Textual Classification of SEC Comment Letters

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Abstract

I utilize Naive Bayesian text classification to signal important SEC comment letters, where negative abnormal returns following comment letter disclosure is the measure of importance. In a holdout sample, classification identifies important comment letters between 10 and 40 percent better than chance. The average market response to signaled comment letters is a -5.8 percent abnormal return over the subsequent 90 days, but only when the comment letters were viewed on EDGAR, indicating market underreaction to these disclosures. Signaled comment letters are associated with lower persistence of profits and increased levels of restatements in the year following comment letter disclosure. Together these results suggest that text classification can be used to signal important comment letters and that these letters are associated with with lower future performance and undisclosed financial reporting deficiencies.

Keywords: SEC comment letters, text classification, material restatements

JEL: M41, G14, G18

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1. Introduction

Comment letters arise from mandated periodic examinations by the Securities and Exchange Commission (SEC) of public companies' financial reports. The purpose of the review process is to ensure that investors are "...provided with material information and to prevent fraud and manipulation..."(SEC, 2001). The Sarbanes Oxley Act of 2002 mandates that the SEC conduct such reviews, including an examination of the annual financial statements, at least once every three years (SOX, 2002). While conducting their reviews, SEC examiners issue written questions to management, and management provides written responses. These communications receive little attention from the media, analysts, investors, and the accounting literature.

This study uses statistical text classification to signal important comment letters, utilizing significantly negative stock returns following comment letter disclosure as the measure of importance. Since the SEC targets disclosure deficiencies, important comment letters could encourage managers to reveal strategically withheld information and identify firms with insufficient financial reporting practices or internal controls to comply with disclosure requirements. Textual analysis techniques are particularly well-suited for this setting, because comment letters consist of unstructured text, without consistent quantitative information or summary statistics. After testing the ability of the classification model to identify important comment letters, I examine the association between signaled comment letters, financial performance, and reporting quality measures.

Comment letters are more difficult to access and interpret than other commonly-used filings. A comment letter "conversation" consists of several separate letters from the SEC to the registrant and the associated responses from management.

The median conversation has four letters, and the 90th percentile has eight, requiring investors to identify, read, and process the information contained all related filings to understand the full extent of the conversation. When the review is complete, all comment letters in the conversation are disclosed on the SEC's Electronic Data Gathering and Retrieval (EDGAR) website, though each letter in the conversation is filed separately according to the date the original letter was issued, not the date the entire conversation was disclosed.[1]

Prior research indicates that comment letters are infrequently read by investors and have a limited overall impact on returns. Perhaps the cost of finding and interpreting information contained in comment letters is costly and markets underreact to their disclosure, or alternatively, comment letters may be generally uninformative. There are stakeholders whose actions indicate that comment letters are important. Public accountants are heavily involved in the comment letter process, both from involvement in their clients' responses, and because the existence and and magnitude comments on their audit clients may reflect negatively on financial reporting quality and audit quality. Accounting firms produce commentaries on comment letter trends, though these tend to be compilations of frequently-raised issues, as opposed to analyses of implications for issuers or financial statement users (e.g., Deloitte & Touche LLP, 2014). Analysts associated with short-sellers utilize comment letters in their research, indicating that comment letters are more likely to identify negative information. Accounting research is starting to examine the causes and consequences of comment letters, and to use comment letters as a

[1]Disclosure services such as FactSet and Morningstar Document Research allow investors to set up "alerts" so that any newly disclosed filing, including comment letters, are identified when disclosed.

proxy for financial reporting and audit quality.

Using a comprehensive set of 10-K-related comment letter text and disclosure dates collected from the EDGAR web site, I build a textual classification model to signal important comment letters. First, I create a training sample of comment letters. Second, I classify comment letters in the training sample as important if the firms' abnormal returns are significantly negative following comment letter disclosure. I focus on negative returns as the signal of importance because the SEC aims to identify disclosure weakness in their reviews. Third, I use the training sample to build a Naive Bayesian classification model to identify text features (words or short phrases) that occur with greater frequency in important comment letters. Fourth, I test the effectiveness of the model to predict returns in a holdout sample that was not used to fit the model.

The holdout sample provides a pool of comment letters with signal of importance. I investigate underreaction to signaled comment letters by testing a subset of comment letters known to be viewed on EDGAR, finding that the signal is more powerful and predictive of negative post-disclosure returns when the comment letters were viewed. The classification model detects important comment letters in the holdout sample by identifying those with subsequent price declines 10 to 40 percent more accurately than chance. For comment letters viewed by investors, the signal is associated with abnormal returns of -1.2 percent over the next three days, and -5.8 percent over the next 90 days.

Since the focus of the SEC's review process is disclosure quality and investor protection, I examine the association between signaled comment letters and earnings, earnings persistence, material restatements, and internal control weaknesses. I find that firms with signaled comment letters have lower future persistence of profits and increases in restatements. Signaled comment letters are associated with an increase in material restatements of 47 percent in the following year.

This study extends the literature relating to textual analysis of accounting disclosures by studying larger passages of text, and avoids typical hand-coding of training documents by utilizing the stock market response to a document's disclosure to provide a signal of importance that is unaffected by potential researcher bias or error. This study is also the first to examine the association between important comment letters and earnings, earnings persistence, material restatements, and internal control weaknesses. These measures provide evidence that comment letters can be used to identify companies with weaker financial reporting and disclosure quality.

A limitation of this study is that textual analysis techniques distill large amounts of text into broad signals, and the underlying mechanisms that relate these signals to observed characteristics such as stock returns or internal control weaknesses cannot be precisely determined. Furthermore, textual analysis techniques involve subjective model parameter selections, so similar results may not hold in different settings or for different research design choices. I attempt to address these issues by illustrating model performance across a range of parameters and providing specific text features the model identifies as associated with important comment letters.

Overall, this study suggests that textual analysis techniques can be useful for analyzing larger passages of unstructured financial disclosures, and further that interested parties such as investors, management, directors, auditors, and regulators can realize information about firm financial reporting quality from comment letters.

2. Motivation and Prior Literature

2.1. Importance of SEC Comment Letters

As a result of the bankruptcies and frauds in the early 2000's, Section 408 of the Sarbanes-Oxley Act of 2002 mandates that the SEC review the disclosures, including the annual financial statements, of every registrant at least once every three years, for the protection of investors (SOX, 2002). If a review identifies issues that warrant additional disclosure, correction, or clarification, a comment letter is issued, and a written correspondence with the issuer proceeds until the SEC is satisfied that all questions are resolved. Beginning with comments on filings made after August 1, 2004, the SEC began posting all comment letters and the issuer's responses on the EDGAR web site for public dissemination 45 calendar days (20 business days beginning in 2012) after the review completion. Considerable resources are expended by the SEC, companies, and public accounting firms in making and responding to these comment letters: in 2014, the SEC conducted 4,350 reviews, an activity that represented the significant majority of the Division of Corporation Finance's headcount and $135 million budget (SEC, 2015).

It is an empirical question as to whether comment letters contain material information. On one hand, these comment letters are issued on already-public filings, and if markets are efficient at incorporating publicly available information, it is not clear why the questions of a single, albeit knowledgeable, analyst, should have information content. On the other hand, comment letters sometimes result in management disclosing additional information in their responses, questions from the SEC may require companies to amend prior filings, and insiders sometimes trade on comment letters surrounding their disclosure, with negative returns surrounding comment letter issuance for firms with both insider sales and high short interest (e.g., Dechow, Lawrence, and Ryans, 2015).

Academic studies consider comment letters as evidence of financial reporting quality (e.g., Ertimur and Nondorf, 2006; Gietzmann and Pettinicchio, 2013; Hribar, Kravet, and Wilson, 2014) and effective governance (e.g., Ettredge, Johnstone, Stone, and Wang, 2011; Robinson, Xue, and Yu, 2011). This study considers 10-K-related comment letters because annual reports are specifically mentioned in SOX Section 408 as an item to be included in reviews. Cassell, Dreher, and Myers (2013) study determinants of receiving a comment letter and the costs of compliance. Johnston and Petacchi (2012) provide evidence that comment letters provide new information at the time of comment letter disclosure, or in subsequent filings, improving the information environment. Bozanic, Dietrich, and Johnson (2013) find that firms make detectable changes to subsequent 10-Ks in response to comment letter issues. Dechow et al. (2015) provides evidence that there is information content in comment letters from abnormal insider trading around comment letter disclosure, but note a limited effect on stock prices immediately following disclosure. If comment letters are costly to process, then a delayed or limited market response is not surprising (Hirshleifer and Teoh, 2003).

2.2. Textual Classification of Financial Disclosures

Statistical text analysis is now commonly used in accounting research as a response to the difficulty and cost of manual data collection for content analysis, which necessitates small sample sizes (e.g., Bryan, 1997). Dictionary based techniques use wordlists with pre-supposed meanings to identify the tone of a text (e.g., Tetlock, 2007; Kothari, Li, and Short, 2009a; Davis, Piger, and Sedor, 2012). Document length or reading difficulty have been used as measures of reporting complexity (e.g., Li, 2008; You and Zhang, 2009; Peterson, 2012), or of management deceptiveness (e.g., Larcker and Zakolyukina, 2012). Feldman, Govindaraj, Livnat, and Segal (2010) find significant market reaction to 10-Q and 10-K reports, conditioned on the tone of filings. These studies indicate that textual analysis based on word lists can be effective, despite evidence that commonly used dictionaries can be misleading or ambiguous in the financial setting (Loughran and McDonald, 2011). Loughran and McDonald (2015) survey textual analysis techniques used in the accounting and finance literature.

Comment letters present a challenge to researchers studying the economic impact of their information content because they have an unstructured format and do not present consistent numerical statistics, such as earnings. This setting naturally lends itself to textual analysis techniques, in particular the concept of text classification, which attempts to determine the class of a document based upon its textual features. In this study, I use the Naive Bayesian technique to classify comment letter documents as important.

The Naive Bayesian classification method is one of the most established methodologies used to analyze text (e.g., Lewis, 1998; Loughran and McDonald, 2015), and has been used in the past to classify authorship (e.g., Mosteller and Wallace, 1984), genre (e.g., Karlgren and Cutting, 1994; Kessler, Numberg, and Schütze, 1997), news category (e.g., Feldman and Dagan, 1995; Dagan, Feldman, and Hirsh, 1996), and the sentiment of movie reviews (e.g., Pang, Lee, and Vaithyanathan, 2002). In the law literature, Talley and O'Kane (2012) identifies the properties of specific clauses within merger agreements. In accounting research, Li (2010) uses a Naive Bayesian approach to determining individual sentence tone, and De Franco, Vasvari, Vyas, and Wittenberg-Moerman (2013) study debt analyst report tone, with both studies finding that Naive Bayesian classification is economical for classifying large volumes of texts, and can provide predictive power when standard dictionary approaches fail. However, Naive Bayesian classification requires a set of training documents, for which the researcher typically hand-codes each document's class (e.g., Li, 2010; De Franco et al., 2013). Manually coding document class may be subject to researcher bias (Loughran and McDonald, 2015).

This study utilizes realized abnormal returns following comment letter disclosure to classify documents in the training set as *important* or *unimportant*, an approach that eliminates the possibility of researcher coding bias. I focus on negative returns because comment letters result from a review that targets disclosure deficiencies and is intended to protect investors from fraud (SEC, 2001; SOX, 2002). If managers are more likely to withhold bad news (Kothari, Shu, and Wysocki, 2009b), and if the SEC reviewers succeed in identifying disclosure deficiencies, then important comment letters will be more likely to result in a negative abnormal stock return when the information is revealed. Reviews finding compliant disclosure would either not generate a comment letter in the first place, or the identified issues would be minor, and therefore any resulting letter would be unimportant. Therefore, I use significant negative stock returns (bottom quartile), following comment letter issuance to classify importance. If text features associated with these negative returns are predictive of important comment letters, then other firms with similar comment letter text should also experience negative stock returns following disclosure.

If important comment letters lead to the disclosure of bad news, and if textual classification techniques can identify language differences between important and unimportant comment letters, then the first hypothesis follows (in alternative form):

H1: Signaled comment letters are associated with negative post-disclosure returns.

2.3. Investor Inattention and EDGAR Views

Comment letters are more difficult to find and interpret than other commonly-read filings, which raises the possibility of investor inattention to this information source. The information contained in a comment letter conversation is distributed among several different EDGAR filings, and an investor needs to identify and read each related comment letter (Form UPLOAD) and the company's responses (Form CORRESP). The SEC's EDGAR website organizes comment letters chronologically according to filing date, the date that the document was processed by EDGAR, usually the date the letter was sent to the recipient or the reply was received by the SEC. With comment letters, this can be weeks or months prior to the disclosure date. The mean length of time between the issuance of the first comment letter and the conversation's disclosure is 151 days for comment letters used in this study, hence the investor has to search through approximately six months of filings to find all related documents.

There is little evidence that comment letters are commonly used by investors, although the presence of commercial data vendors with comment letter products, such as Audit Analytics, indicates that there is demand for related data. Prior research using the EDGAR download logs either omits analysis of comment letters because they are so infrequently accessed (Drake, Roulstone, and Thornock, 2015), or notes that downloads occur at approximately 1 percent of the rate of downloads for the comment letter's associated 10-K report (Dechow et al., 2015).

The CFA Institute does not identify comment letters as an information source in financial analyst traning materials (CFA Institute, 2014), nor do widely used textbooks on financial analysis (e.g., Revsine, Collins, Johnson, and Mittelstaedt, 2011). The financial press also makes very little use of comment letters as news sources.[2] A Factiva search of the Wall Street Journal during calendar 2013 reveals just five articles reporting on an SEC comment letter conversation with an individual company. The most prominent users of comment letters appear to be short sellers (e.g., Bloomberg, 2013), who have the most incentive to identify negative information and publicize their results (Ljungqvist and Qian, 2014).[3]

Stock prices appear to have a delayed response to earnings news (e.g., Bernard and Thomas, 1989; Chan, Jegadeesh, and Lakonishok, 1996). There are various explanations for this drift, including overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998), mean reversion (Barberis, Shleifer, and Vishny, 1998), and underreaction due to processing limitations (Hong and Stein, 1999). The only model that predicts investor inattention leading to greater drift is the underreaction explanation. There is evidence of underreaction to new information depending on both the salience of information (e.g., Chetty, Looney, and Kroft, 2009) and investor inattention (e.g., DellaVigna and Pollet, 2009), as well as the difficulty investors have processing information about related firms (Cohen and Frazzini, 2008). The comment letter setting may experience underreaction due to processing costs and limited salience. Gietzmann and Isidro (2013) find evidence

[2] Although there are infrequent examples of media articles sourced from comment letters (e.g., WSJ, 2014).

[3] Examples of short-oriented research that makes use of issues raised in comment letters include presentations by Greenlight Capital on Green Mountain Coffee (Greenlight Capital, 2011), Pershing Square on Herbalife (Pershing Square, 2013), and Prescience Point on Boulder Brands (Prescience Point, 2013).

of investor inattention to SEC comments on IFRS issues.

A direct way to proxy for comment letter consumption is through the EDGAR web log of downloads. A caveat to the use of this data is that EDGAR is not the only way for investors to access SEC filings, so I do not observe all occasions when a document is viewed. The EDGAR data itself is disseminated in two ways, through EDGAR's public web site (including an FTP file service), the traffic recorded by the log files used in this study. EDGAR filings are also made available to data vendors via the Public Dissemination Service feed, which is a stream of all accepted filings (Drake et al., 2015). Therefore while the EDGAR logs represent a large volume of views, and can are assumed to include view from investors, the media, and other stakeholders, we cannot capture all EDGAR filing views. These feeds typically populate services such as Bloomberg, FactSet, and third party financial websites such as Morningstar Document Research. Comment letters are not as widely available outside EDGAR as are other popular filings. Many corporate investor relations websites which claim to provide copies of all SEC filings exclude comment letters (Dechow et al., 2015). As of September 2015, the most popular financial information sites, Yahoo Finance and Google Finance, do not provide access to comment letters despite offering firm-specific "SEC filings" pages. Dechow et al. (2015) uses the EDGAR log files and finds rates of comment letter downloads to be approximately 1 percent of the rate of the associated 10-K, and note a faster stock price response to comment letters with contemporaneous insider sales.

Given that investors appear to pay limited attention to comment letters, information in comment letters may not immediately affect returns. However, under investor inattention, information may be incorporated with a delay, and if this is the case, longer-term abnormal returns may provide an improved signal of importance. Secondly, using the EDGAR log files, it is possible to identify comment letters that are known to have been read immediately after disclosure, and in these cases, short term returns are likely to incorporate comment letter information and hence provide a stronger signal. If comment letter views more quickly and accurately reflect comment letter information in stock returns, then the second hypothesis follows (in alternative form):

H2: The market response to signaled comment letters is greater when they are viewed.

2.4. Comment Letters and Financial Reporting Quality

SEC reviews conducted in accordance with SOX Section 408 and the SEC's Full Disclosure Program aim to protect investors from fraud and misrepresentation, and to ensure that disclosures comply with relevant laws and regulations (SEC, 2001; SOX, 2002). If some managers strategically avoid disclosing bad news, and that information may not be completely reflected in market prices (e.g., Grossman and Stiglitz, 1980; Bloomfield, 2002), then efforts by the SEC to improve disclosures through the review process should reveal information when related correspondence is disclosed, or in amendments or periodic disclosures while the review process is underway, or in subsequent periods.

If the comment letter process either reveals that a firm had no significant disclosure deficiencies, or if the comments resulted in disclosure improvements with no bad news being revealed, then earnings should not be affected by the review process, and the stock market response could be positive, consistent with prior literature regarding disclosure quality and performance (e.g., Lang and Lundholm, 1993; Francis, LaFond, Olsson, and Schipper, 2005; Francis, Nanda, and Olsson, 2008). On the other hand, more important comment letters could result in the release of significant negative information that management was withholding (e.g. Kothari et al., 2009b), and earnings could be negatively impacted in the year of the comment letter conversation, or in future years if management estimates are more skeptically evaluated by auditors in subsequent periods. The third hypothesis follows (in alternative form):

H3: Signaled comment letters are associated with lower earnings and earnings persistence.

Comment letters may also impact financial accounting and audit process within firms subject to important comment letters. Auditors are often included in the comment letter correspondence (Laurion, Lawrence, and Ryans, 2015), and the auditor may modify their assessment of audit risk and may identify areas of financial reporting weakness and internal control weaknesses as a result of issues raised by the SEC. Management investigations made to provide responses to SEC questions could lead to changes in accounting assumptions and policies, and may identify errors leading to material restatements. Material restatements reflect financial reporting quality and have an effect on returns (e.g., Hribar and Jenkins, 2004; Kinney, Palmrose, and Scholz, 2004; Palmrose, Richardson, and Scholz, 2004; Liu, Raghunandan, and Rama, 2009; Dechow, Ge, Larson, and Sloan, 2011; Francis, 2011). The fourth hypothesis follows (in alternative form):

H4: Signaled comment letters are positively associated with material restatements.

While comment letters may identify actual errors or material misstatements requiring a restatement, this same process may reveal failures of internal controls over financial reporting. If the SEC correctly identifies material disclosure requirements with which the issuer has not complied, than this is evidence that the issuer does not have adequate financial reporting practices. Internal control weaknesses are associated with information uncertainty and negative announcement returns (e.g., Doyle, Ge, and McVay, 2007; Beneish, Billings, and Hodder, 2008; Hammersley, Myers, and Shakespeare, 2008; Ashbaugh-Skaife, Collins, LaFond, et al., 2009). The fifth hypothesis follows (in alternative form):

H5: Signaled comment letters are positively associated with internal control weaknesses.

3. Data and Research Design

I collect firm fundamentals from Compustat, returns from CRSP, insider trades from Thompson Reuters Insider, and material restatements and internal control effectiveness reports from Audit Analytics. See Appendix A for definitions of all variables. I obtain copies of the daily EDGAR web logs from the SEC, for the period from June 2006 through January 2012, the extent of the available daily log files with no gaps. The data is cleaned using a procedure similar to Drake et al. (2015).

I calculate cumulative abnormal returns from CRSP, for firms that trade on the NYSE, NASDAQ, or Amex exchanges, using a procedure similar to Campbell, Lo, and MacKinlay (1997). Specifically, cumulative abnormal returns are calculated using the market model: $CAR[a,b]_i = \prod_{t=a}^{b}(1 + AR_{it}) - 1$, where $CAR[a,b]_i$

is the cumulative abnormal return for firm i for day a through day b. AR_{it} is calculated as $AR_{it} = R_{it} - [\hat{\alpha}_i + \hat{\beta}_i R_{mt}]$, where AR_{it} is the abnormal return for firm i on day t, R_{mt} is the market return for day t using the S&P 500 index, and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated from the equation: $R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$, using a pre-event period from event day -300 to event day -46 trading days. I drop observations with less than 30 days of returns data in the estimation period, and observations without 90 days of post-event returns. Results are similar using size adjusted returns.

I collect the full text of all SEC comment letters (Form UPLOAD) and company responses (Form CORRESP) directly from the ftp.sec.gov file transfer service, from June 2006 through January 2012, as this date range corresponds to the availability of EDGAR web logs. The daily EDGAR index files are utilized to determine each document's filing and disclosure dates. Filings may have different formats (PDF, HTML, and text), so I convert all to plain text. Comment letters and responses for the same CIK identifier, disclosed on the same day, are combined into a single conversation document.

Beginning with 209,323 individual UPLOAD and CORRESP filings, comprising 55,688 separate conversations, I keep filings whose CIKs match to a firm in CRSP, the CRSP-Compustat Annual Fundamentals file, and Thomson Reuters Insider Trading database, 21,243 conversations. I keep conversations relating to Form 10-K filings, and those with sufficient returns data in CRSP to calculate abnormal returns for the 90 days post-comment letter disclosure, resulting in a final textual classification sample of 6,566 comment letter conversations for 3,527 unique firms. This sample is randomly divided into a training sample of 3,283 observations and a holdout sample of 3,283 observations.[4] I count the number

[4]A 50% holdout sample is used as it provides the lowest risk of inference errors (Schorfheide

of comment letters and responses in the conversation, count the number of questions in the comment letter, and identify if the comment letter relates to a revenue recognition topic, as prior research has shown that this is an important comment letter topic (e.g., Cassell et al., 2013; Dechow et al., 2015). Appendix B provides details on the preparation of the comment letter text for analysis.

Table 1a provides descriptive statistics for the textual classification sample. The mean market capitalization of firms in the sample is \$6,021 million, which is somewhat larger than the mean Compustat population of \$3,952 million over the same period, and is consistent with Cassell et al. (2013), who show that size is positively associated with comment letter receipt. The mean Book to Market ratio is 0.65, comparable to the Compustat population of 0.73 over the same period. Table 1b presents descriptive statistics for the sample of conversations known to be viewed more than median (2 times) over the three days post-disclosure, with 2,546 observations for 1,965 unique firms. The mean market value in this sample is \$8,026 million, slightly larger than the full sample.

For all firms with comment letter conversations, $CAR[0,3]$ is negligible (0.000), while $CAR[0,90]$ is 0.018. The mean positive return for all firms can be attributed to some small-firm outliers. Excluding firms with market capitalization of less than \$25 million reduces the mean $CAR[0,90]$ to 0.005 ($p > .35$), all other results are unaffected by excluding these firms. Firms where the comment letters are downloaded more than 2 times have a mean $CAR[0,3]$ of -0.002, while $CAR[0,90]$ is -0.020. This provides preliminary indications that comment letters that were read soon after disclosure appear to disclose bad news on average, though the mechanism is unclear. Investors may become aware of comment

and Wolpin, 2012).

letters that contain bad news, or bad news released through some other channel may cause investors to find and download concurrently released comment letters. Earnings announcements and filings of 10-Ks and 10-Qs are evenly distributed throughout the event window for both groups of firms, and as a result such such announcements should not bias the results.

The mean number of questions in the initial comment letter is 6.513 for all 10-K comment letters, and 6.896 for comment letters viewed more than 2 times. The number of items in a conversation (SEC comment letters and company responses) is nearly identical at 4.912 for all comment letters and 4.944 for comment letters viewed more than 2 times. The fraction of all 10-K comment letters mentioning revenue recognition issues is 0.200 for all conversations, and 0.165 for comment letters viewed more than 2 times. Insider sales as a percentage of shares outstanding sold by officers and directors in the window from disclosure date -15 days to +15 days is a mean of 0.052% for all 10-K comment letters, and 0.052% for comment letters viewed more than 2 times. In untabulated tests, size is the main factor associated with greater numbers of EDGAR views.

To study financial performance and reporting quality in the years adjacent to comment letter issuance, I use comment letters in the textual classification hold-out sample that have the required Compustat control variables for two years before and one year after comment letter disclosure, resulting in a sample of 2,544 conversations for 1,801 unique firms. Table **??** provides descriptive statistics for these firms, which have a mean market capitalization of $7,908 million, slightly larger than the all comment letter sample of $6,021 million and slightly smaller than the above-median EDGAR view sample of $8,026 million.

3.1. Textual Classification of SEC Comment Letters

In general terms, the Naive Bayesian classification procedure estimates the class of a document based on the frequencies of words or short phrases (also called features) present in the document. Classes are arbitrarily defined, for example: authorship, subject matter, or in this setting, importance. To implement Naive Bayesian classification, a model is trained by calculating the relative frequencies of each feature appearing in the training documents of each class. When an "unknown" document is examined, the feature frequencies are calculated and the document is assigned the class with the most-similar feature distribution.

Formally: let d be a document in a set $D = \{d_1, ..., d_k\}$ consisting of k documents. Let $F = \{f_1, ..., f_m\}$ be the set of m possible *features* that can appear in D. Let $n_i(d)$ be the number of times feature f_i appears in document d. Then each document will have a vector representation $\mathbf{d} = (n_1(d), ..., n_m(d))$.

The naive Bayes classifier assigns a document to a class c^* from among n classes $(c_1, ..., c_n)$, where $c^* = \arg\max_c P(c|d)$. If we consider Bayes' rule:

$$P(c|d) = P(c) \times \frac{P(d|c)}{P(d)} \quad ,$$

then under the assumption that the f_is are conditionally independent given the document's class, the probability that a document belongs to class c is:

$$P(c|d) = P(c) \times \frac{\prod_{i=1}^{m} P(f_i|c)^{n_i(d)}}{P(d)} \quad . \tag{1}$$

I prepare the text for analysis by converting all characters to lowercase, and removing all punctuation and numbers. The document set is converted into a term document matrix, using either single words as the feature set (unigram), or single words and consecutive 2-word combinations (unigram + bigram).[5] The term document matrix has one row for each document vector. Finally, I remove any features that appear in fewer than 5 percent of the documents, which makes the computations less costly, and generally consist of items such as web site addresses, companies' and individuals' names, and hence don't have a consistent information value for the classification. The total feature set is 2,549 words in the unigram feature set and 4,472 in the unigram + bigram feature set.

The probabilities in Equation 1 are calculated from the sample: $P(c)$ is the prior probability, or the relative frequency of class c in the sample, in this case, bottom quartile returns occur with frequency 0.25; $P(f_i|c)$ is the conditional probability, the relative frequency of f_i among all features in the sample; $P(d)$ is the probability of the predictor—a document—and is the same for every observation and so can be dropped without affecting the maximization. $P(c|d)$ then is the posterior probability, the probability the document belongs to a class, given its feature set. I randomly select 50 percent of the comment letter sample as a training sample, which is a set of documents of known class to to calculate the probabilities $P(c)$ and $P(f_i|c)$ in Equation 1.

Two adjustments are made to the basic naive Bayesian procedure. First, since the number of features is large, it is possible that a feature never appears in any document in a given class. This would result in a posterior probability of zero, and so a method of compensating is "add one smoothing", where one is added to the count of each feature in calculating the frequency numerator, and m is added to the

[5] E.g., the text "internal controls" appearing in a document would be represented by two features ("internal", "controls") in a unigram representation of the document, one feature ("internal controls") in a bigram representation, and three features ("internal", "controls", "internal controls") in a unigram + bigram representation.

denominator. Secondly, the multiplication of many small probabilities can lead to floating point overflow errors, and we can correct for this by instead adding the logarithms of each probability. Supposing we limit our analysis to two classes: c_I and c_U for *important* and *unimportant* respectively, the maximization problem simplifies to:

$$\log(P(c_I|d)) = \log(P(c_I)) + \sum_{i=1}^{m} \log(P(f_i|c_I)) \times n_i(d)$$
$$\log(P(c_U|d)) = \log(P(c_U)) + \sum_{i=1}^{m} \log(P(f_i|c_U)) \times n_i(d) \quad ,$$

where

$$P(c_j) = \frac{|c_j|}{|D|} \quad \text{and}$$
$$P(f_i|c_j) = \frac{\left(\sum_{d \in c_j} n_i(d)\right) + 1}{\left(\sum_{d \in D} n_i(d)\right) + k} \quad .$$

A document is assigned to class c_I if $\log(P(c_I|d)) > \log(P(c_U|d))$ and class c_U otherwise. Hereinafter, I refer to documents classified as *important* by the Naive Bayesian algorithm as having a *Signal* value of TRUE, or simply "signaled", but otherwise documents classified as *unimportant* have a *Signal* value of FALSE.

To test H1, that signaled comment letters are associated with post disclosure returns, I first check the precision that signaled comment letters have bottom-quartile abnormal returns in the three or 90-days post disclosure, and I test H2 by conditioning the precision performance on above-median EDGAR downloads. To test the statistical significance of abnormal returns associated with the signal, I examine the following OLS regression model:

$$
\begin{aligned}
\text{CAR}_i = {} & \beta_0 + \beta_1 I(\text{Signal})_i + \beta_2 \log(\text{Num. Questions})_i \\
& + \beta_3 I(\text{Revenue Recognition})_i + \beta_4 \text{Insider Sales Rank}_i + \varepsilon_{i,t} \quad , \qquad (2)
\end{aligned}
$$

where *CAR* is either the three-day (*CAR[0,3]*) or 90-day (*CAR[0,90]*) cumulative abnormal return. *Number of Questions*, *Revenue Recognition*, and *Insider Sales Rank* are included to observe if the signal has power to explain returns in addition to other possible indicators of important comment letters. Refer to Appendix A for variable definitions.

3.2. Signaled Comment Letters and Financial Reporting Quality

To study the effect of signaled comment letters on financial performance, I test H3 by examining the relationship between signaled comment letters, earnings, and earnings persistence. To study the relation between earnings and signaled comment letters, I examine the following logit regression model:

$$
\begin{aligned}
I(\text{Signal})_{i,o} = {} & \beta_0 + \beta_1 I(\text{Earnings})_{i,t} + \beta_2 \text{Accruals}_{i,t-1} \\
& + \beta_3 I(\text{Dividend})_{i,t-1} + \beta_4 \text{Special Items}_{i,t-1} \\
& + \beta_5 \text{Num. Bus. Segments}_{i,t-1} + \beta_6 \text{Num. Geo. Segments}_{i,t-1} \\
& + \beta_7 I(\text{Secondary Offering})_{i,t-1} + \beta_8 I(\text{Acquisition})_{i,t-1} \\
& + \beta_9 \text{Age}_{i,t} + \beta_{10} \text{Book to Market}_{i,t-1} \\
& + \beta_{11} \log(\text{Market Capitalization})_{i,t-1} + \varepsilon_{i,t} \quad . \qquad (3)
\end{aligned}
$$

To study the relation between signaled comment letters and earnings persistence, I examine the following OLS regression model:

$$
\begin{aligned}
\text{Earnings}_{i,t} = \beta_0 &+ \beta_1 I(\text{Signal})_{i,0} + \beta_2 \text{Earnings}_{i,t-1} \\
&+ \beta_3 I(\text{Signal})_{i,0} * \text{Earnings}_{i,t-1} \\
&+ \beta_4 \text{Accruals}_{i,t-1} + \beta_5 I(\text{Dividend})_{i,t-1} + \beta_6 \text{Special Items}_{i,t-1} \\
&+ \beta_7 \text{Num. Bus. Segments}_{i,t-1} + \beta_8 \text{Num. Geo. Segments}_{i,t-1} \\
&+ \beta_9 I(\text{Secondary Offering})_{i,t-1} + \beta_{10} I(\text{Acquisition})_{i,t-1} \\
&+ \beta_{11} \text{Age}_{i,t} + \beta_{12} \text{Book to Market}_{i,t-1} \\
&+ \beta_{13} \log(\text{Market Capitalization})_{i,t-1} + \varepsilon_{i,t} \quad . \qquad (4)
\end{aligned}
$$

I also include fixed effects for year and Fama-French 49 industry membership. The fiscal year in which the comment letter is disclosed is defined as $t = 0$. These models are estimated for $t = -1$, the year before the comment letter is disclosed, $t = 0$, the year of disclosure, and $t = 1$, the year following disclosure. Firm-comment letter observations, i, are from the Naive Bayesian holdout sample with available control variables. $Signal_{i,0}$ is equal to 1 if the Naive Bayes classification model indicated importance, but 0 otherwise, and can only be evaluated at $t = 0$. The measure of earnings is return on assets (Compustat $ibadj_{i,t}/at_{i,t}$). See Appendix A for all other variable definitions. Control variables have been shown in prior literature to affect earnings persistence (e.g., Li, 2008), and are defined in Appendix A. The coefficient of interest is β_3, the interaction term between *Signal* and the prior years' earnings. If *Signal* is associated with lower earnings persistence, then β_3 will be negative.

To study the association between signaled comment letters and higher rates of material restatements, I test H4 by examining the following logit regression model:

$$
\begin{aligned}
I(\text{Restatement})_{i,t} = \beta_0 &+ \beta_1 I(\text{Signal})_{i,0} + \beta_2 I(\text{Restatement})_{i,t-1} \\
&+ \beta_3 \text{Accruals}_{i,t} + \beta_4 I(\Delta\text{Receivables})_{i,t} + \beta_5 \Delta\text{Inventory}_{i,t} \\
&+ \beta_6 \text{Soft Assets}_{i,t} + \beta_7 \text{Leverage}_{i,t} \\
&+ \beta_8 I(\text{Secondary Offering})_{i,t} + \beta_9 \Delta\text{Earnings})_{i,t} \\
&+ \beta_{10} \text{Big4}_{i,t} + \beta_{11} \text{Age}_{i,t} + \beta_{12} \text{Book to Market}_{i,t-1} \\
&+ \beta_{13} \log(\text{Market Capitalization})_{i,t-1} + \varepsilon_{i,t} \quad . \qquad (5)
\end{aligned}
$$

I also include fixed effects for year and Fama-French 49 industry membership. As with Equation 3, $t = 0$ is the fiscal year in which the firm receives a comment letter, and this model is estimated for t =-1, 0 , and 1. *Restatement*$_{i,t}$ is an indicator variable equal to 1 if Audit Analytics reports a material restatement announced during year t, but 0 otherwise. See Appendix A for all other variable definitions. Control variables have been shown in prior literature to predict restatements (e.g., Dechow et al., 2011), and are defined in Appendix A. The coefficient of interest is β_1 which will be positive if firms with signaled comment letters are more likely to materially restate their financials in year t.

To study the association between signaled comment letters and increased internal control weaknesses, I test H5 by examining the following logit regression model:

$$
\begin{aligned}
I(\text{Weakness})_{i,t} = {} & \beta_0 + \beta_1 I(\text{Signal})_{i,0} + \beta_2 I(\text{Weakness})_{i,t-1} \\
& + \beta_3 \log(\text{Market Capitalization})_{i,t-1} + \beta_4 \text{SalesGrowth}_{i,t} \\
& + \beta_5 \text{Inventory}_{i,t} + \beta_6 \text{Accruals}_{i,t} + \beta_7 \text{Leverage}_{i,t} \\
& + \beta_8 \Delta\text{Receivables}_{i,t} + \beta_9 \Delta\text{Inventory}_{i,t} + \beta_{10} \text{Soft Assets}_{i,t} \\
& + \beta_{11} I(\text{Secondary Offering})_{i,t} + \beta_{12} \Delta\text{Earnings}_{i,t} \\
& + \beta_{13} \text{Big4}_{i,t-1} + \beta_{14} \text{Age} + \beta_{15} \text{Book to Market} + \varepsilon_{i,t} \quad . \qquad (6)
\end{aligned}
$$

I also include fixed effects for year and Fama-French 49 industry membership. *Weakness*$_{i,t}$ is an indicator variable equal to 1 if Audit Analytics reports that internal controls were ineffective during year t, but 0 otherwise. This model is estimated for t =-1, 0 , and 1. Control variables have been shown in prior literature to predict restatements (e.g., Ogneva, Subramanyam, and Raghunandan, 2007), and are defined in Appendix A. The coefficient of interest is β_1 which will be positive if firms with signaled comment letters are more likely to report an internal control Weakness in year t.

4. Empirical Results

4.1. Naive Bayesian Classification Performance

Table 3 reports the effectiveness of the Naive Bayes classification model for identifying important comment letters, presenting the results given varied parameter choices. This table gives the precision of the signal to identify comment letters with subsequent bottom-quartile abnormal returns, as a first test of H1. Results are listed for the full sample (*All*) and for the sample known to have been viewed on EDGAR (*Views* > 2) in the three days post-disclosure. Stronger results for the *Views* > 2 sample provide evidence supporting H2.

The *Signal* is *CAR[0,3] (CAR[0,90])* when training documents are classified as important if cumulative abnormal return are in the bottom quartile from day 0 after disclosure through day +3 (+90). *Frequency* identifies whether the Naive Bayes classifier uses the *frequency* count of each feature, or *presence*, which assigns a value of 1 if a feature appears at least once. *Documents* refers to the number of conversations in the combined training and holdout sample (50% of the documents are used for training, and 50% for testing the classifier effectiveness). *Precision* is the ability of the classification to correctly predict the importance of a comment letter, as realized by the relevant CAR signal. The baseline precision is approximately 25 percent for full sample, because we base the signal on bottom-quartile returns, but the exact frequency in the training sample varies somewhat as the observations are randomly selected but the bottom quartile threshold value is fixed. The increase in precision column (*Inc. Prec.*) presents the percent improvement in the rate at which the model signals bottom quartile firms over the rate at which bottom quartile abnormal returns appear in the holdout sample, e.g. if important documents were identified at a rate of 27.5 percent when the baseline is 25 percent, the increase in precision is 10 percent ($(27.5-25)/25*100$ percent).

The results reported in Table 3 support H1 and H2. The models provide predictive power to signal comment letters in the holdout sample that have bottom-quartile abnormal returns following disclosure. Considering the 90-day CARs as the signal, the ability to identify important comment letters is between 10.66 percent and 40.11 percent greater than random chance. The improvement in power is significantly stronger using the 90-day CAR signal, as opposed to the three-day

CAR signal, indicating underreaction to comment letter disclosures. The three-day CAR signal appears to provide little ability to identify important comment letters (0.55 to 5.09 percent increase in precision) in the all comment letter sample, though the precision improves to 8.08 to 20.68 percent when the comment letters have above median views. For the 90-day CAR signal, precision improves from 10.66 to 15.70 percent in the all comment letter sample to 15.23 to 40.11 percent in the above median view sample. This ability to more precisely identify important comment letters when we know that they have been viewed provides evidence that H2 can also be answered in the affirmative.

A benefit of the Naive Bayesian classification procedure is that the model reveals the features that appear with greatest frequency in each class—allowing researchers to gain insight into specific features driving the classification. Table 4 provides a list of the features with the greatest frequency differential between important and unimportant comment letters. For example, the feature with the greatest ratio of frequency in important letters to frequency in unimportant letters is "continue monitor", which has a frequency of 0.08 in important comment letters but a frequency of only 0.02 in unimportant comment letters. As an example of how this term may be used in an important comment letter, consider the following excerpt from a company correspondence in the sample:

> "...We have explored different borrowing alternatives with Key Bank, the lender under that facility, and other parties, but to date determined that the terms of these alternatives were not acceptable. We *continue* to *monitor* whether credit facilities may be available to us on acceptable terms. We may also have to pursue various other strategies to secure any necessary additional financing, which may include, without

limitation, public or private offerings of debt or equity securities..."

This conversation provides evidence that management has liquidity concerns, and reveals consideration of a secondary equity offering. The three- and 90-day CAR for this firm after this comment letter conversation was disclosed was -3.1% and -35.3% respectively.

Inspecting important comment letters with features identified in the Table 4 list such as *senior management* and *payout* may indicate that broad issues such as governance plays a role in some important comment letters. Features such as *loan portfolio*, *recoveries*, *severity*, *allowance loan*, and *credit quality* indicate that financing and distress related issues may be important. These are also terms associated with management estimates, and thus examination of these issues could reflect both on the potential for restatements, as estimates are revisited, and on internal controls, which ensure reliable financial reporting and compliance with disclosure regulations.

The following empirical tests are limited to the holdout sample, and the estimated signal for important comment letters is Model 5 in Table 3, the 90-day CAR classification model with the lowest increase in precision (+10.66 percent). The following results should therefore be downward-biased if other model parameter selections result in a greater discriminatory power to identify important comment letters.

4.2. Signaled Comment Letters and Abnormal Returns

Figure 1a illustrates the mean CAR from comment letter disclosure date -10 days to +90 days, for holdout sample comment letter conversations, partitioned by the signal. 90 days after disclosure, firms whose comment letters are not signaled have a mean CAR of +1.77%, and firms with signaled comment letters have a mean CAR of -1.84%, providing support for H1. Figure 1b illustrates mean CAR over the same period for firms with above median views from the EDGAR web site. Firms with above median EDGAR views whose comment letters are not signaled have a mean CAR of -1.52% at disclosure date +90 days, and firms with signaled comment letters have a mean CAR of -9.54%, providing evidence supporting H2, that the classification is more powerful for comment letters known to have been read by investors. In addition, the lower returns for signaled comment in this setting indicates that it is not solely the investor views of the comment letters that cause the price decline, but that the signal is effective at identifying firms with lower returns.

Table 5 examines the statistical significance of abnormal return differences associated with the signal, utilizing Equation 2. I regress the signal on short term (three-day) and long term (90-day) CAR, for holdout sample firms. Columns (1) to (4) consider the ability of signal to predict three-day abnormal returns. There is no statistical significance for the signal to predict returns in Columns (1) and (2), where all comment letters are used. In Column (3) I test the set of observations where the the comment letters were viewed, and the coefficient on signal is -0.013 percent ($p < 0.05$), when no additional comment letter characteristics are included as controls. Column (4) reports a similar coefficient of -0.012 ($p < 0.1$) when controls for other features related to comment letter importance are included (e.g., Cassell et al., 2013; Dechow et al., 2015). See Appendix A for variable definitions. The results of Columns (1) to (4) imply a -1.2 to -1.3 percent abnormal return in the three-days post-comment letter disclosure for signaled comment letters, but only when the comment letters are viewed.

Columns (5) to (8) regress the signal on 90-day abnormal returns. When the comment letters were not viewed, in Columns (5) and (6), the coefficient on the signal is insignificant. When the comment letters were viewed, in Columns (7) and (8), the coefficients are negative and significant at -0.058 ($p < 0.1$) when no controls are included and -0.059 ($p < 0.05$) when controls are added. The results of Columns (5) to (8) imply a -5.8 to -5.9 percent abnormal return in the 90-days post-comment letter disclosure for signaled comment letters, but only when the comment letters were viewed. Together these results indicate that when investors are known to have viewed the comment letters, the signal predicts negative returns over both the three- and 90-day period following disclosure, jointly supporting H1 and H2.

4.3. Signaled Comment Letters, Earnings, and Earnings Persistence

Figure 2a illustrates the level of earnings for firms in the holdout sample, partitioned by the signal of comment letter importance. Firms receiving important comment letters have significantly lower—on average, negative—earnings in the year prior to the year the comment letter was disclosed ($t = -1$), compared to firms without signaled letters. Year $t-1$ is the fiscal year that the SEC reviews for the comment letter disclosed in year $t = 0$, indicating that firms with lower profits are more likely to generate signaled comment letters. Earnings tend to increase but remain negative in year $t = 0$ and $t = 1$. Table 6 reports on the difference in means for the key analysis and control variables in year $t = 0$, conditioned on the signal. Firms with lower *Earnings*, higher incidences of *Restatement*, and higher incidences of internal control (*Weakness*) are more likely to have signaled comment letters. Signaled firms also tend to have larger *Market Capitalization* ($p < 0.1$), a greater proportion of *Soft Assets* ($p < 0.05$), greater *Leverage* ($p < 0.05$), a greater *Book to Market* ratio ($p < 0.05$), a higher rate of secondary equity offerings (*Secondary Offerings*; $p < 0.05$), but lower *EDGAR Views* ($p < 0.05$), lower incidence of *Dividend* payments ($p < 0.05$), and *Special Items* ($p < 0.1$). Other characteristics are similar.

Table 7 models Equation 3 to study the relation between firms' *Earnings* and *Signal*. Columns (1) to (3) examine profitability in the year before, during and after the comment letter conversation, respectively. *Earnings* only predict *Signal* if they are low in the year prior to comment letter issuance (Column (1) coefficient on *Earnings* of -1.228 ($p < 0.01$)). Signaled comment letters do not appear to be associated with significantly different earnings in the year the comment letter is issued ($t = 0$) or the following year ($t = 1$). The marginal effect of a 1 percent decline in return on assets is a 3 percent increase in having a comment letter identified as important. While neither the SEC's stated policies nor Section 408 of SOX target firms with low earnings or losses, this result builds on Cassell et al. (2013), who note that loss firms are more likely to receive a comment letter, as this result indicates that firms with lower earnings are more likely to receive important comment letters. It does not appear that signaled comment letters help to predict lower future earnings, controlling for other determinants of profitability, the level of earnings may not be a mechanism for signaled comment letters to affect returns.

I study the relation between signaled comment letters and earnings persistence in Table 8, implementing Equation 4, including year and industry fixed effects. The coefficient on the interaction term, I(*Signal*) * $Earnings_{t-1}$, captures the change in persistence for firms receiving important comment letters. Columns (1) to (3) examine earnings persistence in the year before, during and after the comment letter conversation, respectively, for profit firm-years. The coefficient on I(*Signal*) * $Earnings_{t-1}$ in Column (1) of -0.493 ($p < 0.01$) indicates that for profit firms with signaled comment letters, earnings persistence declines in the year prior to the comment letter review. The interaction coefficient is also negative in Column (3) at -0.334 ($p < 0.01$), indicating that profit firms with signaled comment letters have lower earnings persistence in the year following the review. This finding could have a valuation impact, as information disclosed in signaled comment letters may reveal uncertainty about future earnings for profit firms. Columns (4) to (6) analyze loss firms. The interaction term in Column (4) of 0.655 ($p < 0.01$) relates to the year prior to the comment letter ($t = -1$), as firms with higher loss persistence were more likely to receive a signaled comment letter. In the year of the comment letter conversation, losses were less persistent, with the coefficient on the interaction term being -0.173 ($p < 0.05$). In the year following the comment letter conversation, reported in Column (6), the effect of signal on persistence is insignificant. Overall these results support H3, specifically that receiving a signaled comment letter is associated with a lower persistence of profits in the following year, a result that may explain some of the negative abnormal returns associated with signaled comment letters.

4.4. Signaled Comment Letters and Restatements

To study the effects of important comment letters on restatements, Table 9 gives the results of the regression model specified in Equation 5. Columns (1) to (3) used the signal and lagged restatements as the only control, including industry and year fixed effects. In Column (1), the coefficient on I(*Signal*) of 0.770 ($p < 0.01$) indicates that past restatements are positively associated with receipt of a signaled comment letter, consistent with the SEC targeting firms with material restatements, as required by SOX Section 408. The magnitude of this effect is similar to that of Column (2) where the coefficient on *Signal* of 0.745 ($p < 0.01$) indicates that important comment letters are also associated with increases in material restatements during the year of the SEC review. Column (3) indicates a lower, but still positive impact of signaled comment letters on restatements in the year following disclosure, with a coefficient on *Signal* of 0.354 ($p < 0.1$, one-tailed). Including controls in Columns (4) to (6), results are similar. In Column (6) the coefficient on *Signal* of 0.382 ($p < 0.1$, one-tailed, as we predict an increase in restatements) indicates a 47 percent increase in the odds of a restatement, a result that is not diminished by including controls shown in prior research to explain restatements. These results support H4. While the association between comment letters and past and current restatements has already been shown (e.g., Cassell et al., 2013; Dechow et al., 2015), the finding that signaled comment letters may be able to identify future restatements indicates that the review process identifies undisclosed financial reporting deficiencies. Prior research has demonstrated an effect of restatements on returns, so this association may also be a source of negative announcement returns for signaled comment letters (e.g., Hribar and Jenkins, 2004).

4.5. Signaled Comment Letters and Internal Control Weaknesses

To study the effects of important comment letters on restatements, I implement the regression model specified in Equation 6 and report the results in Table 10. Columns (1) to (3) used the signal, with lagged internal control weaknesses as the only control, including industry and year fixed effects. In Column (1), the coefficient on *Signal* of 1.123 ($p < 0.01$) indicates that past weaknesses are positively associated with receipt of a signaled comment letter. Column (2) reports no significant increase in internal control weaknesses due to the signaled comment letter, likely because any weaknesses identified in the comment letter reivew will not be disclosed until the following annual report in time $t = 1$. The coefficient on *Signal* in Column (3) is 0.551 ($p < 0.05$, one tailed, as we predict an increase in weaknesses) indicates an increase in weaknesses reported in the year following receipt of a signaled comment letter, representing an increase in the odds of reporting a material weakness of 74 percent, controlling for past internal control weakness. Columns (4) to (6) include additional control variables shown in prior literature to be associated with internal control weaknesses. Signaled comment letters in are associated with weaknesses reported in year $t - 1$, with a coefficient of 1.170 ($p < 0.01$). Column (5) reports no significant increase in weakness in the year of the signaled comment letter disclosure, similar to Column (2). Column (6) reports that the signal no longer has a significant effect on weaknesses reported in the year following, indicating that the increase in internal control weaknesses reported in the following year can be explained by the control variables. While internal control weaknesses have been shown to have an effect on returns (e.g., Hammersley et al., 2008), the limited association between signaled comment letters and internal control weaknesses indicates that even if signaled comment letters help to reveal internal control weaknesses to management and auditors, remedial steps can be taken to resolve the weaknesses prior to the next audit report.

4.6. Further Analyses

To provide evidence that the naive Bayes classification technique provides power to identify important comment letters in time-series out of sample settings, I test the robustness of the technique using documents from the first three-quarters of the sample, by disclosure date, to train the classifier, and the remaining out of sample comment letters as the holdout sample. Table 11 illustrates that the increase in precision for identifying comment letters versus random chance is generally comparable to the results from the random holdout sample reported in Table 3. Although two of the models provide no additional identification precision, the remaining six models provide an increase in precision for identifying important comment letters of between +8.45% and +61.15%.

I also investigate whether insider sales surrounding comment letter disclosure can be used to signal importance, as an alternative to market returns, for the Naive Bayes model (e.g., Dechow et al., 2015). In untabultated results, I find that the classification model is ineffective using this specification, insofar that predicted important comment letters have no greater levels of insider trading than unimportant comment letters. While market returns may be expected to give an unbiased response to new information, executive behavior may not be unbiased. Some executives may decide to sell stock surrounding the release of a comment letter that they deem important, though other executives may consider this a violation of insider trading norms. If important comment letters generate insider trades for some observations but not for others, than the Naive Bayes classification algorithm would have difficulty distinguishing the text features of the important comment letters.

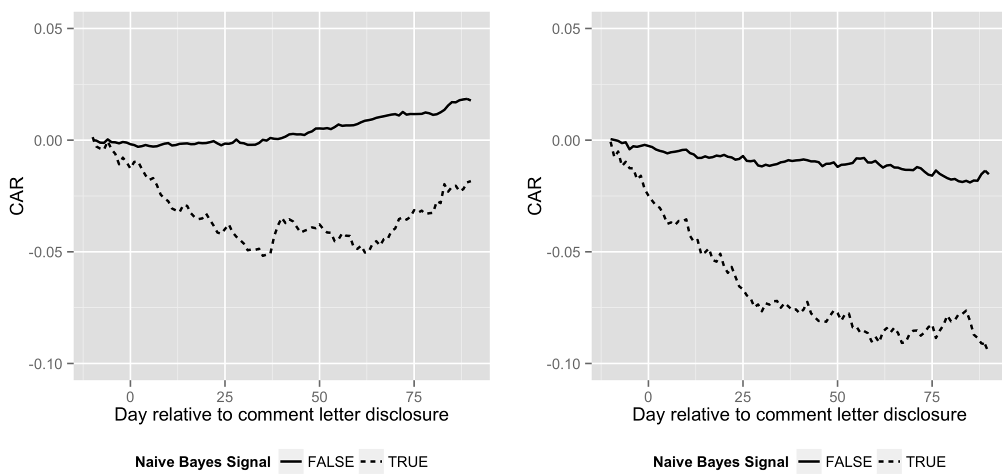
5. Conclusions

This study uses Naive Bayesian text classification to signal important SEC comment letters, using negative stock returns following disclosure as the measure of importance. The resulting signal is used on a holdout sample of comment letters, to demonstrate that text analysis is effective (10 to 40 percent more precise than chance) at identifying comment letters associated with negative abnormal returns. I study the effects of signaled comment letters on returns, and find some evidence of underreaction to comment letters, as the signal is only predictive of abnormal returns for comment letters that were known to be viewed on EDGAR in the days immediately after disclosure. For firms with above-median comment letter views, abnormal returns following signaled disclosure is significantly more negative 90 days after disclosure (-5.8 percent) than three days after disclosure (-1.3 percent). I study the effect of signaled comment letters on earnings and earnings persistence, noting lower persistence of profits in the year before and the year following signaled comment letters. I study the effect of signaled comment letters on material restatements, finding higher levels of material restatements both in the year before and the year after signaled comment letters. Signaled comment letters are related to internal control weaknesses the year prior to the SEC review, however future weaknesses do not appear to be explained by signaled comment letters. The implications of this study are that comment letters can be used to identify firms with undisclosed performance and financial disclosure deficiencies, supporting their use as a source of information about firms' financial reporting and audit quality.

Figure 1: Comment Letter Disclosure Cumulative Abnormal Returns

(a) Holdout Sample

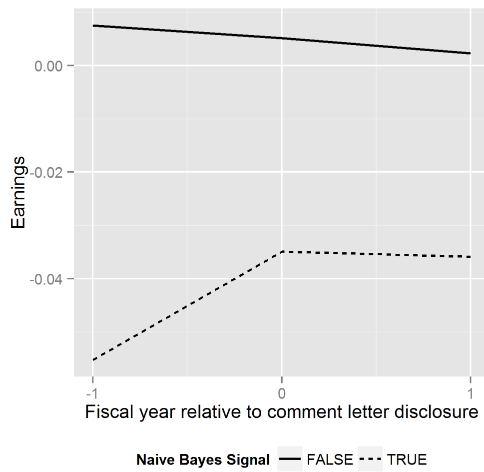
(b) Holdout Sample Views > 2



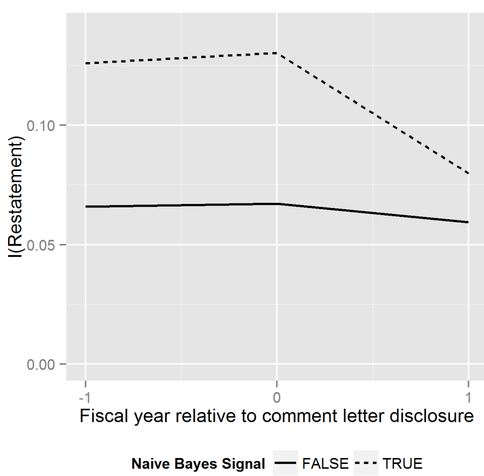
This figure illustrates cumulative abnormal returns from ten days prior to 90 days after disclosure of holdout sample comment letters, partitioned on the Naive Bayes signal of importance. Panel A illustrates the results for all firms, and Panel B illustrates the results for firms whose comment letters were observed to be viewed on the EDGAR web site more that twice in the three days following disclosure. Refer to Appendix A for variable definitions.

Figure 2: Earnings, Restatements, and Internal Control Weaknesses for Fiscal Years Surrounding Comment Letter Disclosure

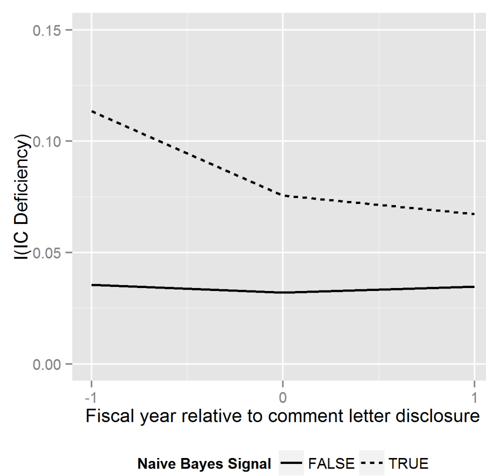
(a) Earnings, Partitoned by *Signal*



(b) Incidence of Restatments, Partitioned by *Signal*



(c) Incidence of Internal Control Weaknesses, Partitioned by *Signal*



This figure illustrates the differences in financial performance and reporting quality variables for holdout sample firms in the year before ($t = -1$), the year of ($t = 0$), and the year after ($t = 1$) comment letter disclosure, partitioned by the signal of importance. Panel a illustrates the difference in earnings for signaled comment letter firms. Panel b illustrates the difference in the rate of material restatements for signaled comment letter firms. Panel c illustrates the difference in internal control weaknesses for signaled comment letter firms. Refer to Appendix A for variable definitions.

Table 1: Textual Analysis Sample Descriptive Statistics

(a) All 10-K Comment Letters

	N	mean	sd	q10	q25	median	q75	q90
Market Capitalization	6,566	6,020	22,557	60	189	809	3,358	11,697
Book to Market	6,566	0.650	0.671	0.145	0.291	0.511	0.832	1.278
CAR[0,3]	6,566	-0.000	0.071	-0.059	-0.027	-0.003	0.021	0.055
CAR[0,90]	6,566	0.018	0.479	-0.372	-0.196	-0.036	0.127	0.390
Number of Questions	6,566	6.513	6.554	1.000	2.000	5.000	8.000	13.000
Conversation Items	6,566	4.912	2.514	3.000	3.000	4.000	6.000	8.000
Revenue Recognition	6,566	0.200	0.400	0.000	0.000	0.000	0.000	1.000
Insider Sales (% of shares out.)	6,566	0.052	0.421	0.000	0.000	0.000	0.000	0.062
EDGAR Views	6,566	2.164	2.605	0.000	1.000	2.000	3.000	4.000

(b) Above Median View 10-K Comment Letters

	N	mean	sd	q10	q25	median	q75	q90
Market Capitalization	2,546	8,026	25,680	68	226	1,020	4,617	16,787
Book to Market	2,546	0.664	0.687	0.144	0.296	0.523	0.858	1.340
CAR[0,3]	2,546	-0.002	0.076	-0.058	-0.028	-0.004	0.019	0.050
CAR[0,90]	2,546	-0.020	0.391	-0.360	-0.197	-0.051	0.096	0.295
Number of Questions	2,546	6.896	6.637	1.000	3.000	5.000	9.000	14.000
Conversation Items	2,546	4.944	2.421	3.000	3.000	5.000	6.000	8.000
Revenue Recognition	2,546	0.165	0.372	0.000	0.000	0.000	0.000	1.000
Insider Sales (% of shares out.)	2,546	0.052	0.456	0.000	0.000	0.000	0.000	0.050
EDGAR Views	2,546	3.992	3.323	3.000	3.000	3.000	4.000	5.000

This table presents descriptive statistics for all comment letter firms used in the textual classification sample in Panel a and the subset of firms with above median EDGAR views (> 2) in Panel b. Refer to Appendix A for variable definitions.

Table 2: Earnings, Restatement, and Internal Control Sample Descriptive Statistics

	N	mean	sd	q10	q25	median	q75	q90
Naive Bayes Signal	2,544	0.094	0.291	0.000	0.000	0.000	0.000	0.000
CAR[0,3]	2,544	0.001	0.082	-0.055	-0.027	-0.003	0.020	0.056
CAR[0,90]	2,544	0.016	0.494	-0.362	-0.198	-0.038	0.123	0.373
Earnings	2,544	0.001	0.182	-0.123	0.001	0.032	0.077	0.121
I(IC Deficiency)	2,544	0.036	0.187	0.000	0.000	0.000	0.000	0.000
I(Restatement)	2,544	0.073	0.260	0.000	0.000	0.000	0.000	0.000
EDGAR Views	2,544	2.256	3.503	0.000	1.000	2.000	3.000	4.000
Market Capitalization	2,544	7,907	28,661	61	209	981	3,970	14,722
ΔReceivables	2,544	-0.002	0.043	-0.040	-0.015	-0.000	0.012	0.034
ΔInventory	2,544	0.000	0.027	-0.019	-0.003	0.000	0.004	0.021
Soft Assets	2,544	0.591	0.261	0.195	0.393	0.622	0.812	0.930
Leverage	2,544	3.067	5.336	0.215	0.580	1.559	3.560	8.820
Book to Market	2,544	0.666	0.637	0.163	0.305	0.511	0.827	1.302
I(Dividend)	2,544	0.463	0.499	0.000	0.000	0.000	1.000	1.000
I(Acquisition)	2,544	0.123	0.328	0.000	0.000	0.000	0.000	1.000
ΔEarnings	2,544	-0.000	0.149	-0.085	-0.022	0.000	0.022	0.085
Sales Growth	2,544	0.085	0.260	-0.168	-0.035	0.067	0.179	0.344
Accruals	2,544	-0.019	0.083	-0.100	-0.048	-0.008	0.018	0.055
Special Items	2,544	-0.014	0.052	-0.032	-0.009	-0.000	0.000	0.002
Business Segments	2,544	2.281	1.736	1.000	1.000	1.000	3.000	5.000
Geographic Segments	2,544	2.697	2.588	1.000	1.000	2.000	4.000	6.000
I(Secondary Offering)	2,544	0.058	0.233	0.000	0.000	0.000	0.000	0.000
Age	2,544	18.131	8.998	6.000	11.000	17.000	27.000	31.000
I(Big4)	2,544	0.789	0.408	0.000	1.000	1.000	1.000	1.000

This table presents descriptive statistics for all comment letter firms the holdout sample with sufficient data for tests of earnings persistence, the incidence of restatements, and the incidence of internal control weaknesses. *Signal* indicates that the comment letter was identified as important by the Naive Bayesian classification. Refer to Appendix A for variable definitions.

Table 3: Naive Bayes Classification Performance

	Signal	Sample	Frequency	Documents	Precision (%)	Inc. Prec. (%)
1	CAR[0,3]	All	frequency	6,566	24.93	0.55
2	CAR[0,3]	All	presence	6,566	26.06	5.09
3	CAR[0,3]	Views > 2	frequency	2,546	28.27	8.08
4	CAR[0,3]	Views > 2	presence	2,546	31.57	20.68
5	CAR[0,90]	All	frequency	6,566	28.82	10.66
6	CAR[0,90]	All	presence	6,566	30.13	15.70
7	CAR[0,90]	Views > 2	frequency	2,546	32.47	40.11
8	CAR[0,90]	Views > 2	presence	2,546	26.70	15.23

This table presents the effectiveness of the Naive Bayes classifier where the training documents are a random sample of 50 percent of the conversations, selected from the entire sample period. The feature set used is all unigrams + bigrams (all single words as well as all consecutive two word sequences) that appear in more than 5 percent or more of the sample documents. *Signal* refers to the measure used to identify important comment letters in the training sample (50 percent of documents): *CAR[0,3]* signals an important comment letter if the cumulative abnormal return is in the bottom quartile of returns from disclosure day 0 to disclosure day +3, and *CAR[0,90]* signals an important comment letter if the cumulative abnormal return is in the bottom quartile of returns from disclosure day 0 to disclosure day +90. Classification testing is run on *All* comment letter conversations, or on only those that are known to have been viewed on EDGAR more than the median number of times in the three days after disclosure (*Views* > 2). *Frequency* refers to whether the classifier uses the *frequency* or the count of the number of times each feature appears in the document, or *presence*, which equals 1 if the feature is present at least once in the document. *Documents* is the number of conversations in the combined training and testing sample (50% of the documents are used for training, and 50% for testing the classifier effectiveness). *Precision* refers to the fraction of comment letter conversations classified as important in the test sample that did in fact have bottom quartile CAR per the relevant signal. The increase in precision *Inc. Prec.* is the percentage increase in the fraction of comment letters identified as important the fraction occurring in the test sample, and represents the ability of the Naive Bayes classifier to identify important comment letters versus random chance.

Table 4: Terms with Greatest Frequency Differential Between Signaled Important and Unimportant Comment Letters

	Feature	Freq. Important	Freq. Unimportant	Ratio
1	continue monitor	0.08	0.02	4.78
2	quantitatively	0.10	0.02	4.27
3	straightline	0.13	0.03	3.94
4	severity	0.24	0.07	3.29
5	income continuing	0.19	0.06	2.94
6	rental	0.49	0.17	2.93
7	loan portfolio	0.37	0.13	2.84
8	accounting guidance	0.21	0.07	2.81
9	recoveries	0.19	0.07	2.78
10	brand	0.32	0.11	2.78
11	allowance loan	0.74	0.27	2.75
12	pension	0.67	0.25	2.72
13	commodity	0.31	0.11	2.70
14	real estate	1.77	0.66	2.68
15	estate	1.92	0.72	2.67
16	revised disclosures	0.13	0.05	2.66
17	leased	0.22	0.08	2.65
18	publicly traded	0.11	0.04	2.62
19	historical experience	0.15	0.06	2.61
20	senior management	0.23	0.09	2.61
21	payout	0.75	0.29	2.57
22	revising	0.13	0.05	2.55
23	credit quality	0.25	0.10	2.54
24	note consolidated	0.13	0.05	2.53
25	real	1.97	0.78	2.52
26	effective tax	0.39	0.15	2.51
27	safety	0.56	0.23	2.47
28	prior period	0.18	0.07	2.47
29	revenues expenses	0.06	0.03	2.41
30	monitor	0.37	0.16	2.37

This table presents the training sample features with the greatest difference in frequencies among documents signaled as important and unimportant based on having bottom-quartile 90-day post-disclosure abnormal returns. For example, feature (1), *continue monitor*, appears with a frequency of 0.08 per conversation in important documents, but with a frequency of only 0.02 in unimportant documents, thus it appears 4.78 times more frequently in important than in unimportant documents.

Table 5: Signaled Comment Letters and Abnormal Returns

	CAR[0,3]				CAR[0,90]			
	All	All	Views > 2	Views > 2	All	All	Views > 2	Views > 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Signal)	0.008	0.007	-0.013^{**}	-0.012^{*}	0.012	0.018	-0.058^{*}	-0.059^{**}
	(1.228)	(1.021)	(−2.103)	(−1.918)	(0.343)	(0.493)	(−1.936)	(−1.963)
Num. questions		0.0003		0.00003		-0.002^{*}		0.001
		(1.514)		(0.115)		(−1.775)		(0.309)
Revenue recognition		−0.005		-0.009^{*}		0.040		−0.020
		(−1.510)		(−1.846)		(1.461)		(−0.780)
Insider sales rank		−0.001		0.001		-0.022^{***}		-0.016^{**}
		(−0.908)		(0.755)		(−4.137)		(−2.243)
Constant	0.001	0.001	−0.002	−0.003	0.011	0.053^{***}	−0.007	0.020
	(0.390)	(0.318)	(−0.791)	(−0.527)	(1.297)	(3.071)	(−0.547)	(0.721)
Observations	3,283	3,283	1,273	1,273	3,283	3,283	1,273	1,273
Adjusted R^2	0.0004	0.001	0.001	0.001	−0.0003	0.003	0.001	0.001

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table presents regression results for Equation 2, using all observations in the holdout sample in Columns (1), (2), (5), and (6), and the subset of observations with above median EDGAR views (> 2) in Columns (3), (4), (7), and (8). Standard errors are robust. Columns (1) to (4) utilize three-day CAR as the dependent variable, and Columns (5) to (8) utilize 90-day CAR as the dependent variable. Refer to Appendix A for variable definitions.

Table 6: Characteristics of Signaled Comment Letter Firms

	N.B. Signal=1	N.B. Signal=0	Difference	
CAR[0,3]	0.010	0.000	0.009	
CAR[0,90]	0.011	0.016	-0.005	
Earnings	-0.035	0.005	-0.040	***
I(IC Deficiency)	0.076	0.032	0.044	**
I(Restatement)	0.130	0.067	0.063	***
EDGAR Views	2.008	2.281	-0.273	**
Market Capitalization	11,824.090	7,503.800	4,320.290	*
ΔReceivables	-0.001	-0.002	0.001	
ΔInventory	0.001	0.000	0.000	
Soft Assets	0.627	0.587	0.040	**
Leverage	3.928	2.978	0.951	**
Book to Market	0.779	0.654	0.125	**
I(Dividend)	0.395	0.471	-0.076	**
I(Acquisition)	0.134	0.121	0.013	
ΔEarnings	0.020	-0.002	0.023	
Sales Growth	0.110	0.082	0.027	
Accruals	-0.018	-0.019	0.001	
Special Items	-0.021	-0.013	-0.008	*
Business Segments	2.168	2.292	-0.124	
Geographic Segments	2.479	2.719	-0.240	
I(Secondary Offering)	0.105	0.053	0.052	**
Age	17.546	18.191	-0.645	
I(Big4)	0.765	0.791	-0.027	

This table compares differences in means of key variables for holdout sample firms with comment letters, conditioned on the Naive Bayesian classification signaling an important comment letter. Variables are measured at the end of the fiscal year in which the comment letter is disclosed ($t = 0$). N = 238 observations where the Naive Bayesian Signal is 1 and N = 2,306 observations where it is 0. Refer to Appendix A for variable definitions.

Table 7: Signaled Comment Letters and Earnings

	I(Signal)$_0$		
	t=-1	t=0	t=1
	(1)	(2)	(3)
Intecept	-34.080	-34.212	-34.199
	(-0.008)	(-0.008)	(-0.008)
Earnings$_t$	-1.228^{***}	0.085	-0.323
	(-2.734)	(0.172)	(-0.727)
Accruals$_t$	-0.041	0.463	0.472
	(-0.047)	(0.473)	(0.485)
I(Dividend)$_t$	-0.321^{*}	-0.273	-0.376^{**}
	(-1.673)	(-1.414)	(-1.987)
Special Items$_t$	1.221	-2.636^{*}	-0.361
	(0.839)	(-1.842)	(-0.244)
Business Segments$_t$	0.027	0.024	0.035
	(0.579)	(0.508)	(0.748)
Geographic Segments$_t$	-0.025	-0.031	-0.034
	(-0.699)	(-0.885)	(-0.995)
I(Secondary Offering)$_t$	-0.251	0.597^{**}	0.171
	(-0.772)	(2.054)	(0.538)
I(Acquisition)$_t$	0.011	0.183	-0.192
	(0.048)	(0.837)	(-0.830)
Age$_t$	0.004	0.004	0.002
	(0.379)	(0.436)	(0.193)
Book to Market$_{t-1}$	0.348^{***}	0.313^{**}	0.389^{***}
	(2.761)	(2.488)	(3.298)
Log(Market Capitalization)$_{t-1}$	0.069	0.047	0.077^{*}
	(1.526)	(1.029)	(1.708)
Observations	2,544	2,544	2,544
Pseudo R^2	0.075	0.074	0.074

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table presents results of the Equation 3 logit regression of *Earnings* on *Signal*, the Naive Bayesian signal of comment letter importance, for holdout sample firms, including industry and year fixed effects. Year $t = -1$ is the fiscal year prior to comment letter disclosure, and is the year under review by the SEC, year $t = 0$ is the year of disclosure, and $t = 1$ is the year following. Refer to Appendix A for variable definitions.

Table 8: Signaled Comment Letters and Earnings Persistence

	Earnings$_t$ (Profit Firms)			Earnings$_t$ (Loss Firms)		
	t=-1	t=0	t=1	t=-1	t=0	t=1
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.028	−0.012	0.012	−0.027	−0.077	0.038
	(−0.277)	(−0.143)	(0.123)	(−0.356)	(−0.338)	(0.156)
I(Signal)$_0$	0.026**	−0.009	0.010	0.064**	−0.005	0.038
	(2.329)	(−1.066)	(1.041)	(2.335)	(−0.157)	(1.074)
Earnings$_{t-1}$	0.727***	0.595***	0.765***	0.573***	0.656***	0.641***
	(15.701)	(15.969)	(17.586)	(14.231)	(11.809)	(12.028)
I(Signal)$_0$ * Earnings$_{t-1}$	−0.493***	−0.019	−0.334***	0.655***	−0.173**	0.144
	(−3.875)	(−0.174)	(−2.807)	(8.387)	(−2.182)	(1.449)
Accruals$_{t-1}$	−0.147***	0.010	0.014	−0.278***	−0.185**	−0.170*
	(−4.462)	(0.348)	(0.443)	(−3.569)	(−2.223)	(−1.760)
I(Dividend)$_{t-1}$	0.015***	0.011***	0.009*	0.014	0.016	−0.014
	(2.773)	(2.629)	(1.960)	(0.603)	(0.562)	(−0.440)
Special Items$_{t-1}$	−0.305**	−0.666***	−0.937***	−0.755***	−0.750***	−0.775***
	(−2.484)	(−6.996)	(−8.068)	(−7.175)	(−6.291)	(−5.974)
Business Segments$_{t-1}$	0.002	−0.0005	−0.0003	0.007	−0.003	−0.0003
	(1.377)	(−0.445)	(−0.235)	(1.232)	(−0.466)	(−0.046)
Geographic Segments$_{t-1}$	−0.002	0.0002	0.001	0.001	0.008*	0.001
	(−1.612)	(0.288)	(1.131)	(0.198)	(1.833)	(0.194)
I(Secondary Offering)$_{t-1}$	−0.049***	−0.047***	0.012	−0.041*	−0.085***	−0.078**
	(−4.250)	(−4.599)	(0.974)	(−1.763)	(−2.865)	(−2.525)
I(Acquisition)$_{t-1}$	0.001	−0.005	−0.008	−0.019	0.004	−0.035
	(0.132)	(−0.975)	(−1.413)	(−0.708)	(0.135)	(−1.066)
Age$_{t-1}$	0.0003	−0.0001	−0.00004	0.0004	0.001	0.002
	(1.176)	(−0.303)	(−0.156)	(0.418)	(1.028)	(1.472)
Book to Market$_{t-1}$	−0.040***	−0.028***	−0.018***	−0.022*	−0.013	−0.009
	(−6.554)	(−6.074)	(−3.878)	(−1.867)	(−0.888)	(−0.636)
Log(Market Cap.)$_{t-1}$	0.002*	0.004***	0.004***	−0.003	0.006	0.017**
	(1.779)	(4.267)	(3.304)	(−0.565)	(0.911)	(2.448)
Observations	1,871	1,899	1,925	673	645	619
Adjusted R^2	0.241	0.283	0.260	0.508	0.433	0.434

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table presents results of the Equation 4 OLS regression of I(*Signal*), $Earnings_{t-1}$, and I(*Signal*) * $Earnings_{t-1}$ on $Earnings_t$, for holdout sample firms, including industry and year fixed effects. Standard errors are robust. Profit firms are shown in Columns (1) to (3) and loss firms are shown in Columns (4) to (6). Year $t = -1$ is the fiscal year prior to comment letter disclosure, and is the year under review by the SEC, year $t = 0$ is the year of disclosure, and $t = 1$ is the year following. Refer to Appendix A for variable definitions.

Table 9: Signaled Comment Letters and Restatements

	I(Restatement)$_t$					
	t=-1	t=0	t=1	t=-1	t=0	t=1
	(1)	(2)	(3)	(4)	(5)	(6)
I(Signal)$_0$	0.770***	0.745***	0.354*	0.740***	0.692***	0.382*
	(3.467)	(3.376)	(1.332)	(3.300)	(3.054)	(1.414)
I(Restatement)$_{t-1}$	0.084	0.567**	0.491*	0.080	0.523**	0.425
	(0.322)	(2.242)	(1.781)	(0.304)	(2.051)	(1.525)
Accruals$_t$				0.617	−1.226	−0.574
				(0.603)	(−1.234)	(−0.505)
ΔReceivables$_t$				−2.200	3.170*	−0.148
				(−1.269)	(1.947)	(−0.090)
ΔInventory$_t$				−0.312	−0.769	1.927
				(−0.131)	(−0.261)	(0.764)
Soft Assets$_t$				0.404	0.409	−0.173
				(0.911)	(0.948)	(−0.370)
Leverage$_t$				−0.004	0.010	0.008
				(−0.199)	(0.607)	(0.497)
I(Secondary Offering)$_t$				0.408	0.570*	0.566
				(1.221)	(1.864)	(1.592)
ΔEarnings$_t$				−0.683	0.608	0.251
				(−1.215)	(1.225)	(0.464)
I(Big4)$_t$				0.280	0.117	0.895***
				(1.201)	(0.532)	(3.353)
Age$_t$				−0.001	0.007	−0.005
				(−0.074)	(0.678)	(−0.436)
Book to Market$_{t-1}$				0.182	−0.070	−0.047
				(1.143)	(−0.433)	(−0.309)
Log(Market Cap.)$_{t-1}$				−0.075	−0.183***	−0.204***
				(−1.399)	(−3.294)	(−3.385)
Intecept	3.740	−33.004	4.071	3.900	−31.747	5.329
	(0.001)	(−0.007)	(0.001)	(0.001)	(−0.007)	(0.001)
Observations	2,544	2,544	2,544	2,544	2,544	2,544
Pseudo R^2	0.061	0.070	0.069	0.069	0.092	0.091

*p<0.1; **p<0.05; ***p<0.01

This table presents results of the Equation 5 OLS regression of I(*Signal*) on I(*Restatement*)$_t$, for holdout sample firms, including industry and year fixed effects. Standard errors are robust, and significance is one-tailed for I(*Signal*) as it is expected to increase restatements, and two-tailed for all other variables. Columns (1) to (3) include only the signal and lagged restatements as predictor variables, and Columns (4) to (6) include controls shown in prior literature to affect restatements. Year $t = -1$ is the fiscal year prior to comment letter disclosure, and is the year under review by the SEC, year $t = 0$ is the year of disclosure, and $t = 1$ is the year following. Refer to Appendix A for variable definitions.

Table 10: Signaled Comment Letters and Internal Control Weaknesses

	I(Weakness)$_t$					
	t=-1	t=0	t=1	t=-1	t=0	t=1
	(1)	(2)	(3)	(4)	(5)	(6)
I(Signal)$_0$	1.123***	0.388	0.551**	1.170***	0.280	0.377
	(4.222)	(1.171)	(1.716)	(4.192)	(0.801)	(1.076)
I(Weakness)$_{t-1}$	2.460***	3.212***	2.750***	2.361***	3.141***	2.407***
	(9.975)	(11.137)	(9.440)	(9.163)	(10.152)	(7.673)
Sales Growth$_t$				−0.471	−0.402	−0.049
				(−1.161)	(−0.858)	(−0.119)
Inventory$_t$				0.382	−0.592	−1.191
				(0.265)	(−0.364)	(−0.849)
Accruals$_t$				−1.324	0.080	−2.479*
				(−1.051)	(0.058)	(−1.861)
Leverage$_t$				0.034	0.059***	0.053***
				(1.410)	(3.090)	(2.905)
ΔReceivables$_t$				−3.502	−3.939	6.436***
				(−1.566)	(−1.577)	(2.842)
ΔInventory$_t$				−2.495	4.548	−0.826
				(−0.969)	(1.007)	(−0.267)
Soft Assets$_t$				−0.044	0.335	0.149
				(−0.071)	(0.525)	(0.238)
I(Secondary Offering)$_t$				−0.091	−0.274	0.583
				(−0.210)	(−0.572)	(1.292)
ΔEarnings$_t$				−1.960***	0.696	0.534
				(−2.814)	(0.998)	(0.882)
I(Big4)$_t$				−0.574**	0.117	−0.466
				(−2.001)	(0.357)	(−1.528)
Age$_t$				−0.009	−0.027	−0.014
				(−0.574)	(−1.633)	(−0.915)
Book to Market$_{t-1}$				−0.035	0.302	0.098
				(−0.168)	(1.381)	(0.535)
Log(Market Cap.)$_{t-1}$				−0.206**	−0.215**	−0.290***
				(−2.471)	(−2.393)	(−3.181)
Intecept	20.349	−40.405	−36.443	23.050	−37.805	−32.847
	(0.002)	(−0.003)	(−0.003)	(0.002)	(−0.003)	(−0.003)
Observations	2,544	2,544	2,544	2,544	2,544	2,544
Pseudo R^2	0.220	0.259	0.175	0.274	0.303	0.258

*p<0.1; **p<0.05; ***p<0.01

This table presents results of the Equation 6 OLS regression of I(*Signal*) on I(*Weakness*)$_t$, for holdout sample firms, including industry and year fixed effects. Standard errors are robust, and significance is one-tailed for I(*Signal*) as it is expected to increase weaknesses, and two-tailed for all other variables. Columns (1) to (3) include only the signal and lagged internal controls weakness as predictor variables, and Columns (4) to (6) include controls shown in prior literature to affect internal controls weakness. Year $t = -1$ is the fiscal year prior to comment letter disclosure, and is the year under review by the SEC, year $t = 0$ is the year of disclosure, and $t = 1$ is the year following. Refer to Appendix A for variable definitions.

Table 11: Naive Bayes Classification Performance for Time Based Training Sample

	Signal	Sample	Frequency	Documents	Precision (%)	Inc. Prec. (%)
1	CAR[0,3]	All	frequency	6,566	24.42	10.02
2	CAR[0,3]	All	presence	6,566	31.75	43.05
3	CAR[0,3]	Views > 2	frequency	2,546	18.37	-5.00
4	CAR[0,3]	Views > 2	presence	2,546	20.97	8.45
5	CAR[0,90]	All	frequency	6,566	20.12	-2.73
6	CAR[0,90]	All	presence	6,566	33.33	61.15
7	CAR[0,90]	Views > 2	frequency	2,546	24.00	12.18
8	CAR[0,90]	Views > 2	presence	2,546	24.24	13.31

This table presents the effectiveness of the Naive Bayes classifier, where the training documents are the first 50 percent selected by date disclosed. The feature set used is all unigrams + bigrams (all single words as well as all consecutive two word sequences) that appear in more than 5 percent or more of the sample documents. *Signal* refers to the measure used to identify important comment letters in the training sample (50 percent of documents): *CAR[0,3]* signals an important comment letter if the cumulative abnormal return is in the bottom quartile of returns from disclosure day 0 to disclosure day +3, and *CAR[0,90]* signals an important comment letter if the cumulative abnormal return is in the bottom quartile of returns from disclosure day 0 to disclosure day +90. Classification testing is run on *All* comment letter conversations, or on only those that are known to have been viewed on EDGAR more than the median number of times in the three days after disclosure (*Views* > 2). *Frequency* refers to whether the classifier uses the *frequency* or the count of the number of times each feature appears in the document, or *presence*, which equals 1 if the feature is present at least once in the document. *Documents* is the number of conversations in the combined training and testing sample (50 percent of the documents are used for training, and 50 percent for testing the classifier effectiveness). *Precision* refers to the fraction of comment letter conversations classified as important in the test sample that did in fact have bottom quartile CAR per the relevant signal. The increase in precision *Inc. Prec.* is the percentage increase in the fraction of comment letters identified as important the fraction occurring in the test sample, and represents the ability of the Naive Bayes classifier to identify important comment letters versus random chance.

Appendix A. Variable Definitions

Variable	Definition
Accruals	Operating earnings - cash flow from operations, normalized by total assets (Compustat $(oiadp - oancf)/at$.
I(Acquisition)	Indicator variable if the firm made a material acquisition (greater than 5 percent of assets) during the fiscal year (Compustat 1 if $acq/at > 0.05$ but 0 otherwise).
Age	Number of years the firm has appeared in the Compustat annual file.
I(Big4)	Indicator variable if the firm had a material issuance of equity during the fiscal year (Compustat 1 if $au < 9$ but 0 otherwise).
Book to Market	Book value of equity divided by market value of equity (Compustat $seq/(csho * prcc_f)$), winsorized at the one percent level.
Business Segments	Number of business segments (Compustat segment file *stype*="BUSSEG").
CAR[0,3]	Three day cumulative abnormal return from the close prior to comment letter disclosure date through the close three trading days after the disclosure date. Calculation details are described in Section **??**.
CAR[0,90]	90 day cumulative abnormal return from the close prior to comment letter disclosure date through the close 90 trading days after the disclosure date. Calculation details are described in Section **??**.
Conversation Items	Number of total letters (Form UPLOAD) and company responses (Form CORRESP) in the comment letter conversation.
I(Dividend)	Indicator variable if the firm paid a dividend during the fiscal year (Compustat 1 if $dvc > 0$ but 0 otherwise).
Earnings	Income before extraordinary items - adjusted for common stock equivalents normalized by total assets, winsorized at the one percent level (Compustat $ibadj/at$).
ΔEarnings	Earnings_t - Earnings_{t-1}.

Continued.

Variable	Definition
EDGAR Views	Number of document downloads of the first comment letter (Form UPLOAD) in a conversation (SEC EDGAR web log files).
Geographic Segments	Number of geographic segments (Compustat segment file *stype*="GEOSEG").
I(Weakness)	Indicator variable if an internal control Weakness is reported at the fiscal year end (Audit Analytics). 1 if NOTEFF_ACC_RULE=1 or NOTEFF_FIN_FRAUD=1 or NOTEFF_OTHER=1 or NOTEFFERRORS=1.
Insider Sales	Insider sales as a percentage of shares outstanding. Sum of the number of shares (SHARES) sold from disclosure date -15 days to disclosure date +15 days for officers and directors having ROLECODE of CEO, D, O, H, DO, OD, VC, OB, OP, OT, CB, AV, CFO, CI, CO, CT, EVP, OX, P, S, SVP, VP (Thompson Reuters Insider Trading), divided by shares outstanding at the prior year end (Compustat *csho*) * 100.
Insider Sales Rank	Equals 1 if Insider Sales is 0, and is set to 2 to 5 for firms with Insider Sales in the first to fourth quartile of non-zero insider sales.
Inventory	Inventory as a fraction of total assets, winsorized at the one percent level (Compustat $invt/at$)
ΔInventory	Change in inventories as a fraction of total assets, winsorized at the one percent level (Compustat $invt_t/at_t - invt_{t-1}/at_{t-1}$)
Leverage	Debt to equity (Compustat $(dltt + lt)/seq$).
Market Capitalization	Market capitalization of common equity ($ millions) (Compustat $csho * prcc_f$).
Number of Questions	Number of itemized questions asked by the SEC in the first comment letter of the conversation. The methodology for determining the number of questions is described in Appendix B
ΔReceivables	Change in receivables as a fraction of total assets, winsorized at the one percent level (Compustat $rect_t/at_t - rect_{t-1}/at_{t-1}$)

Continued.

Variable	Definition
I(Restatement)	Indicator variable if a material restatement was announced during the fiscal year (Audit Analytics).
I(Revenue Recognition)	Indicator variable if revenue recognition questions are asked by the SEC in the first comment letter of the conversation. The methodology for determining if a revenue recognition question is present is described in Appendix B
Sales Growth	Sales growth, winsorized at the one percent level (Compustat $(sale_t - sale_{t-1})/sale_{t-1}$)
I(Secondary Offering)	Indicator variable if the firm had a material issuance of equity during the fiscal year (Compustat 1 if $sstk/at > 0.1$ but 0 otherwise).
I(Signal)	Indicator variable if the Naive Bayesian classification algorithm identifies a comment letter conversation as *important*, based on the methodology discussed in Section 3.1. The classification settings are: Unigram+Bigram feature set, term frequency, and bottom quartile of CAR[0,90] by year as the signal of importance for the training comment letters.
Soft Assets	Fraction of assets that are neither cash nor property, plant, and equipment, winsorized at the one percent level (Compustat $(at - ppent - che)/at$.
Special Items	Special items as a fraction of total assets winsorized at the one percent level (Compustat spi/at).

Appendix B. Comment Letter Preparation

1. Remove common english "stop words", i.e. frequent words that are ineffective in distinguishing important from unimportant documents:

   a, about, above, after, again, against, all, am, an, and, any, are, as, at, be, because, been, before, being, below, between, both, but, by, cannot, could, couldn't, did, do, does, doing, down, during, each, few, for, from, further, had, has, have, having, he, her,here, hers, herself, him, himself, his, how, i, if, in, into, is, it, its, itself, me, more, most, my, myself, no, nor, not, of, off, on, once, only, or, other, ought, our, ours, ourselves, out, over, own, same, she, should, so, some, such, than, that, the, their, theirs, them, themselves, then, there, these, they, they've, this, those, through, to, too, under, until, up, very, was, we, were, what, when, where, which, while, who, whom, why, with, would, you, your, yours, yourself, yourselves

2. Determine if document is related to a Form 10-K: Text between the string `"Re:"` and `"Dear "` contains the string `"Form 10-K "`

3. Count the number of questions in the first comment letter:
   Identify paragraphs that begin with the regular expression

   ```
   "( |\n|\t)([1-9][.]|[1-9][)]|[1-9][0-9][.]|[1-9][0-9][)])
   (Please|We|It|Pursuant|Refer|In|To|Revise|Tell|You|
   On|The|Discuss|For|Although|Further|If|Describe)"
   ```

   This extracts a list of questions, as well as the number at the beginning of each question (e.g., {"3", "3. Please revise your discussion of..."}). The number of items in the list is compared to the extracted number of the final question, and if there is a disagreement, the smaller number is selected. I manually check 100 documents and find that this method identifies the number of comments exactly correctly in 90% of documents, and the total number of questions identified is 96% accurate.

4. Identify revenue recognition related comment: True if text between `"Dear "` and the end of the document satisfies the regular expression

```
"([Rr]evenue [Rr]ecognition)|([Rr]ecognize [Rr]evenue)|
(ASC 605)|(SAB 101)|(SAB 104)|(EITF 99-19)|(FAS 48)|
(EITF 01-9)|(FAS 45)|(SOP 97-2)|(SOP 98-9)|(EITF 00-21)|
(EITF 08-1)|(EITF 08-2)|(EITF 08-9)|(EITF 01-3)|(EITF 00-24)|
(EITF 95-1)"
```

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