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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2021: Climate Economics

Provided in Cooperation with:
Verein für Socialpolitik / German Economic Association

Suggested Citation: Mansouri, Sasan (2021) : Does firm's silence drive media's attention away?, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2021: Climate Economics, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:
https://hdl.handle.net/10419/242433

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Does firm's silence drive media's attention away?*

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February 27, 2021

ABSTRACT

In this study, using a comprehensive dataset on business media coverage and textual analysis of the discussions in firms' quarterly earnings conference calls, we show that firms whose management fail to satisfy the demand for information, ceteris paribus, receive less media coverage. Poor information environment hurts the information-creation capacity of the media, while such an environment does not show a similar association with the media's information-dissemination role. Furthermore, this association is more prominent for the professional business media, compared to their non-professional counterparts such as blogs and alternative articles. Our results add nuance to the literature on media coverage bias by showing that the coverage of the firms is mainly driven by the supply-side factors, i.e. the factors affecting the suppliers of the coverage, rather than being demand-driven.

Keywords: non-answers; conference calls; media coverage; non-professional business media.

JEL-Classification: D82, G14, G30.

*I benefited from the comments of Andreas Barth, Alexander Hillert, Stephan Hollander, Beatriz Garcia Osma, and Mark Wahrenburg I declare that I have no relevant or material financial interests that relate to the research described in this paper. All errors are my own.

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1 Introduction

Among different information intermediaries, the media platforms enjoy the broadest audience (Zingales, 2000). This enables media to play a crucial role in the financial markets in several ways. Media coverage cause movements in stock prices (Fang and Peress, 2009; Hillert et al., 2014), decisions in corporate governance (Dyck et al., 2008) and firm behavior (Baloria and Heese, 2018), and are a whistle-blower of corporate wrongdoings (Dyck et al., 2010; Miller, 2006). Despite the abundance of literature on the effects of media attention, we know less about the driving forces behind the media coverage.

In this paper, we put the media coverage of the big corporations under the spotlight and test two competing hypotheses regarding the media attention on the firms. We use the variations in the quality of information environment around the firms, and ask if the media coverage is associated with the richness of this information environment. Specifically, we say the media attention to a firm is "demand-driven" if business media respond to the stakeholders' demand for more information/analysis about the firms with poorer information environment. On the other hand, for firms with a poor information environment, media sources have a more challenging task to gather enough publishable materials. In other words, a firm's media exposure is "supply-driven", if the media sources, as suppliers of information, reduce the coverage of the firm that is more difficult to cover.

To measure the quality of the information environment around the firms, we rely on the literature on the informativeness of firms' quarterly earnings conference calls and advancements in computational linguistics. The Q&A sessions of earnings conference calls offer a unique setting for our study. In these calls, investors can directly glean information about the company by questioning senior managers. When responding to a question, the management decides to whether to fulfill this need for information or leave the demand for information "non-answered". We quantify the level of non-answers in a call using the $Non - Answer$ measure proposed by Barth et al. (2020). This measure is trained on a set of Q&As between the management and equity analysts during the earnings calls, and is calculated using a bag-of-word approach with a glossary of 1,227 trigrams like '[let me get] back to you', ' [I] do not know', '[it's] hard to predict', '[let's] wait and see', '[it's] too early to', etc.. These trigrams are found to be frequently used to refrain from answering a question

in a factual manner where it could be either a direct rejection, i.e. refusals to answer a question, as documented by Gow et al. (2019), or a less noticeable symptom of non-answers, i.e. beating around the bush by blathering, as outlined in Barth et al. (2019).

We follow a survivorship bias-free sample of firms appeared in the S&P500 index for the period of 2007 to 2019, and utilize their quarterly earnings conference calls' transcripts to measure the $Non-Answer$ in the management responses. Furthermore, we collect the media coverage information before and after each earnings call using Ravenpack (RP). RP includes millisecond timestamped media coverage data from tens of thousands of news sources like Dow Jones Newswires, Wall Street Journal, Financial Times, Bloomberg, Reuters, Seeking Alpha, as well as blogs like Zero Hedge and The Motley Fool. We set our analysis window to be from the day after the earnings call to the 60th day. This time frame allows us to capture the time frame between the current call and before the next call of the same company.[1] We measure the media coverage by considering the number of unique news sources who publish contents during our analysis window, i.e. $Sources$, and the number of all the contents published on the firm during the same window, i.e. $Counts$.

We begin our analysis by examining the association of non-answers in the calls with the media coverage that the firm receives in the next quarter. Figure 1 illustrates binned scatter plots of our media coverage variables versus the non-answer earnings calls. We put the negative correlation shown in Figure 1 under scrutiny using a regression analysis framework, and we find that, in line with the supply-driven media coverage hypothesis, the more a firm turns down the demand for information in its earnings call, the less media attention the firm receives in the coming quarter. In other words, while the demand for firm-specific information increases due to the management non-answers, media also reduces the supply of contents due to supply-side difficulties to acquire and provide content.

[Figure 1 about here]

Next, we investigate if the supply-driven decrease in coverage is more substantial for the contents that are more difficult to create. Ravenpack categorizes the coverage entries as either a full-article, a

[1] While it seems natural to consider a 90 days window between two calls, in 25% of the cases, two calls of the same company hosted in less than 90 days from each other, but it is only in less than a percent of cases that two calls hosted in less than 60 days. We also set the window to be fixed at 60 days to allow for the media coverage measures to be comparable across firms.

(hot-)news-flash, or a tabular-material. We separate different types of media coverage based on their production cost for the media sources, i.e. full-articles versus other types, and repeat our analysis. The results confirm the supply-driven coverage hypothesis only for the full-articles. Contrarily, the variation in the non-full-articles' coverage is mainly explained by the firm's initiated press releases. Overall, this suggests that the poor information environment around the firm only curtails the information-production role of the media and does not hurt their information-dissemination role.

Business media fall into a spectrum of professionalism, and both professional and non-professional media play significant roles in shaping investors' opinion (Chen et al., 2014; Drake et al., 2017).[2] We continue our analyses by asking how non-answer earnings calls associate to extend of (non-)professional media coverage. First, in line with the previous results, we find there are fewer media sources of both categories that publish content for the firms with poorer information environment. The professional media, however, publish significantly fewer articles which results in a lower ratio of professional coverage for the non-answering firms.

All of the above-mentioned results are robust to controlling for several confounding factors. First, we control for common factors, such as size, profitability, and book-to-market that are found to be a driver of media attention by the preceding literature. Second, we control for the common language measures of the management answers, e.g. tone, uncertainty, and complexity, that have shown to contain value-relevant information for the stock market. Furthermore, we absorb the difference between the market (analyst) expectations and the actual quarterly results, i.e. earnings surprise. Third, we use a topic-modeling algorithm to develop and control for 25 news topics to address the topic-specific tendencies in attracting more media coverage. Finally, we absorb several observable and unobservable factors by including several fixed effects; we remove common time trends with quarter fixed effects and control for any time-constant firm-specific factors by firm fixed effects. In some of the specifications, instead of firm fixed effects, we either include industry-year fixed effects or, more conservatively, firm-year fixed effects that enables us to study the same firm within a year.

We finally verify the above-mentioned findings from the perspective of the media sources' coverage portfolio, and specifically, we ask if the non-answer earnings calls shift the attention of the

[2] In this analysis we don't consider a spectrum, instead, we divide the media sources into two categories as defined in Subsection 3.2.

media to the peers of a firm. We restrict our sample to earnings calls of the firms in the same industry that hold their conference calls on the same day, and measure the share of the articles belonging to each of these firms in the media level one month before and after the earnings call date. We find that media sources shift their coverage from the non-answering firms to the firms with more informative earnings calls. This result is robust to the inclusion of media fixed effects.

Our paper contributes to the existing literature in number of ways. First, we add to the literature on the factors that skew the attention of the media. Previous literature has uncovered several factors as, for example, the advertisement (Reuter and Zitzewitz, 2006), local proximity Gurun and Butler (2012), and firm size and reputation Miller (2006). We add to this literature by showing that media coverage is inclined toward firms with a better information environment. Second, the literature of accounting and finance separates the role of media that a) disseminates the currently available information, and b) create new information through active journalism (Bushee et al., 2010). We add to this literature by showing that the"supply-driven" decrease of media coverage is associated only to the information-creation role of the media. Third, the emergence of Ravenpack News Analytics provides researchers with a wonderfully detailed data on media coverage (Miller and Skinner, 2015), and our topic-modeling approach enables researchers to enhance the practicality of the news taxonomy data provided in Ravenpack. Finally, we further demonstrate the importance of non-professional business media for the financial markets (Chen et al., 2014; Drake et al., 2017), and show that non-professional analysts/business journalists, compared to their professional counterparts, are less susceptible to reduced coverage in poor information environments.

The remainder of this paper is organized as follows: section 2 reviews the relevant literature and outlines the testable hypotheses. In section 3, we describe in detail the dataset we use in our empirical analyses. We describe our empirical analyses and show the results in section 4. section 5 concludes.

2 Background literature and hypotheses

2.1 Information content of earnings calls

To fill the information gap among equity investors, firms voluntarily hold earnings conference calls regularly (Brown et al., 2004) which are indeed very informative for the market participants (Bushee

et al., 2004; Matsumoto et al., 2011) compared to a firm's other types of disclosure, as they contain more forward-looking details about the firm's expected performance and direction (Kimbrough and Louis, 2011). Earnings calls usually begin with a previously prepared management presentation of the earnings results of the past quarter, and then they follow with a Q&A session between the management and participants who are mainly equity analysts. While both the presentation part and the Q&A session are enlightening for the market, Matsumoto et al. (2011) show that the latter is more informative.

With the advances in computational linguistics and particularly the development of the finance-specific glossaries of Loughran and McDonald (2011), a growing body of empirical literature deals with the information contents of management responses to the question asked during the earnings calls. Price et al. (2012) show the investors react to the soft information, i.e. tone of the management answers in the earnings calls. Furthermore, they show that while the market digests the hard information (e.g. earnings surprise) in the short one-day window the call, the tone predicts the stock price drift up to 60 days post-call. Furthermore, Dzieliński et al. (2017) and Zhou (2018) show, respectively, that the management use of uncertain language, as well as the ratio of numeric contents in the management responses, contain value-relevant information.

Although earnings calls are a medium to provide investors with value-relevant information, firm's management can obscure the flow of information in several ways. Most severely, Mayew (2008) and Cohen et al. (2013) provide evidence showing that the management discriminates against questions raised by the analysts whose stock recommendations are considered unfavorable, during the calls. Moreover, management can avoid answering unfavorable questions by "obfuscating" using complex language (Bushee et al., 2018), "blathering", i.e. beating around the bush (Barth et al., 2019), direct refusing/rejecting (Hollander et al., 2010; Gow et al., 2019), or a mix of them (Barth et al., 2020).

Investors react to the discussions of the earnings calls; nevertheless, they also rely on information intermediaries to digest earnings calls' contents. Sell-side analysts are one of the most studied information intermediaries. Frankel et al. (2006) show that the information content of the analysts' report is a complement to the firms' disclosures. Huang et al. (2018) show that when the management withholds value-relevant information during the call, equity analysts intensify their "discovery" role (as opposed to solely "interpretation" of discussions in the call). In this study, we

shed light on the other types of information intermediaries, namely the business media, and verify how they respond to the management withholding information.

2.2 Media as an information intermediary

Media causally affects firms' security prices, corporate governance, and investors' attention.[3] The media coverage takes two main roles namely, disseminating/packaging the available information and stale news or, creating new information through active journalism practices. A growing number of accounting literature deals with the disentangling of these two roles. Bushee et al. (2010) eliminates the journalists' interpretations from media coverage and shows that the further dissemination of available information leads to lower information asymmetry among investors. Drake et al. (2014) confirms the role of media dissemination in the incorporation of accounting information into the stock prices. Blankespoor et al. (2018) similarly show that the dissemination of information, identified by the introduction of robo-journalism, increases the trading volume and liquidity. Engelberg and Parsons (2011) show that, controlling for the available information, local media coverage of S&P500 companies strongly predicts local tradings.

In addition to the dissemination role, media coverage can change investors' behavior by creating new content (Dougal et al., 2012; Guest, 2018). Above all, the information-creation role makes the media a watchdog for accounting frauds (Miller, 2006)[4]. More generally, media is one of the most diligent whistle-blowers for corporate frauds (Dyck et al., 2010). Investors also value the monitoring role of the media. Specifically, Gao et al. (2020) show that the closure of local newspapers results in a 5 to 11 basis points increase in municipal borrowing costs. Therefore, we contribute to this literature by investigating if the media's information-creation ability declines when firm's management withholds value-relevant information.

Media coverage is prone to several biases.[5] Media may engage in "sensationalism" by disproportionately covering the news that could be interesting for a broader set of audience. For example, media tend to cover the CEOs with more option exercises, disproportionately more negative, and

[3] See Tetlock (2015); Miller and Skinner (2015); Blankespoor et al. (2020) for a comprehensive literature review.

[4] Media, compared to other information intermediaries, benefit from a broader audience that enables the media to play a governance role by shaping investors' beliefs(Zingales, 2000) by only disseminating the available information (Rogers et al., 2016)

[5] There are many empirical papers showing the existence of media bias in political coverage. See Puglisi and Snyder Jr (2015) for a comprehensive literature review. Here we discuss only the case of media bias regarding the corporations' coverage.

ignoring the total salary (Core et al., 2008). Moreover, the watchdog role is mostly limited to the cases where the fraudulent activities are related to a famous/large corporation that could be interesting for a broad audience (Miller, 2006). There are also shreds of evidence concerning other sources of bias. To name a few, advertisement pressure (Reuter and Zitzewitz, 2006), reciprocity between journalists and corporations (Dyck and Zingales, 2003; Westphal and Deephouse, 2011), and favoritism toward socially-responsible firms (Zavyalova et al., 2012; Cahan et al., 2015).

Finally, we contribute to the discussion on professional versus non-professional business media. Drake et al. (2017) argue that professionalism falls on a spectrum, and they classify the sample of media in their studies into three groups of professional, semi-professional, and non-professional. They show that the coverage by the first two groups has positive capital market effects, while the coverage by non-professional business media contains more noise than real information. Drake et al. (2017) classify the Seeking-Alpha (SA) as a semi-professional media. SA is a platform where non-professional analysts share their stock recommendations. Chen et al. (2014) show that the articles as well as the commentaries in SA predict future stock returns and earnings surprises. In this study, we compare the coverage behavior of professional and non-professional business media when they face firms with poor information environment.

2.3 Research question

This section examines two main "demand-driven" versus "supply-driven" media coverage hypotheses[6].

A demand-driven media coverage hypothesis postulates that several stakeholders of a firm demand information and a media source covers the firm to address this demand. Stakeholders of a company rely on the discussions in earnings calls to expand their 'understanding' of the company (Barker et al., 2012). The management's refusal to provide the requested information in an earnings call keeps the demand for value-relevant information unfulfilled. Therefore, the stakeholders rely on other intermediaries to acquire the missing information that they demand. Investors are especially receptive to the missing value-relevant information from the discussions in earnings calls (Huang et al., 2018). Since the investors' demand for more information and analyses is one of the most

[6]See Puglisi and Snyder Jr (2011) for the literature review on different supply- versus demand-side factors contributing to the bias of political newspapers.

important drivers of the coverage decision for equity analysts (Brown et al., 2015), as an important information intermediary, the media is expected to cover more the firms for which the management rejects investors' demand for information.

Hypothesis ("Demand-driven coverage"). *Firms with higher non-answers in their earnings calls receive c.p. coverage from* ***more*** *media sources.*

A supply-driven media coverage hypothesis, on the other hand, suggests that the media sources provide coverage of firms based on their own preferences rather than the level of demand by their readers/subscribers. Firms deliberately reject the demand for more information because of proprietary costs associated with providing such information (Gow et al., 2019). These costs affect the firms' disclosure preferences and put them in a poorer information environment (Ellis et al., 2012). Such an environment around a firm makes it more difficult for media sources/journalists to acquire enough information to publish news articles on a firm (Guest and Kim, 2020). In light of the theoretical model of Bhushan (1989), a poorer information environment shifts the supply curve of media to the left, resulting in less total supply of coverage[7].

Hypothesis ("Supply-driven coverage"). *Firms with higher non-answers in their earnings calls receive c.p. coverage from* ***less*** *media sources.*

3 Data

For our study, we construct a survivorship bias-free S&P 500 dataset. This selection helps us to overcome the concerns over unobservable factors that may play a role in the media coverage of the smaller firms. First, the firms included in S&P500 are all explicitly in the spotlight of the media (Miller, 2006; Hillert et al., 2014) and analysts (Martineau and Zoican, 2020). Second, these firms are all high-volume publicly traded companies about which the investors' demand for information is high. Finally, the substantial costs of wrongdoing discourage the management to use non-answers for concealing potential fraudulent activities.

In the following subsections, we first define the main variables used in this paper, and finally, subsection 3.4 provides the descriptive statistics of the main variables in our empirical analyses.

[7]Lang and Lundholm (1996) shows empirically that more equity analysts tend to follow the firms with more clear disclosure policies.

Table A1 summarizes the variables and their corresponding definitions used in this study.

3.1 Measurement of management's withholding information

To quantify the management's withholding information, we use the so-called "non-answer" measure proposed by Barth et al. (2020). This measure is based on the two symptoms, namely management 'rejecting' (Gow et al., 2019) and management 'blathering' (Barth et al., 2019), by employing a Multinomial Inverse Regression (MNIR) technique (Taddy, 2013). Barth et al. (2020) identify a glossary of 1,227 trigrams such as 'back to you', 'do not know', 'hard to predict', etc., which are found to be frequently used in English Q&As[8] to refrain from answering a question concisely and factually. Figure 2 shows the word cloud of the most important trigrams of this glossary.

[Figure 2 about here]

We collect transcripts of all earnings calls held by the companies included in S&P 500 index from Thomson Reuters' StreetEvents for 2007 to 2019[9]. These calls are released quarterly and usually take place on the same day as the corresponding earnings release. Calls mostly start with the management presentation of a (previously prepared) statement, and then analysts (and investors) are invited to a Q&A session. The spontaneous nature of the Q&A session is a unique laboratory to measure the degree to which the management avoids providing factual responses in the context of the analysts' questions. Since we focus on the questions and answers in the call rather than the prepared presentation, we exclude all earnings calls without a Q&A session.

We define $NonAnswer^{\phi}$ as the weighted count of the terms in the glossary provided by Barth et al. (2020) for all the management answers in the earnings call of the company i in quarter t:

$$NonAnswer_{it}^{\phi} = \frac{\sum_{k=1}^{K} \phi_k \times Non\text{-}Answer\ Glossary\ Token_{it}^{k}}{Total\ Words_{it}},$$

where ϕ_k is the loading associated with trigram $k \in \{1, 2, ..., K\}$ in the glossary of Barth et al. (2020). We limit our observations to the transcripts where we can find at least 500 words in the

[8] Barth et al. (2020) show that their glossary not only measures the non-answers in the financial context but also the political context (e.g. US presidential interviews and US senate hearings) and sports' press conferences.

[9] We have the data since 2002 but we cut the data points before 2007 because of the missing data in our media coverage dataset. We use the full data for some of the robustness checks in Appendix D

management answers. This helps to avoid the extreme values of the non-answer measure due to a small denominator.

3.2 Media coverage

We use RavenPack News Analytics (RPNA) to obtain the media coverage of the firms in our sample. RavenPack dataset consists of three main editions; Dow Jones Edition provides the historical coverage, since 2000, of Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's, and MarketWatch. The Web Edition, starting from January 2007, includes hundreds of thousands of articles a day from leading publishers and web aggregators with more than 22,000 sources (Hafez and Xie, 2014). Finally, the PR Edition including the PR-Newswire. News coverage of RPNA is timestamped to the millisecond and includes several sentiment metrics as well as the news taxonomy. These features make RavenPack an interesting dataset for many asset managers, investment bankers, and hedge funds(RavenPack, 2017).

We merge our sample of firms with RavenPack using the 8-digit CUSIP code of the firms. For the unmatched sample, we perform a fuzzy match of the company names in the Compustat with the company name in the RavenPack and manually check if the matching score is less than 95%. We further filter for all the news contents that have a "Relevance" score of at least 90% to the firm.

Coverage *Sources* is the main coverage measure we use throughout this paper, and it is defined as the natural logarithm of one plus the count of unique media sources (or channels) that publish contents in the form of full-article, (hot-)news-flash, and/or tabular-material in a two-month period after firms' earnings conference calls. Similarly, we define $Sources^F$ if we filter only for the full-articles, and $Sources^{NF}$ if we only consider the (hot-)news-flashes and tabular-materials. Additionally, *Counts* is defined as the natural logarithm of one plus the count of all the above-mentioned types of contents. We exclude the day of the conference call as well as the day after, to avoid our measures being overloaded with lots of news regarding the quarterly earnings results of the company.

Figure 3 shows the time trends for the average distinct Sources and news Counts for all the firms in a given quarter. The spike of both measures at the beginning of 2007 refers to the initiation of RavenPack Web Edition. In the period after 2007, the Web Edition of RP added the coverage of

many news sources. Although we can address this problem with quarter fixed effects, we trim the sample and focus only on the observations from 2007, as we require a consistent sample for some of our analyses. For the robustness check of the main results, we repeat our analysis with the full sample as well.

[Figure 3 about here]

Press releases Furthermore, we control for the amount of firms' press releases in our analysis window, i.e. PR. To do so, we follow Bushee and Miller (2007); Core et al. (2008); Bushee et al. (2010) and assume all the articles on press release wire as well as the entries with "NEWS_TYPE" being "PRESS-RELEASE" are firm-initiated disclosures.

Professional versus non-professional business media Inspired by Drake et al. (2017), we divide the sample of coverage sources to either professional or non-professional business media. We consider a media as professional if it or its parent company is listed among Barron's (with RavenPack ID: 18A55F), Bloomberg News (208421), Business Insider (C75B8C), CNBC (AA1167), Dow Jones Newswires (B5569E), Entrepreneur (938822), Financial Times (FD0B00), Forbes (22AC8B), MarketWatch (1E5E35), Morningstar (E04BE4), Reuters (751371), or Wall Street Journal (AA6E89). By this definition, in our list of professional business media we, for example, include sources like "FT Alphaville - Hedge funds" (with the Financial Times as the parent) and "Bloomberg Businessweek" (Bloomberg). This list includes 65 sources as listed in the Appendix C. Included as non-professional media, we have mostly blogs and news websites associated with the non-professional analysts/journalists; to name a few, Seeking Alpha (B61D8F), Zero Hedge (5E506B), and The Motley Fool (C81722).

In line with our coverage variables, $Sources_{Pro}(Sources_{N-Pro})$ and $Count_{Pro}(Count_{N-Pro})$ refer to the coverage provided if we filter the media sources to be (Non-)professional.

Newsworthiness inspired by Dyck et al. (2008), we define $NewsWorthiness$ as the natural logarithm of one plus the number of articles referring to a company in the Wall Street Journal (RavenPack ID "AA6E89") and the Financial Times (RavenPack ID "FD0B00") during the 6-month period before the earnings call (excluding the day of earnings call and the day immediately

before it).

News contents To control for the news contents that are relevant to the firms in our analysis window, we collect news taxonomy information, i.e. "Category" field, for all the coverage entries of the firms in our analysis window from one day after the call to the 60th day. In total, it sums up to 526 distinct categories. To efficiently control for the news content, we reduce the dimension of 526 categories to 25 "news topics" using the LDA topic modeling algorithm of Blei et al. (2003)[10].

In a conventional LDA for the language modeling, one needs to tokenize the document by breaking down the sentences into smaller linguistic units like a word, a bi-gram, or other higher-order n-grams, and form a "document-term-matrix" that tabulates the counts of the tokens in several documents of the training set. Here we consider each news category in the list of all the categories that appeared in the news following a firm's earnings call as a token in a document. LDA clusters the tokens that co-occur frequently, and form a topic. One feature that contributes to the popularity of the LDA is that the formation of the topics is independent of the researchers' prejudgment. The only input from the researcher's side is the number of topics. We select 25 topics as it suggests the best goodness of fit according to the metrics developed in computer science literature (Nikita and Chaney, 2016)[11].

[Figure 4 about here]

Figure 4 shows the most important news categories associated with each of the news topics. β is the weight of each token in the given topics. For example, Topic 10 (or 19) consists of the news most relevant to acquisitions (or layoffs). The distribution of weights in topic 7 on the other hand, is more homogeneous among the different news related to the technical analysis of the shares.

[Figure 5 about here]

In the next stage, we measure the distribution of each of 25 topics in the list of all news after an earnings call. γ_{ijt} is the portion of the news that belongs to the topic j after the earnings call

[10]LDA stands for Latent Dirichlet Allocation and is an unsupervised machine learning algorithm. The resulted topics of a fitted LDA model are very similar to the factors in a factor analysis model. LDA is a very popular topic modeling algorithm for textual analysis in finance and accounting. See Gentzkow et al. (2019) for topic modeling methodology overview and Eickhoff and Neuss (2017) for the literature review.

[11]Figure B1 in Appendix B shows the metrics for the goodness of the LDA fit for the different number of topics in the range of 5 to 95.

of the firm i at quarter t. We have $\sum_j \gamma_{ijt} = 1$ and each topic has a log-normal distribution among documents. Figure 5 shows the histograms of $log(\gamma)$ for each topic.

3.3 Other variables

Alternative speech characteristics The common finance and accounting literature offers several standard metrics to quantify earnings calls' language contents. Following the literature, we adopt a dictionary (bag of words) approach. In this approach, one calculates the desired sentiment by counting the words' occurrences in a corresponding word-list divided by the total words in the document.

We calculate the *Negativity* (as a mesure of tone) and *Uncertainty* of management answers using the "negative" and "uncertainty" word lists offered by Loughran and McDonald (2011), respectively. We do not consider the "positive" word-list for the tone calculations, as suggested by Loughran and Mcdonald (2016).

Additionally, we control for the *Complexity* in the management language using the word-list of Loughran and McDonald (2020). Loughran and McDonald (2020) show that the complexity measure of 10-k filings[12], is associated with the stock returns around the filing date and unexpected earnings.

Earnings surprise We collect analysts' Earnings per Share (EPS) forecasts for the firms in our sample from Institutional Brokers' Estimate System (IBES) database and define *EarnSurp* following Dzieliński et al. (2017). More precisely, we calculate Earnings Surprises as the difference between the actual and consensus forecast earnings, divided by the closing share price on the 5th trading day before the earnings announcement in every quarter. We then group the (zero and) positive as well as the negative numbers separately into five quantiles (i.e. quintiles). Finally, we sort all the created ten categories and label the earnings surprises from 1 (most negative) to 5 (least negative) and from 6 (least positive) to 10 (most positive).

[12]Here, we deviate from Loughran and McDonald (2020) in the sense that they measure complexity by counting the number of unique words, in a given document, that appear in their word-list of 374 words, compared to our dictionary approach of counting the frequency of the words in their word-list divided by the total words.

Firm characteristics We use Compustat to obtain quarterly balance sheet data. We control for Book-to-Market (BTM) ratio, and the firm size as the natural logarithm of total assets($ln(Assets)$). We calculate Tobin's Q as the book value of assets minus book value of common equity plus the market value of common equity, divided by the total book value of assets.

3.4 Descriptive statistics

[Table 1 about here]

Table 1 presents descriptive statistics for the variables in this analysis. For $NonAnswer^{\phi}$, the magnitude is in line with the distribution presented in Barth et al. (2020). The median firm in our sample receives coverage of 200 published contents from around 30 media sources, and the firm itself initiates around 4 press releases during our analysis window of two months after the earnings call.

4 Empirical analysis

Section 4.1 analyzes the association of our media coverage measure with the management withholding of information in earnings calls. We further explore this relationship by separating several types of media coverage in section 4.2. Section 4.3 compares the coverage choice of professional versus non-professional business media. Finally, in section 4.4, we investigate the above-mentioned association from the perspective of media preferences.

4.1 Media coverage

We first investigate if management's earnings call non-answers is associated with the media coverage that a firm receives during the next quarter. We model the count of media sources that cover firm i in a window of two months after the call[13] in quarter t, as indicated in the following equation:

$$\begin{aligned} Sources_{it} = \beta_0 + \beta_1 \cdot NonAnswer^{\phi}_{it} + \beta_2 \cdot PR_{it} \\ + \beta_3 \cdot X_{it} + \alpha_{\mathbb{I}(i)} + \alpha_t + \epsilon_{it}, \end{aligned} \tag{1}$$

[13]Results for a short window analysis, i.e. the first 48 hours after the call, are consistant with this analysis, and are provided in the appendix Table D1

$NonAnswer_{it}^{\phi}$ is the main variable of interest, measuring management's degree of non-answers in the call. According to the "demand-driven coverage" hypothesis, $NonAnswer_{it}^{\phi}$ is a proxy for the demand for a firm's information after the earnings call, and therefore, a positive β_1 means that the media answers this demand by providing more coverage on the firms withholding more information. On the contrary, the "supply-driven coverage" predicts a negative β_1 reflecting less media coverage of the firms for which the cost of acquiring information is higher.

We control for several important variables that contribute to the media coverage of firms. PR_{it} is the amount of firm disseminated news and contributes directly to the firm's coverage because of the dissemination role of the media. We also control for several other firm-quarter observations in X_{it}; Earnings Surprise ($EarningsSurp$) captures the difference between analysts' expectations about earnings and the realized earnings in quarter t. The natural logarithm of total assets($ln(Assets)$), Book-to-Market ratio(BTM), and Tobin's Q, as a measure of profitability, are all standard variables to control for determinants of the firm media coverage (Miller, 2006; Bushee et al., 2010). Furthermore, we control for the information contents of the calls via several standard measures available in the literature.

In particular we control for the pessimism in the management's response tone (Neg) as Price et al. (2012) show that not only tone is a significant predictor of abnormal returns and trading volume in the initial reaction window, but it also dominates earnings surprises over the 60 trading days following the conference call's date. Dzieliński et al. (2017) show that investors punish the $Uncertainty$ of the management's answers and tone with a lower valuation. We further control for $Complexity$ in the answers, as Loughran and McDonald (2020) suggest that this measure complements the size of a corporation. Complexity also controls for the required informativeness of a firm's disclosure (Guay et al., 2016). To control for the particular newsworthy timings around companies, inspired by Dyck et al. (2008), we include $NewsWorthiness$ in the X_{it}. Finally, X_{it} includes the prevalence of each 25 news topics during the analysis window to address the possibility of certain news categories (e.g. legal issues or M&A) driving more media coverage.

Additionally, we include various fixed effects to capture several unobservable characteristics of the firms and quarters that contribute to both the media coverage and earnings calls' non-answers. $\alpha_{\mathbb{I}}(\alpha_i)$ denotes industry (firm) fixed effects. In some specifications, instead of firm fixed effects, we control for firm-year dummy variables to absorb time-varying heterogeneity at the firm level. α_t

absorbs time trends of coverage. To allow for a potential serial correlation of media coverage within each firm and within each quarter, we employ a two-way clustering of standard errors (Cameron et al., 2011) at the firm and quarter dimensions.

[Table 2 about here]

Table 2 summarizes the results of this analysis. In all of the specifications, $NonAnswer^{\phi}$ has a negative coefficient for the media coverage, supporting the "supply-driven coverage" hypothesis. In particular, column (2) shows that one standard deviation increase in our $NonAnswer^{\phi}$ measure is associated with approximately 3% less media coverage. The results hold in the within-firm-year variation, i.e. comparing the same firm with different $NonAnswer^{\phi}$ in different quarterly earnings calls in the same fiscal year. A positive and statistically significant coefficient for the number of PR releases also confirms the role of media in the dissemination of firms' press releases. $NewsWorthiness$ positively contributes to media coverage.

4.2 Coverage type

Media sources/channels spend different amounts of time, energy, and resources to publish different types of content about a firm. Media disseminate the currently available information mostly via "news-flash" which includes a headline or a link to other sources' coverage. On the contrary, publishing a "full"-article requires the media source to put more effort by providing editorial content Drake et al. (2014). In line with the supply-driven coverage hypothesis, we postulate that the firms with higher non-answers score, experience a lower media coverage for full-articles, as this type of coverage is more costly the poorer the information environment around the firm is. Moreover, we expect to find no significant correlation between the management withholding information and the publications of non-full-articles.

Our dataset allows us to decompose the coverage types to full-articles and non-full-articles according to the tags provided by the RavenPack. We then repeat our analysis of the previous section (Equation 1) except that we differentiate between these two types of coverage.

[Table 3 about here]

Table 3 shows that the decrease in the coverage only occurs in the case of the full articles. The regression coefficient for the non-answer measure is negative and statistically significant in the first three columns. Column (1) shows that a one standard deviation increase in the within-firm non-answer measure is associated with 0.9% fewer media sources that publish at least one full article for a firm in the two-month window after the earnings call. On the other hand, for non-full articles, shown in columns (4) to (6), the coefficient of non-answer variable is not significantly different from zero. Comparing columns (4) and (5), the count of PR releases absorbs most of the heterogeneity regarding the non-full-article coverage.

4.3 Professional and non-professional business media

In this section, we ask if the professionalism of the media plays a role in reduction of the coverage provided by them. Non-professional business media, alongside the professional business media, play a significant information intermediary role. Investors react to the tenor of the articles posted by non-professional analysts and journalists (Chen et al., 2014; Drake et al., 2017).

In the light of analyses in section 4.1, we first verify if the coverage reduction differs for professional and non-professional business media. In other words, we verify whether the higher non-answer score of a firm is related to less media coverage on the firm, regardless of the media type. We identify the professional business media according to the definition in subsection 3.2 and repeat the analysis using equation 1.

[Table 4 about here]

Table 4 shows the result of this analysis with several specifications. The negative coefficient of the $NonAnswer^{\phi}$ variable shows that the coverage reduction is the case for both professional and non-professional business media.

Next, we ask which of these two media types are more sensitive to the firms' disclosure style. Compared to professional media coverage, bloggers and non-professional journalists/analysts have different incentives to cover a company. First, skin in the game, i.e. their open positions in the underlying stock, motivates them to follow a specific firm diligently (Campbell et al., 2019). Second, non-professional media have an incentive to signal their quality by providing coverage for the firms with less available coverage. Third, non-professional media sources are limited in the sense of the

alternative choices they have for coverage. Most bloggers/non-professional business journalists are specialized and interested in coverage of certain firms, on the contrary, professional sources like Bloomberg could easily shift their coverage portfolio to any other peers of a firm. To summarize, although the poorer information environment discourages media sources from covering a firm, non-professional media sources have the incentive to fill the void by publishing more articles about that firm. To clarify this point, we analyze if the count of articles is also negatively associated with the management withholding information for both the professional and non-professional media. We repeat the analysis using equation 1, where the dependent variable is the natural logarithm of one plus the count of news, separately, for professional and non-professional media.

[Table 5 about here]

Table 5 shows the results of this analysis. In columns (1) & (2), for the professional coverage, we see a negative correlation between the count of articles and the non-answer variable. In column (3) & (4), on the other hand, such a significant association is absent. This suggests that although less media sources are covering a company in the analysis window after a non-answer earnings call, the total count of non-professional coverage is not less for the within-firm and within firm-year non-answer.

Furthermore, in columns (5) & (6), the dependent variable is the share of the full-articles provided by the professional media to total full-articles. The negative coefficient of the non-answer variable suggests that management withholding information is associated with a lower ratio of professional coverage.

4.4 Coverage shift within the industry

In this subsection, we verify the implications of the supply-driven coverage hypothesis for media level observations, and we ask if media sources substitute the coverage of a firm with poorer information environment with a peer firm that does provide factual responses to the requested information during the earnings calls. Unlike the previous analyses, here we limit our focus on the media sources that already have a set of peers in their coverage portfolio which allows us to compare the change in the coverage weights before and after an earnings call. To do so, we restrict our sample to earnings calls of the firms, within an industry, held on the same day.

We first define our coverage shift measure and then verify the association of coverage shift with management non-answers in a regression analysis.

Coverage shift For the firm i of industry $\mathbb{I}$ on the earnings call day t we define the "prior" coverage weight of ω_{mit} for a media m as:

$$\omega_{mit} = \frac{\sum_d Counts_{mid}}{\sum_{i\in\mathbb{I}}\sum_d Counts_{mid}}, \quad d \in [t-60, ..., t-1] \tag{2}$$

where $Counts_{mid}$ counts the number of contents in the form of full-article, (hot-)news-flash, and tabular-material published on the day d. By definition we have $\omega_{mit} \geq 0$ and $\sum_{i\in\mathbb{I}} \omega_{mit} = 1$. Similar to the prior weights in Equation 2, we define the "posterior" coverage weights, $\omega^{'}_{mit}$, where $d \in [t+1, ..., t+60]$.

We define the coverage shift as the distance between the posterior and prior coverage weights. More specifically, the coverage shift after the earnings call of firm i on earnings call of date t is

$$\Delta\omega_{mit} = Ln(\frac{1+\omega^{'}_{mit}}{1+\omega_{mit}}). \tag{3}$$

Here we clarify this definition by an example. On April 14th, 2015 (t), J.P. Morgan (JPM) and Wells Fargo & Co (WFC) held their earnings conference call with $NonAnswer^{\phi}$ of 0.12 and 0.07, respectively. These two firms both belong to the industry 44 base on the 48 Fama-French industry classification ($\mathbb{I}$). Here, we verify the shifts in the coverage of WSJ (m) for these two firms. In the two months before t, WSJ published 23 articles for JPM and 2 for WFC. This translates to the prior weights of $\omega_{m,JPM,t} = 23/(1+(2+23)) = 0.885$ and $\omega_{m,WFC,t} = 2/(1+25) = 0.077$. In the two months after t, WSJ published 14 contents in total for these two banks, 12 of which were for JPM and 2 were for WFC. So, the posterior coverage weights are $\omega^{'}_{m,JPM,t} = 12/(1+14) = 0.8$ and $\omega^{'}_{m,WFC,t} = 2/(1+14) = 0.133$. Finally, we can calculate the shift in coverage as in Equation 3 which is $\Delta\omega_{m,JPM,t} = Ln(1+0.8/1+0.885) = -0.046$ and $\Delta\omega_{m,WFC,t} = Ln(1+0.133/1+0.077) = +0.051$

Analysis We model the shift in the firm's coverage weight within industries with the following linear equation:

$$\Delta\omega_{mit} = \beta_0 + \beta_1 \cdot NonAnswer_{it} + \beta_2 \cdot X_{it} + \alpha_m + \alpha_{\mathbb{I}t} + \epsilon_{mit} \tag{4}$$

where $NonAnswer_{it}$ is interchangeably the $NonAnswer^{\phi}$ or the non-answer rank of firm i among its industry peers on date t. Firm i achieves rank $1(N)$ if it has the highest (lowest) $NonAnswer^{\phi}$ among all the other N firms in the same industry that hold the earnings call on the date t.

X_{it} controls for firm-quarter level observations as in Equation 1. We include α_m, media fixed effects, to exploit within-media variations. We also control for $\alpha_{\mathbb{I}t}$ dummies to absorb common characteristics of an industry's earnings calls on a given date[14]. Finally, we cluster the standard errors at the earnings call level.

[Table 6 about here]

Table 6 Shows the results of this analysis. In columns (1) & (2), results confirm that the top ranked non-answer firms, comparing to their peers, witness a statistically significant reduction in coverage weight in media level. Column (3) & (4) show the same results using the level of $NonAnswer^{\phi}$. In other words, ceteris paribus, media shifts the coverage to the firms where the flow of information is less obstructed. Similarly, the language complexity of an earnings call is negatively associated with the shift in the coverage weight of the firms. These results hold after controlling for the media fixed effects.

5 Conclusion

Firm's earnings conference calls are disclosures that aim to reduce information asymmetries among investors, shareholders, and market participants, and the management must assure that this information is broadly available (Bushee et al., 2004). During these conference calls, management should respond to the demanded information directly in a Q&A session with the call participants. Faced

[14]For example, firms tend to shift bad news announcements to the weekend (Damodaran, 2015) or macro news (Hirshleifer and Sheng, 2019) and policy/regulators announcements may alter the attention to the firm and industry level news

with a question, the management can faithfully address all the demand for information, or she can "non-answer" by either direct rejection like "we cannot provide this information" or indirectly by blathering, i.e. beating around the bush. The management's non-answer leaves the demand for information unmet and hence, the stakeholders should rely on other information intermediaries to provide them with the missing value-relevant knowledge.

In this paper, we examine how the business media cover companies with different information environment richness. We state two competing hypotheses to verify if 1) the media coverage increases when there exists a higher demand for information (a 'demand-driven' media coverage hypothesis), or 2) the media coverage decreases as supplying information for the firms in poorer information environment is more challenging (a 'supply-driven' media coverage hypothesis).

We use the data on media coverage of the firms in S&P500 from 2007 to 2019, and we show that the management decision to non-answer the requests for information during the firms' quarterly earnings calls, in line with the supply-driven coverage hypothesis, is associated with significantly less media attention on the firm in the next quarter. Separating the types of coverage, we show this decline is mainly due to the fewer number of media sources publishing full-articles, which requires more (editorial) effort and resources to prepare compared to other types of coverage, for the firms. Moreover, the drop in the count of articles published by the professional media sources, like Dow Jones Newswire and Bloomberg, is more severe compared to that of the non-professional media like Seeking-Alpha or stock blogs. Finally, we verify these findings in the media-level observations and show that among the firms within a given industry, media sources rank the firms by the level of their non-answers, and shift their attention to the firms who provide more factual answers in their earnings calls.

The recent increase in the body of the literature regarding the media coverage is mainly because of the emerging of new datasets like RavenPack (Tetlock, 2014), which is still evolving and increasing the scope of its data availability among other internet sources (Miller and Skinner, 2015). This would help future research to benefit from an extended timeline of coverage provided by ever-growing media sources and focusing on more firms which will pave the way for deeper media-level analysis in the literature.

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Figure 1: Media coverage and non-answer earnings call
This figure shows binned scatter plots for the main analyses of the paper.

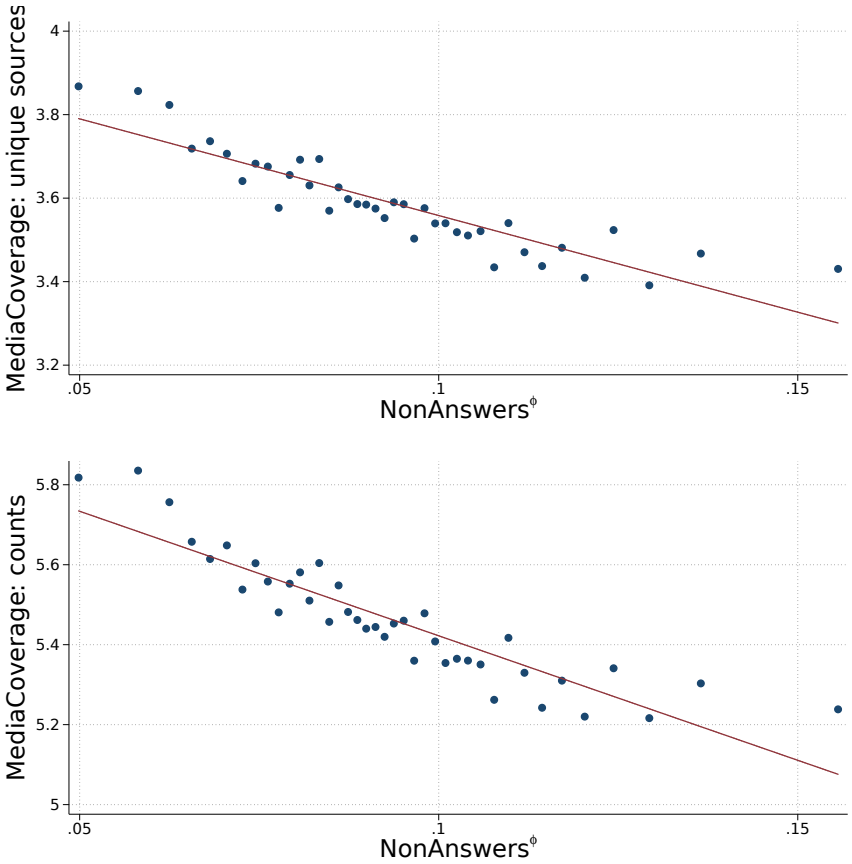


Figure 2: Non-answer glossary.
The glossary consists of 1,227 trigrams provided by Barth et al. (2020). Larger font size indicates a higher factor load. A machine-readable version of the glossary is available at econlinguistics.org

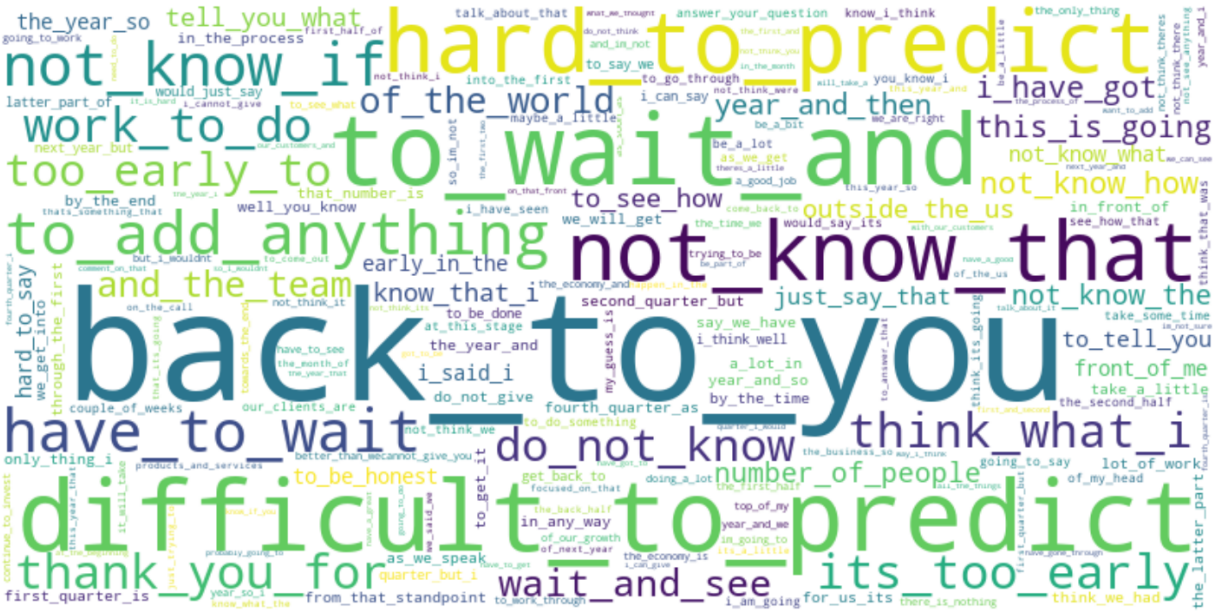


Figure 3: Time-trend of news coverage
The figure shows the number of media sources who published at least one content with more than 90% relevance to the firms in our sample within two months after the firms' quarterly earnings call (left axis) as well as the total count of the published contents (right axis). From January 2007, RavenPack includes the WEB Edition (RP-WEB) which covers articles from leading (online) publishers & web aggregators. Many other news sources are added gradually to the universe of RavenPack; e.g. for "Reuters", the RP-WEB includes only the contents after 2011. In all of the analyses in this paper, we include the quarter fixed effects to address the time-trends of news coverage.

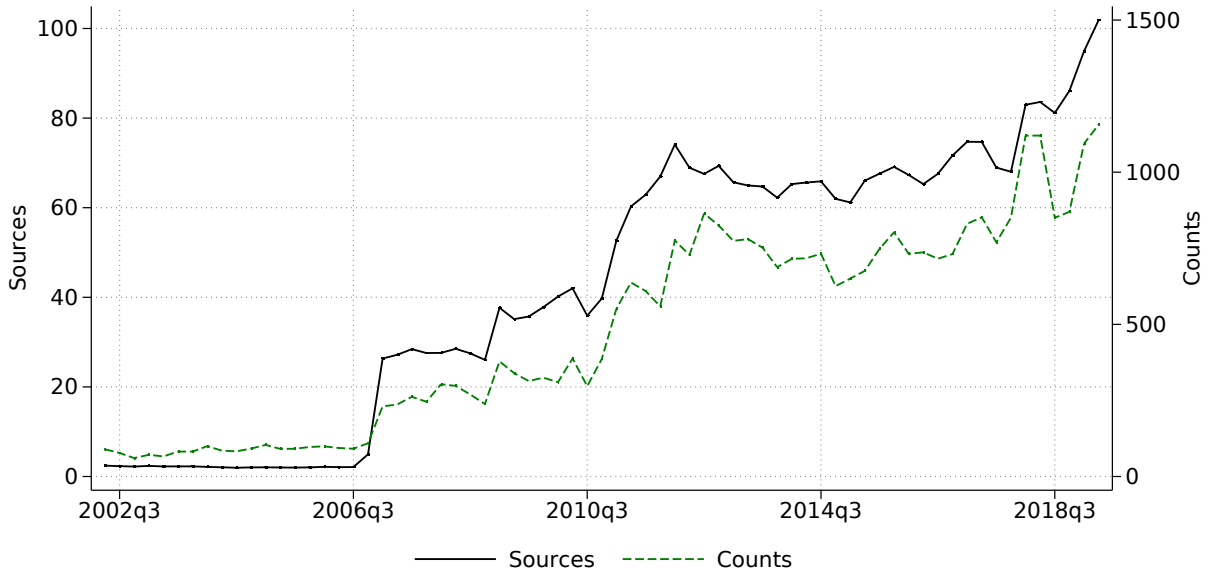


Figure 4: News categories

The figure shows the resulting 25 topics using the topic modeling analysis of the most common 200 news categories in the analysis window of the two months after the earnings calls in our sample. β shows the weights of each news category in the topics. For each topic, the first two important news category is shown here.

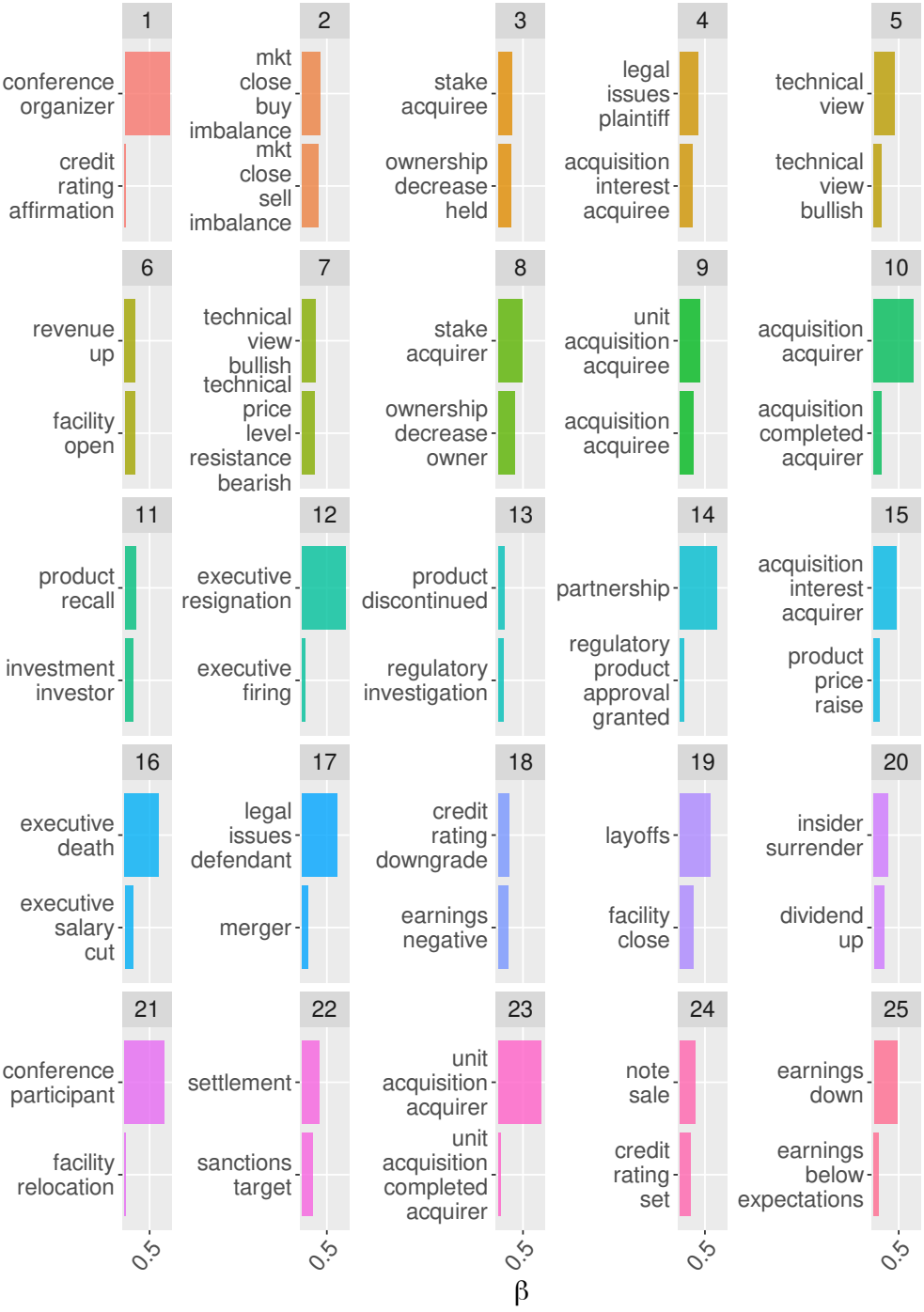


Figure 5: Earnings calls topic distribution
The figure shows the distributions of the topic probabilities for each of the resulted 25 topics using the topic modeling analysis of the most common 200 news categories in the analysis window of two months after the earnings calls in our sample. γ shows the probability that a document belongs to a topic.

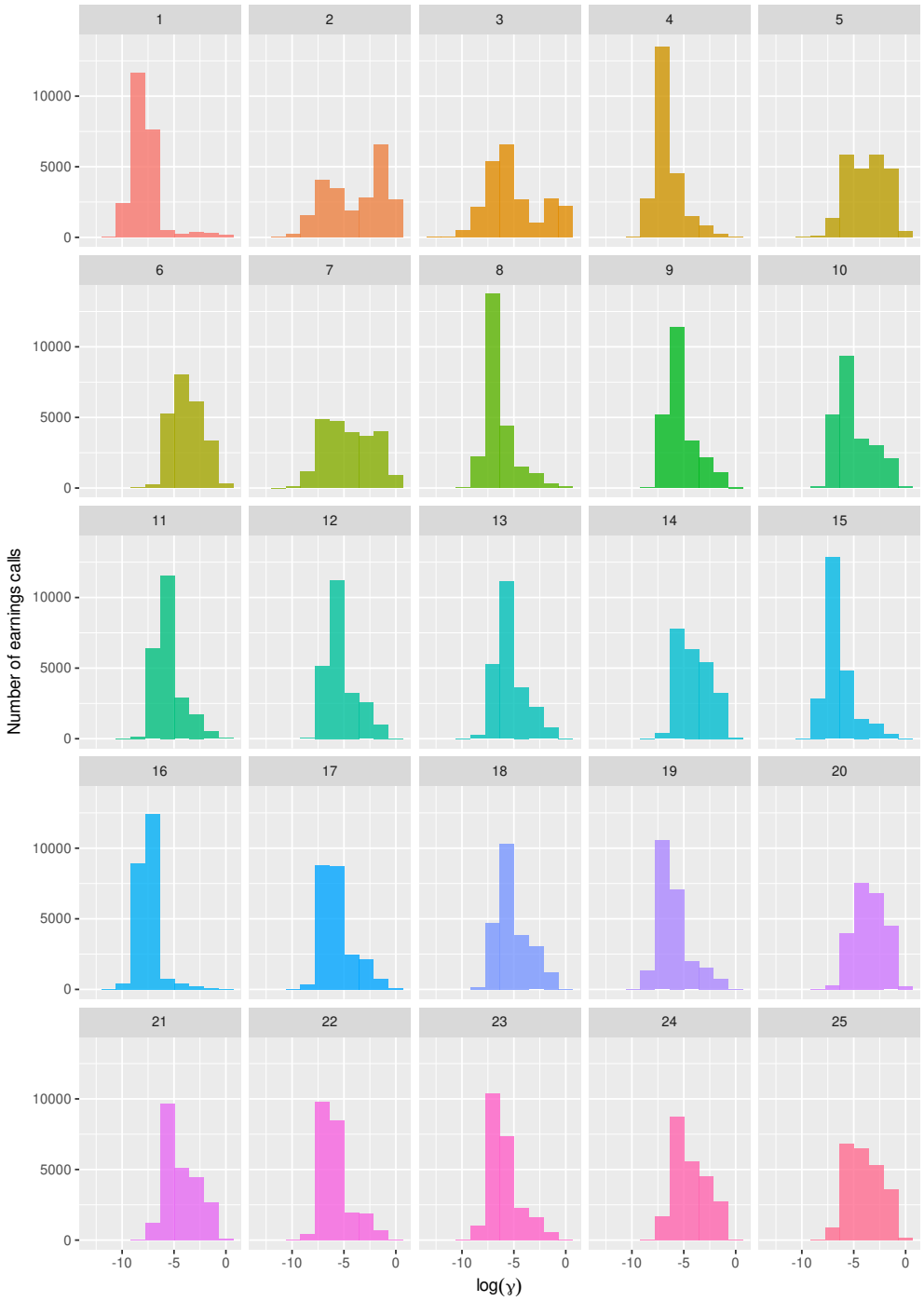


Table 1: Descriptive statistics.
This table shows descriptive statistics of the variables used in the analyses. The sample consists of 18,275 earnings calls of the companies in the S&P500 index from 2007 to the end of 2019. All variables are defined in Table A1.

Variable	Obs.	Mean	Std. Dev.	Min	P10	P50	P90	Max
$NonAnswer^{\phi}$	18,275	.094	.022	.032	.067	.092	.12	.22
$Sources$	18,275	3.6	.9	.69	2.6	3.4	4.8	7.4
$Sources^{F}$	18,275	3.5	.91	.69	2.6	3.4	4.8	7.3
$Sources^{NF}$	18,275	2.1	.75	.69	1.1	1.9	3	6.2
$Sources^{F}_{Pro}$	17,661	2	.45	.69	1.4	1.9	2.6	3.3
$Sources^{F}_{N-Pro}$	17,661	3.3	1	.69	2.1	3.2	4.7	7.3
$Counts$	18,275	5.5	1.1	1.6	4.2	5.3	6.9	11
$Counts^{F}_{Pro}$	17,661	3.9	1.1	.69	2.6	3.8	5.4	8.9
$Counts^{F}_{N-Pro}$	17,661	4.8	1.5	.69	2.8	4.9	6.5	11
$Share - Pro$	17,661	.33	.22	.0029	.087	.27	.67	.99
PR	15,910	1.3	.37	.69	.69	1.4	1.8	2.6
$NewsWorthiness$	18,275	.97	1.3	0	0	.69	2.8	7.9
$Negativity$	18,275	.028	.0071	.0075	.02	.027	.037	.079
$Uncertainty$	18,275	.016	.0056	0	.0089	.015	.023	.056
$EarnSurp$	18,275	5.7	2.9	1	2	6	10	10
BTM	18,275	.44	.41	-3.2	.099	.35	.88	17
$ln(Assets)$	18,275	9.8	1.4	6.2	8.2	9.6	12	15
Q	18,275	2.1	1.4	.63	1	1.7	3.8	36
$Complexity$	18,275	.0071	.0039	0	.0028	.0065	.012	.029

Table 2: Management withholding information and media coverage

Notes: OLS regressions for Equation (1). The dependent variable in columns (1) to (5) is the natural logarithm of one plus the number of distinct news agencies who published at least one article for the firm from the day after the earnings call to the 60th day after it. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	Sources				
	(1)	(2)	(3)	(4)	(5)
$NonAnswer^{\phi}$	-4.630***	-1.411***	-0.369**	-0.498***	-0.501***
	(-3.73)	(-3.97)	(-2.20)	(-3.14)	(-3.19)
PR		0.544***	0.264***	0.208***	0.208***
		(18.70)	(18.14)	(14.21)	(14.05)
$Negativity$		-3.074***	0.689	0.491	0.510
		(-2.71)	(1.17)	(1.01)	(1.05)
$Uncertainty$		-5.780***	-0.473	-0.413	-0.444
		(-5.60)	(-0.78)	(-0.70)	(-0.76)
$Complexity$		0.804	1.156	0.959	0.942
		(0.38)	(1.20)	(0.97)	(0.96)
$NewsWorthiness$		0.295***	0.082***		
		(22.65)	(10.06)		
Observations	18275	15763	15903	15459	15459
R^2	0.013	0.778	0.895	0.944	0.944
Firm Controls	No	Yes	Yes	Yes	Yes
News Categories	No	No	No	No	Yes
QuarterYear FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Implied	Implied	Implied
Firm FE	No	No	Yes	Implied	Implied
FirmYear FE	No	No	No	Yes	Yes

Table 3: Management withholding information and different types of media coverage

Notes: OLS regressions for Equation (1). The dependent variable in columns (1) to (3) is the natural logarithm of one plus the number of distinct news agencies who published at least one full-article for the firm from the day after the earnings call to the 60th day after it, and in columns (4) to (6), the same measure for all the coverage types except for full-articles. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All specifications include dummies for industry multiply by the date of earnings calls. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	$Sources^F$			$Sources^{NF}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$NonAnswer^\phi$	-0.447***	-0.344**	-0.521***	-0.280	-0.264	-0.082
	(-2.74)	(-2.07)	(-3.15)	(-1.59)	(-1.47)	(-0.40)
PR		0.275***	0.221***		0.209***	0.170***
		(18.18)	(14.42)		(12.15)	(12.10)
$Negativity$	0.566	0.846	0.542	0.146	0.340	0.472
	(0.94)	(1.39)	(1.04)	(0.22)	(0.53)	(0.78)
$Uncertainty$	-0.251	-0.442	-0.449	-0.812	-1.003	-0.711
	(-0.40)	(-0.71)	(-0.77)	(-1.22)	(-1.45)	(-0.87)
$Complexity$	1.186	0.874	0.687	-0.378	-0.686	0.386
	(1.26)	(0.87)	(0.68)	(-0.33)	(-0.58)	(0.35)
$NewsWorthiness$	0.080***	0.079***		0.103***	0.102***	
	(9.05)	(9.41)		(10.40)	(9.97)	
Observations	18269	15903	15459	18269	15903	15459
R^2	0.882	0.892	0.942	0.769	0.784	0.870
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
News Categories	No	No	Yes	No	No	Yes
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Implied	Yes	Yes	Implied
FirmYear FE	No	No	Yes	No	No	Yes

Table 4: Management withholding information and the professional vs. non-professional media coverage

Notes: OLS regressions for Equation (1). The dependent variable in columns (1) & (2) is the natural logarithm of one plus the number of distinct news professional news agencies who published at least one full-article for the firm from the day after the earnings call to the 60th day after it, and in columns (3) & (4), is the same measure for non-professional media coverage. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All specifications include dummies for industry multiply by the date of earnings calls. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	$Sources^{F}_{Pro}$		$Sources^{F}_{N-Pro}$	
	(1)	(2)	(3)	(4)
$NonAnswer^{\phi}$	-0.273**	-0.327**	-0.398**	-0.504**
	(-2.05)	(-2.28)	(-2.04)	(-2.66)
PR		0.130***		0.234***
		(10.37)		(12.88)
$Negativity$	0.878**	0.726*	0.409	0.405
	(2.26)	(1.78)	(0.61)	(0.71)
$Uncertainty$	0.335	0.033	-0.347	-0.467
	(0.75)	(0.06)	(-0.51)	(-0.74)
$Complexity$	0.808	0.562	1.285	1.164
	(1.14)	(0.63)	(1.11)	(0.94)
$NewsWorthiness$	0.041***		0.091***	
	(7.71)		(8.44)	
Observations	17653	15007	17653	15007
R^2	0.709	0.831	0.884	0.943
Firm Controls	Yes	Yes	Yes	Yes
News Categories	No	Yes	No	Yes
QuarterYear FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Implied	Yes	Implied
FirmYear FE	No	Yes	No	Yes

Table 5: Management withholding information and (non-)professional media attention

Notes: OLS regressions for Equation (1). In columns (1)-(2), the dependent variable is the natural logarithm of one plus the count of full-articles that professional business media provided for the firm in the window of the first to the 60th day after the earnings call. In columns (3)-(4), the dependent variable is the same measure for the non-professional media coverage. In columns (5)-(6), the dependent variable is the share of full-articles by the professional media to the total count of the full-articles available in the RavenPack for the same analysis window. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	$Counts^{F}_{Pro}$		$Counts^{F}_{N-Pro}$		$Share-Pro$	
	(1)	(2)	(3)	(4)	(5)	(6)
$NonAnswer^{\phi}$	-0.709**	-1.152***	0.233	-0.440	-0.160**	-0.114**
	(-2.22)	(-3.88)	(0.76)	(-1.67)	(-2.15)	(-2.16)
PR	0.400***	0.348***	0.420***	0.351***	-0.005	-0.002
	(15.33)	(12.62)	(15.08)	(16.18)	(-0.95)	(-0.39)
$Negativity$	1.664	0.114	0.984	0.685	0.102	-0.145
	(1.64)	(0.12)	(0.99)	(0.93)	(0.50)	(-0.88)
$Uncertainty$	-0.482	-0.924	-0.355	-0.623	0.058	-0.001
	(-0.44)	(-0.86)	(-0.33)	(-0.68)	(0.25)	(-0.01)
$Complexity$	1.132	1.270	0.124	-0.743	0.029	0.194
	(0.70)	(0.80)	(0.06)	(-0.50)	(0.10)	(0.75)
$NewsWorthiness$	0.120***		0.134***		-0.002	
	(8.62)		(7.09)		(-0.82)	
Observations	15499	15007	15499	15007	15499	15007
R^2	0.806	0.895	0.907	0.956	0.840	0.925
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
News Categories	No	Yes	No	Yes	No	Yes
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Implied	Yes	Implied	Yes	Implied
FirmYear FE	No	Yes	No	Yes	No	Yes

Table 6: Management withholding information and media coverage shift

Notes: OLS regressions for Equation (4). The sample is limited to earnings call's date at which there are at least two firms of the same Fama-French 48 industries classification holding their calls. Observations are at the media source level. The dependent variable is the changes in prior to posterior firms' weight in a media source's portfolio compared to their peers who hold earnings call on the same day. In columns (1)-(2), the non-answer measure is the rank of the non-answer scores of the firms holding their calls on the same date. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the earnings call level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	$\Delta\omega$			
	(1)	(2)	(3)	(4)
$NonAnswer^{rank}$	0.002***	0.002***		
	(2.69)	(2.68)		
$NonAnswer^{\phi}$			-0.078*	-0.078*
			(-1.89)	(-1.88)
$Negativity$	-0.212	-0.212	-0.210	-0.210
	(-1.48)	(-1.47)	(-1.46)	(-1.45)
$Uncertainty$	0.269*	0.269*	0.259	0.259
	(1.70)	(1.69)	(1.62)	(1.61)
$Complexity$	0.148	0.148	0.153	0.153
	(0.56)	(0.56)	(0.58)	(0.57)
Observations	1487854	1487854	1487854	1487854
R^2	0.028	0.037	0.028	0.037
Firm Controls	Yes	Yes	Yes	Yes
News Categories	Yes	Yes	Yes	Yes
Industry×Call date	Yes	Yes	Yes	Yes
Source FE	No	Yes	No	Yes

Appendix A

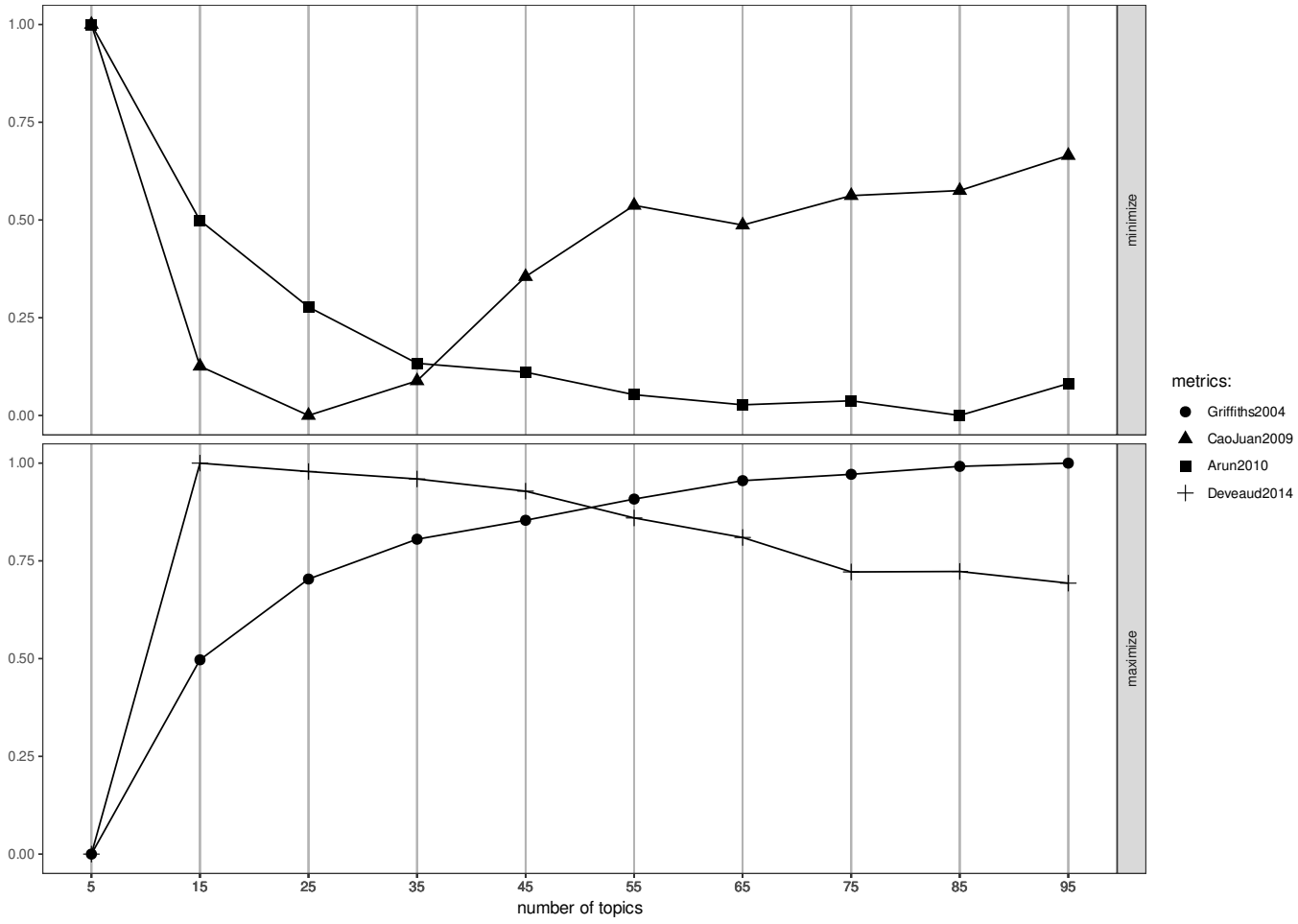
Table A1: Definition of variables.

Variable	Definition
BTM	Book-to-Market ratio; defined as total Common/Ordinary Equity divided by the market value of equity (from Compustat)
$Complexity$	the ratio of the complex words to the total words in the management answers. "Complexity" word-list provided by Loughran and McDonald (2020)
$EarningsSurp$	represents the grouping of all firms in deciles of earnings surprise following Dzieliński et al. (2017) (defined as the difference between the actual and the consensus forecast earnings (from I/B/E/S) as a ratio to the share price 5 trading days before the announcement)
$ln(Assets)$	the natural logarithm of total assets. (from Compustat)
$Counts$	the natural logarithm of 1 plus the total number news contents in a two month period after firms' earnings conference calls
$Sources$	the natural logarithm of 1 plus the number of unique news sources that publish a content in a two month period after firms' earnings conference calls (From Ravenpack)
$Sources^F_{N-Pro}$	the $Sources^F$ variable filered for the sources that we do not identify as professional sources.
$Sources^F_{Pro}$	the $Sources$ variable filered for the professional sources. We label a source as professional if it is associated with Dow Jones newswire, Barrons, Marketwatch, Bloomberg news, Thomson Reuters, Wall Street Journal, Financial Times, Enterpreneur, Bussiness Insider, CNBC, and Forbes.
$Negativity$	the ratio of the negative words to the total words in the management answers. "negative" word-list provided by Loughran and McDonald (2011)
$NewsWorthiness$	inspired by Dyck et al. (2008), defines as the natural logarithm of one plus the number of articles referring to a company in the Wall Street Journal and the Financial Times during the 6-month period before the earnings call (excluding the day of earnings call and one day before it)
$NonAnswer^{\phi}$	the ratio of trigrams weighted by their corresponding loadings in the non-answer glossary of Barth et al. (2020) to the total words
PR	The natural logarithm of 1 plus the firm's initiated press releases (from Ravenpack PR-edition)
Q	the Tobin's Q; the book value of assets minus book value of common equity plus the market value of common equity, divided by the total book value of assets (from Compustat)

Uncertainty	the ratio of the uncertain words to the total words in the management answers. "Uncertainty" word-list provided by Loughran and McDonald (2011)

Appendix B Topic modeling of news

Figure B1: News categories
The figure shows LDA's goodness of fit for our data of news categories by different number of topics ranging from 5 to 95 according to measures provided in the R-package "ldatuning" of Nikita and Chaney (2016).



Appendix C List of the professional media

RavenPack ID	Name
18A55F	BARRONS
8B4BD7	BARRONS.COM BLOG
97AF0A	BARRONS.COM ONLINE
6DFE43	BLOOMBERG BUSINESSWEEK
5F78A9	BLOOMBERG GOVERNMENT
208421	BLOOMBERG NEWS
CAF003	BLOOMBERG VIEW
FA7478	BLOOMBERG-QUINT
DCD6DA	BREAKINGVIEWS
8B7199	BRUSSELS BLOG
87C2EA	BUSINESS BLOG
C75B8C	BUSINESS INSIDER
E38558	CAPITOL REPORT - MARKET WATCH
AA1167	CNBC
B5569E	DOW JONES NEWSWIRES
A89221	DOW JONES ONLINE
0FDF1E	ECONOMISTS' FORUM
F67012	EMERGING MARKETS DAILY
DF7445	ENCORE
2143AD	ENERGY TICKER
938822	ENTREPRENEUR
931400	FAITHWORLD
0B0728	FAST MONEY
D335E4	FELIX SALMON
35913F	FELIX SALMON - ALL POSTS
90CE21	FINANCIAL REGULATORY FORUM
FD0B00	FINANCIAL TIMES
75B2CD	FINDLAW
DE57D6	FOCUS ON FUNDS
22AC8B	FORBES.COM
BF0799	FROM REUTERS.COM
0EB1B3	FT ADVISER
8E9A55	FT ADVISER MONEY MANAGEMENT
766283	FT ALPHAVILLE
895559	FT DATA
6DDC36	FT INVESTMENT ADVISER
EF1ABD	FT.COM - CREDIT SQUEEZE

RavenPack ID	Name
F1D2BD	GAVYN DAVIES
D3E2F8	GLOBAL INVESTING
8A7104	HUGO DIXON
358DFE	INCOME INVESTING
B4A99C	INDIA INSIGHT
A0588D	JAMES SAFT
AF0676	MACROSCOPE
A0099A	MAD MONEY WITH JIM CRAMER
1E5E35	MARKETWATCH
C325FC	MARKETWATCH (ONLINE)
E04BE4	MORNINGSTAR
A92D7D	PHOTOGRAPHERS BLOG
751371	REUTERS
806C8E	SILICON ALLEY INSIDER
C76E42	SMART MONEY
3F9DB7	STOCKS TO WATCH
499718	TECH BLOG
F707BB	TECH CHECK WITH JIM GOLDMAN
9BA337	TECH TRADER DAILY
13A271	THE A-LIST

RavenPack ID	Name
ADFD64	THE BANKER
DE348B	THE GREAT DEBATE
C0AB6A	THE TELL
F73069	THE WORLD
3EA04F	THOMSON REUTERS FOUNDATION NEWS
AA6E89	WALL STREET JOURNAL
9AE635	WALL STREET JOURNAL (ONLINE)
0BBE7B	WESTMINSTER BLOG

Appendix D Robustness

Table D1: Management withholding information and media coverage - The first 48 hours after the conference call

Notes: OLS regressions for Equation (1). The dependent variable in columns (1) to (3) is the natural logarithm of one plus the number of distinct news agencies who published at least one news content in the first 48 hours after the earnings call. In columns (4)-(6), the dependent variable is the natural logarithm of one plus the count of contents published for the firm in the same window. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	Sources			*Counts*		
	(1)	(2)	(3)	(4)	(5)	(6)
$NonAnswer^{\phi}$	-1.093***	-0.380**	-0.377*	-1.530***	-0.340*	-0.337*
	(-2.83)	(-2.04)	(-2.00)	(-3.24)	(-1.79)	(-1.77)
PR	0.334***	0.141***	0.141***	0.480***	0.242***	0.242***
	(11.59)	(8.61)	(8.55)	(11.10)	(11.24)	(11.30)
$Negativity$	-1.643	1.473***	1.534***	-2.203	2.988***	3.007***
	(-1.46)	(3.23)	(3.29)	(-1.47)	(4.28)	(4.28)
$Uncertainty$	-4.769***	-0.752	-0.766	-5.669***	-0.833	-0.832
	(-4.78)	(-1.25)	(-1.25)	(-4.09)	(-1.06)	(-1.05)
$Complexity$	-3.424*	-0.600	-0.660	-3.076	-2.023	-2.067
	(-1.71)	(-0.55)	(-0.60)	(-1.12)	(-1.61)	(-1.63)
$NewsWorthiness$	0.257***			0.322***		
	(18.69)			(19.73)		
Observations	11036	10208	10208	11036	10208	10208
R^2	0.764	0.936	0.937	0.760	0.938	0.938
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
News Categories	No	No	Yes	No	No	Yes
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Implied	Implied	Yes	Implied	Implied
Firm FE	No	Implied	Implied	No	Implied	Implied
FirmYear FE	No	Yes	Yes	No	Yes	Yes

Table D2: Management non-answer and media coverage

Notes: OLS regressions for Equation (1). The dependent variable in columns (1) to (5) is the natural logarithm of one plus the number of distinct news agencies who published at least one article for the firm from the day after the earnings call to the 60th day after it. Firm controls include $EarningsSurprise$, BTM, $ln(Assets)$, and Tobin's Q. News categories refer to the association of the companies' news in the analysis window with the 25 groups of news classified using the topic modeling algorithm described in Subsection 3.2. Industry classification is based on the Fama-French 48 industries. All variables are defined in Table A1. t-statistics are given in parentheses. Standard errors are clustered in the firm and quarter level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	Sources				
	(1)	(2)	(3)	(4)	(5)
$NonAnswer^{\phi}$	-5.496***	-1.602***	-0.541**	-0.336*	-0.345**
	(-4.08)	(-4.66)	(-2.47)	(-1.99)	(-2.06)
PR		0.484***	0.235***	0.179***	0.179***
		(14.56)	(11.68)	(11.37)	(11.28)
$Negativity$		-3.288***	0.095	0.570	0.572
		(-3.14)	(0.12)	(1.24)	(1.26)
$Uncertainty$		-4.433***	-0.182	-0.366	-0.417
		(-4.20)	(-0.27)	(-0.69)	(-0.79)
$Complexity$		-0.737	1.134	0.329	0.295
		(-0.37)	(0.91)	(0.39)	(0.35)
$NewsWorthiness$		0.268***	0.084***		
		(18.00)	(8.87)		
Observations	22604	18923	19066	18513	18513
R^2	0.009	0.873	0.924	0.970	0.970
Firm Controls	No	Yes	Yes	Yes	Yes
News Categories	No	No	No	No	Yes
QuarterYear FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Implied	Implied	Implied
Firm FE	No	No	Yes	Implied	Implied
FirmYear FE	No	No	No	Yes	Yes