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Laudatio by Alexander Hillert for "*"Let me get back to you" – A machine learning approach to measuring non-answers*" by Andreas Barth, Sasan Mansouri, and Fabian Woebbeking, forthcoming in *Management Science*

Imagine that you are an analyst following a publicly listed company that has just released its quarterly financial results. You read the firm's earnings press release and also look at its quarterly financial report, but you still do not fully understand what is going on at the firm and why the firm's earnings did not come in as expected. What would you do in this situation? You decide to join the firm's earnings conference call to ask the CEO directly to get, hopefully, a helpful answer.

This setting is very common, as most publicly listed companies host a conference call after announcing their earnings. During the call, the firm's management – typically the CEO and CFO – will discuss the firm's performance in the previous quarter and will provide an outlook on the current and future quarters. After the management's presentation, analysts can ask questions.

This question-and-answer session gives market participants the rare opportunity to get unfiltered information directly from the firms' top executives. Thus, earnings calls play an important role in lowering information asymmetries between top management and market participants like analysts and investors. However, this exchange of information only works if managers provide informative answers to analysts' questions.

Whether management's answers are informative is exactly what Andreas, Fabian, and Sasan analyze in their paper: they train an algorithm to detect non-answers, i.e., uninformative answers, and then, explore investors' reaction to non-answers.

For analysts and investors, it is easy to tell whether a question has been answered or not. For an algorithm, it is a tough task. This is particularly true if managers beat around the bush, i.e., if they talk without saying much, as these non-answers can come in many different forms and can use quite different vocabulary.

Andreas, Fabian, and Sasan solve this challenging task by using supervised machine learning, i.e., they provide the algorithm with a data set of questions and answers that have been labelled as informative answers or as non-answers. The algorithm then uses this training data set to identify expressions that are predictive of non-answers.

To assure that an algorithm makes accurate predictions, you need thousands or even tens of thousands of observations in the training data. However, manually reading and classifying that many question-and-answer pairs is hardly feasible.

To solve this problem, the authors make a very clever choice: They automatically generate training data by focusing on the earnings calls of financial companies and by only including analyst questions that ask about financial topics. Why is this set of questions helpful? Because an informative answer to such a question should also deal with finance. If it does not, then it is likely that the answer is a non-answer.

Andreas, Fabian, and Sasan, apply this simple classification method to the earnings conference calls of the financial firms in their sample. Thereby, they obtain a large data set of more than 60,000 answers to train the algorithm.

After the training, the algorithm returns a list of expressions that are highly predictive of non-answers. The list comprises more than 1,300 three-word combinations like "back to you," "hard for me," "comment on that," or "too early to," which indeed sound like a manager does not provide precise information.

In the next step, Andreas, Fabian, and Sasan analyze the economic effects of non-answers. More specifically, they apply the trained algorithm to more than 23,000 earnings conference calls from non-financial firms to determine the amount of non-answers in a call. This analysis is strictly out-of-sample, i.e., these earnings calls have not been used to train the algorithm.

Andreas, Fabian, and Sasan find that non-answers are negatively related to the abnormal returns around the earnings call. In other words, the more managers beat around the bush the more negative is investors' reaction to the call. The authors do a great job in identifying this effect by controlling for a large set of variables in their regressions including other text-based measures like negativity and uncertainty and by including firm, manager, and time fixed effects to absorb many potential confounds.

Next, Andreas, Fabian, and Sasan analyze how non-answers are associated with investors' uncertainty about the firm's prospects measured by changes in option implied volatility. They find that more non-answers go in line with higher uncertainty which makes sense as non-answers leave investors wondering what is going on at the firm.

Andreas, Fabian, and Sasan have many more very interesting analyses, for example, how analysts adjust their forecasts in response to non-answers and which types of analyst questions are more likely to receive a non-answer from management.

Taken together, the authors make a very nice contribution in deepening our understanding of information transmission in finance.

Moreover, the paper has also implications outside the domain of finance. In their appendix, the authors show that their algorithm also works in different settings like U.S. presidential interviews, U.S. senate hearings, and even for press conferences after NBA and NFL games.

Last, I would like to applaud the authors for their open-science approach. Their dictionary of non-answers is publicly available on the webpage econlinguistics.org. Moreover, they have developed a web-based app which allows users to insert a text and get the text's non-answer score. I highly recommend reading the paper and visiting the webpage.

Let me conclude with a personal note. I still remember when I taught my Ph.D. course "Textual Analysis in Finance" in the summer term of 2017 for the first time at Goethe University. My goal was to motivate students to use textual analysis methods to approach new research questions and to provide them with the knowledge and skills to start their own project. Sasan and Fabian were two students in my class. I am more than happy to see that my course may have helped them to write this great paper.

Andreas, Fabian, Sasan, congratulations, very well done. I wish you all the best for your future research agenda and hope to see many more such great textual analysis papers!