B/E/S scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

TP = target price from I/B/E/S scaled by the stock price 50 days before the report date, winsorized at the top and bottom 1 percent;

ROA_t = operating income in year t scaled by the total assets in year t ;

$SIZE$ = logarithm of the firm's market value of equity; and

BM = firm's book value of equity to its market value of equity.

nature of the textual information in analyst reports and supplement the earlier finding of text's information content evaluated with reference to stock returns.

VIII. CONCLUSION

The emphasis that market participants place on analysts' written reports greatly exceeds the amount of effort researchers have made to understand them. The lack of empirical evidence on analyst report text prevents the extant literature from developing a comprehensive understanding of analysts' information role. We use the naïve Bayes machine learning approach to address the challenge of extracting information from a large volume of unstructured textual data. This approach enables us to extract textual opinions from 363,952 analyst reports issued for S&P 500 firms, providing the basis upon which to conduct tests on the information content of analyst report text.

We find that investors generally react to analyst report text conditional on the quantitative summary measures issued contemporaneously and that the market reaction triggered by text is economically significant. Moreover, investors react to the favorable (unfavorable) quantitative summary measures more strongly when the textual opinion is more positive (negative), indicating that text is also useful in helping investors interpret quantitative signals. A non-market-based test indicates that text has predictive value for future earnings growth for up to five years, confirming its informativeness. Our study also provides important insights into the cross-sectional determinants of the information content of analyst report text. We show that investors find text more useful when it conveys bad news, when it places more emphasis on nonfinancial topics, when it is written more assertively and concisely, and when the perceived validity of other information signals in the reports is low. Overall, we contribute to a better understanding of analysts' information role by providing the first large-sample evidence on the information content of analyst report text.

Finally, our finding that the naïve Bayes approach is more effective in extracting textual opinions from analyst reports than dictionary-based methods has implications for future research in this area, because using a less-effective technique understates the economic significance of textual information.

REFERENCES

- Abarbanell, J. S., and B. J. Bushee. 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (1): 1–24.
- Altinkılıç, O., and R. S. Hansen. 2009. On the information role of analyst recommendations. *Journal of Accounting and Economics* 48 (1): 17–36.
- Altinkılıç, O., V. Balashov, and R. S. Hansen. 2013. Are analysts' forecasts informative to the general public? *Management Science* 59 (11): 2550–2565.
- Antweiler, W., and M. Z. Frank. 2004. Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance* 59: 1259–1294.
- Asquith, P., M. Mikhail, and A. S. Au. 2005. Information content of equity analyst reports. *Journal of Financial Economics* 75: 245–282.
- Barber, B. M., R. Lehavy, and B. Trueman. 2010. Ratings changes, ratings levels, and the predictive value of analysts' recommendations. *Financial Management (Summer)*: 533–553.
- Barth, M. E., M. B. Clement, G. Foster, and R. Kasznik. 1998. Brand values and capital market valuation. *Review of Accounting Studies* 3: 41–68.
- Bradley, D. J., J. Clarke, S. S. Lee, and C. Ornathanalai. 2014. Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays. *Journal of Finance* 69 (2): 645–673.
- Bradshaw, M. 2002. The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizon* 16 (1): 27–40.

- Bradshaw, M. 2009. Analyst information processing, financial regulation, and academic research. *The Accounting Review* 84 (4): 1073–1083.
- Bradshaw, M. 2011. *Analysts' Forecasts: What Do We Know After Decades of Work?* Working paper, Boston College.
- Brav, A., and R. Lehavy. 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *Journal of Finance* 58 (5): 1933–1968.
- Call, A., S. Chen, and Y. H. Tong. 2013. Are analysts' cash flow forecasts naïve extensions of their own earnings forecasts? *Contemporary Accounting Research* 30 (2): 438–465.
- Clement, M. B. 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27: 285–303.
- Daniel, K. D., D. Hirshleifer, and S. H. Teoh. 2002. Investor psychology in capital markets: Evidence and policy implications. *Journal of Monetary Economics* 49 (1): 139–209.
- Das, S., C. B. Levine, and K. Sivaramakrishnan. 1998. Earnings predictability and bias in analysts' earnings forecast. *The Accounting Review* 73 (2): 277–294.
- Das, S. R., and M. Y. Chen. 2007. Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science* 53 (9): 1375–1388.
- De Franco, G., O. Hope, D. Vyas, and Y. Zhou. 2014. Analyst report readability. *Contemporary Accounting Research* (forthcoming).
- Dhaliwal, D. S., O. Z. Li, A. Tsang, and Y. G. Yang. 2011. Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review* 86 (1): 59–100.
- Emery, D., and X. Li. 2009. An anatomy of all-star analyst rankings. *Journal of Financial and Quantitative Analysis* 44: 411–437.
- Epstein, L. G., and M. Echnieder. 2008. Ambiguity, information quality, and asset pricing. *Journal of Finance* 63 (1): 197–228.
- Ertimur, Y., J. Livnat, and M. Martikainen. 2003. Differential market reaction to revenue and expense surprises. *Review of Accounting Studies* 8: 185–211.
- Francis, J., and L. Soffer. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 35 (2): 193–211.
- Francis, J., D. Nanda, and X. Wang. 2006. Re-examining the effects of Regulation Fair Disclosure using foreign listed firms to control for concurrent shocks. *Journal of Accounting and Economics* 41: 271–292.
- Givoly, D., and J. Lakonishok. 1979. The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency. *Journal of Accounting and Economics* 1 (3): 165–185.
- Givoly, D., C. Hayn, and R. Lehavy. 2009. The quality of analysts' cash flow forecasts. *The Accounting Review* 84 (6): 1877–1911.
- Gleason, C. A., and C. M. C. Lee. 2003. Analyst forecast revisions and market price discovery. *The Accounting Review* 78 (1): 193–225.
- Heflin, F., K. R. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *The Accounting Review* 78 (1): 1–37.
- Henry, E. 2006. Market reaction to verbal components of earnings press releases: Event study using a predictive algorithm. *Journal of Emerging Technologies in Accounting* 3: 1–19.
- Hirshleifer, D., and S. H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36: 337–386.
- Hirst, D. E., L. Koonce, and P. Simko. 1995. Investor reactions to financial analysts' research reports. *Journal of Accounting Research* 33 (2): 335–351.
- Hong, H., T. Lim, and J. C. Stein. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance* 55 (1): 265–294.
- Huang, A., R. Lehavy, A. Zang, and R. Zheng. 2014. *A Thematic Analysis of Analyst Information Discovery and Information Interpretation Roles*. Working paper, The Hong Kong University of Science and Technology.
- Institutional Investor. 2011. *The Best Analysts of All Time*. London, U.K.: Euromoney Institutional Investor.

- Irvine, P. J. A. 2001. Do analysts generate trade for their firms? Evidence from the Toronto stock exchange. *Journal of Accounting and Economics* 30 (2): 209–226.
- Ittner, C. D., and D. F. Larcker. 1998. Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research* 36: 1–35.
- Ivers, M. 1991. *The Random House Guide to Good Writing*. New York, NY: Random House.
- Ivković, Z., and N. Jegadeesh. 2004. The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73: 433–463.
- Jacob, J., T. Z. Lys, and M. A. Neale. 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28: 51–82.
- Jegadeesh, N., J. Kim, S. D. Krische, and C. M. C. Lee. 2004. Analyzing the analysts: When do recommendations add value? *Journal of Finance* 59 (3): 1083–1124.
- Koehler, J. 1993. The influence of prior beliefs on scientific judgments of evidence quality. *Organizational Behavior and Human Decision Processes* 56: 28–55.
- Kothari, S. P., S. Shu, and P. D. Wysocki. 2009. Do managers withhold bad news? *Journal of Accounting Research* 47 (1): 241–276.
- Lehavy, R., F. Li, and K. Merkley. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review* 86 (3): 1087–1115.
- Lev, B., and S. R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (2): 190–215.
- Lev, B., and D. Nissim. 2004. Taxable income, future earnings, and equity values. *The Accounting Review* 79 (4): 1039–1074.
- Lewis, D. 1998. Naïve (Bayes) at forty: The independence assumption in information retrieval. *Proceedings of ECML-98, 10th European Conference on Machine Learning, No. 1398*, 4–15.
- Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45 (1): 221–247.
- Li, F. 2010. The information content of forward-looking statements in corporate filings—A naïve Bayesian machine learning approach. *Journal of Accounting and Research* 48 (5): 1049–1102.
- Lin, H., and M. F. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25: 101–127.
- Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66 (1): 35–65.
- Lys, T., and S. Sohn. 1990. The association between revisions of financial analysts' earnings forecasts and security price changes. *Journal of Accounting and Economics* 13 (4): 341–363.
- Manning, C. D., and H. Schütze. 1999. *Foundations of Statistical Natural Language Processing*. Cambridge, MA: MIT Press.
- McNichols, M., and P. C. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35: 167–199.
- Mercer, M. 2004. How do investors assess the credibility of management disclosures? *Accounting Horizons* 18 (2): 185–196.
- Mikhail, M., B. Walther, and R. Willis. 1997. Do security analysts improve their performance with experience? *Journal of Accounting Research* 35: 131–166.
- Miller, G. 2002. Earnings performance and discretionary disclosure. *Journal of Accounting Research* 40 (1): 173–204.
- Pang, B., and L. Lee. 2008. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval* 2: 1–135.
- Penman, S. H. 1992. Return to fundamentals. *Journal of Accounting, Auditing and Finance* 7 (4): 465–483.
- Previts, G. J., R. J. Bricker, T. R. Robinson, and S. J. Young. 1994. A content analysis of sell-side financial analyst company reports. *Accounting Horizons* 8 (2): 55–70.
- Price, P. C., and E. R. Stone. 2004. Intuitive evaluation of likelihood judgment producers: Evidence for a confidence heuristic. *Journal of Behavioral Decision Making* 17: 39–57.
- Ramnath, S., S. Rock, and P. Shane. 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting* 24 (1): 34–75.

Sniezek, J. A., and L. M. Van Swol. 2001. Trust, confidence, and expertise in a judge-advisor system. *Organizational Behavior and Human Decision Processes* 84 (2): 288–307.

SRI International. 1987. *Investor Information Needs and the Annual Report*. Morristown, NJ: Financial Executives Research Foundation.

Stickel, S. 1992. Reputation and performance among security analysts. *Journal of Finance* 47: 1811–1836.

Stocken, P. C., and R. E. Verrecchia. 2004. Financial reporting system choice and disclosure management. *The Accounting Review* 79 (4): 1181–1203.

Twedt, B., and L. Rees. 2012. Reading between the lines: An empirical examination of qualitative attributes of financial analysts’ reports. *Journal of Accounting and Public Policy* 31 (1): 1–21.

Verrecchia, R. E. 1983. Discretionary disclosure. *Journal of Accounting and Economics* 5: 179–194.

Womack, K. L. 1996. Do brokerage analysts’ recommendations have investment value? *Journal of Finance* 51: 137–167.

Yu, H., and V. Hatzivassiloglou. 2003. Towards answering opinion questions: Separating facts from opinions and identifying the polarity of opinion sentences. *Proceedings of the 2003 Conference on Empirical Methods in Natural Language Processing*, Volume 10.

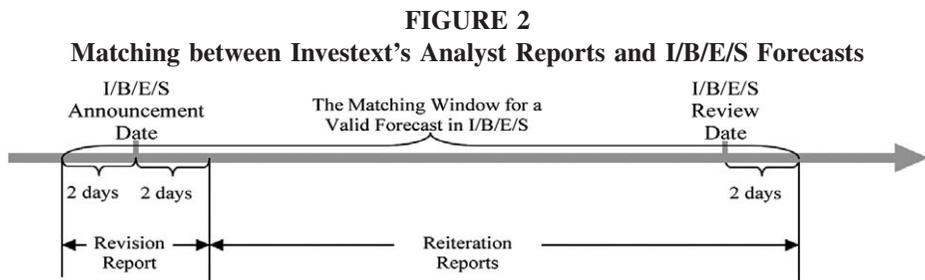
Zarnoth, P., and J. A. Sniezek. 1997. The social influence of confidence in group decision making. *Journal of Experimental Social Psychology* 33: 345–366.

APPENDIX A

Investext Analyst Reports and I/B/E/S Forecasts Matching Methodology

Here, we outline the approach we use to match the Investext analyst reports in our sample with the I/B/E/S forecast data. Our first step in this process is to match the analyst-brokerage name combinations in the two databases. After completing this step, we delete 65,265 reports from our analyst report sample because we cannot locate their respective analyst-brokerage combinations in I/B/E/S. This yields a sample of 16,091 analyst-brokerage name combinations obtained from the Investext database and located in I/B/E/S. For these, we match companies that are covered by the same combinations in both databases, using company tickers and names.

We then match specific reports to their corresponding forecasts in I/B/E/S. While Investext organizes data at the report level, I/B/E/S organizes data at the valid forecast level. Thus, in I/B/E/S, the only information that identifies the timing of a forecast (a stock recommendation, an earnings forecast, or a target price) are its announcement date, on which the analyst revises her estimate, and review date, which is the most recent date that I/B/E/S confirms this estimate as accurate. A forecast is considered valid during the period from its announcement date until its review date. During this period, multiple reports may be issued by the same analyst to reiterate the forecast; however, such reports have no separate data entries in I/B/E/S. Therefore, we match a report with an I/B/E/S valid forecast if the report date falls within the “matching window” in Figure 2, which is the window



from two days before the I/B/E/S forecast announcement date until two days after the I/B/E/S forecast review date.

We then categorize all matched reports as either revision or reiteration reports. A report is considered a revision report if the report date is within two days of the I/B/E/S forecast announcement date because the announcement date is the date the analyst revised her forecasts. All other reports are considered reiteration reports. We randomly select 100 reiteration reports and confirm that they contain the same forecast numbers as in I/B/E/S.