"Let me get back to you" – A machine learning approach to measuring non-answers*

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Abstract

It is *relatively* easy for us humans to detect when a question we asked has not been answered – we teach this skill to a computer. Using a supervised machine learning framework on a large training set of questions and answers, we identify 1,027 trigrams that signal non-answers. We show that this glossary has economic relevance by applying it to contemporaneous stock market reactions after earnings conference calls. Our findings suggest that obstructing the flow of information leads to significantly lower cumulative abnormal stock returns and higher implied volatility. Our metric is designed to be of general applicability for Q&A situations, and hence, is capable of identifying non-answers outside the contextual domain of financial earnings conference calls.

Keywords: Econlinguistics, textual analysis, natural language processing, multinomial inverse regression, non-answers

JEL-Classification: D80, D82, G10, G14, G30.

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1 Introduction

"Senator, [...] I can certainly have my team get back to you on any specifics there that I don't know, sitting here today." — Mark Zuckerberg, *US Senate Hearing, April 2018*

The asymmetric distribution of information is considered a key friction in economics. Different mechanisms aim at transferring information from the better-informed agent to the less informed, where a question and answer (Q&A) setting is the most targeted form of information exchange. Faced with a question, the addressee can respond in two ways. First, she can supply the requested information by faithfully answering the question, which requires having the specific knowledge within the context of the question.[1] Second, she can refuse to supply the requested information, which, in contrast, does not require a context-specific answer. While it is *relatively* easy for humans to detect whether a question has been answered or not, we teach this skill to a machine. Using a supervised machine learning framework on a large textual training set of 47,892 classified responses to questions, we identify 1,027 trigrams that signal non-answers.

We build on the research in linguistics to better understand how humans request and process information through questions and answers. Specifically, the Gricean norms in communication describe the cooperative principle of how people achieve effective conversational communication (Grice, 1989). These principles state that effective communication contains (i) the appropriate quantity of information, (ii) is truthful, (iii) is delivered in an appropriate manner and (iv) is relevant to the topic at hand. A violation of any of these principles results in 'deceptive' communication.

From violations of Gricean norms, we derive a measure that identifies the absence of requested information in an answer, i.e. non-answers. At its core, our glossary based measure employs a trained set of trigrams, which are markers for non-answers. The glossary is derived from financial markets, which are heavily characterized by and sensitive to asymmetric information. More precisely, we derive the glossary from a training set of earnings conference calls, where investors and analysts can directly question senior executives' during a Q&A session. The glossary, despite being derived from financial markets, is applicable to any other Q&A context. We conduct several tests to investigate the economic relevance of the measure using a large validation set of earnings conference calls.

We document that within the same earnings call, managers avoid responding to arguably tougher questions, as indicated by negative-toned questions and follow-up ques-

[1] Alternatively, the respondent could answer the question with a lie, which also requires knowing the specific context of the question. As there are generally heavy sanctions attached to lies, this paper focuses on the refusal to answer and not the detection of lies.

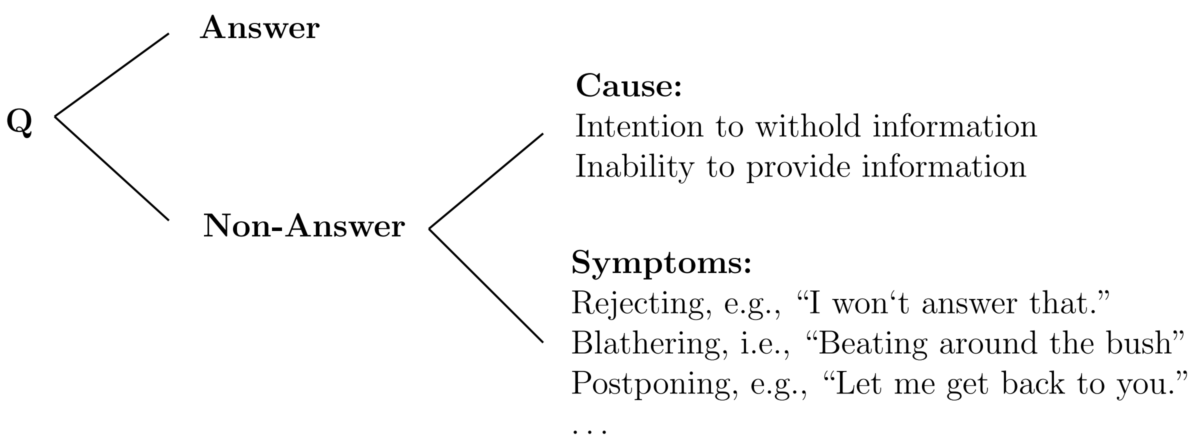

Figure 1: Anatomy of an answer. The response to a question consists of either the attempt to provide the requested information with an appropriate answer or the lag thereof, i.e. a non-answer. We will later use the symptoms blathering and rejecting to classify non-answers in our training set and show that this is sufficient to capture additional symptoms, such as postponing. Non-answers have in common that they can be free of context, e.g. one could reject to answer without even knowing the questions, which is an important distinction that allows for generalizing our glossary.

tions by the same analyst. Similarly, it appears that non-answers are more frequent when questions are ‘forward looking’, hence, when managers’ might be less able to provide the requested information. Furthermore, we apply the method to market reactions following the respective conference call. We observe negative stock returns after an earnings call with a distinct avoidance of answers by the management. Moreover, we find larger implied volatilities after these calls, indicating higher investor uncertainty.

Conceptually, a question can be understood as the illocutionary act that attempts to extract information from its addressee. The addressee can respond in two ways, as outlined in Figure 1. First, she can supply the requested information by faithfully answering the question, which requires having the specific knowledge within the context of the question. Second, she can refuse to supply the requested information, which, in contrast to effective communication, does not depend on the context of the question. This potentially deceptive communication in answering is henceforward called a non-answer.

Non-answers are characterized by different symptoms. The most obvious symptom would be to openly refuse to provide the requested information, as for example, Elon Musk, the CEO of Tesla Inc, did during an earnings call in May 2018.[2] A second symptom of refusing context-specific information is the more indirect and deceptive behavior of

[2] On the question of Sanford Bernstein’s analyst Toni Sacconaghi: “And so where specifically will you be in terms of capital requirements?”, Musk replied: “Excuse me. Next. Boring, bonehead questions are not cool. Next?”

dodging a question or "blathering", i.e. 'beating around the bush'.[3]

We base our measure on the two symptoms *'rejecting'* and *'blathering'*, and show that by employing a Multinomial Inverse Regression (MNIR) technique (Taddy, 2013), we are able to construct a measure that allows quantifying non-answers from focusing on a few symptoms alone.[4] The input for the MNIR are all Q&As of earnings conference calls for financial firms in the S&P 500 for the period of 2002 to 2017 (the training set). For each management answer within these calls, we quantify the two symptoms rejecting as described in Gow et al. (2019) and blathering as outlined in Barth et al. (2019).

MNIR, as a supervised generative model, then maps the high dimensional choice set of available trigrams into the two observable attributes in the classified training set.[5] The final result of this procedure is a list of 1,027 trigrams. Using this glossary allows to deduct a scoring metric for non-answers. The trigrams in the glossary are not industry-specific and allow us to apply our glossary to various economic sectors. Even further, as the glossary is not specific to a certain context, we show that it applies as a measure for non-answers in any Q&A setting, such as press conferences by national banks, after sports events, as well as in senate hearings and interviews with US politicians.

We conduct various tests in order to document the plausibility of the glossary. To this extent, we collect the earnings conference calls of companies that appeared in the S&P 500 Index in the period from 2002 to 2017 that are not part of the training set (the validation set). For all these earnings calls, we delete the presentation part of the call and apply our glossary to managements' answers in response to analysts' questions. Earnings conference calls provide an ideal setting to test our glossary: the listener is more likely to detect whether a question has been answered when her attention was diverted from social goals (Rogers and Norton, 2011), and thus, we would expect an immediate market reaction.

We first document that, within an earnings call, managers try to avoid answering tougher and more critical questions. This is, the non-answer score is higher for managements' responses to follow-up questions by the same analyst, i.e. when the analyst asks a (typically more drilling) clarification question, as well as for managements' responses to more negative questions. Furthermore, questions with forward looking sentences, i.e., questions that refer to (potentially unknown) future outcomes, are more likely to receive

[3]There might clearly be other symptoms, however, we will later show that a limited number of symptoms is sufficient to train the model.

[4]In fact, focusing on blathering as the only symptom would be sufficient. Rejecting alone, however, appears to insufficiently capture a broad spectrum of non-answers.

[5]While the usage of multinomial text regressions is novel in finance literature, it has been applied in the context of political science, for example to derive the subject-specific document sentiment in political posts (Taddy, 2013) or to measure time trends in partisanship in congressional speeche s(Gentzkow et al., 2019).

a non-answer.

Next, in regressions with multiple control variables, we show that not answering analysts' questions leads on average to significantly negative abnormal stock returns following the conference call. We also link our measure to option implied volatilities after earnings conference calls and show that investor uncertainty is higher if the requested information has not been provided, i.e. investors are willing to pay more for insurance against adverse stock price movements. Both the stock price reaction as well as higher implied volatility suggest that the non-answer score measures an obstruction of information flow, which retards the reduction of information asymmetries between the management and investors.

Finally, using a Monte Carlo simulation, we validate that the glossary is not a product of sheer randomness. In the Monte Carlo simulation, we draw 1,000 randomly selected dictionaries with 1,027 trigrams from all words that appear at least once in the training set of our earnings calls. We repeat the textual analysis for each of these random draws, derive a corresponding placebo non-answer score and test for an effect of this score on cumulative abnormal returns. It turns out that it would be extremely unlikely to produce economically significant results by randomly drawing a glossary from the universe of trigrams.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. In Section 3, we describe in detail how we generate our novel glossary. We describe several tests for the validity of the word list in Section 4. Section 5 concludes.

2 Background and literature

Our paper contributes to the literature in two ways. First, we build on the literature of textual analysis in accounting and finance. Textual analysis has become a multifarious tool in finance and accounting in the recent past with the aim to convert qualitative information in quantitative measures. One common approach for quantifying language has been a word categorization (bag of word / dictionary) approach. For example, the Harvard-IV and Lasswell dictionaries, which are part of Harvard General Inquirer Word Lists, consist of word lists referring to many psychological and sociological topics.[6] To overcome issues with noise from general dictionaries, researchers have introduced finance-specific dictionaries to measure the tone of financial reports. Henry (2008), for example, published one such list for the telecommunications and computer services industries. Loughran and McDonald (2011) produced other widely recognized word lists that were

[6] For more details on the different available dictionaries and the list of words, see: http://www.wjh.harvard.edu/~inquirer/homecat.htm

extracted from 10-K reports to measure inter alia positive and negative tone, and most recently a word list to measure firm complexity (Loughran and McDonald, 2019). Harvey (2016) also created a glossary of factual finance terminology, which has been used by Loughran and McDonald (2014), for example, to develop a measure of financial readability of 10-K reports. We extend this literature by providing a novel glossary that allows for quantifying the informational content of a response to a question, and thus, a new dimension of quantifiable language that can be used in several contexts.

Second, we add to the interdisciplinary literature on the precise and efficient transfer of information, or lack thereof. In linguistics, for example, there are many studies that describe how effective conversational communication can be achieved, with some of the most influential content being the cooperative principles by Grice (1989). Building on this work, several studies show how a violation of the cooperative principles is perceived by listeners, or in which situations a listener is more likely to detect deceptive communication.[7]

The effects of precise information sharing are also of particular interest in the field of economics, where it has been documented that, e.g., obscuring information is associated with lower stock returns, lower earnings and higher risks. The related studies use various proxies for the characterization of imprecise information, such as, for example, vague communication measured by the frequency of words such as "vague" and "uncertainty" in management statements (Loughran and McDonald, 2011; Dzielinski et al., 2016), the ratio of numeric to textual content in earnings conference calls (Zhou, 2018), readability of 10-K reports measured by the popular Gunning (1952) "Fog-Index" of linguistic complexity (Li, 2008; Bloomfield, 2008),[8] calling on bullish analysts in conference calls (Cohen et al., 2013), or managers responding to questions during earnings conference calls from prepared scripts (Lee, 2015).

Most closely related to our work in the interdisciplinary literature is the paper by

[7]See, for example, Buller and Burgoon (1996), who state in their Interpersonal Deception Theory that the process and outcome of interpersonal deception is grounded within a conversational context and an interpersonal relationship. McCornack et al. (1992) show that perceived message deceptiveness and perceived message competence are significantly influenced by the manipulations of amount, veracity, relevance, and clarity of information. The paper by Rogers and Norton (2011) shows that deception is more likely to be detected when listeners' attention was to determine the relevance of the speakers' answers, i.e. if it was diverted from social goals. It is also shown that speakers were more negatively rated once their deception was detected.

[8]Based on this work, there are several studies offering different measures of linguistic complexity (Loughran and McDonald, 2014; Bonsall et al., 2017) or providing a rationale for the usage of complex language. Bushee et al. (2018), for example, analyze the linguistic complexity of Q&As in earnings calls and argue that the source of complexity can be composed into its latent components *obfuscation* and *information*. Specifically, they argue that complex responses to complex questions should be understood as information, whereas complex responses to simpler questions should be understood as obfuscation. In line with that, Guay et al. (2016) show that managers employ voluntary disclosures as a tool to mitigate the negative impacts of their complex financial statements.

Clayman (1993), which shows that evading a question is frequently characterized by the response practice to reformulate the question. More narrowly in the field of economics, our work is closest to the work by Hollander et al. (2010) and Gow et al. (2019). These two papers measure withholding information in the most direct sense by manually reviewing call transcripts to deduct regular expressions that identify answers such as ‘No, we do not want to provide that information.’

Our glossary is a significant step towards the general identification of non-answers. First, it reflects not only one very specific symptom, e.g. ‘rejecting’, but allows for capturing a non-answer across several symptoms (see Figure 1) and in a much broader setting. Second, while we quantify symptoms of non-answering as an input to the MNIR, the resulting glossary is less subjective as it is determined by a machine learning algorithm.[9]

3 The glossary

A machine readable version of the glossary is available at econlinguistics.org

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The glossary contains trigrams that are markers for non-answers.[10] This section lays out how these trigrams were identified from a training set of questions and answers.

As outlined in Figure 1, when faced with a question, the addressee can respond using effective communication and supply the requested information, or she can be deceptive in the sense of Grice (1989) by violating any of the four Gricean cooperation principles. When developing the glossary, we focus on the first and the fourth Gricean maxim, i.e. whether the respondent provides any information at all and whether she provides factual content in the answer that is relevant for the topic at hand.

To understand general factuality in a linguistic sense, one would need to understand the context of the question and the expected information gain. The supervised machine learning approach, however, allows for deriving a glossary that is context-independent. Thus, we do not approach factuality from a context and audience specific perspective but

[9]When applying the regular expressions for rejecting an answer of Gow et al. (2019) to the analysis of economic relevance in Section 4, we find only very weak evidence of abnormal stock returns following an earnings call and obtain hardly any variation in the distribution for any Q&A setting outside the financial domain.

[10]A trigram is a continuous sequence of 3 elements from a text. The literature in natural language processing shows a significant improvement in modeling the language when going up from unigrams (Dave et al., 2003; Bekkerman and Allan, 2004). While higher-order n-grams better capture the sentiments of expressions, they come at the cost of lower coverage in the data (Pak and Paroubek, 2010). Trigrams have been, for many years, a favorite model choice, as they can simultaneously reflect the syntax and the pragmatics of the text domain (Jelinek, 1991).

rather focus on vocabulary that indicates the intention not to respond to a question in a broader, more general sense.

3.1 Multinomial Inverse Regression

Multinomial Inverse Regression is a supervised generative model developed by Taddy (2013, 2015) that allows for mapping a high dimensional choice set of words within a text into an observable attribute. A text is defined as a combination of several tokens, where a token can be understood as just a single word or a combination of n words (n-gram). For a given tokenization, a document i in the universe of all available documents $\mathcal{I}$ is represented by a sparse vector of token counts $\mathbf{x_i} = [x_{i1}, ..., x_{ip}]'$ and frequencies $\mathbf{f_i} = \mathbf{x_i}/m_i$, where $m_i = \sum_{j=1}^{p} x_{ij}$, for all available tokens p in $\mathcal{I}$.

A naive approach is to fit a linear regression model of the attribute measure of any document i on the token counts (x_i),

$$y = \beta \mathbf{x}^{\mathsf{T}},$$

and find the loadings β that each token contributes to the attribute. However, as the choice set of tokens within a text and thus, the dimension of x, is usually quite large, a normal regression cannot provide an efficient estimate of the conditional distribution of y_i. Building on the pioneering work of Cook et al. (2007), Taddy (2013, 2015) developed an inverse regression methodology that utilize the *inverse conditional distribution* in order to achieve a low-dimensional score, i.e. it exploits the conditional distribution of x given y. As described in Taddy (2013), a basic multinomial inverse regression (MNIR) model is given by

$$\begin{aligned}
\mathbf{x_y} &\sim MN(\mathbf{q_y}, m_y), \quad \text{with} \\
\mathbf{x_y} &= \sum_{i:y_i=y} \mathbf{x_i}, \\
m_y &= \sum_{i:y_i=y} m_i, \\
q_{yj} &= \frac{exp[\alpha_j + y\phi_j]}{\sum_{k=1}^{p} exp[\alpha_k + y\phi_k]} \\
\text{for} \;\; j = 1, ..., p, y &\in \mathcal{Y} \;\; \text{and} \;\; m_i = \sum_{j=1}^{p} x_{ij}.
\end{aligned}$$

Each MN is a p-dimension multinomial distribution of size m and probabilities $\mathbf{q}$ that are a linear function of y through a logistic link with token loadings ϕ. We follow Taddy (2013) in finding ϕ via ML estimation, i.e. for each token p in $\mathcal{I}$, we estimate its loading

as its contribution to the attribute measure.

The response factor does not have to be a single attribute measure y_i, but MNIR can be generalized to support K-dimensional response factors $\mathbf{v_i}$, in which case the multinomial model collapses to the levels of $\mathbf{x_v}$. In our case, the usage of several response factors comes with the advantage that we can employ measures for several forms of violating the Gricean norms of effective conversational communication (Grice, 1989).

We use measures for the violation of the first and fourth Gricean maxim as response factors.[11] A violation of the first Gricean norm, the lack of appropriate quantity of information is derived in the spirit of Gow et al. (2019), using regular expressions that identify answers with a direct rejection to provide the requested information. The violation of the fourth Gricean maxim, the relevance of the response to the topic at hand, is proxied with the metric for blathering introduced in Barth et al. (2019).

By using these response factors, the resulting list of trigrams and their corresponding weights indicate the degree to which a given trigram predicts a violation of the effective conversational communication principles of Grice (1989) in any response to a question.

3.2 Data

The glossary is extracted from textual data that originates from earnings conference calls. These calls offer a relatively standardized Q&A format in a controlled contextual environment, have an economically relevant impact and are available in regular intervals and large numbers. Earnings calls do not have an identical structure, however, they often follow a similar pattern: first, the management, typically the CEO or CFO, presents the latest financial results and earnings outlooks in a speech that is usually prepared by the investor relations department. This presentation is then followed by a question and answer discussion between the management and financial analysts.

We collected every transcript of earnings calls held by companies listed in the S&P 500 index available from Thomson Reuters' StreetEvents for the period of 2002 to 2017. These calls are released quarterly and usually take place on the same day as the corresponding earnings release.[12] As we focus on a question and answer setup as a specific form of communication rather than the prepared presentation, we exclude all earnings calls without a Q&A session. We also restrict our sample to managements' responses that contain at least 30 words to mitigate any bias in our attribute measures.

[11] As described below, we derive the glossary based on Q&As in financial markets. As there are generally heavy sanctions attached to lies, and answers by management were usually delivered in an appropriate manner, we abstract from measures of violations of the second and third Gricean norms.

[12] 92.8% of all calls in our sample take place on the same day as the earnings release and 6.9% take place one day after the earnings announcements. In only six cases is the call scheduled for more than one day after the earnings announcement.

3.3 Training set

The full sample of earnings calls is divided into a training set $\mathcal{I}$, where we have a clean measure for both response factors, and a validation set that helps to *validate* our glossary by showing its economic relevance. We split the sample across industries and use all financial firms in the training set.[13] More precisely, we use each single answer given by the management of a financial firm in response to an analyst's question as an observation in the training set $\mathcal{I}$. For these answers, we derive our two response factors.

As a first attribute measure, we follow Gow et al. (2019) and use regular expressions to identify the rejection of answers. Rejections can take several forms, such as, for example the refusal to provide the requested information ("we do not provide this disclosure") or the inability to provide the requested information ("I do not know"). We flag these answers with a dummy y^1_{ijt} that equals 1 if the response j in an earnings call of company i at time t contains any rejection phrase, i.e.

$$y^1_{ijt} = \begin{cases} 1 & \text{, if rejection phrase} \in \text{response } j \\ 0 & \text{, else.} \end{cases}$$

As a second attribute measure for non-answers, we calculate blathering as introduced by Barth et al. (2019). Blathering – from the Oxford English Dictionary: *"[To] talk in a long-winded way without making very much sense."* – is capturing 'information' that is volunteered but does not meet or purposefully avoids a precise answer. This metric assumes that for *financial firms*, the factual content in managements' responses to analysts' questions is mirrored by the usage of *finance-related words.*[14]

Given the context of an earnings call, where the financial situation as well as the strategy and business model of the firm is discussed, a factual answer for financial firms should hinge on financial words. Non-financial words, however, consist of noise that is not required for answering the initial question, as well as of words that are required to formulate a sentence in plain English.[15] Non-financial firms might provide factual and relevant information on their business model, products and strategy, which would be falsely classified as non-factual according to the blathering measure. The idea of why finance related questions to financial firms provide an ideal training set is also shown

[13] We classify all firms with an industry code 44 and 47 in Fama-French's 48 industry portfolios as financial firms.

[14] This logic is obviously only applicable for financial firms and would be violated for earnings calls of non-financial firms.

[15] As the latter is relatively constant, a variation in non-financial words can be used as a proxy for the variation in non-factual content, i.e. *blathering.*

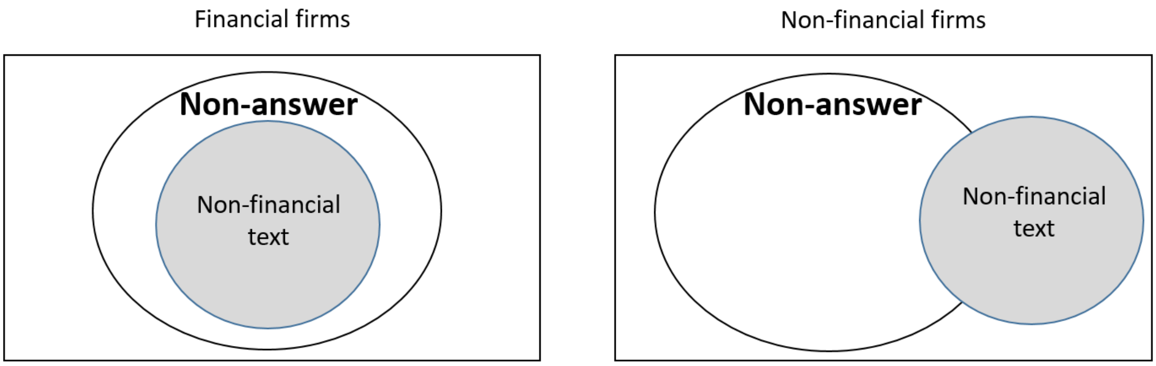

Figure 2: Venn diagram showing the relation between a non-answer and non-financial text in Q&A responses for financial vs. non-financial firms.

graphically in Figure 2: for financial firms, blathering measures a symptom of a context-free response so that non-financial text is a strict subset of non-answers. For non-financial firms, however, the set of non-financial text is only an intersection of non-answers. In order to further reduce noise in this attribute measure for non-answers, we restrict our training set to answers in response to questions that have at least one finance related word. This ensures that we do not involuntarily assign a high score for blathering to a response of a question that was not related to any finance context.

Words are classified as financial words based on the Hypertextual Finance Glossary by Campbell R. Harvey, consisting of more than 8,500 entries.[16] The degree of blathering in the response j in an earnings call of company i at time t is then defined as

$$y_{ijt}^2 = 1 - \frac{Finance\ Glossary\ Words_{ijt}}{Total\ Words_{ijt}}.$$

Our training set comprises 47,892 management answers from 1,860 earnings calls for 42 financial firms listed in the S&P 500, which accounts for roughly 10% of the textual data from earnings calls of all S&P 500 firms. As the remaining textual data of earnings calls of non-financial firms in the S&P 500 is used for validation, we end up with a very large validation set, which avoids typical problems of machine learning algorithms such as over-fitting and data mining.

3.4 Fitted glossary

For each answer in the training set, we form an answer-term-matrix of trigrams. The response factors are metrics for rejection and blathering as described above. We employ

[16]See Campbell Harvey's webpage at Duke University, `http://people.duke.edu/~charvey/`.

two cleaning procedures to make sure that the answers contain meaningful words and that the resulting glossary is of general use. First, we aim to avoid company specific trigrams to achieve the most general language in the glossary. To this extent, we focus on the most common trigrams of all responses that appear in at least 100 of all management answers. Second, we want to remove common trigrams consisting mostly of (meaningless) stop words. In order to provide a directly applicable glossary to spoken English sentences, we do not filter for stop words before forming trigrams, but would like to remove those trigrams from the glossary that appear in more than 50% of the answers.[17] This cleaning procedure leaves us with around 3,400 trigrams.[18]

The model returns 446 (999) trigrams with a positive (negative) loading for the rejection response factor and 844 (748) trigrams with a positive (negative) loading for the blathering response factor. Unlike a non-answer, an answer is always specific to the context of the question. Therefore, by construction, trigrams with a finance meaning show a strong negative loading. These trigrams, however, are only meaningful in a context-specific Q&A setting of earnings conference calls of financial firms.[19]

We only keep the 1,027 trigrams with a positive factor loading for either the attribute measure y^1 or y^2 in order to increase the scope of the glossary and to allow the glossary to measure a non-answer independent of the context.[20] We note that the algorithm draws more explanatory power from y^2 (blathering) than y^1 (rejecting).[21] However, adding rejecting as a symptom further broadens the scope of the glossary.

Figure 3 shows trigrams from the glossary with font sizes weighted by their respective factor loading ϕ.[22] We find that phrases like "back to you", "hard to predict" or "not know that" are particularly strong markers for non-answers.[23]

The glossary allows for calculating for each response j to a question a non-answer score, defined as

$$NonAnswer_j = \frac{Non\text{-}Answer\ Glossary\ Tokens_j}{Total\ Words_j}.$$

[17]Note that this restriction is not binding, i.e. we do not delete any trigram by applying this filter.

[18]Loosening the first filtering criteria will result in a less generic and lengthier word-list that contains more trigrams specific to the financial industry, similar to our training set. It does not, however, affect the results shown later in the validation analysis.

[19]Context specific trigrams with a high negative factor load include, e.g.: money market funds, basis points in, the investment portfolio, net interest margin, the securities portfolio, the loan portfolio.

[20]The intersection of the two word-lists contains 263 trigrams. Interestingly, the intersecting trigrams often show high loadings ϕ^1 and ϕ^2 for both of the attribute measures y^1 and y^2.

[21]In fact, using the attribute measure blathering alone would already produce economically significant results, similar to those presented in Section 4.

[22]The factor loading of each trigram ϕ is defined as $\max(\phi^1, \phi^2)$.

[23]A full glossary of trigrams with a positive loading is provided in the Online Appendix and at econlinguistics.org.

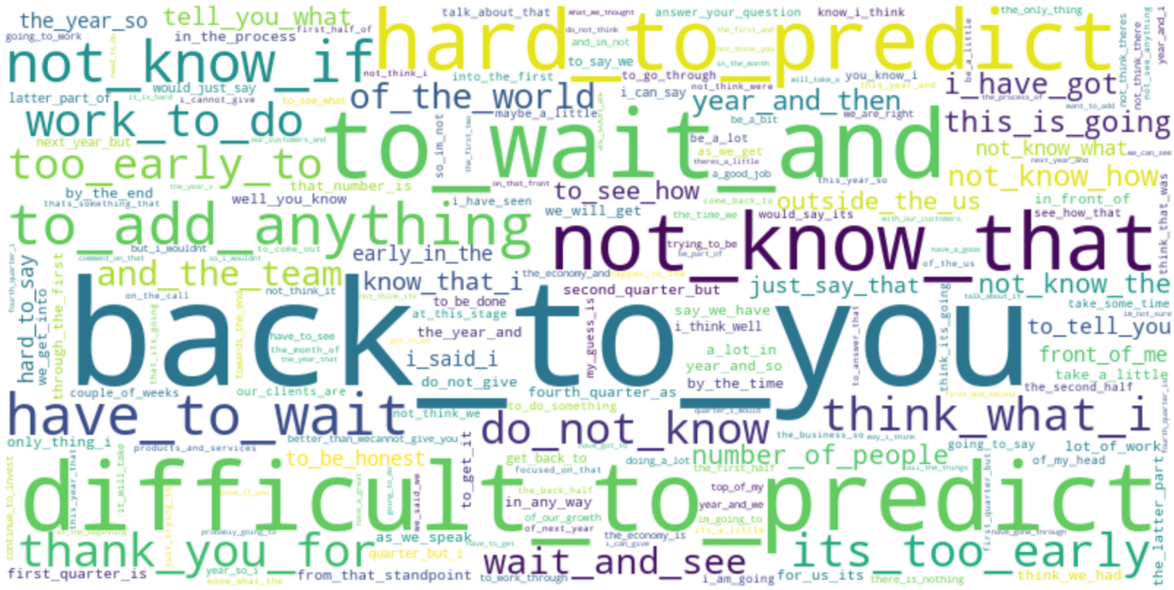

Figure 3: The glossary consists of 1,027 trigrams. A larger font size indicates a higher factor load.

As financial economists, we naturally focus on applying *NonAnswer* on textual data related to our discipline. We thus measure non-answers for management answers in earnings calls of all S&P 500 non-financial companies that were not used to train the model, i.e., the validation set. The validation set contains 23,815 earnings calls and is significantly larger than the training set (1,860 earnings calls) and, hence, minimizes the risk of over-fitting. The distribution of *NonAnswer* for each of these calls is shown in Figure 4 (left panel). Based on this data, we will provide evidence for the economic relevance of our glossary in the following Section 4.

As explained in Figure 1, a non-answer does not require a specific context. We therefore believe that the measure is applicable to other fields with a question and answers setup, such as politics or even sports. To support this claim, we explore alternative Q&A settings. One alternative source of extensive Q&A type data are press conferences after major sports events, such as NBA basketball games and NFL football games. We collect 51534 interviews from asapsports.com and present the corresponding histogram of *NonAnswer* in the center panel of Figure 4.

Additionally, presidential interviews, as collected by UCSB's American Presidency Project, provide another alternative Q&A setting.[24] Starting in 1864 with an interview with Abraham Lincoln, we analyze the answers of roughly 900 presidential interviews. The right panel in Figure 4 shows the histogram of resulting *NonAnswer*. Distributional properties appear to be very similar across all analyzed Q&A settings.

[24] See www.presidency.ucsb.edu

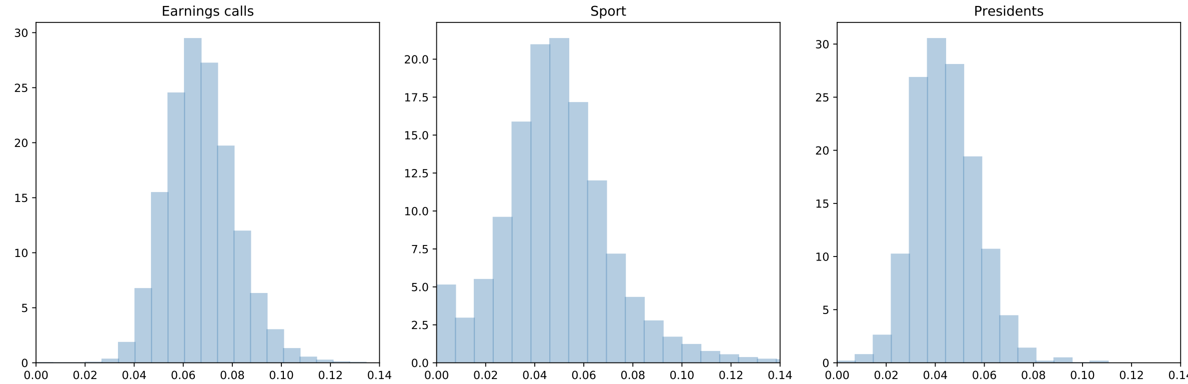

Figure 4: Distribution of $NonAnswer$ for the validation set of S&P 500 earnings calls (left), press conferences after basketball and football games (center) and all US presidential interviews since 1864 (right).

As an anecdotal reference point, consider Mark Zuckerberg's responses to the US Senate during the Cambridge Analytica hearing, such as: "Senator, [. . .] I can certainly have my team get back to you on any specifics there that I don't know, sitting here today.", which results in a high $NonAnswer$ of 0.14.

4 Economic relevance

We conduct a variety of tests to evaluate the plausibility of our glossary. First, we investigate within an earnings conference call to which questions managers try to avoid a response. Second, we examine cumulative abnormal stock returns and implied volatilities following earnings conference calls for the validation set of non-financial S&P 500 firms.

Financial markets are perfectly suited to assess the economic relevance of our measure for two reasons. First, economic theory gives a prior expectation on the effect that we would expect for avoiding an answer to questions by analysts. Second, in a financial markets' context, 'artful dodgers', as described in Rogers and Norton (2011), should be detected, as social evaluation does not play a role and the listeners' attention is directed towards the goal of identifying whether a person is answering a question. Thus, in the context of finance, we have a clear prior of a negative perception of the avoidance of an answer.

Investors participate in the Q&A session of earnings conference calls in order to reduce uncertainty about a firm's expected future performance. The theoretical asset pricing literature suggests that higher uncertainty translates to larger risk premia (Andrei and

Hasler, 2014).[25]

Faced with a non-answer, an investor's uncertainty is reduced less compared to a precise, context specific response. Even more, for a given prior expectation, a context free response might even increase uncertainty. Thus, we would expect a more negative reaction of market participants in response to non-answers. In fact, there is some empirical literature in line with this expectation showing that not conveying information leads to a negative stock market reaction. For example, Zhou (2018) argues that obscuring information by increasing textual rather than numeric content is associated with lower cumulative abnormal returns around the earnings call date. Similarly, Hollander et al. (2010) shows that stock returns in a 90 or 120 minute window after an earnings conference call react significantly more negative if the management refused to answer a question in the call. Taking these results at face value, a necessary condition for the validity of our glossary is to observe a negative correlation between $NonAnswer$ and stock returns after an earnings conference call.

4.1 Data

Non-answer score We apply our glossary to derive a metric that captures non-answers. For the earnings call of company i in quarter t, we count the occurrence of trigrams from the glossary in all responses of the Q&A session and divide by the total number of words, hence,

$$NonAnswer_{it} = \frac{Non\text{-}Answer\ Glossary\ Tokens_{it}}{Total\ Words_{it}}.$$

In addition, to incorporate the information on the loadings, we measure a $NonAnswer^{\phi}$ by weighting each trigram in the glossary with its respective factor loading,

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

where ϕ_k is the loading associated with trigram $k \in \{1, 2, ..., K\}$.

Cumulative abnormal returns We obtain daily adjusted stock returns from CRSP and calculate daily abnormal return for the stock of company i at time t with the Fama-

[25] See also Pástor and Veronesi (2013) or Liu et al. (2017) for a discussion on the impact of policy uncertainty on risk premia or Carlin et al. (2014) for the effect of disagreement as some special cases of uncertainty on asset prices.

French three-factor (1993) and five-factor (2015) model returns,[26]

$$r_{i,t}^{abnormal} = r_{i,t} - r_{i,t}^{FF}.$$

We investigate the short term effect using cumulative abnormal returns from the day of the earnings call to the day after, $CAR_{i,t}^{0;1}$. As a robustness test, we enlarge the event window and consider cumulative abnormal returns including the day before the earnings call, $CAR_{i,t}^{-1;1}$ (Zhou, 2018; Price et al., 2012).

$$CAR_{i,t}^{0;1} = \prod_{d=0}^{1} \left(1 + r_{i,t+d}^{abnormal}\right) - 1.$$

Alternative speech characteristics The literature provides evidence that investors recognize tone sentiment and the uncertainty of the language used in earnings calls.[27] As we want to test whether our measure of non-answers is not purely capturing management tone and uncertainty, we compute standard metrics from the literature to control for these language characteristics.

For tone, we count the number of negative words in earnings calls that appear on the negative word list by Loughran and McDonald (2011). Then, we define *Negativity* of company i's earnings call in quarter t as the ratio of negative words relative to total words:

$$Negativity_{it} = \frac{Negative\ Words_{it}}{Total\ Words_{it}},$$

To measure uncertainty we use the word list from Loughran and McDonald (2011).[28] Similar to the tone measure, we quantify the uncertainty of statements by counting the number of words in the earnings call that appear on this word list. *Uncertainty* for the earnings call of company i at time t is then defined as the ratio of uncertain words to

[26] The model is calibrated to 40 trading days preceding an earnings call, with data from the Fama-French data library at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[27] See, inter alia, Price et al. (2012), Blau et al. (2015), Brockman et al. (2015) or Davis et al. (2015) for evidence on tone sentiment and Dzielinski et al. (2016) for evidence on uncertainty.

[28] Note that this word list contains also the word list of weak modals from Loughran and McDonald (2011).

total words:

$$Uncertainty_{it} = \frac{Uncertainty\ Words_{it}}{Total\ Words_{it}},$$

We follow the approach in Zhou (2018) to generate a variable $Numbers$ that accounts for the usage of numbers in managements' answers relative to textual words. Specifically, we use a regular expression to capture all numbers preceded by a space or a dollar sign and calculate $Numbers_{it}$ for the earnings call of company i at time t :

$$Numbers_{it} = \frac{NumberCounts_{it}}{TotalWords_{it} + NumbersCounts_{it}}.$$

We further calculate for the responses of the management the complexity score proposed by Loughran and McDonald (2019).[29] Using the list of 255 words that proxy for complexity, we build the measure for the earnings call of company i at time t as follows:

$$Complexity_{it} = \frac{Complex\ Words_{it}}{Total\ Words_{it}},$$

Finally, we flag follow-up questions by the same analyst within an earnings call and derive a measure of forward-looking words within analysts' questions. For a single question q during the earnings call of company i at time t, we define the share of forward looking words according to the word-lists provided by Bozanic et al. (2018) and Matsumoto et al. (2011):

$$ForwardSentiment_{qit} = \frac{Forward\text{-}Looking\ Words_{qit}}{Total\ Words_{qit}}.$$

Earnings surprise and firm characteristics We collect analyst data from IBES to calculate earnings surprises for individual companies. As is standard practice in the literature, we calculate earnings surprises as the difference between the actual and consensus forecast earnings, divided by the share price at 5 trading days before the announcement in every quarter. Thus, any positive (negative) number indicates better (worse) performance than expected. As in Dzielinski et al. (2016), we rank all firms' earnings surprises into deciles and categorize earnings surprises from 1 (most negative) to 5 (least negative) and from 6 (least positive) to 10 (most positive).

In addition, we collect quarterly balance sheet statistics from Compustat as well as

[29] We also calculate the Gunning (1952) Fog index as an alternative measure of complexity. The Fog index is a function of the number of words per sentence (length of a sentence) and the share of complex words (words with more than two syllables) relative to total words. Using this measure does not change any of our results.

firms' market capitalization from CRSP.

Option implied volatility The implied volatility derived from prices of exchange-traded equity options reflects the premium that investors are willing to pay for insuring against price movements in the underlying and thus proxies for investor uncertainty.[30] We collect the daily implied volatility $\sigma_{i,t}$ derived from liquid at-the-money options with 91 days maturity from OptionMetrics, LLC. We calculate two measures to capture the instantaneous update of investors beliefs on future volatility after a conference call. The first approach follows Rogers et al. (2009), and compares the implied volatility of company i on the day just after the call to that of the day just before the call,

$$IV_{i,t}^{-1;1} = \ln\left(\frac{\sigma_{i,t+1}}{\sigma_{i,t-1}}\right).$$

Second, we compare the change in $\sigma_{i,t}$ with a counterfactual change in the implied volatility, which we calculate as the average change in implied volatility for the 60 trading days preceeding the earnings call,

$$\Delta IV_{i,t} = \frac{\sigma_{i,t+1} - \sigma_{i,t-1}}{2} - \frac{\sigma_{i,t-1} - \sigma_{i,t-60}}{59}.$$

Descriptive statistics Table 1 presents descriptive statistics for the variables in this analysis. For $NonAnswer$ and $NonAnswer^{\phi}$, the magnitude is in line with the other sentiments that resulted from the dictionary approach i.e. $Negativity$ and $Uncertainty$. In our sample, measures for $Negativity$ and $Uncertainty$ show an average of 2.8% and 1.6%, which are comparable to estimates found in the literature, see, e.g., Price et al. (2012) and Dzielinski et al. (2016). All measures for cumulative abnormal returns share very similar distributional characteristics.

4.2 Empirical analysis

We first investigate to which questions managers avoid a precise response within an earnings conference call. It is reasonable to assume that the management is more likely not to answer disadvantageous and tougher questions, as they want to evade answering these critical questions.[31] We proxy for critical questions in two ways. First, we calculate for each question the tone, assuming that a more critical question is reflected by a more

[30] See Rogers et al. (2009) for a discussion of the advantages to measure investor uncertainty by using implied volatility over other possible measures such as realized volatility or the dispersion in analyst forecasts.

[31] See, for example, Mayew (2008) or Cohen et al. (2013) who show that managers try to avoid unfavorable questions by not allowing unfavorable analysts to ask a question.

Table 1: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	P10	P50	P90	Max
Panel A: Firm-quarter data								
$NonAnswer$	23,815	.067	.014	0	.05	.066	.085	.13
$NonAnswer^{\phi}$	23,815	.095	.022	0	.068	.093	.12	.22
$Negativity$	23,815	.028	.0071	0	.02	.028	.038	.08
$Uncertainty$	23,815	.016	.0057	0	.0093	.015	.023	.056
$EarnSurp$	23,815	5.7	2.9	1	2	6	10	10
$FF3-CAR_{0;1}$	23,815	.0021	.057	-.17	-.063	.0013	.069	.17
$FF5-CAR_{0;1}$	23,815	.002	.054	-.16	-.059	.0015	.066	.16
$IV_{-1;1}$	20,217	.96	.065	.8	.88	.96	1	1.2
ΔIV	20,212	-.0072	.012	-.047	-.021	-.006	.0049	.029
BTM	23,815	.41	.55	-44	.11	.35	.8	17
$Ln(Assets)$	23,815	9.2	1.3	4.1	7.6	9.1	11	14
Q	23,815	2.1	1.3	.59	1.1	1.7	3.6	17
$Numbers$	23,815	.012	.0057	0	.0051	.011	.019	.056
$Complexity$	23,815	.007	.0038	0	.0027	.0064	.012	.036
Panel B: Q&A-level data								
$NonAnswer$	1,147,273	.046	.052	0	0	.036	.11	.69
$NonAnswer^{\phi}$	1,147,273	.066	.097	0	0	.04	.16	2.5
$IsFollowUp_q$	1,147,273	.68	.47	0	0	1	1	1
$Tone_q$	1,147,273	.0014	.073	-1.5	-.059	0	.052	1.3
$ForwardSentiment_q$	1,147,273	.1	.074	0	0	.1	.19	1

Notes: **Panel A** shows descriptive statistics for our firm-quarter level data with language measures aggregated over all Q&As within an earnings call. **Panel B** provides summary statistics for the language measures on the dimension of individual Q&As. $NonAnswer$ ($NonAnswer^{\phi}$) is the ratio of trigrams in our non-answer glossary (weighted by loadings) to the total words. $Negativity$ and $Uncertainty$ are the ratio of negative and uncertain words to the total words. The list of negative and uncertain words are from Loughran and McDonald (2011) word-lists. $EarnSurp$ represents the grouping of all firms in deciles of earnings surprise (defined as the difference between the actual and the consensus forecast earnings as a ratio to the share price 5 trading days before the announcement). $CAR_{0;1}$ is the cumulative abnormal returns in the [0;1] interval around the earnings call. $FF3\_CAR_{0;1}$ and $FF5\_CAR_{0;1}$ use Fama-French three (1993) and five (2015) factor model returns respectively. $IV_{-1;1}$ and ΔIV are the change in option's implied volatility around the earnings call as defined in Section 4.1. BTM defined as total Common/Ordinary Equity divided by the market value of equity. $ln(Assets)$ is the natural logarithm of total assets. Q is the Tobin's Q. $Numbers$ is the share of numbers to the sum of total words and numbers calculated as in Zhou (2018). $Complexity$ is the complexity measure derived from the Loughran and McDonald (2019) complexity word list. $IsFollowUp_q$ is a dummy variable that equals one if a question is a follow up question by the same analyst. $Tone_q$ is the positivity minus negativity sentiment of the question calculated by word count of the corresponding word-lists provided by Loughran and McDonald (2011). $ForwardSentiment_q$ measures the ratio of forward-looking words in a question according to the word-lists provided by Bozanic et al. (2018) and Matsumoto et al. (2011). All return variables are truncated at the 1/99% percentiles.

negative tone. Second, we flag whether a question is a follow-up question by the same analyst.[32]

Moreover, it is also likely to assume that the management might not be able to answer questions that refer to future outcomes. We therefore add the ratio of forward-looking phrases in a question as an additional dimension that might result in a non-answer. We then regress $NonAnswer$ on these measures. Note that by analyzing questions and answers within the same earnings conference call, we can control for many observable and unobservable factors, such as, for example, management or firm characteristics.

Table 2: $NonAnswer$ in response to follow-up questions.

	$NonAnswer$			$NonAnswer^{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$IsFollowUp_q$	0.0014***	0.0005***	0.0017***	0.0039***	0.0026***	0.0041***
	(11.27)	(4.19)	(14.11)	(18.33)	(12.71)	(19.82)
$Tone_q$		-0.0787***	-0.0828***		-0.1130***	-0.1183***
		(-103.71)	(-104.35)		(-88.95)	(-89.81)
$ForwardSentiment_q$			0.0414***			0.0539***
			(54.43)			(38.64)
Observations	1147273	1147273	1147273	1147273	1147273	1147273
R^2	0.054	0.065	0.068	0.044	0.051	0.052
EarningsCall FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the results for OLS regression with the dependent variable $NonAnswer$ ($NonAnswer^{\phi}$) in columns 1 to 3 (4 to 6). $IsFollowUp_q$ is a dummy variable that equals one if a question is a follow up question by the same analyst. $Tone_q$ is the positivity minus negativity sentiment of the question calculated by word count of the corresponding word-lists provided by Loughran and McDonald (2011). $ForwardSentiment_q$ measures the ratio of forward-looking words in a question according to the word-lists provided by Bozanic et al. (2018) and Matsumoto et al. (2011). All the specifications control for earnings call fixed effects. t-statistics are given in parentheses. Standard errors are clustered at the earnings call level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

The results are shown in Table 2 for $NonAnswer$ (column 1 and column 2) and $NonAnswer^{\phi}$ (column 3 and column 4). We find that $NonAnswer$ is higher in responses to follow up questions, in line with our expectation. In addition, we observe that a more positive (negative) tone of the question is associated with a lower (higher) value for $NonAnswer$, indicating that managers more often dodge critical questions. Finally, we find higher values for $NonAnswer$ in response to forward looking questions.

We next attempt to explain cumulative abnormal stock returns for the day of an earnings conference call. For this purpose, we model cumulative abnormal returns of firm

[32]The second proxy is based on Clayman (1993), who argues that analysts have the capacity to recognize and counter evasive answers by asking a follow-up question, so that follow-up questions by the same analyst are usually more critical.

i with management m around the days of the earnings call in quarter t as follows:

$$\begin{aligned} CAR_{imt} = {} & \alpha + \beta_1 \cdot NonAnswer_{imt} + \beta_2 \cdot EarnSurp_{imt} \\ & + \beta_3 \cdot Tone_{imt} + \beta_4 \cdot Uncertainty_{imt} \\ & + \theta \cdot X_{imt} + \mu_i + \nu_m + \gamma_t + \epsilon_{imt}. \end{aligned} \tag{1}$$

CAR_{imt} represents the cumulative abnormal return for the initial, short-term, reaction ($CAR^{0;1}_{i,t}$) for firm i with management m in quarter t. $NonAnswer$ is the main variable of interest generated from our glossary, measuring management's degree of non-answers in the call in quarter t. If our glossary generates a valid measure for not conveying information, we should observe lower abnormal stock returns for earnings calls with a high $NonAnswer$ and thus expect a negative coefficient for β_1.

We control for three important variables to ensure that the effect of $NonAnswer$ is not driven by outside factors. First, we include a metric that captures investors' expectations of future earnings. As is standard in the literature, we measure the difference between analysts' expectations about earnings and realized earnings as earnings surprise and, for a given point in time, cluster all firms into 10 different groups, $EarnSurp$, with a larger number indicating a more positive earnings surprise.

Second, we control for two variables that have been shown to impact returns after an earnings conference call. One of these measures is $Negativity$, defined as the ratio of negative words over total words used in management's answers. In line with Price et al. (2012), we would expect a negative coefficient for β_3. We also control for the vagueness of managements' language, $Uncertainty$. As Dzielinski et al. (2016) show that uncertainty in managements' answers to investors' questions leads to lower stock returns, we would expect a negative coefficient for β_4.

Finally, we remove all observable and unobservable firm-specific time-constant variation by including firm fixed effects, μ_i, as well as time (quarter-year) fixed effects, γ_t, to control for firm-constant factors and common trends of abnormal returns in a given quarter, respectively. We further include CEO fixed effects, ν_m, in order to absorb a manager specific component, which neither the current and future performance of the company nor strategic incentives can explain (Davis et al., 2015). This enables us to separate the effect $NonAnswer$ from personal specific unobservable time-constant characteristics. To account for autocorrelations of the errors, we employ two-way clustering (Cameron et al., 2011) and cluster standard errors at the firm and time dimensions.

Results Table 3 and Table 4 display the results of the regression model outlined in Equation 1 for $CAR^{0;1}_{i,t}$ using $NonAnswer$ and the loading-weighted $NonAnswer^{\phi}$. In

both tables, we observe a negative and highly significant coefficient, highlighting the negative effect that not answering to analysts' questions has on short-term cumulative abnormal returns. These results are in line with our expectation, provided our glossary measures non-answers. Note that this result also holds if we control for earnings surprises, other characteristics of management language, as well as industry, firm and CEO fixed effects and common time trends by quarter-year fixed effects.

Moreover, the coefficients of all control variables are in line with our expectations and with the existing literature: we find a positive and highly significant coefficient for the earnings surprise group, i.e. a greater difference in the actual earnings and earnings expected by analysts leads to more positive abnormal returns. Regarding our measures of management tone, we find a negative point estimate for the variable capturing the ratio between negativity and total words of managements' statements. Finally, we confirm the findings of Dzielinski et al. (2016) and obtain a negative coefficient for the uncertainty measure: vague language leads to a greater perceived uncertainty, which translates into smaller abnormal returns.

Option implied volatility We next investigate whether non-answering questions affects the implied volatility as a proxy for investor uncertainty. If dodging a question retards the information flow and, hence, hinders the reduction of information asymmetries between the management and investors, we will observe that investor uncertainty is reduced more after earnings calls with low $NonAnswer$. To this extent, we analyze the short term change as well as the abnormal change in implied volatility, similar to the analysis of abnormal returns above. The results are shown in Table 5.

We observe a higher post-earnings-call implied volatility for earnings calls with high $NonAnswer$, i.e. investors are willing to pay a higher premium in order to insure themselves against stock price changes after conference calls in which managers more often not answer questions.

Monte Carlo Simulation In order to show that negative abnormal returns are indeed due to wording that indicates non-answers, we run a Monte Carlo simulation by randomly drawing 1000 times a number of 1,027 trigrams from the training set. For each of these placebo dictionaries, we run regressions as in column 2 of Table 3. The distribution of t-statistics for the $NonAnswer$ coefficient is roughly normal and centered around zero, as shown in Figure 5.[33] The t-statistic for $NonAnswer$ for our original glossary is -4.08 (see Table 3, column 2). This clearly shows that it would be extremely unlikely to produce

[33]We consider the distribution of the t-statistic from the 1,000 regression coefficients as we are not only after the effect of the glossary, but also the precision of the point estimate for each draw (glossary).

Table 3: Management $NonAnswer$ and abnormal returns ($CAR_{0;1}$)

	$FF3 - CAR_{0;1}$			$FF5 - CAR_{0;1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$NonAnswer$	-0.099***	-0.110***	-0.085**	-0.090***	-0.079***	-0.075**
	(-3.82)	(-4.08)	(-2.37)	(-3.66)	(-2.69)	(-2.26)
$Negativity$	-0.451***	-0.446***	-0.639***	-0.400***	-0.520***	-0.597***
	(-7.19)	(-7.04)	(-7.70)	(-6.84)	(-8.43)	(-7.61)
$Uncertainty$	-0.054	-0.043	-0.088	-0.041	-0.076	-0.098
	(-0.73)	(-0.58)	(-0.86)	(-0.59)	(-0.99)	(-0.99)
$EarnSurp$	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***
	(18.45)	(18.52)	(15.87)	(18.63)	(17.45)	(15.94)
BTM	0.002**	0.002**	0.006*	0.002***	0.002**	0.005*
	(2.57)	(2.65)	(1.71)	(2.81)	(2.25)	(1.77)
$Ln(Assets)$	-0.002***	-0.002***	-0.011***	-0.002***	-0.008***	-0.010***
	(-6.33)	(-6.40)	(-4.63)	(-6.61)	(-5.06)	(-4.65)
Q	-0.001**	-0.001***	-0.010***	-0.001***	-0.006***	-0.009***
	(-2.57)	(-3.39)	(-9.41)	(-2.81)	(-8.06)	(-9.29)
$Numbers$		-0.160*	-0.123	-0.143*	-0.088	-0.114
		(-1.95)	(-1.07)	(-1.93)	(-1.00)	(-1.08)
$Complexity$		0.109	0.356**	0.136	0.158	0.343**
		(0.97)	(2.31)	(1.31)	(1.25)	(2.40)
Observations	23815	23689	22557	23815	23815	22557
R^2	0.044	0.047	0.125	0.044	0.077	0.124
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Implied	No	Implied	Implied
Firm FE	No	No	Yes	No	Yes	Yes
CEO FE	No	No	Yes	No	No	Yes

Notes: OLS regressions for Equation (1). The dependent variable is the abnormal returns over the Fama-French three (1993) and five (2015) factor model returns cumulated from the day of the earnings call to the day after it, $FF3 - CAR_{0;1}$ ($FF5 - CAR_{0;1}$). $NonAnswer$ is the ratio of trigrams in our non-answer glossary to the total words. $Negativity$ and $Uncertainty$ are the ratio of negative and uncertain words to the total words. List of negative and uncertain words are from Loughran and McDonald (2011) word-lists. *EarnSurp* represents the grouping of all firms in deciles of earnings surprise (defined as the difference between the actual and the consensus forecast earnings as a ratio to the share price 5 trading days before the announcement). BTM defined as total Common/Ordinary Equity divided by the market value of equity. $ln(Assets)$ is the natural logarithm of total assets. Q is the Tobin's Q. $Numbers$ is the share of numbers to the sum of total words and numbers calculated as in Zhou (2018). *Complexity* is the complexity measure derived from the Loughran and McDonald (2019) complexity word list. 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.

Table 4: Management $NonAnswer$ and abnormal returns ($CAR_{0;1}$)

	$FF3-CAR_{0;1}$			$FF5-CAR_{0;1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$NonAnswer^{\phi}$	-0.075***	-0.080***	-0.073***	-0.066***	-0.061***	-0.064***
	(-4.41)	(-4.68)	(-3.44)	(-4.16)	(-3.48)	(-3.29)
$Negativity$	-0.447***	-0.441***	-0.636***	-0.397***	-0.517***	-0.594***
	(-7.16)	(-6.98)	(-7.64)	(-6.80)	(-8.38)	(-7.56)
$Uncertainty$	-0.047	-0.036	-0.086	-0.036	-0.074	-0.096
	(-0.63)	(-0.49)	(-0.84)	(-0.52)	(-0.95)	(-0.97)
$EarnSurp$	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***
	(18.42)	(18.51)	(15.85)	(18.61)	(17.45)	(15.93)
BTM	0.002**	0.002**	0.006*	0.002***	0.002**	0.005*
	(2.51)	(2.63)	(1.71)	(2.76)	(2.25)	(1.77)
$Ln(Assets)$	-0.002***	-0.002***	-0.011***	-0.002***	-0.008***	-0.010***
	(-6.33)	(-6.38)	(-4.63)	(-6.62)	(-5.05)	(-4.65)
Q	-0.001**	-0.001***	-0.010***	-0.001***	-0.006***	-0.009***
	(-2.59)	(-3.39)	(-9.40)	(-2.81)	(-8.07)	(-9.28)
$Numbers$		-0.150*	-0.124	-0.136*	-0.085	-0.115
		(-1.84)	(-1.08)	(-1.83)	(-0.98)	(-1.09)
$Complexity$		0.102	0.348**	0.129	0.152	0.336**
		(0.91)	(2.28)	(1.25)	(1.21)	(2.38)
Observations	23815	23689	22557	23815	23815	22557
R^2	0.045	0.047	0.125	0.044	0.077	0.124
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Implied	Yes	Implied	Implied
Firm FE	No	No	Yes	No	Yes	Yes
CEO FE	No	No	Yes	No	No	Yes

Notes: OLS regressions for Equation (1). The dependent variable is the abnormal returns over the Fama-French three (1993) and five (2015) factor model returns cumulated from the day of the earnings call to the day after it, $FF3-CAR_{0;1}$ ($FF5-CAR_{0;1}$). $NonAnswer^{\phi}$ is the ratio of trigrams in our non-answer glossary weighted by loadings to the total words. $Negativity$ and $Uncertainty$ are the ratio of negative and uncertain words to the total words. List of negative and uncertain words are from Loughran and McDonald (2011) word-lists. $EarnSurp$ represents the grouping of all firms in deciles of earnings surprise (defined as the difference between the actual and the consensus forecast earnings as a ratio to the share price 5 trading days before the announcement). BTM defined as total Common/Ordinary Equity divided by the market value of equity. $ln(Assets)$ is the natural logarithm of total assets. Q is the Tobin's Q. $Numbers$ is the share of numbers to the sum of total words and numbers calculated as in Zhou (2018). $Complexity$ is the complexity measure derived from the Loughran and McDonald (2019) complexity word list. 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.

Table 5: Management $NonAnswer$ and option implied volatility (Δ IV and $IV_{-1;1}$)

	ΔIV				$IV_{-1;1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NonAnswer$	0.024***	0.027***			0.101**	0.116**		
	(2.86)	(3.17)			(2.27)	(2.60)		
$NonAnswer^{\phi}$			0.017***	0.018***			0.067**	0.070***
			(3.51)	(3.67)			(2.57)	(2.66)
$Negativity$		0.018		0.017		0.255**		0.246**
		(0.95)		(0.86)		(2.65)		(2.57)
$Uncertainty$		0.037*		0.035*		0.222**		0.218**
		(1.93)		(1.87)		(2.40)		(2.37)
$Numbers$		0.039		0.037		0.195		0.183
		(1.57)		(1.47)		(1.61)		(1.51)
$Complexity$		0.036		0.037		-0.030		-0.028
		(1.16)		(1.18)		(-0.19)		(-0.18)
Observations	20108	20108	20108	20108	20113	20113	20113	20113
R^2	0.138	0.139	0.138	0.139	0.162	0.164	0.162	0.164
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QuarterYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions with the dependent variable $IV_{-1;1}(\Delta IV)$ in the columns 1-4 (5-8) indicating the change in an option's implied volatility around the earnings call as defined in Section 4.1. $NonAnswer$ ($NonAnswer^{\phi}$) is the ratio of trigrams in our non-answer glossary (weighted by loadings) to the total words. $Negativity$ and $Uncertainty$ are the ratio of negative and uncertain words to the total words. List of negative and uncertain words are from Loughran and McDonald (2011) word-lists. $Numbers$ is the share of numbers to the sum of total words and numbers calculated as in Zhou (2018). $Complexity$ is the complexity measure derived from the Loughran and McDonald (2019) complexity word list. Firm control variables include $EarnSurp$, BTM, RoE, $ln(Assets)$, and Q. $EarnSurp$ represents the grouping of all firms in deciles of earnings surprise (defined as the difference between the actual and the consensus forecast earnings as a ratio to the share price 5 trading days before the announcement) to 5 negative and 5 (zero and) positive groups . BTM defined as total Common/Ordinary Equity divided by the market value of equity. RoE denotes return on equity. $ln(Assets)$ is the natural logarithm of total assets. Q is the Tobin's Q. 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.

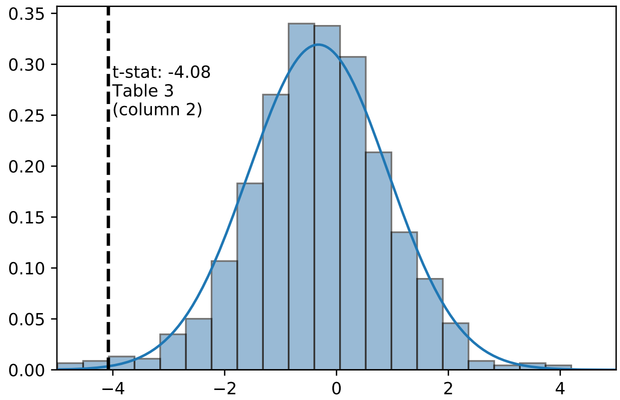

Figure 5: The histogram of t-statistics for the $NonAnswer$ coefficient from Equation 1 with 1000 word-lists of 1,027 trigrams randomly selected from the universe of trigrams. The dashed line shows the t-statistic of a regression with our non-answer glossary (column 2 of Table 3).

economically significant results by randomly drawing a glossary from the universe of trigrams.

5 Conclusion

The asymmetric distribution of information is considered a key friction in economics. While question and answer (Q&A) settings are intended to remove information asymmetries, the addressee of a question does not necessarily provide the requested information. Building on a large textual dataset of questions and answers and employing a supervised machine learning framework, we generate a generalizable glossary that allows for identifying non-answers.

Using a Multinomial Inverse Regression (Taddy, 2013), we identify a glossary of 1,027 trigrams such as 'back to you', 'do not know', 'hard to predict', etc., which are found to be frequently used in order to refrain from answering a question in a concise and factual manner. The glossary is derived from earnings conference calls, where investors and analysts can directly question senior managers' during a Q&A session. However, as non-answers do not contain any context- or industry-specific vocabulary, the glossary is applicable to a broad Q&A context, such as sports or political interviews and senate hearings.

We provide evidence for the plausibility and economic relevance of the glossary. First, we document that within an earnings call, non-answers are observed more prevalently for tougher and more critical questions, which is in line with Mayew (2008) and Cohen

et al. (2013): within the same conference call, *NonAnswer* is higher for managements' responses to follow-up questions by the same analyst and for managements' responses to more negative questions. In addition, we observe higher *NonAnswer* for questions with forward looking sentences, i.e., questions that refer to (potentially unknown) future outcomes.

Second, we apply the glossary to market reactions after earnings conference calls for a large sample of firms over a timespan of 16 years. In regressions with multiple control variables, we show a strong negative impact for the measure derived from our glossary, i.e., not answering analysts' questions leads on average to negative abnormal stock returns after an earnings call. We also link our measure to option implied volatilities after earnings conference calls and show that investor uncertainty increases if the requested information in the call has not been provided by the management. Both results are in line with the theoretical asset pricing literature, which suggests that higher uncertainty translates to larger risk premia (Andrei and Hasler, 2014).

Using a Monte Carlo simulation, we validate that the glossary is not a product of sheer randomness. In the Monte Carlo Simulation, we draw 1,000 randomly selected dictionaries with 1,027 trigrams from all words that appear at least once in the training set of our earnings calls. We repeat the textual analysis on our sample of earnings calls for each of these random draws of word lists, derive a corresponding placebo *NonAnswer* and test for an effect of this score on cumulative abnormal returns. It turns out that it would be extremely unlikely to produce economically significant results by randomly drawing a glossary from the universe of trigrams.

Both our method and glossary are free of financial context and hence applicable to alternative settings. In order to corroborate this claim, we briefly explore textual data from sports events and presidential interviews, thereby motivating additional research into alternative settings. To stimulate further research, we publish a machine-readable version of the glossary at econlinguistics.org.

References

Andrei, D. and Hasler, M. (2014). Investor Attention and Stock Market Volatility. *Review of Financial Studies*, 28(1):33–72.

Barth, A., Mansouri, S., Woebbeking, F., and Zörgiebel, S. (2019). How to talk down your stock returns. Working paper.

Bekkerman, R. and Allan, J. (2004). Using bigrams in text categorization. Technical report, Technical Report IR-408, Center of Intelligent Information Retrieval, UMass Amherst.

Blau, B. M., DeLisle, J. R., and Price, S. M. K. (2015). Do sophisticated investors interpret earnings conference call tone differently than investors at large? Evidence from short sales. *Journal of Corporate Finance*, 31:203–219.

Bloomfield, R. (2008). Discussion of "annual report readability, current earnings, and earnings persistence". *Journal of Accounting and Economics*, 45(2-3):248–252.

Bonsall, S. B., Leone, A. J., Miller, B. P., and Rennekamp, K. (2017). A plain english measure of financial reporting readability. *Journal of Accounting and Economics*, 63(2-3):329–357.

Bozanic, Z., Roulstone, D. T., and Van Buskirk, A. (2018). Management earnings forecasts and other forward-looking statements. *Journal of Accounting and Economics*, 65(1):1–20.

Brockman, P., Li, X., and Price, S. M. (2015). Differences in conference call tones: Managers vs. analysts. *Financial Analysts Journal*, 71(4):24–42.

Buller, D. B. and Burgoon, J. K. (1996). Interpersonal deception theory. *Communication Theory*, 6(3):203–242.

Bushee, B. J., Gow, I. D., and Taylor, D. J. (2018). Linguistic complexity in firm disclosures: Obfuscation or information? *Journal of Accounting Research*, 56(1):85–121.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

Carlin, B. I., Longstaff, F. A., and Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics*, 114(2):226 – 238.

Clayman, S. (1993). Reformulating the question: A device for answering/not answering questions in news interviews and press conferences. *Text - Interdisciplinary Journal for the Study of Discourse*, 13.

Cohen, L., Lou, D., and Malloy, C. (2013). Playing favorites: How firms prevent the revelation of bad news. Technical report, National Bureau of Economic Research.

Cook, R. D. et al. (2007). Fisher lecture: Dimension reduction in regression. *Statistical Science*, 22(1):1–26.

Dave, K., Lawrence, S., and Pennock, D. M. (2003). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *Proceedings of the 12th international conference on World Wide Web*, pages 519–528.

Davis, A. K., Ge, W., Matsumoto, D., and Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies*, 20(2):639–673.

Dzielinski, M., Wagner, A. F., and Zeckhauser, R. J. (2016). In no (un)certain terms: Managerial style in communicating earnings news. Working Paper.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Gentzkow, M., Shapiro, J. M., and Taddy, M. (2019). Measuring group differences in high-dimensional choices: Method and application to congressional speech. *Econometrica*, 87(4):1307–1340.

Gow, I. D., Larcker, D. F., and Zakolyukina, A. A. (2019). Non-answers during conference calls. Chicago Booth Research Paper 19-01.

Grice, P. H. (1989). *Studies in the Way of Words*. Harvard University Press., Cambridge, MA.

Guay, W., Samuels, D., and Taylor, D. (2016). Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics*, 62(2-3):234–269.

Gunning, R. (1952). *The technique of clear writing*. McGraw-Hill, New York.

Harvey, C. R. (2016). Harvey's hypertextual finance glossary. *URL: https://people. duke. edu/˜ charvey/Classes/wpg/bfglosm. htm [Version 8 November 2016.].*

Henry, E. (2008). Are Investors Influenced By How Earnings Press Releases Are Written? *Journal of Business Communication*, 45(4):363–407.

Hollander, S., Pronk, M., and Roelofsen, E. (2010). Does silence speak? an empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, 48(3):531–563.

Jelinek, F. (1991). Up from trigrams!-the struggle for improved language models. In *Second European Conference on Speech Communication and Technology*.

Lee, J. (2015). Can investors detect managers' lack of spontaneity? adherence to predetermined scripts during earnings conference calls. *The Accounting Review*, 91(1):229–250.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2-3):221–247.

Liu, L. X., Shu, H., and Wei, K. J. (2017). The impacts of political uncertainty on asset prices: Evidence from the bo scandal in china. *Journal of Financial Economics*, 125(2):286 – 310.

Loughran, T. and McDonald, B. (2011). When is a Liability not a Liability? *Journal of Finance*, 66(1):35 – 65.

Loughran, T. and McDonald, B. (2014). Measuring readability in financial disclosures. *Journal of Finance*, 69(4):1643–1671.

Loughran, T. and McDonald, B. (2019). Measuring firm complexity. Working paper.

Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? the information content of managers' presentations and analysts' discussion sessions. *The Accounting Review*, 86(4):1383–1414.

Mayew, W. J. (2008). Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research*, 46(3):627–659.

McCornack, S. A., Levine, T. R., Solowczuk, K. A., Torres, H. I., and Campbell, D. M. (1992). When the alteration of information is viewed as deception: An empirical test of information manipulation theory. *Communication Monographs*, 59(1):17–29.

Pak, A. and Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In *LREc*, volume 10, pages 1320–1326.

Pástor, L. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3):520 – 545.

Price, S. M., Doran, J. S., Peterson, D. R., and Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4):992 – 1011.

Rogers, J. L., Skinner, D. J., and Buskirk, A. V. (2009). Earnings guidance and market uncertainty. *Journal of Accounting and Economics*, 48(1):90 – 109.

Rogers, T. and Norton, M. I. (2011). The artful dodger: Answering the wrong question the right way. *Journal of Experimental Psychology: Applied*, 17(2):139 – 147.

Taddy, M. (2013). Multinomial inverse regression for text analysis. *Journal of the American Statistical Association*, 108(503):755–770.

Taddy, M. (2015). Distributed multinomial regression. *The Annals of Applied Statistics*, 9(3):1394–1414.

Zhou, D. (2018). Do numbers speak louder than words? Technical report.

Zuckerberg, M. Facebook, social media privacy, and the use and abuse of data. Joint hearing before the COMMITTEE ON COMMERCE, SCIENCE, AND TRANSPORTATION UNITED STATES SENATE and the COMMITTEE ON THE JUDICIARY UNITED STATES SENATE, One Hundred Fifteenth Congress, Second Session.

Online Appendix

The Non-Answer Glossary

A lists of all trigrams in the glossary with their corresponding loading ϕ. A machine readable version of the glossary is available at econlinguistics.org

Token	ϕ
back.to.you	10.1
difficult.to.predict	6.3
to.wait.and	6.3
hard.to.predict	6.3
not.know.that	6.0
to.add.anything	5.8
have.to.wait	5.7
not.know.if	5.6
thank.you.for	5.3
its.too.early	5.3
work.to.do	5.2
think.what.i	5.0
too.early.to	4.9
do.not.know	4.8
wait.and.see	4.8
of.the.world	4.8
and.the.team	4.7
this.is.going	4.7
not.know.how	4.4
i.have.got	4.4
year.and.then	4.3
not.know.the	4.3
number.of.people	4.3
outside.the.us	4.3
tell.you.what	4.3
to.see.how	4.2
know.that.i	4.2
just.say.that	4.2
to.tell.you	4.1
not.know.what	4.1
front.of.me	4.1
hard.to.say	4.1
i.said.i	4.0
to.be.honest	3.9
the.year.so	3.9
early.in.the	3.9
from.that.standpoint	3.9
second.quarter.but	3.9
a.lot.in	3.9
fourth.quarter.as	3.9
that.number.is	3.8
we.will.get	3.8
in.any.way	3.8
for.us.its	3.8
the.year.and	3.7
year.and.so	3.7
lot.of.work	3.7
by.the.end	3.7
take.a.little	3.7
we.get.into	3.7
to.get.it	3.6
by.the.time	3.6
in.the.process	3.6
as.we.speak	3.6
first.quarter.is	3.6
through.the.first	3.6
well.you.know	3.6
say.we.have	3.5
do.not.give	3.5
in.front.of	3.5
only.thing.i	3.5
think.we.had	3.5
the.latter.part	3.4
would.just.say	3.4
i.can.say	3.4
i.think.well	3.4
quarter.but.i	3.4
next.year.but	3.4
to.be.done	3.4
get.back.to	3.3
to.say.we	3.3
latter.part.of	3.3
answer.your.question	3.3
our.clients.are	3.3
at.this.stage	3.3
you.know.i	3.3
talk.about.that	3.3
take.some.time	3.3
know.i.think	3.3
maybe.a.little	3.3
be.a.lot	3.3
think.that.was	3.2
of.my.head	3.2
couple.of.weeks	3.2
not.think.we	3.2
into.the.first	3.2
to.do.something	3.2
as.we.get	3.2
would.say.its	3.2
i.am.going	3.2
the.second.half	3.2
so.im.not	3.2
to.go.through	3.2
my.guess.is	3.2
i.have.seen	3.2
see.how.that	3.1
going.to.say	3.1
think.its.going	3.1
there.is.nothing	3.1
the.time.we	3.1
the.economy.is	3.1
year.and.i	3.1
not.think.it	3.1
we.are.right	3.1
and.im.not	3.1
year.and.we	3.1
of.our.growth	3.1
continue.to.invest	3.1
be.a.bit	3.1
year.so.i	3.1
as.soon.as	3.0
better.than.we	3.0
the.first.half	3.0
to.see.what	3.0
trying.to.be	3.0
but.i.wouldnt	3.0
not.think.there	3.0
top.of.my	3.0
a.good.job	3.0
to.work.through	3.0
im.going.to	3.0
it.will.take	3.0
not.think.theres	2.9
cannot.give.you	2.9
the.economy.and	2.9
have.to.see	2.9
the.only.thing	2.9
going.to.work	2.8
towards.the.end	2.8
doing.a.lot	2.8
products.and.services	2.8
first.quarter.but	2.8
come.back.to	2.8
the.back.half	2.8
this.year.so	2.8
not.think.i	2.8
the.business.so	2.8
we.said.we	2.8
of.next.year	2.8
i.cannot.give	2.8
on.the.call	2.8
thats.something.that	2.8
focused.on.that	2.8
know.what.the	2.8
not.think.were	2.8
this.year.and	2.8
be.a.little	2.7
not.see.anything	2.7
of.the.us	2.7
that.its.going	2.7
the.month.of	2.7
just.trying.to	2.7
happen.in.the	2.7
first.half.of	2.7
to.come.out	2.7
this.year.that	2.7
to.answer.that	2.7
its.a.little	2.7
probably.going.to	2.7
will.take.a	2.7
know.if.you	2.7
have.to.get	2.6
comment.on.that	2.6
with.our.customers	2.6
way.i.think	2.6
first.and.second	2.6
not.think.its	2.6
the.first.two	2.6
what.we.thought	2.6
the.year.that	2.6
the.year.i	2.6
be.part.of	2.6
theres.a.little	2.6
got.to.be	2.6
quarter.i.would	2.6
want.to.add	2.6
on.that.front	2.6
going.to.do	2.6
at.the.beginning	2.6
have.a.good	2.5
talk.about.it	2.5
the.first.and	2.5
im.not.sure	2.5
our.customers.and	2.5
need.to.do	2.5
the.process.of	2.5
in.the.month	2.5
next.year.and	2.5
it.is.hard	2.5
so.i.wouldnt	2.5
fourth.quarter.i	2.5
fourth.quarter.is	2.5
all.the.things	2.5
have.gone.through	2.5
have.a.great	2.5
i.can.give	2.5
have.got.to	2.4
do.not.think	2.4
not.think.you	2.4
we.can.see	2.4
were.pleased.with	2.4
still.in.the	2.4
think.at.the	2.4
we.are.certainly	2.4
things.that.were	2.4
year.in.the	2.4
would.say.this	2.4
would.say.is	2.4
quarter.of.last	2.4
quarter.or.two	2.4
for.the.year	2.4
the.way.you	2.4
and.were.going	2.4
at.least.for	2.4
have.been.pretty	2.4
we.might.have	2.3
not.see.it	2.3
this.year.but	2.3
to.answer.your	2.3
off.the.top	2.3
talked.about.it	2.3
to.go.back	2.3
the.year.is	2.3
end.of.this	2.3
go.back.and	2.3
to.make.it	2.3
of.the.year	2.3
to.get.more	2.3
actions.that.we	2.3
tell.you.is	2.3
really.focused.on	2.3
are.not.seeing	2.3
to.work.on	2.3
to.help.us	2.3
but.we.havent	2.3
quarter.that.we	2.3
think.that.were	2.3
think.were.going	2.3
half.of.the	2.3
something.that.we	2.3
i.would.like	2.2
fourth.quarter.of	2.2
in.new.york	2.2
that.is.going	2.2
going.to.happen	2.2
little.bit.higher	2.2
for.next.year	2.2
things.we.have	2.2
well.have.to	2.2
the.world.and	2.2
to.be.careful	2.2
second.half.of	2.2
think.youre.going	2.2
i.tried.to	2.2
really.hard.to	2.2
one.way.or	2.2
the.united.states	2.2
but.right.now	2.2
part.of.what	2.2
i.think.youll	2.2
think.you.can	2.2
i.would.have	2.2
you.know.its	2.2
half.of.this	2.2
through.the.year	2.2
we.would.say	2.2
i.would.be	2.2
to.see.if	2.1
we.have.spent	2.1
was.going.to	2.1
it.is.going	2.1
just.a.little	2.1
give.us.a	2.1
to.be.much	2.1
think.there.are	2.1
year.and.the	2.1
it.is.still	2.1
in.europe.and	2.1
what.were.going	2.1

Token	ϕ
guess.i.would	2.1
into.the.second	2.1
our.clients.and	2.1
for.us.but	2.1
said.we.are	2.1
the.third.and	2.1
it.might.be	2.1
fourth.quarter	
.and	2.1
do.you.want	2.1
to.get.there	2.1
into.the.fourth	2.1
we.havent.seen	2.1
we.have.mentio	
ned	2.1
year.so.we	2.0
i.mean.i	2.0
not.think.that	2.0
first.quarter.	
so	2.0
quarter.and.th	
en	2.0
fourth.quarter	
.so	2.0
when.we.get	2.0
pleased.with.t	
he	2.0
we.are.going	2.0
but.you.know	2.0
that.we.may	2.0
that.could.be	2.0
of.this.year	2.0
it.makes.sense	2.0
like.to.see	2.0
a.little.higher	2.0
of.things.that	2.0
number.of.thin	
gs	2.0
i.guess.i	2.0
with.the.regul	
ators	2.0
are.things.that	2.0
the.next.quart	
er	2.0
would.say.in	2.0
know.that.we	2.0
last.year.and	2.0
in.fact.i	2.0
to.pick.up	2.0
going.to.get	2.0
of.years.ago	2.0
of.these.things	2.0
well.we.are	2.0
will.see.that	2.0
think.we.would	2.0
the.next.two	2.0
i.think.from	2.0
of.our.custome	
rs	2.0
going.to.take	2.0
i.think.i	2.0
fair.to.say	1.9
this.quarter.it	1.9

Token	ϕ
this.year.is	1.9
been.a.little	1.9
can.give.you	1.9
i.think.people	1.9
little.bit.bet	
ter	1.9
in.that.regard	1.9
lot.of.things	1.9
things.that.we	1.9
the.year.but	1.9
of.last.year	1.9
we.have.worked	1.9
think.we.were	1.9
in.the.right	1.9
to.our.custome	
rs	1.9
beginning.of.t	
he	1.9
would.say.we	1.9
say.that.we	1.9
again.i.think	1.9
we.are.always	1.9
so.i.cannot	1.9
trying.to.do	1.9
but.i.think	1.9
to.comment.on	1.9
and.then.well	1.9
the.right.way	1.9
year.we.are	1.9
have.to.go	1.9
im.not.going	1.9
with.us.and	1.9
be.the.case	1.9
no.i.think	1.8
good.job.of	1.8
going.through.	
the	1.8
i.think.were	1.8
say.is.that	1.8
see.a.little	1.8
it.i.think	1.8
spend.a.lot	1.8
i.just.think	1.8
feel.very.comf	
ortable	1.8
get.into.the	1.8
will.tell.you	1.8
do.not.want	1.8
are.seeing.the	1.8
last.year.we	1.8
i.will.say	1.8
yes.let.me	1.8
see.how.the	1.8
we.go.into	1.8
trying.to.get	1.8
its.going.to	1.8
you.know.if	1.8
in.the.next	1.8
were.not.seeing	1.8
i.think.about	1.8
would.also.say	1.8
in.the.numbers	1.8
going.to.come	1.8

Token	ϕ
not.want.to	1.8
first.quarter.	
that	1.8
for.this.year	1.8
right.now.but	1.8
the.way.they	1.8
years.ago.we	1.8
year.ago.and	1.7
bit.of.an	1.7
you.look.back	1.7
but.having.said	1.7
a.little.better	1.7
one.thing.i	1.7
from.our.persp	
ective	1.7
an.awful.lot	1.7
in.the.back	1.7
going.to.give	1.7
the.pace.of	1.7
the.things.we	1.7
in.the.year	1.7
think.they.are	1.7
lot.of.time	1.7
the.answer.is	1.7
what.i.said	1.7
going.to.make	1.7
we.expect.it	1.7
i.would.look	1.7
yes.i.mean	1.7
we.get.to	1.7
much.as.we	1.7
that.we.havent	1.7
the.us.and	1.7
do.not.get	1.7
like.that.but	1.7
us.to.do	1.7
well.i.do	1.7
i.think.for	1.7
what.that.means	1.7
think.we.can	1.7
year.and.that	1.7
and.fourth.qua	
rter	1.7
think.we.will	1.7
to.make.a	1.7
see.some.of	1.7
quarter.i.think	1.7
one.or.two	1.6
there.is.going	1.6
later.in.the	1.6
want.to.say	1.6
we.will.see	1.6
able.to.do	1.6
going.on.there	1.6
as.we.work	1.6
have.done.a	1.6
at.a.time	1.6
of.our.business	1.6
is.a.lot	1.6
second.quarter	
.and	1.6
think.as.i	1.6
that.were.look	

Token	ϕ
ing	1.6
last.year.so	1.6
i.think.what	1.6
the.business.we	1.6
is.the.first	1.6
there.is.still	1.6
they.have.got	1.6
to.the.next	1.6
around.the.glo	
be	1.6
first.quarter.	
of	1.6
the.good.news	1.6
be.happy.to	1.6
two.years.ago	1.6
need.to.make	1.6
making.sure.th	
at	1.6
try.to.do	1.6
the.beginning.	
of	1.6
first.quarter.	
and	1.6
is.i.think	1.6
think.youll.see	1.6
end.of.last	1.6
said.i.think	1.6
i.think.they	1.6
as.good.as	1.6
we.have.gone	1.6
say.we.are	1.6
you.know.what	1.6
continue.to.ma	
ke	1.6
a.really.good	1.6
us.and.we	1.6
want.to.be	1.6
very.pleased.w	
ith	1.6
start.to.see	1.6
the.commercial	
.side	1.5
in.our.numbers	1.5
were.very.plea	
sed	1.5
third.quarter.	
so	1.5
opportunities.	
for.us	1.5
to.participate	
.in	1.5
think.we.have	1.5
think.what.we	1.5
very.very.good	1.5
right.now.i	1.5
would.expect.it	1.5
very.difficult	
.to	1.5
it.is.something	1.5
not.expect.that	1.5
we.made.a	1.5
as.an.example	1.5
the.next.few	1.5

Token	ϕ
back.half.of	1.5
based.on.what	1.5
its.hard.to	1.5
i.cannot.tell	1.5
but.i.would	1.5
the.first.quar	
ter	1.5
the.right.thing	1.5
think.it.will	1.5
for.the.next	1.5
to.invest.in	1.5
of.our.busines	
ses	1.5
want.to.comment	1.5
expect.it.to	1.5
think.it.would	1.5
to.say.that	1.5
that.i.think	1.5
i.think.we	1.5
answer.to.that	1.5
have.made.a	1.5
in.the.second	1.5
to.take.a	1.5
for.us.and	1.5
in.the.united	1.5
quarter.so.that	1.5
want.to.get	1.5
the.answer.to	1.5
i.guess.what	1.5
i.can.tell	1.5
to.sort.of	1.5
part.of.this	1.5
little.bit.on	1.5
a.bit.more	1.5
the.people.that	1.5
just.going.to	1.5
you.think.of	1.5
parts.of.our	1.5
i.want.to	1.5
all.the.time	1.5
and.we.certain	
ly	1.4
going.to.have	1.4
i.would.just	1.4
i.wouldnt.say	1.4
want.to.go	1.4
in.the.fourth	1.4
give.you.a	1.4
would.add.to	1.4
think.that.if	1.4
to.take.some	1.4
on.the.first	1.4
it.looks.like	1.4
cannot.tell.you	1.4
in.the.first	1.4
that.we.didnt	1.4
of.the.first	1.4
whats.going.to	1.4
the.fourth.qua	
rter	1.4
that.we.saw	1.4
i.think.it	1.4
well.i.would	1.4

Token	ϕ
i.know.that	1.4
i.will.tell	1.4
of.the.growth	1.4
time.but.we	1.4
a.little.more	1.4
i.said.before	1.4
i.do.believe	1.4
want.to.give	1.4
year.or.two	1.4
terms.of.how	1.4
second.part.of	1.4
comment.on.the	1.4
i.have.said	1.4
big.part.of	1.4
can.tell.you	1.4
across.all.of	1.4
the.last.six	1.4
the.next.year	1.4
think.the.way	1.4
we.see.it	1.3
is.not.something	1.3
into.next.year	1.3
the.last.two	1.3
continue.to.focus	1.3
would.tell.you	1.3
that.right.now	1.3
the.second.part	1.3
the.end.of	1.3
would.love.to	1.3
of.the.second	1.3
we.can.get	1.3
the.first.thing	1.3
you.kind.of	1.3
is.hard.to	1.3
very.focused.on	1.3
talked.about.that	1.3
depending.on.what	1.3
well.be.able	1.3
think.it.was	1.3
right.now.and	1.3
in.the.economy	1.3
to.the.end	1.3
from.the.standpoint	1.3
will.be.able	1.3
are.a.little	1.3
got.a.lot	1.3
think.this.is	1.3
think.its.a	1.3
third.and.fourth	1.3
have.i.think	1.3
well.let.me	1.3
need.to.be	1.3
were.going.to	1.3
because.i.think	1.3
make.sure.that	1.3
to.talk.about	1.3
know.we.do	1.3

Token	ϕ
in.i.think	1.3
have.been.talking	1.3
the.way.i	1.3
along.the.way	1.3
the.year.we	1.2
to.see.it	1.2
of.trying.to	1.2
to.give.you	1.2
i.do.think	1.2
was.a.little	1.2
i.think.thats	1.2
what.is.going	1.2
its.fair.to	1.2
the.business.is	1.2
to.deal.with	1.2
about.the.fact	1.2
little.bit.more	1.2
the.thing.that	1.2
to.get.back	1.2
of.the.question	1.2
think.about.it	1.2
that.is.really	1.2
given.that.we	1.2
and.i.think	1.2
to.get.into	1.2
up.a.little	1.2
that.being.said	1.2
would.like.to	1.2
sure.that.we	1.2
would.think.about	1.2
as.you.said	1.2
the.things.that	1.2
last.year.that	1.2
we.were.going	1.2
not.going.to	1.2
what.we.saw	1.2
a.great.question	1.2
think.we.are	1.2
i.would.tell	1.2
a.big.part	1.2
what.i.would	1.2
still.a.lot	1.2
the.run.rate	1.2
year.but.we	1.2
very.strong.and	1.2
said.we.have	1.2
around.the.world	1.2
of.the.businesses	1.2
and.we.want	1.2
and.i.would	1.1
i.think.there	1.1
terms.of.where	1.1
have.said.that	1.1
well.i.think	1.1
a.few.years	1.1
it.could.be	1.1
the.next.couple	1.1
things.that.i	1.1

Token	ϕ
in.the.early	1.1
to.make.sure	1.1
was.a.lot	1.1
and.you.know	1.1
going.to.continue	1.1
continue.to.do	1.1
would.say.it	1.1
we.are.expecting	1.1
really.do.not	1.1
do.not.really	1.1
people.who.are	1.1
i.think.that	1.1
last.quarter.we	1.1
it.would.be	1.1
i.think.its	1.1
of.the.fourth	1.1
to.us.and	1.1
are.right.now	1.1
lot.of.people	1.1
add.to.that	1.1
things.that.are	1.1
thing.i.would	1.1
think.it.is	1.1
things.i.think	1.1
year.we.had	1.1
the.same.thing	1.1
are.not.going	1.1
going.to.be	1.1
are.very.focused	1.1
last.two.years	1.1
if.you.want	1.0
i.would.say	1.0
have.to.make	1.0
of.the.big	1.0
are.a.lot	1.0
quarter.it.was	1.0
right.now.so	1.0
think.that.is	1.0
question.i.think	1.0
and.i.guess	1.0
in.that.area	1.0
had.a.little	1.0
yes.i.would	1.0
think.that.we	1.0
to.see.the	1.0
our.customer.base	1.0
on.the.consumer	1.0
fourth.quarter.was	1.0
the.third.quarter	1.0
would.have.expected	1.0
a.business.that	1.0
in.some.ways	1.0
the.top.of	1.0
i.think.is	1.0
for.some.time	1.0

Token	ϕ
would.say.that	1.0
we.are.still	1.0
and.theres.a	1.0
but.let.me	1.0
what.we.said	1.0
you.know.that	1.0
we.may.have	1.0
its.something.that	1.0
this.year.we	1.0
they.are.going	0.9
years.we.have	0.9
of.the.third	0.9
the.second.quarter	0.9
its.kind.of	0.9
that.i.would	0.9
the.consumer.side	0.9
i.think.this	0.9
third.quarter.and	0.9
of.the.day	0.9
tell.you.that	0.9
we.know.that	0.9
that.were.going	0.9
i.think.a	0.9
sure.that.were	0.9
for.our.customers	0.9
all.of.us	0.9
that.it.would	0.9
we.didnt.have	0.9
are.going.to	0.9
think.thats.the	0.9
as.i.said	0.9
not.see.that	0.9
in.the.uk	0.9
quarter.last.year	0.9
the.last.quarter	0.9
and.we.expect	0.9
to.go.into	0.9
want.to.do	0.9
the.one.thing	0.9
were.not.going	0.9
of.the.quarter	0.9
a.lot.to	0.9
seem.to.be	0.9
i.would.think	0.9
this.year.i	0.9
they.want.to	0.9
in.the.last	0.9
little.bit.but	0.9
very.hard.to	0.9
year.i.think	0.9
the.first.part	0.9
in.the.third	0.9
i.would.not	0.9
give.you.the	0.9
i.mean.we	0.8
we.really.do	0.8

Token	ϕ
we.need.to	0.8
next.year.we	0.8
first.quarter.we	0.8
at.the.end	0.8
have.a.lot	0.8
we.talked.about	0.8
how.we.think	0.8
part.of.it	0.8
last.year.in	0.8
we.have.got	0.8
do.not.see	0.8
that.we.could	0.8
us.and.i	0.8
were.trying.to	0.8
this.quarter.i	0.8
but.we.think	0.8
business.that.we	0.8
of.our.clients	0.8
as.we.talked	0.8
to.see.some	0.8
i.think.youre	0.8
we.would.like	0.8
expect.that.to	0.7
used.to.be	0.7
of.the.things	0.7
think.there.is	0.7
is.a.little	0.7
is.going.to	0.7
over.the.course	0.7
theyre.going.to	0.7
the.course.of	0.7
spent.a.lot	0.7
having.said.that	0.7
you.want.to	0.7
for.the.last	0.7
we.have.made	0.7
an.area.that	0.7
there.as.well	0.7
of.the.business	0.7
or.may.not	0.7
be.able.to	0.7
so.i.would	0.7
we.have.never	0.7
we.have.done	0.7
this.point.i	0.7
the.board.and	0.7
going.to.go	0.6
that.we.continue	0.6
going.to.try	0.6
fourth.quarter.but	0.6
i.think.you	0.6
end.of.the	0.6
have.got.the	0.6
on.an.annual	0.6
give.you.an	0.6
a.position.to	0.6
are.starting.to	0.6
in.the.us	0.6

Token	ϕ
good.news.is	0.6
give.you.some	0.6
have.given.you	0.6
quarter.of.this	0.6
figure.out.what	0.6
the.last.year	0.6
as.much.as	0.6
number.that.we	0.6
course.of.the	0.6
theres.going.to	0.6
one.of.our	0.6
a.level.of	0.5
we.think.we	0.5
in.interest.rates	0.5
we.sit.here	0.5
the.net.interest	0.5
next.couple.of	0.5
youre.going.to	0.5
i.think.as	0.5
of.the.industry	0.5
talk.about.the	0.5
for.us.to	0.5
a.little.bit	0.5
to.put.a	0.5
in.the.pipeline	0.5
let.me.just	0.5
i.think.in	0.5
for.us.i	0.5
the.extent.we	0.5
that.level.of	0.5
so.i.think	0.5
whether.or.not	0.5
you.a.sense	0.5
to.figure.out	0.5
have.got.a	0.5
the.percentage.of	0.5
in.our.view	0.4
as.we.sit	0.4
business.so.i	0.4
net.interest.margin	0.4
we.have.discussed	0.4
we.would.be	0.4
top.of.that	0.4
a.bit.of	0.4
the.equity.side	0.4
rates.are.going	0.4
money.market.funds	0.4
over.time.so	0.4
over.the.next	0.4
long.as.we	0.4
that.we.might	0.4
that.will.come	0.4
expectation.is.that	0.4
going.forward.but	0.4
a.great.deal	0.4

Token	ϕ
end.up.with	0.4
when.you.see	0.4
those.two.things	0.4
not.trying.to	0.4
in.the.mortgage	0.4
with.regard.to	0.4
same.kind.of	0.4
and.i.believe	0.4
the.mortgage.business	0.4
come.in.and	0.4
it.this.way	0.4
in.this.case	0.4
like.that.so	0.4
going.to.look	0.4
the.timing.of	0.4
the.federal.reserve	0.3
a.range.of	0.3
that.theres.a	0.3
go.back.to	0.3
a.quarterly.basis	0.3
we.havent.really	0.3
sit.here.today	0.3
is.something.that	0.3
back.to.a	0.3
that.would.be	0.3
in.that.range	0.3
our.net.interest	0.3
much.of.that	0.3
on.the.loan	0.3
in.a.position	0.3
not.something.that	0.3
but.we.would	0.3
on.a.lot	0.3
do.not.believe	0.3
a.lot.more	0.3
we.want.to	0.3
to.continue.to	0.3
the.time.of	0.3
you.can.get	0.3
but.in.terms	0.3
to.the.market	0.3
see.what.the	0.3
in.the.investment	0.3
can.look.at	0.3
trying.to.figure	0.3
i.mentioned.in	0.3
of.the.range	0.3
for.the.future	0.3
are.talking.about	0.3
couple.of.years	0.3
were.looking.for	0.3

Token	ϕ
at.the.moment	0.3
other.thing.that	0.3
we.have.given	0.3
at.this.point	0.3
it.depends.on	0.3
to.think.that	0.3
think.i.would	0.3
you.know.it	0.3
that.type.of	0.3
a.number.of	0.3
lot.of.different	0.3
i.think.over	0.3
really.going.to	0.3
of.the.issues	0.3
the.cost.of	0.3
the.first.question	0.3
may.not.be	0.3
going.to.change	0.3
do.not.necessarily	0.3
at.this.time	0.3
a.lot.of	0.3
a.sense.of	0.3
do.not.need	0.3
how.much.of	0.2
i.guess.the	0.2
mentioned.in.my	0.2
the.loan.portfolio	0.2
regard.to.the	0.2
our.view.is	0.2
i.said.earlier	0.2
this.point.in	0.2
the.question.is	0.2
back.into.the	0.2
do.believe.that	0.2
i.think.first	0.2
is.a.function	0.2
the.change.in	0.2
this.point.we	0.2
as.a.percentage	0.2
the.industry.and	0.2
on.a.quarterly	0.2
so.let.me	0.2
thats.what.were	0.2
to.come.down	0.2
that.point.in	0.2
on.top.of	0.2
have.looked.at	0.2
in.the.future	0.2
come.up.with	0.2
net.interest.income	0.2
point.in.time	0.2
the.equity.markets	0.2
one.is.the	0.2
on.the.equity	0.2
do.think.that	0.2

Token	ϕ
top.of.the	0.2
going.forward.so	0.2
its.a.great	0.2
you.saw.that	0.2
we.believe.that	0.2
that.tends.to	0.2
what.you.would	0.2
that.we.want	0.2
that.the.market	0.2
at.some.point	0.2
to.try.to	0.2
a.percentage.of	0.2
on.the.revenue	0.2
depending.on.the	0.2
i.think.the	0.2
relates.to.the	0.1
so.that.would	0.1
as.you.know	0.1
as.long.as	0.1
change.in.the	0.1
that.you.would	0.1
the.size.of	0.1
thats.going.to	0.1
we.are.working	0.1
first.of.all	0.1