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Christian Hofmann, Sebastian Kuhn, Nina Schwaiger

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Keywords: internal control; material weaknesses; financial analysts; earnings conference calls; auditing.
JEL classification: M41; M42; O16.
Current version: February 2023.

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[1] LMU Munich, Chair for Managerial Accounting, Ludwigstrasse 28, 80539 Munich, Germany
* Corresponding author (sebastian.kuhn@lmu.de)

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1. Introduction

We examine whether the discussions between financial analysts and managers during earnings conference calls (ECC) are informative about the quality of firms' internal controls over financial reporting.[1] Feng et al. (2009), Harp and Barnes (2018), and Heitzman and Huang (2019), among others, establish that the quality of firms' internal controls is associated with firms' information quality. Consistently, low quality internal controls are associated with less informative financial reports (Beneish et al. 2008; Doyle et al. 2007b; Ashbaugh-Skaife et al. 2008) and with less accurate management forecasts (Feng et al. 2009). As financial analysts rely on management forecasts and high-quality earnings when forecasting firm performance (Brown et al. 2015), it is plausible that an analyst's questions in the Q&A section of an ECC reflects the analyst's priors about the firm's information quality.[2] Given the link between firms' internal control quality and their information quality, we explore whether ECC discussions between financial analysts and managers are predictive of the disclosure of internal control material weaknesses.[3]

We focus on financial analysts' engagement in the Q&A section of ECCs for several reasons. By collecting, aggregating, and interpreting information, financial analysts serve as information intermediaries for various market participants (e.g., Brown et al. 2015). ECCs are an important information source for financial analysts (Bowen et al. 2002) and complement their macroeconomic and industry knowledge and experience (Hutton et al. 2012). Specifically, ECCs provide financial analysts with the opportunity to interact directly with firms' managers (Matsumoto et al. 2011). The Q&A section of ECCs is not scripted, thus enabling financial analysts

[1] We use the term "discussion" to refer to the combination of a financial analyst's questions and their respective answers by a manager.

[2] For example, Thom Albrecht from BB&T Capital Markets asked "How sure can we be that this kind of [expansion] doesn't portend some sort of major accounting issues (…) such as happened to a freight forwarder that got bought out?" at the ECC of Roadrunner Transportation Systems Inc. on November 5th, 2015.

[3] Internal control material weaknesses are disclosed at the end of the financial year. Consequently, if ECC discussions are informative regarding internal control quality, this information content can be used to help predict the disclosure of future internal control material weaknesses.

to confirm their expectations or gain new information. In a situation where a firm's information quality is low (e.g., due to a merger, an industry shock, or a restatement), we argue that financial analysts have increased information demand. We suggest that in situations of low firm information quality, analysts have incentives to ask systematically different questions compared to situations of high firm information quality. Consequently, financial analysts' questions are potentially indicative about firms' information quality and hence firms' internal control quality.

We analyze the thematic content of discussions between financial analysts and managers through a Latent Dirichlet Allocation (LDA) topic modelling approach. LDA is an unsupervised machine learning technique that finds clusters of words (topics) which often appear in close proximity over a corpus of documents. Using this technique allows us to categorize conference call discussions into topics which capture the thematic content of analyst-manager discussions. We apply this method to a matched control group sample of 3,860 quarterly conference calls of listed U.S. firms between 2010 and 2018 collected from *Thomson Reuters EIKON*. We show that the resulting conference call topics are semantically coherent and distinguishable through an online word intrusion task, which suggests that human raters can distinguish between words from different topics significantly better than random chance (p=0.00).

We then identify topics that are more often discussed in conference calls when a firm's internal control quality is low. We categorize a firm's internal control quality as being low when the firm's auditor releases a report on internal control material weaknesses (ICMW). Our results suggest that the distribution of earnings conference call topics is predictive of future ICMW disclosures, beyond the determinants identified in previous literature. The results are consistent when testing out-of-sample. These results are not only statistically significant but also economically meaningful. When we use a Support Vector Machine approach (SVM) to evaluate the predictive power of the model with the identified conference call topics as input compared to a

SVM without, the topic SVM outperforms the benchmark SVM by 3.16% (area under the curve) and 4.43% (accuracy). This suggests that an analysis of the thematic content of ECC discussions can improve the assessment of firms' internal control quality.

Next, we analyze the association between the type of topic and the type of ICMW. We label ICMWs using reasons provided by auditors for the disclosure of an ICMW collected from *Audit Analytics*. We find an association between the thematic content of topics and the nature of the ICMW. For example, discussions regarding international expansion and global economy are related to personnel and competency issues, suggesting that the ICMW originated in an increase of firm size through international expansion (in line with Ge and McVay 2005 and Doyle et al. 2007a). Similarly, discussions regarding firm segments and structures are strongly related to issues in the firm's accounting segment, reconciliations, and financial restatements. This association is plausible, as larger, multi-segment firms arguably have more complex accounting systems (in line with Brown et al. 2018). Taken together, these results suggest that the predictive power of our model derives from a semantic relation between the nature of the ICMW and the thematic content of ECC discussions, rather than from noise.

Next, we analyze the role of management forecasts. High-quality internal information increases the accuracy of management forecasts (Goodman et al. 2014). Consequently, high management forecast bias may signal to analysts that internal information quality is low. Our results show that ECC discussions are more predictive following years with low management forecast accuracy. This suggests that the predictive power of ECC discussions is driven by analysts' perception of the firm's information quality.

We then document that the predictive power of ECC discussions is driven by analysts' industry knowledge and experience. More specifically, we show that analysts who have been following firms in the same industry for a longer period of time or have more general experience

are involved in conference call discussions that have significantly higher predictive power. This result is in line with Hutton et al. (2012), who find that analysts' information advantage derives from their industry knowledge and experience.

Finally, we examine the informativeness of ECCs regarding firms' internal controls for auditors. Since the passing of the Sarbanes-Oxley Act (SOX), the firm's auditor has been responsible for the audit of the firm's internal controls. SOX section 404 requires the auditor to provide an opinion on internal control effectiveness. However, the audit of internal controls is difficult, time-consuming, costly, and prone to errors. Bhaskar et al. (2019) argue that the assessment of internal control quality is associated with judgment errors because it is subjective by nature. Consistently, literature finds that auditors have trouble adjusting to increases in control risk (Allen et al. 2006) and fail to find significant amounts of material weaknesses (Rice and Weber 2012; Bedard and Graham 2011). As auditors are exposed to litigation or reputational losses in case they fail to identify ICMWs (e.g., Ghosh and Tang 2015), additional information sources may thus be useful in assessing the quality of internal controls with increased precision and at a lower cost.

We find that conference call topics are significantly associated with audit fees, incrementally to determinants identified in previous literature. This result suggests that the information discussed in ECCs is used by auditors.[4] However, when we add audit fees as an additional control variable in our baseline model, conference call topics remain predictive of future ICMW disclosures. This analysis suggests that auditors do not fully use the information present in ECC discussions. Consequently, our model may be useful for auditors in assessing a firm's internal control quality.

[4] Anecdoctal evidence supports the idea that auditors may listen to earnings calls. For example, the PCAOB's Auditing Standard 12.11 notes that auditors should consider observing earnings calls in order to obtain a better understanding of the company.

Our study makes several important contributions to literature. First, we contribute to the literature on the role of financial analysts in capital markets. Prior evidence suggests that analysts provide information to capital markets beyond the information that is contemporaneously released by the firm's management (Huang et al. 2014, 2018). Specifically, prior studies suggest that analysts serve as external monitors of the firm's management. For instance, Bradley et al. (2017) document that coverage by financial analysts with industry expertise mitigates earnings management, financial misrepresentation, and excessive CEO compensation. We add to the latter stream of research by suggesting that analysts may serve as external monitors of the quality of firms' internal control systems. In this role, analysts may be viewed as part of the firm's external corporate governance system.

Second, we contribute to the literature on the determinants and consequences of internal control quality (Doyle et al. 2007a; Beneish et al. 2008). We show that discussions in ECCs significantly predict weaknesses in internal controls beyond determinants identified by prior research (Doyle et al. 2007a). Moreover, we add to the results of Xu and Tang (2012) and Clinton et al. (2014), who provide evidence that analyst forecasts of firm performance depend on the firm's internal control quality. Our findings suggest that the content of ECC discussions is informative about the quality of the firm's internal controls.

Finally, we contribute to the growing accounting literature that makes use of textual analysis methods. Previous literature has used topic models on written communications such as 10-Ks (Brown et al. 2020) and financial analysts' questions in ECCs as well as analyst reports (Huang et al. 2018). Similar to Huang et al. (2018), we use an LDA approach on verbal and unscripted communication. This approach successfully distinguishes semantically different topics in ECC discussions. In addition, we show that the classification that is delivered by the LDA model is useful in assessing internal control quality.

2. Methodology

2.1 Latent Dirichlet Allocation Approach

We analyze the thematic content of financial analyst discussions in ECCs by training an LDA (Latent Dirichlet Allocation) topic model (see Blei et al. 2003). LDA is a Bayesian probabilistic model that identifies words which often appear in close proximity to each other over a corpus of documents. It is based on two assumptions: First, it assumes that the content of every document (i.e., question-answer pair) is drawn from a distribution of *n* word clusters or topics, implying that ECC discussions concern a fixed, limited amount of topics. This assumption is supported by the fact that ECC discussions will usually be limited to different aspects of the firm. Second, LDA assumes that the word list that makes up each topic is itself drawn from a Dirichlet distribution. The algorithm first finds the topics within the corpus by labeling words as thematically related if they often appear in close proximity. It then assigns each question-answer pair to one or more topics. Due to the probabilistic approach, words can appear in multiple topics, and a question-answer pair can be assigned to several topics. This is useful in our setting, as we assume that analyst questions do not always strictly adhere to only one topic. It also has the advantage of capturing semantic ambiguity, as words can have different meanings in different topics (e.g., "model" referring to either the firm's business model or the analyst's forecast model).

Topic models are unsupervised algorithms. In particular, the algorithm identifies the words within each topic based on a probabilistic relation between words and topics. Researcher input is only needed for the amount of topics. This has two advantages in our setting. First, we do not want to limit the analysis by imposing specific expectations regarding the thematic content of analyst

questions in years where internal control systems are weak.[5] Topic modelling suits this exploratory approach well. In addition, unsupervised algorithms have the advantage of being more adaptive than a dictionary approach (Brown et al. 2020). If question strategies of analysts change over time, an unsupervised algorithm will reflect this fact and provide updated results.

LDA has seen increasing use in the accounting and finance literature over the last years. In particular, some prior research analyzes the thematic content of firm disclosures and its relation to misreporting. For instance, Brown et al. (2020) use LDA to classify the content of 10-K disclosures and link the weights of different topics to financial misreporting. Hoberg and Lewis (2017) analyze whether fraudulent firms show abnormal disclosure behavior, and find that certain topics like R&D expenses receive more emphasis in misreporting years. Within the financial analyst setting, Huang et al. (2018) use LDA to structure the thematic content of analyst reports and find that analysts address topics that had not been discussed during conference calls. We differ from the literature above by using LDA to structure the verbal communication of ECCs.

In order to use LDA, some further steps are needed. To ensure meaningful results, we remove common stop words, first names, and words that are used in more than 90% or fewer than 1% of question-answer pairs. Words are also lemmatized for easier handling. Next, we need to choose a number of topics n. A higher number of topics increases the coherence of the model, i.e., the semantic similarity of high scoring words within topics. However, it also increases the similarity between different topics, which makes a distinction between topics more difficult. We set the number of topics n equal to 50. However, we obtain similar results for other n.[6]

[5] We validate this approach by searching for direct references to internal controls within our sample of earnings conference calls (untabulated). We find that only four out of 106,800 questions contain the phrase "internal controls". In addition, we search for questions that address this topic by analyzing the overlap between the questions in our sample and a list of control-specific 2-grams from PCAOB AS 5 (Audit of Internal Control over Financial Reporting) such as "material weakness" and "control risk". Only 41 questions contain such a 2-gram.

[6] In particular, coherence scores for different n on this corpus exhibit no local maximum, and the semantic coherence of topics varies little for different n between 10 and 75.

We then use LDA to structure the corpus of ECC discussions, i.e., both the analyst questions and the managers' answers in our data set. While we are mostly interested in the role of financial analysts, we include manager answers for three reasons. First, it allows for a more accurate topic model by increasing the size of the documents in the corpus. Second, a manager likely presents any information they wish to share in the management presentation part. Any additional information in answers is triggered by the analyst's question, and thus reflects the information and interests of the analyst. Third, it is plausible that a manager has an information advantage over the analyst, which makes it likely that the manager's answers to analyst questions are valuable for predicting ICMWs.[7]

LDA returns a weighted list of words for each topic, i.e., the probability that a word belongs to a topic for every word in every topic. We use this distribution of word weights to assign all question-answer pairs to one or more topics. Categorizing a single question-answer pair into more than one topic is reasonable because analyst questions can be long and include several sub-questions. Finally, we add up the topic weights of all question-answer pairs within an ECC. The resulting topic distribution serves as the basis for the following analyses.

We analyze the overall topic distribution of an entire ECC rather than the topics of single question-answer pairs. This approach is in line with the literature that views the total of analysts and conference calls as a reflection of the firm' information environment (Bowen et al. 2002; Matsumoto et al. 2011). Consequently, we analyze if the distribution of topics within a conference call is shifted if the firm has weak internal controls.

We do not use individual question-answer pairs to identify analysts' information demand, as we assume that analysts follow a certain question strategy in order to manage the trade-off

[7] Our results are qualitatively and quantitatively similar when using only analyst questions as the basis of analysis.

between information generation and relationship building (Mayew 2008). Analysts are also likely to include favorable questions or remarks when they talk to management, as managers may discriminate against analysts who they view as being unfavorable towards the firm (Milian et al. 2017). Analyst speech portions are also insufficient. Since any single financial analyst may be underinformed, we have no specific expectations for individual analysts. Consequently, we conduct our analyses on the ECC level.

2.2 LDA Output and Validation

Table 1 gives an overview over the most strongly weighted words in the topics that are most predictive of future ICMW disclosure (see section 3). We take several steps to ensure that the topics are semantically meaningful and coherent. First, we label each topic manually, based on a subjective understanding of their thematic content. This is in line with prior LDA literature (Huang et al. 2018; Bao and Datta 2014). We argue that our model results in distinct and coherent sets of words that intuitively describe different discussion topics. For example, our most predictive topic includes the words "China", "Asia", "global", "world", and "region", suggesting that discussions in this topic relate to the Asian economy, macroeconomic factors, and international business. Another topic includes words such as "cost", "saving", "reduction", "benefit", and "structure", suggesting that discussions in this topic relate to operational factors, such as potential changes in the firm's operations in order to be more cost efficient.

[Please insert Table 1 here]

Next, we follow the suggestion of Bochkay et al. (2022) to validate the identified topics using human coders. Following Brown et al. (2020) and Chang et al. (2009), we use a word

intrusion task for this purpose. We use the platform Prolific.[8] Prolific allows us to easily access a wide pool of human coders who have analyzed firms for personal investment reasons in the past. This filtering is important as understanding the topics requires some business and financial expertise.

For the intrusion task, 100 subjects are shown ten sets of four words. Three words are randomly chosen from the highest weighted five words of one topic. The fourth word is randomly chosen from the five highest weighted words of another, randomly chosen topic. Subjects are asked to identify this "intruder" word. For a semantically incoherent topic, subjects would be expected to identify the intruder word on the level of random chance, i.e., 25% of the time. In contrast, the subjects identify the intruder word 45.2% of the time. This is significantly more accurate than random chance ($p < 0.01\%$) and in line with the results of the word intrusion task from Brown et al. (2020). This result suggests that the identified topics are semantically coherent and distinguishable from each other.

2.3 Regression Models

a) Topic Distribution Score Calculation

We then analyze if the topic distribution of an ECC is informative about the firm's internal control quality. In order to construct a summary measure of this information content, we first analyze how strongly the different topics relate to the occurrence of ICMWs. We do this by regressing ICMW disclosure at the end of the year (*ICMW*) on the topic distribution of each ECC that was held during this year. Equation 1 summarizes this regression model.

$$ICMW_{i,t} = \beta_0 + \sum Topic_{j,q} + \varepsilon_{i,t} \tag{1}$$

[8] We decide against the use of Amazon Mturk due to well documented issues with Mturk data quality in recent years (Chmielewski and Kucker 2020; Dennis et al. 2020).

Notes: *ICMW* is one if firm *i* disclosed at least one ICMW at the end of the year *t* and zero otherwise. *Topic* is the weight of topic *j* within the earnings call of firm *i* in quarter *q*, where *q* is in *t*.

We view the estimated coefficients from regression model 1 as the prediction weights of the respective topics. A topic with a high estimated coefficient is strongly related to the occurrence of an ICMW. We then use these coefficients to construct a single measure of ICMW likelihood based on topic distribution. This *Topic Score* is calculated by a matrix multiplication of the topic frequency in conference calls with the regression's beta matrix, summarized in equation (2):

$$Topic\ Score_{i,q} = \left[\#questions\ topic_1 ... \#questions\ topic_{50}\right] \times \begin{bmatrix} \beta_1 \\ ... \\ \beta_{50} \end{bmatrix} \tag{2}$$

Notes: The *Topic Score* for firm *i* in quarter *q* is derived by multiplying the weights of all topics within the ECC (1 – 50) with the estimated coefficients (β) from equation 1.

The topic score is thus a measure of the likelihood of ICMW using ECC discussions as an input. In comparison to using the entire distribution of topics, it has two advantages. First, it makes estimation and interpretation of models easier, as the effect of only one score rather than those of a large number of topics needs to be estimated. Second, it is more robust to outliers and reduces the chance that one or more topics return significant results by chance.

The use of topic weights that are derived from a regression that uses *ICMW* as the dependent variable introduces the risk of overfitting. We neutralize this risk by ensuring a strong out-of-sample performance for the initial regression in subsequent analyses.

b) Incremental Predictive Power Model

Next, we analyze if the topic distributions of ECCs are incrementally predictive of the future disclosure of ICMWs compared to determinants of internal control quality from literature. Notably, future *disclosure* of ICMWs is a measure of low internal control quality at the time of the earnings call, as ICMWs only get disclosed at the end of the year. Consequently, assessing the quality of

internal control over financial reporting (ICFR) and predicting future ICMW disclosure refer to the same task in this setting. Figure 1 illustrates the timeline of events.

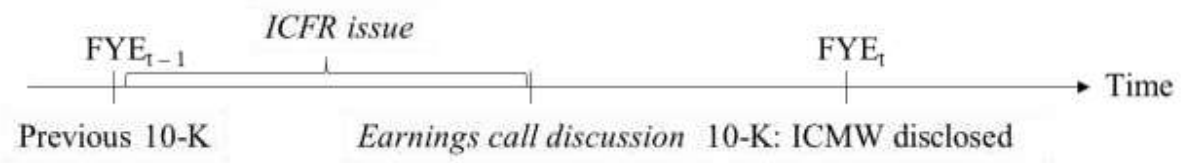

Figure 1: Timeline of ICFR issue, earnings call discussion, and future ICMW disclosure

As a benchmark for internal control quality assessment, we refer to the ICMW determinant model from Doyle et al. (2007a). Doyle et al. (2007a) find that firms with ICMWs are, on average, smaller, younger, more complex, and have higher growth than firms without ICMWs. We regress ICMW occurrence on these firm fundamentals as well as on the topic score. In addition, we add a measure of stock excess return over the S&P500 between the release of financial disclosures and the ECC in order to control for the information content of public disclosures. The logit regression is specified as follows:

$$\begin{aligned} ICMW_{i,t} = {} & \beta_0 + \beta_1 Topic\ Score_{i,q} + \beta_2 Mergers_{i,t} + \beta_3 AggregateLoss_{i,t} + \beta_4 ExtremeSalesGrowth_{i,t} \\ & + \beta_5 Bankruptcy\ Risk_{i,ti,t} + \beta_6 Complexity + \beta_7 Firm\ Age_{i,t} + \beta_8 Size_{i,t} + \\ & \beta_9 ForeignOperations_{i,t} + \beta_{10} Excess\ Return_{i,q} + \sum_k Industry + \sum_n Year \end{aligned} \quad (3)$$

This model regresses the disclosure of an ICMW by firm *i* at the end of year *t* on the topic score of the ECC in quarter *q*, where *q* is in *t*, and on control variables of firm *i* in year *t*. *Mergers* is measured as the logarithm of the firm's current year expenditures for mergers and acquisitions in million $. *Aggregate Loss* is 1 if the firm had negative net income in both the current period and the previous period, and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year, and 0 otherwise. *Bankruptcy Risk* is measured as the firm's leverage, calculated as the firm's total debt divided by its total assets. *Complexity* is measured as the natural logarithm of the mean of the number of geographic and business segments

of the firm. *Firm Age* is calculated as the natural logarithm of the years since the firm was first listed on Compustat. *Size* is the natural logarithm of the firm's market valuation in million $. *ForeignOperations* is 1 if the firm operates at least one foreign geographical segment, and 0 otherwise. *Excess Return* measures the firm's compounded monthly stock return since the disclosure of the 10-K, minus the compounded return on the S&P500 in that time. Moreover, we include industry fixed effects based on one-digit SIC classification[9] as well as year fixed effects to control for heterogeneity over time and across industries. We cluster standard errors on the firm level for all regressions in order to account for heteroscedasticity.

Following Doyle et al. (2007a), we expect firm size to have a negative effect on the likelihood of ICMWs as large firms have more resources to spend on internal controls, and are more likely to develop economies of scale for such systems. Similarly, older firms are more likely to have developed internal control systems that fit the firm's needs, and are thus less likely to have ICMWs. Financial performance is expected to have a negative impact on the occurrence of ICMWs as well, as firms with poor performance might lack adequate resources to invest in internal controls. Thus, we expect firms with a higher ROA and a lower bankruptcy risk to have fewer ICMWs on average.

The remaining determinants focus on the firm's activities and environment. Doyle et al. (2007a) state that "as a firm engages in more complex transactions and has more diverse operations, we expect the need for internal control to be higher, and thus expect the complexity of the firm to be a driver of internal control weaknesses" (Doyle et al. 2007a, p. 201). Consequently, we expect a higher likelihood of ICMWs for firms with high recent M&A activity and for firms with more geographic and business segments.[10]

[9] Results remain qualitatively consistent when using two-digit SIC classification for the fixed effect.

[10] Doyle et al. (2007) also include a measure of restructuring charges in their model. Due to data availability restrictions, including this measure into our model reduces sample size by 55.7%. Consequently, we omit this variable from our

In addition to the model from Doyle et al. (2007a), we control for corporate governance through an aggregate measure from Brown and Caylor (2006) that approximates the effectiveness of the board of directors trough the following variables: CEO is not also chairman, no former CEO on the board, all directors own stock, nomination committee is fully independent, compensation committee is fully independent, more than half of the directors are independent, the CEO is on fewer than three other boards, all directors attended at least 75% of all meetings, all directors own at least 1% but not over 30% of the firm's total shares outstanding. The results (untabulated) remain unchanged.

3. Data

3.1 Sample

We use the transcripts of the Q&A sections of conference calls of large U.S. firms from 2010 to 2018. First, we obtain 64,840 transcripts of quarterly conference calls from *Thomson Reuters EIKON*. We extract the Q&A session of these calls using Python. We match conference call data with financial statement data from *Compustat Fundamentals* and data on internal control audits from *Audit Analytics*. These data contain both the number of ICMWs for each firm year and the date of publication, allowing us to analyze the earnings calls in the year leading up to ICMW disclosure. We match the data from each ECC to the next ICMW disclosure *after* the call. This ensures that our analysis only covers ICMWs that were *not yet disclosed* at the time of the conference call.[11] We then match data from each ECC to the control variables from the last 10-K disclosure *before* the call.

final model. Results remain unchanged when the variable is included. Similarly, Doyle et al. (2007a) include the number of special purpose entities (SPEs) in the firm. We do not include this variable a) for data availability reasons and b) as it is insignificant in the final model of Doyle et al. (2007a).

[11] Several ECCs within the same year may be matched to one ICMW disclosure as long as that ICMW disclosure is the closest one after each ECC.

The prediction of whether an ICMW is disclosed at the end of the year is a classification problem as the outcome variable is binary. In the initial sample, roughly 5% of firm years have one or more ICMWs, which leads to an imbalanced classification problem (e.g., Japkowicz and Stephen 2002). A classifier trained on the entire data set would achieve 95% accuracy by always predicting that no ICMW will be disclosed. Different methods of dealing with this issue exist. Oversampling methods such as the Synthetic Minority Oversampling Technique (SMOTE) increase the risk of overfitting and overstating statistical power (Kang et al. 2016).

We instead make use of an undersampling approach (e.g., Fernández et al. 2018). We use all firm-quarter observations with at least one ICMW disclosed at the end of the year and a one-to-one matched control group of firm-quarter observations that reported no ICMW at the end of the year. The control group is matched by industry (one-digit SIC) and firm size (percentile of the natural logarithm of total assets, calculated for all available firm-year observations).[12] The resulting matched sample includes a total of 3,860 conference calls with 106,800 financial analyst questions and corresponding manager answers. Table 2 reports on the sample selection.

[Please insert Table 2 here]

3.2 Descriptive Statistics

Table 3 shows descriptive statistics of the main constructs. By construction, half of the observations have at least one ICMW. Firm size is strongly skewed to the right, with median total assets of $849.95 million and a mean of $3,135.25 million. Similarly, the median firm has a net income of $57.3 million while the mean is $237.9 million. The median return on assets is three percent while the mean is minus two percent. This is in line with the finding that firms with weak control systems

[12] Our results are not dependent on this matching specification. Matching a control group based on two-digit SIC industry classification leaves the results qualitatively consistent.

are often not profitable (Doyle et al. 2007a). The median firm is 19 years old, has three segments and a market capitalization of $937 million. During the median conference call, 26 questions are asked. On average, these questions are asked by five different analysts.

[Please insert Table 3 here]

Table 4 presents the descriptive statistics of our main variables grouped by treatment and control group. Within the former group, the average firm has two ICMWs with a maximum of 17 in one year. Total assets are similar as we match our control group based on this variable. However, the market value of the firms with ICMWs are significantly lower than for those firms without ICMWs, while bankruptcy risk and the number of firms with continued losses are higher. For these variables, t-tests strongly reject the null hypothesis of mean equivalence ($p < 0.01$). This is in line with expectations (Doyle et al. 2007a). Firm age and the number of segments are similar in both groups.

[Please insert Table 4 here]

Table 5 presents the Pearson correlation coefficients of the main constructs. The correlation coefficients between firm fundamentals are in line with expectations: We find that older firms are less likely to have continued losses ($p<0.01$) and have a higher market value ($p<0.01$). Similarly, larger firms are more profitable ($p<0.01$) and have a higher market value ($p<0.01$). Extreme sales growth is more likely for younger firms ($p<0.01$) and firms with fewer segments ($p<0.01$). Firms with more ICMWs also have, on average, lower market valuation, higher gearing, are more likely to have continued losses, and are younger. All of these associations are in line with Doyle et al. (2007a).

[Please insert Table 5 here]

4 Empirical Results

4.1 Main Regression Results

Table 6 presents the results of estimating regression equation 3.

[Please insert Table 6 here]

Panel A presents the results when using the entire sample. We find that the association between topic score and ICMW occurrence is positive and statistically significant (p-value < 0.01). Moreover, the pseudo-R^2 of the regression increases by 2.12 percentage points or 51.4 percent when adding topic score to the baseline model of control variables. We view this finding as first evidence that ECC discussions are informative about the quality of firms' internal control systems. The results for the control variables are largely in line with Doyle et al. (2007a). Firms with a higher M&A activity, higher bankruptcy risk, and lower market capitalization have a significantly higher risk of ICMW occurrence.[13]

In the next step, we examine the out-of-sample predictive power of the model. Since we estimate regression equation (3) using the entire control sample, our results may be driven by the fact that we are using the same data for regressions equations (1) and (3), which allows our algorithm to overfit on known ICMWs. In this case, our measure would only be useful for explaining *past* ICMWs using *past* data.

To ensure that this is not the case, we test the out-of-sample predictive performance of our approach. For each year *y* in the sample, we first calculate the topic score for all ECCs during year *y* using only financial statement and internal control data from *previous* years. We then use this topic score to predict ICMW disclosure at the end of year *y*. This approach reduces sample size because we cannot predict ICMW disclosure at the end of the first year in the sample. However,

[13] Some of the control variables from the Doyle et al. (2007a) model are not significant in our estimation. Compared to Doyle et al. (2007a), our sample is smaller and contains firms that are significantly larger. In larger firms, some of the associations found by Doyle et al. (2007a) arguably do not hold. When we estimate regression 3 using only the smallest 30% of firms in our sample, we find a significantly positive (negative) effect of extreme sales growth (firm age) on ICMW occurrence.

the approach matches that of an auditor who can only use past data when assessing internal control quality. Consequently, this analysis examines the ability of our model to predict future ICMW disclosure based on the past relation between ICMW disclosure and topic score. Panel B of Table 6 presents the results of the analysis. Despite the decrease in sample size, the topic score remains statistically significant ($p < 0.01$), underlining the model's predictive power.

4.2 Robustness Tests

a) Economic Relevance Analysis

Next, we analyze the economic relevance of our results. To do this, we use our algorithm to predict ICMWs through a Support Vector Machine (SVM) and evaluate its performance (results untabulated). SVM is a type of classifier that divides data points into classes by maximizing the distance between points and a hyperplane through an N-dimensional space, where N is the number of features, i.e., independent variables. We train one SVM on the total set of determinants including our topic score, and a second one using only the Doyle et al. (2007b) determinants, which provides a benchmark.[14]

We find that the SVM that includes the topic score has an accuracy of 65.06% and an area under the curve (AUC) of 66.01%, while the benchmark determinant SVM returns an accuracy of 63.07% and an AUC of 63.21%. This equals an outperformance of the topic SVM by 3.16% and 4.43%, respectively. The topic SVM correctly classifies 119 ICMW years out of 158 within the test sample, while the benchmark finds 102. This represents an increase in performance by 16.67%. These results illustrate that our algorithm may improve the assessment of internal control quality.

[14] Training and evaluating an SVM also requires a split of the data set into a training set and a test set on which the classifier is evaluated, thus providing further evidence on our algorithm's out-of-sample performance. We use a 90-10 train-test split; results are qualitatively similar for other values.

b) Determinants and Predictive Power of Individual Topics

So far, we have used the topic score as an aggregate measure of ECC discussions' predictive power. Next, we analyze the relevance and predictive power of individual topics in ECCs. This allows us to gain a better understanding of the thematic relevance of these topics and to shed some light on the "black box" of our machine learning approach. It also ensures that our results capture the predictive power of specific thematic discussions rather than noise.

First, we are interested in the circumstances under which different predictive topics get mentioned in ECCs. This is relevant for two reasons. First, it allows us to test the plausibility of our results. In particular, we expect to see a thematic relation between the topic of ECC discussions and the firm's economic situation.

In order to conduct this analysis, we regress the occurrence of the ten most predictive topics (Table 1) on the battery of ICMW determinants from Doyle et al. (2007a). This allows us to examine the underlying factors that drive both the occurrence of an ICMW and the discussion of a topic. For the sake of brevity, we do not report the full regression results for all specifications. Instead, Table 7 gives an overview over the statistically significant associations that we find for each of these models.

[Please insert Table 7 here]

Results suggest that topics are thematically related to firm financials. Discussions relating to the Asian economy are strongly related to the firm's number of segments and foreign operations. This is intuitive, as this topic increases in relevance for internationally operating firms with a high number of segments. Similarly, discussions about firm's sales activities are related to extreme sales growth and appear more often for younger and smaller firms, while discussions concerning cost efficiency and cash flow are positively associated with the firm's leverage. We also find that

discussions about future activities are more likely when the firm has operated at a loss in consecutive years, but less likely when the firm is engaged in M&A activity. Taken together, these results suggest that ECC discussions are intuitively thematically related to the firm's characteristics and activities.

Next, we are interested in the association between certain topics and the nature of the firm's internal control issues. SOX 404 requires auditors to categorize the reason for the disclosure of an ICMW, which is reported in *Audit Analytics*. This allows us to analyze the thematic connection between ECC topics and ICMW occurrence. We regress the existence of specific types of ICMW on the weights of the top 10 most predictive topics as well as the fundamental control variables from Doyle et al. (2007a). We then view significant coefficients for combinations of ICMW reasons and specific topics as evidence that discussions on those topics are associated with specific internal control issues. We report an overview of the results of these analyses in Table 8.

[Please insert Table 8 here]

Results show thematically consistent associations between the discussion of topics in ECCs and the underlying internal control issues in the firm. For example, discussions concerning the Asian and global economy significantly predict internal control issues related to personnel and competency. This is in line with Doyle et al. (2007a), who note that growth and expansion put a strain on the effectiveness of internal control over financial reporting, and with Ge and McVay (2005), who list a lack of qualified personnel as a major driver of ICMWs. Discussion related to firm segments and cash flow is predictive of several types of ICMW. This is intuitive as ICMWs are negatively related to firm performance, and are significantly more likely in more complex firms (Doyle et al. 2007a).

In conclusion, we find that different individual topics are predictive of different types of ICMW. This is evidence that analyst discussions are thematically related to the nature of ICMWs. In addition, these results suggest that the predictive power of our main model is driven by associations between categories of internal control issues and analyst discussions that relate to those categories.

4.3 Additional Analyses and Robustness Tests

a) Role of Managers' Earnings Forecasts

We argue that financial analysts ask systematically different questions because they suspect that the firm's information quality is low. To examine this idea, we examine the association between managers' forecast accuracy and the extent to which ECC discussions are predictive of ICMW disclosure. High-quality information allows managers to forecast earnings more accurately (Dorantes et al. 2013). Consequently, earnings guidance accuracy captures information quality (Goodman et al. 2014). In our setting, we expect that financial analysts will ask more predictive questions when they perceive that information quality is low, i.e., when the accuracy of the most recent managers' forecasts was low.

We test this prediction by adding an interaction variable to the baseline regression model (3). *ManagerForecastBias* is measured as the difference between manager's EPS forecast and actual EPS for the previous firm year preceding the earnings call.[15] We expect a positive coefficient on the interaction between this bias and the topic score, suggesting that ECC discussions are more predictive of ICMW disclosure when the previous year's manager forecast was more biased. Table 9 presents the results of the analysis.

[15] We use manager forecast data from I/B/E/S Estimates. Inclusion of this data decreases sample size to 1,090 firm-quarter observations.

[Please insert Table 9 here]

Results support our predictions: The coefficient on the interaction term is positive and statistically significant ($p < 0.05$). This finding suggests that ECC discussions are more predictive of ICMW disclosure when information quality is low.

We further test this association by analyzing the time between the last manager's annual guidance update and the release of the actual EPS. Literature documents a negative capital market effect of withdrawing earnings forecasts, as this signals that previous forecasts may have been based on inaccurate information (Marshall and Skinner 2022, Lee and Buskirk 2017). Consistently, we expect that financial analysts view late updates of earnings guidance as signals of low information quality. We define *MonthsBeforeFYE* as the number of months between the last update of earnings guidance and the release of actual EPS. We then add an interaction effect between the topic score and *MonthsBeforeFYE* into regression model (3). Results (untabulated) are in line with expectations. The coefficient on the interaction term is negative and statistically significant ($p < 0.01$). This suggests that ECC discussions are more predictive of ICMW disclosure when managers have signalled low information quality by providing late updates to earnings guidance. In conclusion, these results support the idea that analysts react to signals of low information quality by asking systematically different questions in ECCs.

b) Financial Analyst Characteristics

Previous results show that analyst discussions are informative about the quality of the firm's internal control systems. Next, we are interested in the circumstances under which financial analyst discussions are more predictive. This also enables us to shed some light on the mechanisms that allow analyst discussions to be informative about internal control quality.

In particular, we examine the role of financial analysts' professional characteristics. Literature finds that financial analysts' forecast performance increases with their experience and industry knowledge. In addition, experienced and previously successful analysts are more likely to act boldly and less likely to fall into herding behavior (Clement and Tse 2005). We assume that the information content of ECC discussions with regard to internal control quality is the result of analysts' industry expertise. Consequently, we expect that more experienced analysts participate in discussions that have a higher predictive power.

We test these predictions by adding interaction effects to the baseline regression model (3). *AnalystExperience* is measured as the number of years since the analyst first appeared in the *IBES* database. *AnalystIndustryExperience* is measured as the number of years since the analyst first covered a firm in the same industry as the firm that is holding the ECC. Both variables and their respective interaction terms with the topic score are calculated on the analyst question level. All four variables are subsequently summarized onto the earnings call level. Consequently, the variables represent the average of financial analyst experience and industry experience during the ECC weighted by the number of questions asked by the respective analyst.

We predict a positive coefficient on the interaction between analyst characteristics and the topic score. Again, we interpret the estimated coefficients as the additional predictive power of discussions that involve analysts with higher experience and industry knowledge. Table 10 presents the results of these analyses.

[Please insert Table 10 here]

Our findings support our predictions. ECC discussions have higher predictive power concerning ICMW disclosure when financial analysts are more experienced in general ($p = 0.06$) and more experienced in the firm's industry ($p = 0.09$). These results suggest that the predictive power of ECC discussions is at least partially driven by analyst experience and industry knowledge.

c) The Association between ECC Information Content and Audit Fees

Finally, we examine the relevance of our results for one group of stakeholders that are highly incentivized to accurately assess internal control quality: the firm's auditors. We assume that financial analysts recognize risks that are related to information quality and consequently ask systematically different questions in ECCs, which allows our model to predict ICMW disclosure. To the extent that these risks are relevant for the auditors' work, they may be reflected in the firm's audit fees for the year, as audit fees increase both through increased audit effort and risk premium (Niemi 2002).

In order to test this prediction, we use the extensive audit fee model from Abernathy et al. (2018). This model controls for firm size, complexity, accounts receivable, inventory, foreign operations, book-to-market ratio, leverage, number of employees, M&A activity, fiscal year end in December, return on assets, a negative ROA, a going concern opinion, a new auditor, auditor tenure, firm age, firm financing, disclosures of internal control problems[16], and financial restatements. We add the topic score as a summary measure of the information content of analyst discussions. Table 11 shows the results of this analysis.

[Please insert Table 11 here]

We find that the topic score is a statistically significant ($p < 0.01$) determinant of audit fees. This strongly suggests that the information content of analyst discussions with regards to internal control quality is relevant for auditors.

Finally, we examine to which degree auditors already make use of the information content in ECCs. The previous analysis shows that audit fees reflect this information to some degree. We

[16] Abernathy et al. (2018) use the variable "IC Opinion" which includes internal control deficiencies. We use ICMW disclosure which captures the same underlying construct.

now add audit fees into regression model (3). If auditors already made use of *all* information in ECCs that relates to internal controls, we would expect an insignificant coefficient on the topic score measure in this model. The results of this analysis (untabulated) show that while audit fees are significantly linked to the disclosure of an ICMW ($p < 0.01$), the topic score is still highly significant in this analysis ($p < 0.01$). This suggests that the approach captures some information that is currently not used by auditors.

5. Conclusion

We examine the incremental predictive power of discussions between financial analysts and managers in ECCs regarding internal control quality beyond firm fundamentals. We argue that analysts ask systematically different questions when they expect the firm's information quality to be low. Information quality is strongly related to internal control quality. This allows us to use analyst questions and their respective answers to assess internal control quality.

We use a LDA topic model to categorize the thematic content of ECC discussions. We regress ICMW disclosure at year-end on the distribution of topics within a call, and then construct a summary measure of the call's incremental prediction power in the product of the call's topic weights and the respective topics' predictive power. We then add this summary measure to a battery of fundamental determinants of internal control quality from literature.

Our results suggest that ECC discussions have information content regarding internal control quality. In particular, the topic score measure is significant at the 1% level and significantly increases the accuracy of an ICMW prediction model that is based on firm fundamentals. The topic score measure remains significant at the 1% level when predicting out-of-sample. This suggests that our algorithm is useful in assessing internal control quality.

In further analyses, we examine under which conditions analysts discuss highly predictive topics. We find that analyst discussion of such topics is strongly linked to firm fundamentals that are a) thematically related to the respective topic, and b) determinants of internal control quality. In addition, we show that individual predictive topics are related to different types of ICMWs. Together, these results suggest that our model is predictive due to a thematic association between analyst discussions and the specific ICMW within the firm, rather than noise.

Next, we analyze under which circumstances ECC discussions are more informative. We predict and find that ECC discussions are more predictive about future ICMW disclosure when the firm's most recent managerial forecast was more biased. Similarly, ECC discussions are more predictive when the managerial forecast was updated at a later point in time. This suggests that ECC discussions are more informative when the firm's information quality is low.

We then analyze which analysts ask the most predictive topics. Previous literature shows that analysts' information advantage and forecast precision derives from experience and industry knowledge. In line with this, we find that more experienced analysts and analysts with more experience in the industry participate in discussions that are significantly more predictive.

Finally, we examine the relevance of our topic score measure for auditors. Auditors have strong incentives to accurately assess internal control quality. Consequently, we expect the information content of analyst discussions with regard to internal control quality to be highly relevant for them. Consistent with this idea, we find that the topic score measure significantly explains audit fees beyond determinants identified in previous literature. This is additional evidence that ECC discussions reflect real and relevant risks for firm stakeholders.

Our study is subject to limitation. First, due to data restrictions, we apply a relatively crude measure of weaknesses in firms' internal control systems by constructing an indicator variable of whether the firm discloses an ICMW. Future research may for instance further explore the nature

and severity of the weakness. Second, it is possible that our model captures information that does not originally stem from financial analyst questions. We take measures to combat this issue by adding excess stock return as a control variable. However, we cannot rule out that sources other than financial analyst questions contain some of the information that we capture. Finally, it may be interesting to shed further light on analysts' questioning behavior by examining analyst performance following certain types of analyst questions.

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Table 1: Top Words of Most Predictive Topics

Label	Words
Asian economy	China, world, global, Asia, economy, region, strong, country
Firm segments	Business, segment, grow, core, piece, commercial, big, small
Planning	Half, second, year, expect, start, ramp, anticipate, expectation
Cost structure	Cost, saving, reduction, benefit, structure, fix, reduce, associate
Sales	Sale, sell, account, force, direct, add, productivity, organization
Industry downturn	Issue, industry, problem, concern, address, cause, bad, situation
Cash flow	Cash flow, capex, free, capital, year, work, generate, expect
Transition	State, average, transition, new, cut, public, example, follow
External effects	Impact, change, currency, positive, net, negative, affect, weather
Future	Want, work, company, try, time, year, need, business

Notes: Table 1 presents the eight highest weighted words for each of the ten topics that most strongly predict future ICMW disclosure. Duplicate words (e.g., “cash”, “flow”, and “cash flow”) were removed.

Table 2: Sample Selection

	# observations	
Q&A sections from 2010-2018 earnings conference calls	95,171	
(Distinct firm years)		(30,037)
(Distinct firms)		(6,743)
Merge with *Compustat* and *Audit Analytics* internal control data	-30,331	
Total aggregated earnings conference calls	**64,840**	
Reduce to sample of ICMWs and matched control firms	-60,980	
Final sample of earnings conference calls used for topic model	**3,860**	
(Q&A pairs)		(106,800)
(Analyst speech portions)		(23,868)
(Distinct firm years)		(2,591)
(Distinct firms)		(1,329)
Missing control variable data	-245	
Final sample for regression analysis	**3,615**	

Notes: Table 2 presents the sample selection approach. We report the number of observations at the firm, firm-year, earnings conference call, and analyst speech portion level.

Table 3: Descriptive Statistics

Variable	Min	p25	Mean	Median	p75	Max	Std Dev
ICMW	0	0	0.49	0	1	1	0.50
#ICMW	0	0	0.96	0	1	17	1.48
Topic Score	-2.80	-0.64	-0.38	-0.33	-0.07	1.87	0.49
Total Assets	11.8	320.6	3,135.3	850.0	2,427.9	208,527	9,019.4
Mergers	-147.96	0	102.35	0	32.77	35,151	692.10
Net Income	-6,917.9	10.0	237.9	57.3	159.2	16,540.0	1,045.5
Market Valuation	3.19	307.39	3,557.44	936.91	2527.26	374,802	12,186.00
Performance	-3.09	-0.03	-0.02	0.03	0.06	4.02	0.26
Sales Growth	0	0	0.50	0	1	1	0.50
Bankruptcy Risk	-12.04	0.00	0.66	0.36	0.94	14.38	2.73
Firm Age	2	11	22.27	19	27	68	14.87
Complexity	1	1.5	3.08	2.50	4	21	2.15
Analysts	1	4	6.18	5	8	25	3.44
Questions	1	17	27.68	26	36	108	14.56
Audit Fees	0	0.78	2.45	1.40	2.71	37.80	3.33

Notes: Table 3 presents the descriptive statistics for the main regression variables. *ICMW* is one if at least one ICMW was disclosed at the end of the year and zero otherwise. *#ICMW* denotes the number of weaknesses disclosed at the end of the year. *Total Assets* is the beginning of year total assets in million $. *Topic Score* is the topic score of the ECC as calculated in equation 2. *Mergers* are acquisition expenditures in million $. *Net Income* is in million $. *Market Valuation* is the firm's market valuation in million $. *Performance* is the return on beginning-of-year assets. *Sales Growth* is the firm's increase in sales in the last year, divided by last year's sales. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the number of years since the firm's first entry in the Compustat database. *Complexity* is calculated as the arithmetic mean of the number of business segments and the number of geographic segments. *Analysts* denotes the number of financial analysts who ask questions during the earnings conference call. *Questions* denotes the total number of questions asked during the earnings conference call. *Audit Fees* denotes the fees paid by the firm to the auditor in million $.

Table 4: Descriptive Statistics for ICMW and Control Firms

	ICMW=1		ICMW=0	
Variable	Mean	Std Dev	Mean	Std Dev
#ICMW	1.95	1.58	0	0
Topic Score	-0.27	0.44	-0.41	0.50
Total Assets (in m$)	3,087.57	7,915.15	3,181.17	9,969.46
Mergers (in m$)	89.38	353.92	114.70	903.28
Aggregate Loss	0.21	0.41	0.19	0.39
Extreme Sales Growth	0.16	0.37	0.18	0.38
Bankruptcy Risk	0.78	3.06	0.55	2.37
Firm Age	21.79	14.79	22.74	14.94
Market Valuation	2,891.44	8,544.68	4,198.60	14,846.39
Complexity	3.09	2.20	3.08	2.10
Foreign Operations	0.66	0.47	0.69	0.46
Analysts	5.84	3.27	6.51	3.57
Questions	26.43	14.12	28.87	14.88
Audit Fees	2.96	3.44	2.24	3.25

Notes: Table 4 presents the descriptive statistics for the main regression variables for ICMW and control firms. *ICMW* denotes the number of weaknesses. *Topic Score* is the topic score of the ECC as calculated in equation 2. *Total Assets (in m$)* is the beginning of year total assets in million $. *Mergers (in m$)* are acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Market Valuation* is the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise. *Analysts* denotes the number of financial analysts who ask questions during the earnings conference call. *Questions* denotes the total number of questions asked during the earnings conference call. *Audit Fees* denotes the fees paid by the firm to the auditor in million $.

Table 5: Pearson Correlation Coefficients

	ICMW	Topic Score	Total Assets	Mergers	Aggregate Loss	Extreme Sales Growth	Bankruptcy Risk	Complexity	Firm Age	Size
Topic Score	0.211***									
Total Assets	-0.00	-0.06***								
Mergers	0.02	-0.04**	0.37***							
Aggregate Loss	0.03*	0.05***	-0.24***	-0.20***						
Extreme Sales Growth	-0.01	-0.05***	-0.10***	0.04**	0.08***					
Bankruptcy Risk	0.04***	-0.00	0.09***	0.07***	-0.09***	-0.00				
Complexity	0.00	0.10***	0.27***	0.16***	-0.11***	-0.07***	0.00			
Firm Age	-0.05***	0.05***	0.24***	0.07***	-0.15***	-0.17***	-0.03*	0.28***		
Size	-0.13***	-0.18***	0.79***	0.37***	-0.27***	-0.01	0.09***	0.20***	0.20***	
Foreign Operations	-0.03**	0.02	0.23***	0.11***	-0.05***	-0.06***	-0.06***	0.40***	0.14***	0.24***

Notes: Table 5 presents the bivariate Pearson correlation coefficients between ICMW occurrence and the key variables. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. *ICMW* is one if at least one ICMW was disclosed at the end of the year and zero otherwise. *Topic Score* is the topic score of the ECC as calculated in equation 2. *Total Assets* is the natural logarithm of the firm's total assets. *Mergers* is the natural logarithm of the firm's acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Size* is the natural logarithm of the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise.

Table 6: Regression Results from Regression Equation 3

Panel A: Entire sample regression

Dependent variable: ICMW		
Variable	Controls only	LDA approach
Topic Score		0.80***
Mergers	0.05**	0.05***
Aggregate Loss	-0.09	-0.09
Extreme Sales Growth	-0.06	0.03
Bankruptcy Risk	0.05**	0.04**
Complexity	0.14	0.06
Firm Age	-0.10	-0.13
Size	-0.29***	-0.23***
Foreign Operations	-0.17	-0.17
Excess Return	0.01	0.03
Observations	3,515	3,515
Pseudo R-squared	4.12%	6.24%
Fixed effects	Industry, year	Industry, year
Clustered standard errors	Firm level	Firm level

Panel B: Out-of-sample regression

Dependent variable: ICMW		
Variable	Controls only	LDA approach out-of-sample
Topic Score		0.28***
Mergers	0.06**	0.06***
Aggregate Loss	-0.14	-0.16
Extreme Sales Growth	-0.15	-0.13
Bankruptcy Risk	0.05**	0.05**
Complexity	0.17	0.14
Firm Age	-0.09	-0.09
Size	-0.30***	-0.29***
Foreign Operations	-0.20	-0.20
Excess Return	0.02	0.01
Observations	2,905	2,905
Pseudo R-squared	4.26%	5.01%
Fixed effects	Industry, year	Industry, year
Clustered standard errors	Firm level	Firm level

Notes: Table 6 presents the results of estimating regression equation 3. Panel A presents the results from estimating the regression using the entire sample. Panel B presents the results for the out-of-sample estimation. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. *ICMW* is one if at least one ICMW was disclosed at the end of the year and zero otherwise. *Topic Score* is the earnings conference call's topic distribution matrix multiplied by the regression coefficients derived from estimating regression equation 1. *Mergers* is the natural logarithm of the firm's acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage

calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Size* is the natural logarithm of the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise. *Excess Return* is the return on the firm's stock between the release of the 10-K and the earnings conference call minus the performance of the S&P500 in the same time period.

Table 7: Determinants of predictive topics

Topic	Mergers	Aggregate Loss	Extreme Sales Growth	Bankruptcy Risk	Firm Age	Size	Complexity	Foreign Operations	Excess Return
Asian economy		(–)*				(+)*	(+)***	(+)***	
Firm segments	(+)***	(–)***			(+)***		(+)***	(+)***	
Planning			(–)***						
Cost structure			(–)***	(+)**	(+)**		(+)***		
Sales			(+)***		(–)*	(–)***			
Industry downturn					(+)**		(+)**		
Cash flow			(–)*	(+)**			(+)***		(–)*
Transition				(–)*		(+)*		(–)***	
External effects		(–)***	(–)***			(+)***			(–)**
Future	(–)***	(+)***				(+)**			

Notes: Table 7 presents the results from regressing the occurrence of the ten most predictive topics on the control variables from regression equation 3. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. The ICMW categories on the top are taken from auditors' SOX 404 reports disclosed with the respective 10-Ks. *Mergers* is the natural logarithm of the firm's acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Size* is the natural logarithm of the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise. *Excess Return* is the return on the firm's stock between the release of the 10-K and the earnings conference call minus the performance of the S&P500 in the same time period.

Table 8: Predictive Power of Individual Topics

Topic	Asian economy	Firm segments	Planning	Cost structure	Sales	Industry downturn	Cash flow	Transition	External effects	Future
Accounting		(+)***					(+)***			
Adjust		(+)*					(+)***			
Competency	(+)**					(+)***	(+)***			
IT		(+)*							(+)***	
Personnel	(+)***						(+)***			
Nonroutine			(+)**				(+)**			
Disclosure					(+)**		(+)***			
Reconciliation		(+)***					(+)***			
Restatement		(+)**	(+)*							
Journal		(+)*				(+)*	(+)**			

Notes: Table 8 presents the results from regressing the occurrence of specific ICMW categories on the weights of the ten most predictive topics and the control variables from regression 3. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. The ICMW categories on the left are taken from auditors' SOX 404 reports disclosed with the respective 10-Ks. The topics on the top are the labels for the most predictive topics from Table 5.

Table 9: Regression Results of Earnings Guidance Analyses

Dependent variable: ICMW		
Variable		
Topic Score	0.56***	0.94***
Topic Score*ManagerForecastBias	1.32**	
ManagerForecastBias	0.71**	
Topic Score*MonthsBeforeFYE		-0.14***
MonthsBeforeFYE		-0.05
Mergers	0.01	0.02
Aggregate Loss	-0.35	-0.36
ExtremeSalesGrowth	-0.23	-0.25
Bankruptcy Risk	0.04	0.04
Complexity	-0.17	-0.15
Firm Age	-0.24	-0.27
Size	-0.05	-0.07
Foreign Operations	-0.49	-0.47
Excess Return	-0.63**	-0.63**
Observations	1,090	1,090
Pseudo R-squared	7.41%	7.34%
Fixed effects	Industry, year	Industry, year
Clustered standard errors	Firm level	Firm level

Notes: Table 9 presents the results of the analysis on the role of managers' earnings guidance. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. *ICMW* is one if at least one ICMW was disclosed at the end of the year and zero otherwise. *Topic Score* is the earnings conference call's topic distribution matrix multiplied by the regression coefficients derived from estimating regression equation 1. *ManagerForecastBias* is measured as the manager's last annual EPS forecast minus that financial year's actual EPS for the last financial year before the ECC. *MonthsBeforeFYE* is measured as the number of months between the manager's last guidance update and the release of the actual EPS at financial year end. *Mergers* is the natural logarithm of the firm's acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Size* is the natural logarithm of the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise. *Excess Return* is the return on the firm's stock between the release of the 10-K and the earnings conference call minus the performance of the S&P500 in the same time period.

Table 10: Regression Results of Financial Analyst Characteristics Analyses

Dependent variable: ICMW		
Variable		
Topic Score	0.51**	0.54***
Topic Score*Analyst Experience	0.11*	
Analyst Experience	0.06	
Topic Score*Analyst Industry Experience		0.11*
Analyst Industry Experience		0.07
Mergers	0.05**	0.05**
Aggregate Loss	-0.09	-0.09
ExtremeSalesGrowth	-0.03	-0.03
Bankruptcy Risk	0.04**	0.04**
Complexity	0.06	0.06
Firm Age	-0.13	-0.13
Size	-0.23***	-0.23***
Foreign Operations	-0.17	-0.17
Excess Return	0.03	0.03
Observations	3,515	3,515
Pseudo R-squared	6.35%	6.20%
Fixed effects	Industry, year	Industry, year
Clustered standard errors	Firm level	Firm level

Notes: Table 10 presents the results of the analysis on the role of financial analyst characteristics. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. *ICMW* is one if at least one ICMW was disclosed at the end of the year and zero otherwise. *Topic Score* is the earnings conference call's topic distribution matrix multiplied by the regression coefficients derived from estimating regression equation 1. *Analyst Experience* is measured as the years since the financial analyst's first entry in the I/B/E/S database. *Analyst Industry Experience* is measured as the years since the financial analyst first covered a firm in this industry. *Mergers* is the natural logarithm of the firm's acquisition expenditures in million $. *Aggregate Loss* is 1 if the firm had negative net income in the current period as well as the previous period and 0 otherwise. *Extreme Sales Growth* is 1 if the firm's sales growth was in the top quintile for the firm's industry in this year and 0 otherwise. *Bankruptcy Risk* is the firm's leverage calculated as total debt divided by equity. *Firm Age* is the natural logarithm of the years since the firm's first entry in the Compustat database. *Size* is the natural logarithm of the firm's market valuation in million $. *Complexity* is calculated as the natural logarithm of the arithmetic mean of the number of business segments and the number of geographic segments. *Foreign Operations* is 1 if the firm has at least one foreign geographical segment and 0 otherwise. *Excess Return* is the return on the firm's stock between the release of the 10-K and the earnings conference call minus the performance of the S&P500 in the same time period.

Table 11: Regression Results from Audit Fee Analysis

Dependent variable: Audit Fees (log)	
Variable	
Topic Score	0.09***
Total Assets	0.49***
Segments	0.04
Inv Receivables	0.70***
Foreign	0.30***
Current Ratio	-0.03***
BtM	-0.67
Leverage	0.04
Employees	0.02*
Merger Activity	-0.15**
December	0.14***
ROA	-0.06
Loss	0.19***
Going Concern	0.30**
New Auditor	0.20
Short	0.69***
Medium	0.67***
Age	-0.05**
Financing	-0.08***
ICMW	0.20***
Restate	-0.03
Observations	3,622
Pseudo R-squared	72.49%
Fixed effects	Industry, year
Clustered standard errors	Firm level

Notes: Table 11 presents the results of regressing audit fees on the content of analyst questions. *, **, and *** indicate two-tailed significance on the 10%, 5% and 1% level, respectively. *Topic Score* is the earnings conference call's topic distribution matrix multiplied by the regression coefficients derived from estimating regression equation 1. *AuditFees* is the natural logarithm of audit fees paid. *Total Assets* is the natural logarithm of total assets. *Segments* is the square root of the number of business segments. *Inv Receivables* is the sum of accounts receivable and inventory. *Foreign* is 1 if the firm has foreign operations, 0 otherwise. *Current Ratio* is current assets divided by current liabilities. *BtM* is the book value of equity divided by market value of equity. *Leverage* is total debt divided by total assets. *Employees* is the square root of the number of employees. *Merger Activity* is 1 if the firm had any M&A activity, 0 otherwise. *December* is 1 if the firm's fiscal year ends in December, 0 otherwise. *ROA* is return on assets. *Loss* is 1 if the firm had a negative ROA, 0 otherwise. *Going Concern* is 1 if the firm received a going concern opinion, 0 otherwise. *New Auditor* is 1 if the firm's auditor has been with the client less than 1 year, 0 otherwise. *Short* is 1 if the firm's auditor has been with the client for 2 or 3 years, 0 otherwise. *Medium* is 1 if the firm's auditor has been with the client for 4 to 14 years, 0 otherwise. *Age* is the natural logarithm of the firm's age in years. *Financing* is 1 if the firm was involved in any new financing, 0 otherwise. *ICMW* is 1 if the firm disclosed an internal control material weakness, 0 otherwise. *Restate* is 1 if the firm restated its financial statements, 0 otherwise.