Non-answers during conference calls

Ian D. Gow David F. Larcker Anastasia A. Zakolyukina*

January 3, 2019

ABSTRACT

We construct a novel measure of disclosure choice by firms. Our measure uses linguistic analysis of conference calls to flag a manager's response as providing an explicit "non-answer" to an analyst's question. Using our measure, about 11% of questions elicit non-answers, a rate that is stable over time and similar across industries. Consistent with extant theory, we find firms are less willing to disclose when competition is more intense, but more willing to disclose prior to raising capital. An important feature of our measure is that it yields several observations for each firm-quarter, which allows us to examine disclosure choice *within* a call as a function of properties of the question. We find product-related questions are associated with non-answers, and this association is stronger when competition is more intense, suggesting product-related information has higher proprietary cost. While firms are more forthcoming prior to raising capital, the *within*-call analyses for future-performance-related questions shows firms are less likely to answer future-performance-related questions shortly before equity or debt offerings when legal liability is higher.

*Gow is at the University of Melbourne. Larcker is at Stanford Graduate School of Business. Zakolyukina is at the University of Chicago Booth School of Business. We thank Christian Leuz, Paul Ma, Max Muhn, Doug Skinner, Hal White, and seminar participants at Dartmouth College, INSEAD, the University of Chicago, the University of Minnesota, Penn State University, the University of Queensland, and Victoria University of Wellington for helpful comments. We also thank Robin Weiss, Vincent Pham, Hossein Pourreza, Jingyu Zhang, Sarah Kervin, Cindy Chung, Hande Turkcapar, Maria Kamenetsky, Simon Jacobs, James Gao, Aleschia Hyde, Mariana Lepecki, and Sisi Liu for outstanding research support. We are grateful to Gerard Hoberg and Gordon Phillips for sharing their product similarity data and to David Dorn and Gordon Hanson for sharing their HS6-to-SIC crosswalk file, code, and trade data. This research was funded in part by the Fama-Miller Center for Research in Finance at the University of Chicago Booth School of Business. Larcker acknowledges support from the Stanford Rock Center for Corporate Governance. Zakolyukina acknowledges financial support from the IBM Corporation Faculty Research Fund and the University of Chicago Booth School of Business, and research support from the University of Chicago Research Computing Center.

1. Introduction

Since Regulation Fair Disclosure was introduced by the United States Securities and Exchange Commission (SEC), corporate conference calls have emerged as an important channel for firms to disclose information to capital markets.[1] One feature of a typical conference call is that a portion of it is devoted to the firm's managers providing responses to questions asked by participants, who are primarily sell-side equity analysts. However, many of these questions are met by explicit *non-answers*, such as "we do not disclose those numbers" or "I can't give you any specifics" or, simply, "I don't know."

In this paper, we use linguistic analysis of managers' responses to construct a measure of disclosure choice of these non-answers. To construct this measure, we first built a sample of randomly selected question-answer pairs and had multiple research assistants examine and tag each response to indicate whether it contains a non-answer or not. We used a random subsample of these tagged question-answer pairs to create a classification algorithm based on a set of carefully crafted regular expressions. We evaluated the *out-of-sample* accuracy of our classifier using the holdout sample of the tagged question-answer pairs and found our algorithm correctly identifies 78.87% of true non-answers and correctly classifies responses in 89.20% of cases.

We use our measure to examine the two long-standing questions in disclosure research. The first question is whether greater product market competition causes firms to be less willing to disclose information to capital market participants. Although several papers have tested the prediction that greater competition leads to less disclosure due to proprietary costs, empirical support for this prediction has been mixed (Beyer, Cohen, Lys, and Walther 2010).

We examine how competition relates to disclosure, using non-answers to measure disclosure and a number of measures of competition, including the Herfindahl-Hirschman

[1] See, for example, Frankel, Johnson, and Skinner (1999) and Bushee, Matsumoto, and Miller (2004).

concentration index (HHI) and text-based measures, one from Hoberg and Phillips (2016) and two based on Li, Lundholm, and Minnis (2013). Unlike many prior studies, we find a robust negative association between competition and disclosure for all four measures of competition.

The granular nature of our disclosure measure enables us to provide a stronger test of the relation between product-market competition and disclosure choice.[2] We first identify questions that plausibly create greater proprietary costs of disclosure and then test whether such questions are (i) less likely to be answered than other questions, and (ii) less likely to be answered when competition is stronger. We use the Stanford Named Entity Recognizer (NER) "Organization" category to identify questions with plausibly greater proprietary costs and label these "product-related" questions because the majority of these relate to products. Because we include *call* fixed effects, our analysis compares the responsiveness of managers to questions *within* a call controlling for firm- and date-specific characteristics. We find evidence of both predicted effects: Disclosure is less forthcoming for product-related questions, and this effect is accentuated when competition is greater.

An important concern in disclosure research is that correlated omitted variables may drive associations between competition and disclosure choice (Berger 2011). To provide credible evidence of the causal relation between competition and disclosure, we draw on recent literature in economics and finance (Autor, Dorn, and Hanson 2013; Autor, Dorn, Hanson, and Song 2014; Hombert and Matray 2018). These papers use industry-level growth in imports from China to eight high-income countries *other than* the U.S. as an instrument for growth in imports from China to the U.S., where imports from China to the U.S. are assumed to increase competition for U.S.-based firms. Using this approach, we find evidence of increased competition leading to less disclosure.

The second question we examine is whether an imminent need to access capital markets causes firms to be more willing to disclose information to capital market participants (Lang

[2]Our classifier can be applied to individual question-answer pairs, allowing us to compute non-answer indicators for 2,017,404 question-answer pairs from conference calls over 2002—2015.

and Sul 2014). Prior research has found that firms are more forthcoming with information when they anticipate raising money in capital markets in the near future. We use four measures of anticipated capital market activity. For the first measure, we use the amount of debt due within one year as a measure of the need to refinance. For the remaining three measures, we use actual capital market activity in the period after each conference call as a proxy for anticipated capital market activity at the time of the call. We construct separate indicators for capital offerings—including public equity, debt, and private placements—occurring during the year after the conference call. Consistent with predictions and prior research, we find evidence of anticipated capital market activity being negatively associated with non-answers for all four measures of capital market incentives.

Again, the granular nature of our disclosure measure also allows us to provide a stronger test of the relation between anticipated capital market activity and disclosure choice. Although forward-looking disclosures are notionally protected by the Safe Harbor provisions of the 1995 Private Securities Litigation Reform Act, plaintiffs frequently challenge these protections (Rogers and Van Buskirk 2009). The litigation risk is higher prior to equity or debt offerings (Healy and Palepu 2001). To identify questions with plausibly heightened litigation risk, we use the measure of forward-looking statements from Bozanic, Roulstone, and Van Buskirk (2018) and the list of finance terms from Matsumoto, Pronk, and Roelofsen (2011) to identify future-performance-related questions. We then test whether future-performance-related questions are (i) less likely to be answered than other questions, and (ii) less likely to be answered in the presence of heightened litigation risk due to anticipated capital market activity. Again, because we include *call* fixed effects, our analysis compares the responsiveness of managers to questions *within* a call controlling for firm- and date-specific characteristics. We find evidence of both predicted effects: Disclosure is less forthcoming for future-performance-related questions, and this effect is accentuated when capital market issuance occurs in the subsequent year.

As with analysis of the effect of competition on disclosure, an important concern is that capital market activity is not exogenous and may be affected by factors that jointly determine capital market activity and disclosure choices. In an effort to address this concern, we exploit the events surrounding Lehman Brothers' bankruptcy in September 2008 as a shock to capital market incentives. With a looming recession and bond spreads shooting above 15% for high-yield bonds immediately after September 2008 (Almeida, Campello, Laranjeira, and Weisbenner 2011), this event was likely associated with sharply increased capital-market needs, especially for financially distressed firms.

We exploit this variation in capital-market needs by estimating a difference-in-differences specification where the dependent variable is non-answer rates, the treatment is an indicator for high levels of financial distress, and the pre- and post-treatment periods are the six-month periods before and after September 30, 2008, respectively. The financial distress is measured by the probability of failure as in Campbell, Hilscher, and Szilagyi (2008). We find the non-answer rate is significantly lower for distressed firms in the wake of the Lehman bankruptcy, consistent with accentuated capital market incentives causing these firms to be more forthcoming with information. As placebo tests, we also estimate the same specification around September 2007 and around September 2009 and find no effects in either of these periods.

Our paper adds to prior literature in a number of ways. Our primary contribution is a novel measure of disclosure choice based on non-answers by managers during conference calls. Although our measure is similar to that in Hollander, Pronk, and Roelofsen (2010), where conference calls of 681 firms from 2004 were manually coded as containing non-answers similar to those in our paper, our measure is based on linguistic analysis applied to a much larger sample.[3] Additionally, our measure can be constructed at the level of individual question-answer pairs rather than on per-call basis like the measure used in Hollander et al. (2010).

We also provide additional evidence of firms' disclosure choices being driven by both

[3]Our classification algorithm for non-answers can be easily applied to a large sample of conference calls.

product-market and capital-market concerns. Although the "proprietary cost hypothesis" is a longstanding theory in disclosure research, and several papers have examined either competition or capital market incentives, the evidence in support of this hypothesis has often been weak (Cheynel and Ziv 2015). Our paper examines both incentives and finds robust evidence in support of their association with disclosure choice.

We believe our measure has a number of strengths over measures used in extant research. Prior research has primarily used two measures of disclosure choice. While being a holistic measure of disclosure quality, the first measure—analyst ratings of disclosure quality—is difficult to relate to specific choices by firms and is increasingly irrelevant, because it not available for fiscal years after 1995 (Core 2001).[4] The second popular measure is based on management earnings forecasts and is really a set of measures, including indicators for whether forecasts were issued, the precision of forecasts, and their accuracy. Although measures based on management forecasts are used in disclosure research, they are not without issues (Healy and Palepu 2001). For example, firms typically adopt a policy of providing, or not providing, earnings forecasts, which means disclosure choices are effectively observed at a relatively low frequency. Consistent with the low-frequency nature, much of the research has been constrained to examine associations between long-run tendencies at the firm level, such as tendencies to access capital markets and to disclose earnings forecasts (e.g., Frankel, McNichols, and Wilson 1995). By contrast, our measure is available for any conference call and, because it reflects relatively spontaneous responses by managers, is effectively observed with greater frequency, including multiple observations during a single call.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Sections 3 and 4 discuss our measure and data, respectively. Sections 5 and 6 discuss the results of our primary and additional analyses, respectively. Section 7 concludes the paper.

[4]The score used by researchers was the AIMR Score, provided by the Association for Investment Management and Research (AIMR), a predecessor organization to the CFA Institute.

2. Related literature

2.1 Voluntary disclosure and competition

An extensive literature has examined the effect of product market competition on disclosure to capital markets (Beyer et al. 2010). While Verrecchia (1983) assumes the costs of disclosure are exogenous and fixed, subsequent research has posited that greater product market competition will lead to higher proprietary costs of disclosure, and hence less disclosure. Nonetheless, Beyer et al. (2010) conclude that "evidence of the impact of product market competition as a proxy for proprietary costs on firms' disclosures is mixed" (p. 306). For example, Verrecchia and Weber (2006) find that firms in more competitive industries appear more willing to withhold (redact) information. By contrast, Bamber and Cheon (1998) find that firms in less competitive industries are less likely to provide earnings forecasts. Beyer et al. (2010) suggest one reason for mixed findings is the challenge of "measuring and quantifying ... the level of competition in an industry" using concentration measures. While Ali, Klasa, and Yeung (2009) highlight practical issues with concentration measures, Cheynel and Ziv (2015) point out that the conceptual basis for the use of industry concentration measures as proxies for competition is not strong.[5]

2.2 Voluntary disclosure and capital market incentives

A critical element of the setting in Verrecchia (1983) is the sale of firms' equity in capital markets. Absent such capital market activity, firms in the Verrecchia (1983) setting would have no reason to incur the cost of disclosing firm value. Empirical research has found evidence of increased voluntary disclosure being associated with future capital market activity. Lang and Lundholm (1993) show firms that issue equity tend to have better

[5] Ali, Klasa, and Yeung (2014) find that in more concentrated industries, "firms' management earnings forecasts are less frequent and have shorter horizons, their disclosure ratings by analysts are lower, and they have more opaque information environments, as measured by the properties of analysts' earnings forecasts" (p. 240).

disclosure based on analyst ratings. Frankel et al. (1995) document a positive association between the tendency of a firm to access capital markets and to disclose earnings forecasts. Healy, Hutton, and Palepu (1999) find firms with improved analyst ratings of disclosure tend to issue more public debt in subsequent periods. Lang and Lundholm (2000) find firms dramatically increase their disclosure activity beginning six months before seasoned equity offerings.

2.3 Measures of disclosure

Most of the papers cited in the discussion in the preceding two subsections use one of two measures of disclosure choice: analyst ratings of disclosure (e.g., Lang and Lundholm 1993) or management forecasts (e.g., Frankel et al. 1995). Each of these measures has limitations. The widely used measure of analyst ratings of disclosure, AIMR ratings, mixes voluntary and mandatory disclosures and was discontinued in 1997 after ranking the fiscal year 1995 (Core 2001). Management forecasts are relatively low-frequency disclosures (e.g., firms might issue quarterly guidance) and the frequency of the actual choice to provide forecasts is effectively much lower, because many firms adopt policies of either providing or not providing guidance that persist for many periods (Beyer et al. 2010).

A number of other measures have been used in empirical research on voluntary disclosure. Some papers have relied on properties of earnings, such as conservatism of reporting (Dhaliwal et al. 2014). Berger and Hann (2007) uses segment disclosure, for which accounting standards allow some discretion in aggregation, as a measure of voluntary disclosure. Verrecchia and Weber (2006) examines the choice to redact information from SEC filings. Li (2008) measures the "tone" of disclosure. Bozanic et al. (2018) captures both quantitative earnings-related and qualitative non-earnings forward-looking statements in earnings press releases. Each of these measures has strengths and weaknesses. Measures based on properties of earnings capture properties of earnings along with disclosure choices. Other measures, such as requirements of SFAS 131 for segment reporting, redactions in

SEC filings, and press releases, incorporate elements of both voluntary and mandatory disclosure.

In contrast, managerial choices not to provide responses to analysts' questions have attributes of disclosure that extant measures do not capture. First, the decision not to answer a questions is a real-time decision, with spontaneity not found in other measures. While conference calls can be scripted and the list of participants can be controlled (Mayew 2008; Cohen, Lou, and Malloy 2017), tightly controlling the content of a real-time exchange is ultimately impossible. Second, questions represent requests for specific pieces of information, and non-answers represent a decision not to provide this information. Third, the frequency of the decision to disclose can be measured at the level of individual questions. In contrast, extant disclosure measures capture disclosure decisions at much lower frequency. Finally, having a measure of the question-answer-level disclosure choice opens the possibility of studying the types of questions or the domains of information about which firms are or are not forthcoming.

3. Measurement

3.1 Non-answers

We classify a managerial response to a question as a non-answer, using regular expressions to detect the presence of key phrases in the response. Non-answers can take a number of forms. Most non-answers contain explicit text indicating that the speaker *refuses* to provide information, such as "we do not provide this disclosure" or "we do not disclose these numbers." Other non-answers suggest the speaker was *unable* to provide the requested information, such as "I do not know" or "I can't give you any specifics." A final, smaller category (*after-call*) involves an undertaking to provide the information after the conference call, such as "let's discuss it after the call" or "we could take that off-line." Appendix A provides examples and presents the set of regular expressions we use to identify non-answers.

3.1.1. *Development of classification algorithm*

To develop our classification algorithm, we constructed a "gold standard" that was divided into training and test samples. To build our gold standard, we selected a random sample of 1,796 managerial responses. Each response was examined by two workers on CrowdFlower, a crowdsourcing marketplace platform.[6] We asked each worker to identify any non-answers in the managerial response and to classify them into one of the three categories above. We had each worker record the shortest phrase from the response that justifies each non-answer classification they identified. One advantage of CrowdFlower over other platforms is that it allowed us to pre-screen participants based on their performance on a set of initial tasks. Using reliable workers reduces the need for costly rework and increases the quality of our data.

Once we collected data from the CrowdFlower platform, we asked skilled research assistants employed by the University of Chicago to examine all cases with inconsistent classifications by the CrowdFlower participants, as well as a random sample of additional cases. These research assistants resolved inconsistencies and finalized our "gold standard" corpus. A key element of this "gold standard" corpus is an indicator variable *Non-answer* for each response, which takes a value of one if the response contains a non-answer, and zero otherwise.

We then split our "gold standard" corpus into two subsamples: a training sample comprising 1,296 responses and a test sample comprising 500 responses. After considering a variety of automated approaches, we determined that carefully crafting a set of regular expressions based on manually identified non-answer phrases would be the best approach. We manually developed these regular expressions using the training sample until in-sample classification performance was deemed satisfactory. Specifically, we sought *in-*

[6]https://www.crowdflower.com/

sample classification accuracy over 90%.[7] Once satisfactory performance was achieved (in-sample accuracy of 90.90%), we fixed the regular expressions.

3.1.2. Out-of-sample classification performance

Having fixed the regular expressions, we applied our measure on the test (holdout) sample. We then compared the *Non-answer* indicator implied by our regular expressions with the *Non-answer* indicator from our gold standard. The *out-of-sample* true positive rate is 78.87%.[8] The *out-of-sample* precision is 58.95%.[9] Finally, the *out-of-sample* classification accuracy of our approach is 89.20%. As expected, this classification performance metrics are worse than their *in-sample* counterparts computed on the training sample. Specifically, the *in-sample* true positive rate is 81.82%, the *in-sample* precision is 68.13%, and the *in-sample* accuracy is 90.90%. Although the *out-of-sample* performance is worse than the *in-sample* performance, the decrease is quite small and suggests our approach did not result in over-fitting to the training sample. We therefore conclude our approach captures non-answers well.[10]

3.1.3. Challenges with automated classifiers

Our algorithm detects relatively straightforward phrases such as "I cannot comment on that" or "I don't know," but it also detects more complex phrases such as "I really wouldn't want to give any specific guidance beyond what we have given before." However, with an out-of-sample (in-sample) true-positive rate of 78.87% (81.82%), the algorithm misses roughly 20% of non-answers (as coded by humans). Some examples of missed sentences

[7]Accuracy is defined as the proportion of responses correctly identified by the algorithm as containing non-answers or not.

[8]The true positive rate is defined as the proportion of actual non-answers correctly identified by the algorithm as non-answers.

[9]Precision is defined as the proportion of actual non-answers among all responses identified by the algorithm as non-answers.

[10]Identifying appropriate benchmarks for the out-of-sample performance of our measure is difficult because few studies creating various measures provide these statistics. For example, the fog index is argued to measure the readability of a text (Li 2008), but its ability to predict readability measured using more sophisticated approaches is unclear. Similarly, how dictionary-based approaches to measuring tone (Loughran and McDonald 2011) would fare relative to a coding of the tone of filings by sophisticated readers is unclear.

include “We are not at liberty to share that right now” and “I don’t think at this point there’s anything more I can say about that.” In the former case, the algorithm fails to recognize “share” as a disclosure-related verb; the algorithm would detect “We are not at liberty to disclose that right now.” In the latter case, the distance between the grammatical phrasing causes our algorithm to fail to detect the non-answer. Our algorithm would correctly classify “I don’t think I can say more about that at this point,” which is similar in meaning, but different in grammatical structure.

Another error our classifier can make is to classify responses that are not non-answers as non-answers. For example, “Ray, I don’t know if you want to provide any additional color . . . ” is in fact a suggestion by one executive to have another address the question, but our classifier interprets “I don’t know” as a claim of inability to answer the question, which is one category of non-answers that our measure is designed to detect. Overall, these errors do not seem to have a systematic pattern and thus do not introduce a systematic bias in the analysis of disclosure choice.

These examples suggest we are able to measure only some of the possible non-answers to a question. But the detection of other non-answers requires a deeper understanding of the meaning of the questions and the responses. For instance, Shantanu Narayen, CEO of Adobe Systems, was asked a question about the higher pricing of Adobe’s traditional software in Australian markets, but persisted in talking about the importance of another Adobe product, Creative Cloud, for Adobe’s future.[11] Our measure is not designed to detect this kind of evasion of questions. Another example is the May 2018 conference call of Tesla Motors, in which CEO Elon Musk interrupted analysts before they even finished asking their questions.[12] Our measure does not detect these interruptions as non-answers, even though they mean questions go unanswered. We recognize the complexity of the phenomenon of non-answers means we only capture a subset of true non-answers.

[11] Video of this event can be found at https://www.youtube.com/watch?v=78yigV0GYGQ.

[12] Video of this event can be found at https://www.wsj.com/video/highlights-from-elon-musk-combative-tesla-earnings-call/FD9A3F61-496D-4EDD-A97D-6FD7B22E9B7E.html by *Wall Street Journal*.

Nonetheless, given the prevalance of the kinds of non-answers that we do detect over time and across industries, we argue this subset is important and our classification has some merit as a measure of disclosure choice.

3.2 Product-related questions

We identify product-related questions using the Named Entity Recognizer (NER) implementation by the Stanford NLP group (Finkel, Grenager, and Manning 2005).[13] The NER algorithm extracts sequences of words in a text that are the names of entities, such as people or organizations. We use NER for a seven-class linguistic model that extracts seven classes of named entities: locations, people, organizations, monetary amounts, percentages, dates, and times. Although the NER does not have a specific "product" category, many organization names extracted by NER from conference calls correspond to product names.

As with managerial responses, we code each question as being product related, using an indicator variable, *Product-related*, that equals one if the list of organization names extracted by NER from a question is nonempty, and zero otherwise. When doing so, we exclude the commonly used finance terms listed in Table B.1, such as EPS, EBIT, and P&L. Tagged NER organizations can be companies and other business entities, regulators, and product names. These questions can be more likely to have a proprietary nature even if the entity identified is not a product name. For instance, the question can be about a regulatory approval, and thus the name of the regulator may be mentioned; or performance of a business division, where the name of the business division may be mentioned; or a relationship with a customer, supplier, or competitor, where the name of another company may be mentioned. Because many of these instances are requests to comment on proprietary information, and questions about products can also have a proprietary nature, we generically refer to these questions as being product related.

[13] https://nlp.stanford.edu/software/CRF-NER.html.

We recognize the limitation of putting a "product-related" label on the *Product-related* indicator. To assess how well the organizations category as extracted by NER captures product names, we asked skilled research assistants to identify the names of products in a random sample of 830 questions, each from a different call. We then compared the *Product-related* indicator implied by the NER organization category with the *Product-related* indicator computed using manually identified product names. The *out-of-sample* accuracy of the NER classifier of 78.67% suggests it roughly captures product names. Appendix B provides details and examples for *Product-related* questions.

3.3 Future-performance-related questions

We identify future-performance-related questions using word lists of forward-looking statements from Bozanic et al. (2018) and finance terms from Matsumoto et al. (2011). We code each question as being future-performance related using an indicator variable, *Future perf.-related*, that equals one if the question contains both a forward-looking statement and a finance term, and zero otherwise. Although Bozanic et al. (2018) have developed a list of forward-looking statements using textual analysis of earnings announcements, this list is sufficiently general to be applied in the conference-call setting. For instance, the list contains individual words such as "expect" and "anticipate" that can be used in question-like phrases such as "Should we expect" and "Do you anticipate."[14] By contrast, Matsumoto et al. (2011) developed their list of finance terms using conference calls.[15] We eliminate the discretion on our part by applying these word lists without any modifications to conference-call questions. Appendix C provides examples of *Future-performance-related* questions.

[14]The word list is in the online appendix to Bozanic et al. (2018), Table A1.
[15]The word list is in appendix A to Matsumoto et al. (2011).

4. Data

4.1 Samples

The data come from several sources. The conference calls are from StreetEvents, the product similarity measure is from the Hoberg-Phillips data library, equity and debt issuance events are from Capital IQ, the financial data are from Compustat and CRSP, the CEO compensation data are from Equilar, and Chinese import data are from the UN Comtrade database.[16] Data availability from the intersection of these sources restricts our sample to 14 years from 2002 to 2015. We keep firms incorporated in the United States and listed on the NYSE, Amex, or NASDAQ. We further exclude firms in the financial and utilities sectors, which we define as the Global Industry Classification Standard (GICS) by MSCI sectors 40, 55, and 60. For firms included into the sample, we require all variables used in the estimation to be non-missing and at least five responses in the Q&A portion of the call. The average total assets for firms in our sample at $4.6 billion are about two times larger than the average assets of all firms in Compustat over the same period at $2.52 billion.

We consider two samples that differ in the unit of observation in each. The first sample contains 18,112 *firm-year* observations that correspond to 2,524 unique firms. The second sample contains 2,017,404 *question-answer pairs*. Table 1 provides the definitions of variables and descriptive statistics.

4.2 Non-answers

In the question-answer-level data, the *Non-answer* measure corresponds to an indicator variable that equals one if the response contains a non-answer phrase, and zero otherwise. To compute our *Non-answer* measure in the firm-year sample, we compute the non-answer rate for each conference call first, and then average these rates over a fiscal year. The

[16] We are grateful to Gerard Hoberg and Gordon Phillips for sharing their product similarity data and to David Dorn and Gordon Hanson for sharing their HS6-to-SIC crosswalk file, code, and trade data.

non-answer rate is defined relative to the total number of responses at the Q&A portion of the call. The average total number of responses per call is 34.67, with the 25th percentile at 23.2 and the 75th percentile at 44 (untabulated).

Figure 1 plots the average non-answer rate over time. The average non-answer rate is stable at 11%, with the 25th percentile at around 7% and the 75th at around 14%. These rates correspond an average of 3.68 responses that contain non-answer phrases per call, with the 25th percentile at 2 and the 75th percentile at 5. The average non-answer rates are similar across industries. Figure 2 plots the average non-answer rates for different GICS sectors. The lowest average rate is in the materials and energy sectors at 9%, and the highest is in telecommunication services and health care at 13%.

In our main analyses, we use the all-encompassing *Non-answer* variable. This measure includes refusal to provide an answer, *Refuse*, inability to provide an answer, *Unable*, and a suggestion to discuss after the call, *After-call*. Table 1, Panel A, shows *Refuse* being the most frequently used category, with a mean rate of 8.2% or 2.65 responses; followed by *Unable*, with a mean rate of 3.6% or 1.26 responses. *After-call* is used less often, with a mean rate of 0.2% or 0.05 responses. The rarity of *After-call* is not surprising given the Regulation Fair Disclosure aimed at preventing selective disclosure.

4.3 Competition

We use four measures of competition. The first measure is the Herfindahl-Hirschman Index (HHI), which is the most common measure used in research testing the proprietary cost hypothesis (Beyer et al. 2010; Cheynel and Ziv 2015). We computed HHI using sales for 3-digit SIC industries, *HHI SIC3*. The second measure, *Similarity*, comes from text-based network industry classifications (TNIC) developed in Hoberg and Phillips (2010) and Hoberg and Phillips (2016).[17] The third and forth measures, *Competition* and *SIC3-level comp.*, are competition measures similar to the ones developed by Li et al. (2013).

[17] Hoberg and Phillips share their data at http://hobergphillips.usc.edu/

The *Similarity* measure is the total product similarity score from Hoberg and Phillips (2016). This measure is developed using product descriptions from firms' annual 10-K reports. The idea is that firms with similar product offerings use similar words to describe their products, and thus the textual similarity of product descriptions is informative of the similarity of their product offerings. This measure is firm-specific and changes year by year as firms' product descriptions change. Hoberg and Phillips (2016) compute total similarity scores as the sum of the pairwise similarities between a firm and all other firms in their sample for a given year. Thus, high total similarity scores are indicative of a firm facing high levels of competition. Hoberg and Phillips (2016) show the product similarity measure explains discussions of high competition in the Management Discussion and Analysis section of the 10-Ks, and that the similarity measure also identifies firms' self-reported peers from 10-Ks.

The third and fourth measures, *Competition* and *SIC3-level comp.*, follow Li et al. (2013) and are based on counts of the number of competition-related words, such as "competition" and "competitor," excluding any cases where "not," "less," "few," or "limited" precede the competition word by three or fewer words. Li et al. (2013) count the number of these words in 10-K filings and scale this number by the total number of words in 10-Ks. Li et al. (2013) argue this measure captures management's perception of the intensity of competition. They also show the mean reversion of a firm's return on net operating assets increasing in this measure.

Similarly, we consider company representatives' utterances in conference call transcripts—both presentation and Q&A sections.[18] For each transcript, we identify utterances that contain competition-related words as defined in Li et al. (2013), and scale the number of these utterances by the total number of utterances. For the firm-year sample, we average call-specific measures for the year, *Competition*. We further compute an industry-specific measure for 3-digit SIC codes by taking the average over firm-specific measures, *SIC3-level*

[18]Utterances are defined as responses during the Q&A portion or spells of uninterrupted speech during the presentation portion of the call.

comp.

Prior research suggests managers obfuscate poor performance (Li 2008) and attribute poor performance to the effects of competition (Li et al. 2013). If attempts to obfuscate poor performance extend to avoiding providing answers to questions, self-reported competition and a higher rate of non-answers will be associated even absent a causal relation. For this reason, we compute an industry level variant of the Li et al. (2013) measure, *SIC3-level comp.*, and exclude the firm itself from this calculation. While this variant of the measure is less subject to issues of confounding, we expect it less precisely measures the competitive environment of the firm, which likely varies within industries.

4.4 Capital markets

We capture the relative importance of capital markets using four variables. The first is the ratio of debt due within one year to cash holdings. The higher this ratio is, the greater the pressure to repay or refinance the debt. The second is equity issuance, defined as the ratio of common and preferred stock sold to the lagged market capitalization when a firm issues equity.[19] Equity issuance events are identified from Capital IQ using event types "Follow-on Equity Offerings" or "IPOs." The third is debt issuance, defined as the ratio of long-term debt issuance to the lagged market capitalization when a firm issues debt. Debt issuance events are identified from Capital IQ using event types "Fixed Income Offerings." Finally, the fourth is private placements, defined as the sum of common and preferred stock sold and long-term debt divided by lagged market capitalization at the time of private placement. Private placement events are identified from Capital IQ using event types "Private Placements."

[19]The value of common and preferred stock sold from Compustat combines equity issuance and stock option exercises together. For this reason, we use these values only when Capital IQ identifies equity offering events.

5. Results

We estimate linear regressions of the non-answer measure on competition and product-related questions to test predictions for voluntary disclosure and competition; capital issuance and future-performance-related questions to test predictions for capital market incentives. Both firm-year and question-answer-level samples include repeated observations on firms over time. Accordingly, we compute two-way clustered standard errors by firm and year for all regressions. All independent continuous variables are standardized to zero mean and unit standard deviation. As a result, these variables are measured in the standard deviation units and coefficients are comparable across variables.

For the firm-year sample, we also estimate specifications that include control variables listed in Table 2. These control variables come from extant voluntary disclosure research. Disclosure theory (Verrecchia 1983) predicts that higher-type firms, that is, those with better future performance, will be more likely to disclose. Accordingly, we include *Future profitability* as a proxy for future performance. Company size, *Log Total assets*, and capital structure, *Leverage*, can both influence the extent of competitive pressures or capital market incentives and the availability of information about the firm (e.g., Lang and Lundholm 1993). To control for firm performance, we include *Return on assets* and stock return, *Return, 12-month* (e.g., Miller 2002). To control for uncertainty and litigation risk, we include *Market-to-book* and stock return volatility *Volatility, 12-month* (e.g., Field, Lowry, and Shu 2005). To control for CEO equity incentives, which may also drive disclosure choice, we include *Equity compensation* and *Log Value of shares held* (Nagar, Nanda, and Wysocki 2003). We include year fixed effects in *firm-year* specifications to control for any unobserved time-varying effects that affect economy-wide disclosure choices.

5.1 Non-answers and competition

In this section, we first examine the hypothesis that greater competition will be associated with an increased rate of non-answers. We then examine whether product-related questions are associated with a higher rate of non-answers and whether this effect is greater when competition is greater. Finally, we exploit a source of plausibly exogenous variation in import competition from China to the U.S. to provide evidence of a causal relation between competition and disclosure choice.

5.1.1. Firm-year analyses

Table 2 reports estimates of the regressions of non-answer rates on competition measures in the firm-year sample. A statistically significant positive association exists between non-answer rates and competition. A one-standard-deviation decrease in *HHI SIC3* or an increase in competition is associated with a 0.320–0.388 percentage-point increase in non-answer rates. Similarly, a one-standard-deviation increase in *Log Similarity*, *Competition*, and *SIC3-level comp.* is associated with 0.405–0.591, 0.929–1.001 and 0.359–0.380 percentage-point increases in non-answer rates, respectively. These results are consistent with the plots in Figure 3.

Among all of the control variables, size as measured by *Log Total assets* and growth as measured by *Market-to-book* exhibit the strongest association with non-answer rates. A one-standard-deviation increase in *Log Total assets* (*Market-to-book*) is associated with an increase of about 0.795–0.921 (0.618–0.713) percentage points in non-answer rates. The effect of competition for various measures is from 35% to 137% of these effects.[20] By contrast, using the call-level measure of disclosure, Hollander et al. (2010) does not find evidence in support of the proprietary cost hypothesis using HHI.[21]

[20]The lowest relative effect is from Table 2, column (2), that is, the absolute effect of *HHI SIC3* at 0.320 to the absolute effect of *Log Total assets* at 0.906. The highest relative effect is from Table 2, column (6), that is, the absolute effect of *Competition* at 0.929 to the absolute effect of *Market-to-book* at 0.676.

[21]See discussion in footnote 9 in Hollander et al. (2010).

A key prediction of Verrecchia (1983) is that firms that anticipate better future performance will be more willing to disclose information. Consistent with this prediction, we find that a one-standard-deviation increase in *Future profitability* is associated with a 0.215–0.393 percentage-point decrease in non-answer rates, controlling for recent financial and stock-market performance.

We also find that non-answer rates are higher when uncertainty, as measured by volatility of stock returns, is higher: A one-standard-deviation increase in *Volatility, 12-month* is associated with a 0.268–0.331 percentage-point increase in non-answer rates. However, in contrast to Hollander et al. (2010), we find no association between CEO equity compensation and non-answer rates.

5.1.2. Product-related questions, non-answers, and competition

Table 3 reports estimates of the linear probability models of an indicator variable for non-answer on product-related questions, *Product-related*, and the interaction terms of product-related questions and competition measures. In these analyses, we include *call* fixed effects, which provides a *within-call* analysis that controls for firm- and date-specific characteristics.

Product-related questions are more likely to remain unanswered. The probability of non-answer increases by about 6.5 percentage points at the mean levels of competition variables. The effect of product-related questions is amplified by competition by from 0.213 percentage points for *HHI SIC3* to 0.538 for *Competition*. This amplification corresponds to between 3% and 8% of the main effects.

In both Tables 2 and 3, the coefficient on firm-specific measure of competition, *Competition*, is larger than the coefficient on the industry-level measure, *SIC3-level comp*. This is consistent with the firm-level variable better capturing the level of competition applicable to the firm making the disclosure choice than the industry-level measure.

5.1.3. Non-answers and competition: An instrumental variable approach

Although a source of exogenous variation in the level of overall competition is difficult to find, we draw on recent research in economics and finance that uses imports from China by non-U.S. countries to study the effect of import competition in the U.S. (e.g. Autor et al. 2013, 2014; Hombert and Matray 2018). For instance, Autor et al. (2014) capture the supply-driven component of U.S. imports from China by using imports from China to high-income non-U.S. countries. The idea is that high-income non-U.S. economies are similarly exposed to growth in imports from China that is driven by supply shocks such as diminishing trade and tariff costs, falling prices, and rising quality. Following these papers, we use growth in imports to the eight high-income countries as an instrument for growth in imports to the U.S., which is assumed to increase competition for domestic manufacturers.

Data on international trade come from the UN Comtrade database, which gives bilateral imports for 6-digit harmonized system (HS) product codes, which are then matched to 3-digit SIC codes using data from Autor et al. (2013).[22]

Our measures of exposure to competition are defined using growth rates imports from China computed relative to average values, which have a theoretical range from −2 to 2. We compute three-year growth rates for imports from China for both the U.S. and for eight high-income non-U.S. countries as used in Autor et al. (2013), namely, Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland ("non-U.S.").

Figure 4 plots manufacturing imports from China to the U.S. and non-U.S. in trillions of 2000 dollars. Total imports track each other well until 2012, at which point imports to the U.S. continue to grow while imports to the non-U.S. stagnate. Figure 5 plots standardized import growth rates to the U.S. against standardized import growth rates to non-U.S. for 3-digit SIC manufacturing industries. A positive relation exists between growth in imports

[22] We are grateful to David Dorn and Gordon Hanson for sharing their crosswalk file and trade data for earlier years. For this paper, we have done a clean download of UN Comtrade data from 1998 to 2017 from https://comtrade.un.org/data/. We downloaded the crosswalk file from https://www.ddorn.net/data.htm. Because the original HS product codes come in several versions, we concord them to the HS codes used in the crosswalk file before applying the crosswalk file.

to the U.S. and non-U.S. Accordingly, we use the three-year growth in imports from China to non-U.S., *3-year SIC3 import growth non-US*$_{t-1}$, as an instrument for the three-year growth in imports from China to the U.S., *3-year SIC3 import growth US*$_{t-1}$. We use the three-year growth rates to capture long-term trends in import competition. We also lag import growth variables to allow firms to learn the extent of competitive effects of imports from China.

An instrument should satisfy two requirements. The first is relevance, which requires that the partial correlation between the instrument and an endogenous variable be sufficiently large. Second is the exclusion restriction, which requires that the instrument affect the outcome only through its effect on the endogenous treatment of interest. Whereas relevance can be tested using a partial F-test with the weak-instrument F-test thresholds specified in Stock, Wright, and Yogo (2002), one can only theorize about the exclusion restriction, and here we draw on prior research (e.g. Autor et al. 2013, 2014; Hombert and Matray 2018).[23]

Results of the instrumental-variables analyses are presented in Table 4. The first-stage partial F-tests are well above the threshold values for weak instruments from Stock et al. (2002), and hence the instrument is relevant. In the second stage, the positive association between instrumented lagged import growth to the U.S. is statistically significant. These results suggest a causal relation between competition and disclosure.

5.2 Non-answers and capital markets

Section 2.2 discussed empirical research on capital market activity and voluntary disclosure that finds a positive association between future capital issuance and disclosure.[24] We follow this literature and examine the association between capital issuance and non-answers. We also take advantage of the question-answer-level nature of our measure and

[23]Note this prior research speaks to the validity of the instrument with respect to imports from China to the U.S. In general, an instrument is valid with respect to only one treatment, because the rigors of the exclusion restriction make it unlikely to hold for other treatment variables. For this reason, we do not use this variable as an instrument for the competition measures we studied above.

[24]See, for example, Lang and Lundholm (1993), Frankel et al. (1995), and Healy et al. (1999).

examine future-performance-related questions. Although forward-looking disclosures are protected by the Safe Harbor provisions of the 1995 Private Securities Litigation Reform Act, uncertainty still exists regarding the effectiveness of this protection, because plaintiff attorneys frequently attempt to argue for why these provisions do not apply (Rogers and Van Buskirk 2009). Accordingly, future-performance-related questions should be more likely to remain unanswered with the likelihood of non-answers increasing shortly before equity or debt offerings when the litigation risk is higher (Healy and Palepu 2001). Finally, we exploit a plausibly exogenous increase in the relative importance of capital markets around the bankruptcy of Lehman Brothers in September 2008 to provide evidence on the causal relation between capital market incentives and disclosure choice.

5.2.1. Firm-year analyses

Table 5 reports estimates of the regressions of non-answer rates on the variables capturing the relative importance of capital markets in the firm-year sample. We find a negative association between non-answer rates and debt due within one year. A one-standard-deviation increase in *Debt due in 1-year-to-cash* is associated with a 0.107–0.180 percentage-point decrease in non-answer rates. Therefore, firms are more likely to answer questions when they have to repay or refinance large amounts of debt.

For capital issuance, we include both capital issuance *after* the call, that is, $\textit{Equity offering}_{t+1}$, $\textit{Debt offering}_{t+1}$, and $\textit{Private placement}_{t+1}$, and *before* the call, that is, *Equity offering*, *Debt offering*, and *Private placement*. Capital markets are expected to be relatively more important shortly before capital is issued (Verrecchia and Weber 2006), suggesting we should see fewer non-answers prior to capital issuance. Indeed, for all types of capital issuance, the association with future capital issuance (but not with recent capital issuance) is negative. A one-standard-deviation increase in $\textit{Equity offering}_{t+1}$ is associated with a 0.172– 0.189 percentage-point decrease in non-answer rates. Similarly, a one-standard-deviation increase in $\textit{Debt offering}_{t+1}$ and $\textit{Private placement}_{t+1}$ is associated with a 0.057–0.094

and 0.149–0.167 percentage-point decrease in non-answer rates, respectively. Lower effects for *Debt offering*$_{t+1}$ than for *Equity offering*$_{t+1}$ are consistent with equity being more sensitive to asymmetric information than debt (Myers and Majluf 1984), and thus the reduction in non-answers is greater for equity offerings.

The negative effects for *Private placement*$_{t+1}$, which can include both debt and equity, are consistent with Verrecchia and Weber (2006). They also find firms are less likely to redact information from material contracts when they issue long-term debt even when the debt is private.[25]

Similar to Table 2, *Log Total assets* and *Market-to-book* exhibit the strongest association with non-answer rates. A one-standard-deviation increase in size is associated with a percentage-point increase of about 0.892–0.910 in non-answer rates, and 0.698–0.717 in growth. The effect of capital market activity for various measures is from 10% to 26% of these effects.[26]

5.2.2. Future-performance-related questions, non-answers, and capital issuance

Table 6 reports estimates of the linear probability models of an indicator variable for non-answer on future-performance-related questions, *Future perf.-related*, and the interaction terms of future performance-related questions and capital issuance variables. As with product-related questions, in these analyses, we include *call* fixed effects, which provides a *within-call* analysis that controls for firm- and date-specific characteristics. While the amount of equity or debt issuance proxies for the importance of the offering in Table 5, the occurrence of the offering itself increases firms' exposure to the litigation risk. For this reason, in Table 6, for equity, debt offerings, and private placements, we include an indicator variable for the offering rather than the amount of the offering.

Future-performance-related questions are more likely to remain unanswered. The

[25]See discussion in Section 6.3 in Verrecchia and Weber (2006).

[26]The lowest relative effect is from Table 5, column (6), that is, the absolute effect of *Debt offering*$_{t+1}$ at 0.094 to the absolute effect of *Log Total assets* at 0.910. The highest relative effect is from Table 5, column (4), that is, the absolute effect of *Equity offering*$_{t+1}$ at 0.189 to the absolute effect of *Market-to-book* at 0.717.

probability of a non-answer increases by about 6 percentage points at the mean levels of capital issuance variables. When a significant amount of debt becomes due, firms are more willing to answer future-performance-related questions. The need to repay or refinance their debt reduces the likelihood of a non-answer by 0.24 percentage points, which corresponds to 4% of the main effect.

By contrast, the effect of future-performance-related questions is amplified shortly before equity or debt offerings by one percentage point, but not shortly after. This amplification corresponds to 15% of the main effect. Although Table 5 shows disclosure is more forthcoming shortly before equity or debt offerings, it is less forthcoming about future-performance-related questions.

5.2.3. Credit crisis, probability of failure, and non-answers

We exploit plausibly exogenous variation in the relative importance of capital markets around the bankruptcy of Lehman Brothers in September 2008 and the deepening of the financial crisis soon after that event, which saw bond spreads increase to close to 7% for investment-grade bonds and above 15% for high-yield bonds (Almeida et al. 2011). This drastic increase in financing costs likely increased the relative importance of capital markets, especially for financially distressed firms. We consider the change in non-answer rates based on the conference calls in the six-month period after September 30, 2008, and the six-month period before.

We measure financial distress by the probability of failure as of September 30, 2008, similar to Campbell et al. (2008). The probability of failure is estimated *out of sample* using rolling-window regressions and failure data starting from January 1973 as described in Ogneva, Piotroski, and Zakolyukina (2018). We also consider two placebo periods centered around September 30, 2007, and September 30, 2009. For these periods, we estimate the probability of failure as of September 30, 2007, and September 30, 2009, respectively.

Table 7 reports the results for September 2008 and two placebo periods. The non-answer rate is higher in the post-Lehman-bankruptcy period. We also find more distressed firms reduce their non-answers to a greater extent than less distressed firms after Lehman's bankruptcy. This decrease is larger for extremely distressed firms. These effects are only present for September 2008 and do not exist for the calls surrounding September 2007 or 2009.

6. Extensions

Our main analyses use the all-encompassing category of non-answers that includes refusals to provide information, inability to provide information, and requests to discuss the matter after the call. Although the argument can be made for the inability to provide information being a non-disclosure choice, refusals to provide information are more directly related to non-disclosure. Accordingly, we replicate all our main analyses replacing the all-encompassing *Non-answers* with *Refusals to answer* in Tables 8–12.

Tables 8, 9, and 10 replicate the analyses for competition. These tables are virtually identical to the main analyses. A robust positive association exists between competition and *Refusals to answer*. In contrast to Table 2, in Table 8, *Equity compensation*, that is, the proportion of equity compensation in the total compensation of CEOs, is positively associated with *Refusals to answer* and *Log Value of shares held*, that is, CEOs' equity holdings, is negatively associated with *Refusals to answer*. A one-standard-deviation increase in *Equity compensation* and *Log Value of shares held* is associated with a percentage-point increase of about 0.178–0.205 and a decrease of about 0.089–0.105 in *Refusals to answer* rates, respectively. By contrast, Hollander et al. (2010) reports a negative association for both the proportion of equity compensation in the total compensation and equity holdings. For product-related questions, the estimate of the main effect goes down from 6.5 percentage points for *Non-answer* to 4.9 for *Refusals to answer*. Similar to the main results, competition amplifies the likelihood of a refusal to provide information. The results for the import competition from China in Table 10 are also virtually identical for *Refusals to answer*.

Tables 11 and 12 replicate the analyses for capital market activity. Again, these results are virtually identical for both firm-year and question-answer-level analyses. A robust negative association exists between capital issuance shortly after the call and *Refusals to answer*. Similar to product-related questions, the estimate of the main effect goes down from 6 percentage points for *Non-answer* to 5.3 for *Refusal* for future-performance-related questions. The findings for the interaction terms remain the same. Firms are more willing to answer future-performance-related questions if they have a substantial amount of debt maturing. However, they refuse to answer these questions shortly before equity or debt offerings. Finally, the results for the post-Lehman-bankruptcy period and the probability of failure become insignificant (untabulated).

7. Conclusion

We introduce a novel text-based measure of managers' unwillingness to answer questions during conference calls. This measure of disclosure captures explicit refusals or claimed inability to provide information in response to analysts' questions. We complement our measure of non-answers, which is computed using the text of managerial responses to analysts' questions, by constructing measures based on features of the questions asked. As a measure of the proprietary nature of questions, we use the Stanford NER classifier to flag plausibly product-related questions. And as a measure of the importance of questions to forming expectations of future performance by capital market participants, we tag questions that match forward-looking statements from Bozanic et al. (2018) and finance terms from Matsumoto et al. (2011).

Using the popular Herfindahl-Hirschman concentration index and text-based measures of competition from Hoberg and Phillips (2016) and Li et al. (2013), we find competition is robustly associated with executives' propensity not to answer questions during earnings conference calls. This association is amplified for product-related questions. Consistent with a causal interpretation of the association between competition and disclosure choice, we find exogenous shocks to import competition from China are associated with decreased disclosure by firms.

We also find capital market incentives are robustly associated with non-answers during conference calls. We find firms are more willing to answer questions when capital market incentives are stronger due to anticipated capital issuance, whether proxied by the amount of debt due or by actual equity or debt issuance in subsequent periods. However, we find the tendency to be forthcoming prior to capital issuance is limited. Specifically, we find firms are less willing to answer questions that are plausibly related to future performance shortly before capital issuance, consistent with concerns about legal liability under the Securities Act of 1933. We also find financially distressed firms increase their responsiveness to questions in the wake of the bankruptcy of Lehman Brothers in 2008.

Although this paper illustrates how our measure can be applied to address long-standing questions in disclosure research, we believe future research will be able to exploit features of the measure and its conference-call setting that are not explored in this paper. For example, whereas we examine whether questions relate to products and future performance to test hypotheses related to competition, capital markets, and disclosure, seemingly innumerable features of questions can be explored, such as the topic of the question, who is asking it (e.g., a favored analyst), and whether the question seems to seek quantitative or qualitative information.

References

Ali, Ashiq, Sandy Klasa, and Eric Yeung, 2009, The limitations of industry concentration measures constructed with Compustat data: Implications for finance research, *Review of Financial Studies* 22, 3839–3871.

Ali, Ashiq, Sandy Klasa, and Eric Yeung, 2014, Industry concentration and corporate disclosure policy, *Journal of Accounting and Economics* 58, 240–264.

Almeida, Heitor, Murillo Campello, Bruno Laranjeira, and Scott Weisbenner, 2011, Corporate debt maturity and the real effects of the 2007 credit crisis, *Critical Finance Review* 1, 3–58.

Autor, David H., David Dorn, and Gordon H. Hanson, 2013, The China syndrome: Local labor market effects of import competition in the United States, *American Economic Review* 103, 2121–2168.

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song, 2014, Trade adjustment: Worker-level evidence, *Quarterly Journal of Economics* 129, 1799–1860.

Bamber, L. Smith, and Youngsoon Susan Cheon, 1998, Discretionary management earnings forecast disclosures: Antecedents and outcomes associated with forecast venue and forecast specificity choices, *Journal of Accounting Research* 36, 167–190.

Berger, Philip G., 2011, Challenges and opportunities in disclosure research: A discussion of 'The financial reporting environment: Review of the recent literature', *Journal of Accounting and Economics* 51, 204–218.

Berger, Philip G., and Rebecca N. Hann, 2007, Segment profitability and the proprietary and agency costs of disclosure, *The Accounting Review* 82, 869–906.

Beyer, Anne, Daniel A. Cohen, Thomas Z. Lys, and Beverly R. Walther, 2010, The financial reporting environment: Review of the recent literature, *Journal of Accounting and Economics* 50, 296–343.

Bozanic, Zahn, Darren T. Roulstone, and Andrew Van Buskirk, 2018, Management earnings forecasts and other forward-looking statements, *Journal of Accounting and Economics* 65, 1–20.

Bushee, Brian J., Dawn A. Matsumoto, and Gregory S. Miller, 2004, Managerial and investor responses to disclosure regulation: The case of Reg FD and conference calls, *The Accounting Review* 79, 617–643.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Cheynel, Edwige, and Amir Ziv, 2015, On market concentration and disclosure, Working paper, Columbia Business School.

Cohen, Lauren, Dong Lou, and Christopher Malloy, 2017, Playing favorites: How firms prevent the revelation of bad news, *CEPR Discussion Paper No. DP12302* .

Core, John E., 2001, A review of the empirical disclosure literature: Discussion, *Journal of Accounting and Economics* 31, 441–456.

Dhaliwal, Dan, Shawn Huang, Inder K. Khurana, and Raynolde Pereira, 2014, Product market competition and conditional conservatism, *Review of Accounting Studies* 19, 1309–1345.

Field, Laura, Michelle Lowry, and Susan Shu, 2005, Does disclosure deter or trigger litigation?, *Journal of Accounting and Economics* 39, 487–507.

Finkel, Jenny Rose, Trond Grenager, and Christopher Manning, 2005, Incorporating non-local information into information extraction systems by Gibbs sampling, in *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics*, 363–370, Association for Computational Linguistics.

Frankel, Richard, Marilyn Johnson, and Douglas J. Skinner, 1999, An empirical examination of conference calls as a voluntary disclosure medium, *Journal of Accounting Research* 37, 133–150.

Frankel, Richard, Maureen McNichols, and G. Peter Wilson, 1995, Discretionary disclosure and external financing, *The Accounting Review* 70, 135–150.

Healy, Paul M., Amy P. Hutton, and Krishna G. Palepu, 1999, Stock performance and intermediation changes surrounding sustained increases in disclosure, *Contemporary Accounting Research* 16, 485–520.

Healy, Paul M., and Krishna G. Palepu, 2001, Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature, *Journal of Accounting and Economics* 31, 405–440.

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Hollander, Stephan, Maarten Pronk, and Erik Roelofsen, 2010, Does silence speak? An empirical analysis of disclosure choices during conference calls, *Journal of Accounting Research* 48, 531–563.

Hombert, Johan, and Adrien Matray, 2018, Can innovation help US manufacturing firms escape import competition from China?, *Journal of Finance* 73, 2003–2039.

Lang, Mark, and Russell Lundholm, 1993, Cross-sectional determinants of analyst ratings of corporate disclosures, *Journal of Accounting Research* 31, 246–271.

Lang, Mark, and Edward Sul, 2014, Linking industry concentration to proprietary costs and disclosure: Challenges and opportunities, *Journal of Accounting and Economics* 58, 265–274.

Lang, Mark H, and Russell J Lundholm, 2000, Voluntary disclosure and equity offerings: Reducing information asymmetry or hyping the stock?, *Contemporary Accounting Research* 17, 623–662.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and Economics* 45, 221–247.

Li, Feng, Russell Lundholm, and Michael Minnis, 2013, A measure of competition based on 10-K filings, *Journal of Accounting Research* 51, 399–436.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance* 66, 35–65.

Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen, 2011, What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions, *The Accounting Review* 86, 1383–1414.

Mayew, William J., 2008, Evidence of management discrimination among analysts during earnings conference calls, *Journal of Accounting Research* 46, 627–659.

Miller, Gregory S., 2002, Earnings performance and discretionary disclosure, *Journal of Accounting Research* 40, 173–204.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.

Nagar, Venky, Dhananjay Nanda, and Peter Wysocki, 2003, Discretionary disclosure and stock-based incentives, *Journal of Accounting and Economics* 34, 283–309.

Ogneva, Maria, Joseph D. Piotroski, and Anastasia A. Zakolyukina, 2018, Accounting fundamentals and systematic risk: Corporate failure over the business cycle, Working Paper, University of Chicago.

Rogers, Jonathan L., and Andrew Van Buskirk, 2009, Shareholder litigation and changes in disclosure behavior, *Journal of Accounting and Economics* 47, 136–156.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo, 2002, A survey of weak instruments and weak identification in generalized method of moments, *Journal of Business & Economic Statistics* 20, 518–529.

Verrecchia, Robert E., 1983, Discretionary disclosure, *Journal of Accounting and Economics* 5, 179–194.

Verrecchia, Robert E., and Joseph Weber, 2006, Redacted disclosure, *Journal of Accounting Research* 44, 791–814.

A. Non-answer phrases

A.1 Measurement details

As discussed in Section 3.1, we identify responses containing non-answers, using the set of regular expressions. The regular expressions and the dictionaries used in these regular expressions are defined in Tables A.1 and A.2.

A.2 Examples

In the conference-call responses presented below, we highlight in **bold** the phrases identified as non-answers for *Refuse*, *Unable*, and *After-call* categories.

A.2.1. Refuse to provide information

Q2 2012 Corning Earnings Conference Call by Corning, Inc.: [...] A small one and supply directly rather than ship in from Korea. But I am **not at liberty to give you much more details** than that. [...]

Q2 2013 DreamWorks Animation SKG, Inc. Earnings Conference Call by DreamWorks Animation LLC: I think the important thing to look at in terms of just our whole CP enterprise, is we are laying the foundation right now today, really are **not at a point where we can give you enough hard numbers**, I think, to have you model this out, because it's just – it's too soon. [...]

Q4 2010 TranSwitch Earnings Conference Call by TranSwitch Corp.: [...] We anticipate there will be derivative products from the platform that we'll announce in second quarter.I ca**n't say more** about that. [...]

Q1 2013 Sigma Designs Earnings Conference Call by Sigma Designs, Inc.: All we can say at this time is we are hopeful we can avoid an expensive and disruptive proxy contest, but we **cannot comment** any further at this time.

Q1 2014 Restoration Hardware Holdings Inc Earnings Conference Call by RH: We believe that's competitive information that we're **not going to disclose**.

A.2.2. Unable to provide information

Q1 2004 Integrated Silicon Solution, Inc. Earnings Conference Call by Integrated Silicon Solution, Inc.: **I don't have it** in the room. So – 31.9 at the end of the current quarter. But there will be some averaging up from that.[...]

Q2 2015 Gentherm Inc Earnings Call by Gentherm, Inc.: **I do not know** how much it increases the cost of the car to the consumer.[...]

Q3 2011 Gulfmark Offshore Inc Earnings Conference Call by GulfMark Offshore, Inc.: [...] Obviously, the spot market is always something that's **difficult to predict**. [...] **We don't know** how much additional tonnage will be taken out to cover seasonal backup for some of the larger players.[...]

Q2 2014 Chevron Corp Earnings Call by Chevron Corp.: [...] **We don't always know** exactly what asset sales will actually occur. [...] But I ca**n't give you the details** on those because we are very value driven. We are going to make the best decision on getting the greatest value for anything we sell.

Q2 2009 Greif Brothers Earnings Conference Call by Greif, Inc.: **We don't have the** data at our fingertips nor do we I think know sitting here right now if the order size decrease. [...]

A.2.3. Offer to discuss after the call

Q3 2010 Fisher Communications, Inc. Financial Results Conference Call by Sinclair Broadcast Group, Inc. [...] And the other–the percentage you're talking about today that's on our financials, it's kind of apples and oranges because it includes some things that I didn't envision when I made the digital comment two years ago. And I can take this **offline** and have that conversation with you, Bishop.

Q1 2015 Rexnord Corp Earnings Call by Rexnord Corp.: It is not a tailwind. It is a little bit account-ese that I think Mark and Rob can take you through **off-line**.[...]

Q3 2009 Media General Earnings Conference Call by Media General, Inc.: Yes, we could do that. I think maybe that is a better handle on a call **after the call**, and we can give you a primer on how that works. [...]

Q2 2006 Exxon Mobil Corporation Earnings Conference Call by Exxon Mobil Corp.: [...] We may want to take that **off-line**. **I don't really have it.** It's currently running about 200,000 barrels a day but **I don't know** what the actual delta was for the quarter.

Q2 2014 Steel Dynamics Inc Earnings Call by Steel Dynamics, Inc.: No, Sal, we can go **offline** with this if you'd like. The number that you're looking at for Minnesota is actually net of tax. It's not pretax and it's not the operating level, so the number that you're looking at for metals recycling and for the whole segment is operating and the number we gave you for Minnesota is net, so there's a bridge to do and I'm happy to do that with you **offline.**

Table A.1:
Regular expressions used to identify non-answers

```
# Refuse non-answers
TYPE=REFUSE

# {Disclosure Verb}..."no"...{Disclosure Noun}
(?i)\b{DISC_VERB_NOUN}\b\s?({WORD_CHAR}+\s){0,2}no\b\s?({WORD_CHAR}+\s){0,2}{DISC_NOUN}\b

# {Disclosure Verb}..."no"
(?i)\b{DISC_VERB_NO_NOUN}\b\s?({WORD_CHAR}+\s){0,2}no\b

# {Negation}...{Disclosure Verb}
(?i)(n('|‘)t|\bnot|cannot|without)\b\s?({WORD_CHAR}+\s){0,8}{DISC_VERB_NO_NOUN}\b

# {Negation}...{Disclosure Verb}...{Disclosure Noun}
(?i)(n('|‘)t|\bnot|cannot|without)\b\s?({WORD_CHAR}+\s){0,8}{DISC_VERB_NOUN}\b\s?({WORD_CHAR}+\s){0,8}{DISC_NOUN}\b

# {Deferral}...{Disclosure Verb}
(?i)\b{DEFERRAL}\b\s?({WORD_CHAR}+\s){0,8}{DISC_VERB_NO_NOUN}\b
(?i)\b{DEFERRAL}\b\s?({WORD_CHAR}+\s){0,8}{DISC_VERB_NOUN}\b\s?({WORD_CHAR}+\s){0,8}{DISC_NOUN}\b

# Unable non-answers
TYPE=UNABLE
(?i)\b(I|we)\b\s?({WORD_CHAR}+\s){0,2}((do(n('|‘)t| not))|(can('t|not| not)))\b\s?({WORD_CHAR}+\s){0,2}(know|recall|remember)\b
(?i)\b(I|we) have no idea\b
(?i)\b(I|we) do(n('|‘)t| not)\b\s?({WORD_CHAR}+\s){0,2}(have (the|it|that|this|those))\b
(?i)(n('|‘)t|\bnot|cannot|without)\b\s?({WORD_CHAR}+\s){0,8}(share|sharing|shared)\b\s?({WORD_CHAR}+\s){0,8}(with)\b

# After-call non-answers
TYPE=AFTERCALL
(?i)\b(off-line|offline|after the call|after call|another (time|day))\b
```

Table A.2:
Dictionaries for the regular expressions

```
{DISC_VERB_NO_NOUN}:
(be\b\s?([\w',&@#$%_\-\(\)\[\]]+\s){0,1}specific|announce|announced|announcing|answer|answered|answering|breakdown|breakout|
break out|breaking out|broken out|break that out|break it out|break those out|breaking that out|breaking it out|
breaking those out|broken that out|broken it out|broken those out|comment|commented|commenting|disclose|disclosed|
disclosing|discuss|discussed|discussing|divulge|divulged|divulging|elaborate|elaborated|elaborating|estimate|estimated|
estimating|forecast|forecasted|forecasting|guide|guided|guiding|predict|predicted|predicting|report|reported|reporting|
reveal|revealed|revealing|speculate|speculated|speculating|say about|say anything|say more|say any more|say much more|
say too much|said about|said anything|said more|said any more|said much more|said too much|talk about|talked about)

{DISC_VERB_NOUN}:
(address|addressed|addressing|explain|explanation|get into|get|getting|give|given|giving|go into|going into|got into|
gotten into|mention|mentioned|mentioning|on record|present|presented|presenting|provide|provided|providing|quantified|
quantify|quantifying|release|released|releasing|speak|speaking|specified|specify|specifying|spoke|supplied|supply|supplying|
talk|talked|talking|tell|told|update|updated|updating)

{DEFERRAL}:
(difficult|impossible|infeasible|hard|decline|refuse|refrain|unable|never|all I can|all we can|all I will|all we will|about all)

{DISC_NOUN}:
(too much|much more|account|accounts|acquisition|acquisitions|activity|activities|amount|amounts|analysis|answer|
answers|anything|asset|assets|backlog|backlogs|balance|balances|breakdown|budget|budgets|capital|cash|change|changes|
comparison|comparisons|component|components|condition|conditions|content|contract|contracts|cost|costs|coverage|
credit|data|deal|deals|debt|demand|demands|detail|details|development|developments|direction|directions|distribution|
dollar|dollars|earnings|equity|equities|estimate|estimates|expansion|expansions|expectation|expectations|expense|expenses|
exposure|fact|facts|factor|factors|fee|fees|figure|figures|financing|forecast|forecasts|funding|growth|guidance|income|
incomes|information|interest|inventory|inventories|investment|investments|liquidity|loan|loans|loss|losses|magnitude|
magnitudes|management|margin|margins|marketing|metric|metrics|model|models|money|name|names|needs|news|number|numbers|
operations|option|options|order|orders|partner|partners|percent|percentage|percentages|performance|plan|plans|point|points|
policy|policies|portfolio|portfolios|price|prices|pricing|profit|profits|profitability|progress|project|projects|projection|
projections|quality|quantification|quantity|quantities|range|ranges|rate|rates|ratio|ratios|reason|reasons|reserve|reserves|
result|results|revenue|revenues|risk|risks|sale|sales|savings|share|shares|size|sizes|specific|specifics|specifically|spending|
statement|statements|statistic|statistics|strategy|supplier|suppliers|supply|supplies|target|targets|tax|taxes|term|terms|
transaction|transactions|trend|trends|value|values|volume|volumes)
```

B. Product-related questions

B.1 Measurement details

As discussed in Section 3.2, we identify questions with higher proprietary costs using the "Organization" tag from Stanford NER classification algorithm. When we compare "Organization" tags with manually identified product names from a random sample of 830 questions, the *out-of-sample* accuracy of the NER tag is 78.67%. For this reason, we label questions which NER has flagged with an "Organization" tag as product-related questions. Not all of these questions are product related: "Organization" tags can capture the names of business divisions, customers, or suppliers. But these questions often are proprietary in nature too.

We exclude common words used in the business context, such as finance terms or the names of regulators. Table B.1 provides the list of these words. We create this list by extracting the words with the total count above 0.10% of words tagged as "Organizations," that is, above 630 occurrences. We next read this list of words to confirm if they are finance terms or the names of regulators. We further perform a context search in a random set of questions to confirm these words are indeed used as finance terms or names of regulators. Overall, we find the frequency of the identified terms is less than 1% of all words identified as "Organizations." Nevertheless, we exclude them.

B.2 Examples

In the conference-call questions presented below, we highlight in **bold** the words identified by the NER "Organization" tag. These named entities can contain other names besides names of products, such as competitor names or names of business divisions.

Q2 2010 Stanley Black & Decker, Inc. Earnings Conference Call by Stanley Black & Decker, Inc.: Good morning. Two questions. The margin performance in the tools business and the industrial business I guess is the first thing I love to get more color on, to get to historic peak margins in the second quarter of 2010 and the legacy **Stanley** and legacy **Black & Decker** when the revenues are still 25% off the peak and the cost saves from the combination are still relatively limited.[...]

Q4 2009 Ashland Earnings Conference Call by Ashland, Inc.: [...] When you announce your price increases for **Valvoline** to offset the increase in base oil price, are you – is your magnitude of price increase basically designed to offset what's already been announced or are you trying to anticipate where base oil prices are going to go over the next quarter? I'm just interested in the pricing mechanism.

Q4 2015 Woodward Inc Earnings Call by Woodward, Inc.: Okay. And then just on aerospace, you know, as the NEO cuts in, should we and we start to see **Airbus** transition to more production of the NEO, I mean should we be thinking about a different kind of ramp in the aerospace segment, just as the cadence of NEOs versus the current engine ramps up?

Q4 2003 LTX Corporation Earnings Conference Call by Xcerra Corp.: Hi, this is actually Dan for Tim Arcuri. Couple of questions. You talked about **HFi** shipments increasing. Can you give us an idea of what the ratio is of **HFi** to **HF** shipments currently and maybe give us an idea of how the **HF** are going to tail off over the next couple of quarters?

Q3 2004 MRV Communications Earnings Conference Call by MRV Communications, Inc.: Speaking of GPON and **EPON**, would that make any difference to you as far as on your opportunities concerned? I guess internationally or Japan is looking at more of a GPON versus – the domestic guys are more of an **EPON**. Does that make any difference as far as your dollar content is concerned?

Q2 2005 Intel Corporation Earnings Conference Call by Intel Corp.: Okay. Thanks. And just a housekeeping question. The revenues from Xbox, is that recognized in the all other section, or is that part of **Digital Enterprise**, where do you put that?","

Q3 2012 ConocoPhillips Earnings Conference Call by ConocoPhillips: And then a more specific question, just coming in on the **Eagle Ford**. Obviously, you've got some good production performance there.[...]

Q4 2012 ITT Corporation Earnings and 2013 Outlook Conference Call by ITT Corp.: Just lastly, I know you did that small divestiture of that somewhat unrelated business in the **Control Technologies** segment. How are you guys feeling about the portfolio? Do you see any other little divestiture pruning to occur? Or are we mostly set?

Q2 2013 Sangamo BioSciences Earnings Conference Call by Sangamo Therapeutics, Inc.: Okay. And also, just staying on the hemoglobinopathies, how does your electroporation approach compare to **Bluebird Bio**'s HIV-based approach? Any general or specific comments on that?

Q3 2009 Archer Daniels Midland Company Earnings Conference Call by Archer Daniels Midland Co.: Okay, great. And then if you could talk about how you feel about the industry. Whether you feel like it is right sized in light of **Cargill** shutting down a plant and – a little bit of capacity for a few weeks here. Have you guys been running full out and what are your plans in that segment regarding your utilization rates?

Table B.1:
Common business terms excluded from NER "Organization"

Word	Meaning
EPS	Earnings Per Share
EBIT	Earnings Before Interest and Taxes
P&L	Profit and Loss
G&A	General and administrative expenses
NOI	Net Operating Income
EBITDA	Earnings Before Interest, Tax, Depreciation and Amortization
ASP	Average Selling Price
GAAP	Generally Accepted Accounting Principles
DSO	Days Sales Outstanding
FFO	Funds From Operations
IRR	Internal Rate of Return
SKU	Stock Keeping Unit
NPL	Non-Performing Loan
NOL	Net Operating Loss
D&A	Depreciation and Amortization
FDA	U.S. Food and Drug Administration
SEC	Securities and Exchange Commssion
FDIC	Federal Deposit Insurance Corporation
IRS	Internal Revenue Service

C. Future-performance-related questions

C.1 Measurement details

As discussed in Section 3.3, we identify future-performance-related questions using word lists of forward-looking statements from Bozanic et al. (2018) and finance terms from Matsumoto et al. (2011).

C.2 Examples

In the conference-call questions presented below, we highlight in **bold** the words identified from the word lists of forward-looking statements and finance terms.

Q3 2010 Tesoro Corporation Earnings Conference Call by Tesoro Corp.: [...] I mean, do you **anticipate** announcements about a more proactive, if you like, that's not quite the right word, perhaps, but a more **asset** changing type strategy?

Q2 2009 Insituform Technologies, Inc. Earnings Conference Call by Aegion Corp.: **Will** there be a **CapEx investment** for this growth?

Q4 2014 PAREXEL International Corp Earnings Call by PAREXEL International Corp.: [...] I'm just curious if you could give us a little bit more details surrounding why we saw this spike, in absolute **dollar** amounts, in the June quarter; and then how we should **expect** to see that trend in the near-term. Thanks.

Q2 2014 Jamba Inc Earnings Call by Jamba, Inc." Thank you. James and Karen, I wonder if we could talk a little bit about this 80% franchise and Company-owned ratio you **are targeting** and how you view that within the timing and extent of G&A **cost** reductions? [...]

Q4 2011 Advance Auto Parts Inc Earnings Conference Call by Advance Auto Parts, Inc.: [...] Should we actually **expect** flat to down SG&A **dollars** in the first quarter followed by sizable increases in the balance of the year? So two questions there.

Q1 2004 FactSet Research Systems Earnings Conference Call by FactSet Research Systems, Inc.: Yes, a follow-up on the soft-dollar question – can you help us by quantifying a little more your exposure in that area, whether it impacts you (indiscernible) remains to be seen but is it correct to **assume** that about 45 percent of your **revenue** is paid through soft-dollar arrangements? [...]

Q1 2010 MGM MIRAGE Earnings Conference Call by MGM Resorts International: Okay. Great. And then just moving to Macau, we **estimate** that **revenues** in the quarter were about $400 million. Is that correct?

Q2 2010 Auxilium Pharmaceuticals, Inc. Earnings Conference Call by Auxilium Pharmaceu-

ticals, Inc. [...] Could you comment on whether you **expect** the XIAFLEX contribution to mitigate somewhat in 2011 or if you **expect** it to effectively remain the same as it is now as XIAFLEX **sales** potentially ramp?

Q3 2014 Integra LifeSciences Holdings Corp Earnings Call by Integra LifeSciences Holdings Corp.: Pete, I'm just trying to get a sense for the longer-term outlook for new Integra. So old Integra, your **revenue** goals where 5% to 7% and I **believe EPS** goals for kind of low-double digits or low teens.[...]

Q4 2008 CA Earnings Conference Call by CA, Inc.: Okay. Okay. Great. And the – what was – because you said the guidance for next quarter **assumes** a flat effective **cash tax** rate. What was the effective **cash tax** rate for '07?

Figure 1: **Non-answer rate by year**

This figure depicts non-answer rates by fiscal year. The bottom and top lines are the 25th and 75th percentiles, and the middle line is the average value over the firm-year sample. To compute the non-answer rate for each firm, for each conference call, we first compute the rate of answers that contain non-answer phrases as described in Section 3. We then average these rates for all conference calls for the fiscal year to obtain *Non-answers* for a firm-year observation.

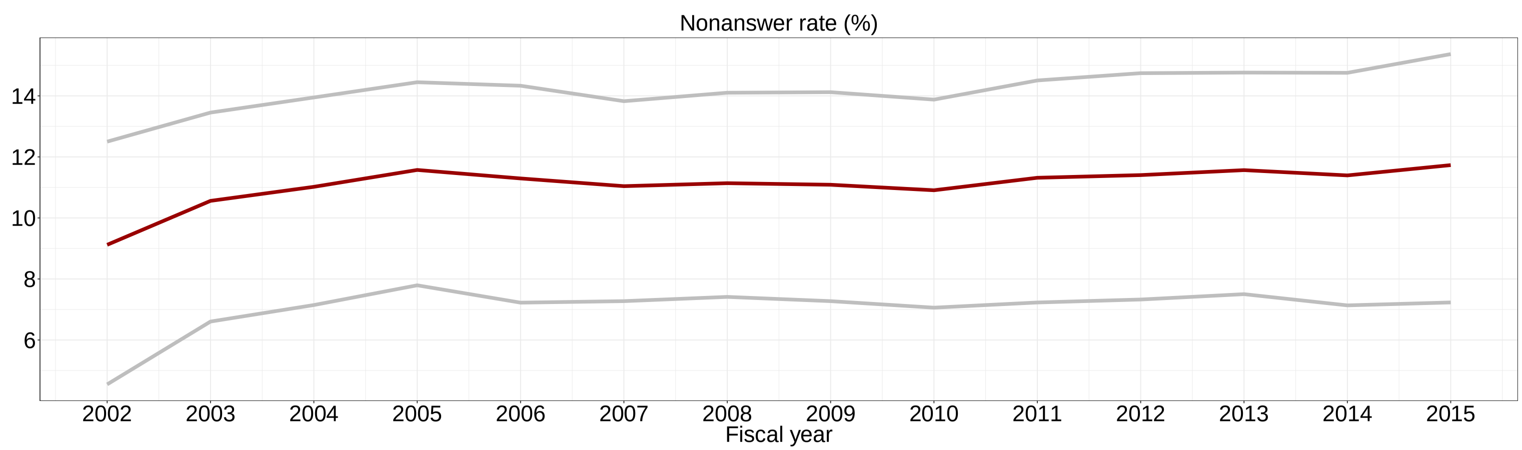


Figure 2: **Non-answer rate by industry**

This figure depicts non-answer rates by industrial sectors according to the Global Industry Classification Standard (GICS) by MSCI for the firm-year sample. To compute the non-answer rate, for each conference call, we first compute the rate of answers that contain non-answer phrases as described in Section 3. We then average these rates for all conference calls for the fiscal year to obtain *Non-answer* for a firm-year observation.

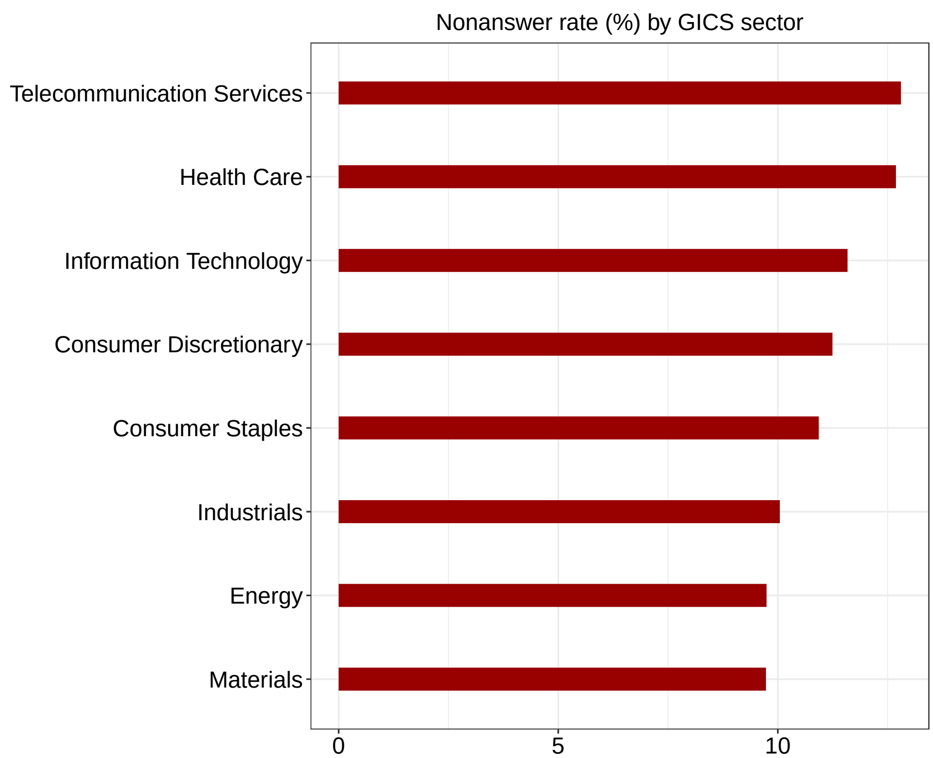


Figure 3: **Regressions of non-answer rates on competition measures**

This figure depicts regression lines of non-answer rates on competition measures, in which non-answer rates and competition measures are averaged by firm in the firm-year sample. To compute the non-answer rate, for each conference call, we first compute the rate of answers that contain non-answer phrases as described in Section 3. We then average these rates for all conference calls for each firm and fiscal year to obtain *Non-answer* for each firm-year observation. *HHI SIC3* is the Herfindahl-Hirschman Index computed using sales for 3-digit SIC industries. *Similarity* is the product market similarity measure from Hoberg and Phillips (2016). *Competition* is the competition intensity measure computed using conference call transcripts similar to Li et al. (2013). *SIC3-level comp.* is the average of *Competition* over firms in the same 3-digit SIC industry, excluding the firm itself. Competition measures are standardized to zero mean and unit standard deviation. Standard errors are in parentheses.

(a) HHI SIC3 (b) Log Similarity (c) Competition (d) SIC3-level comp.

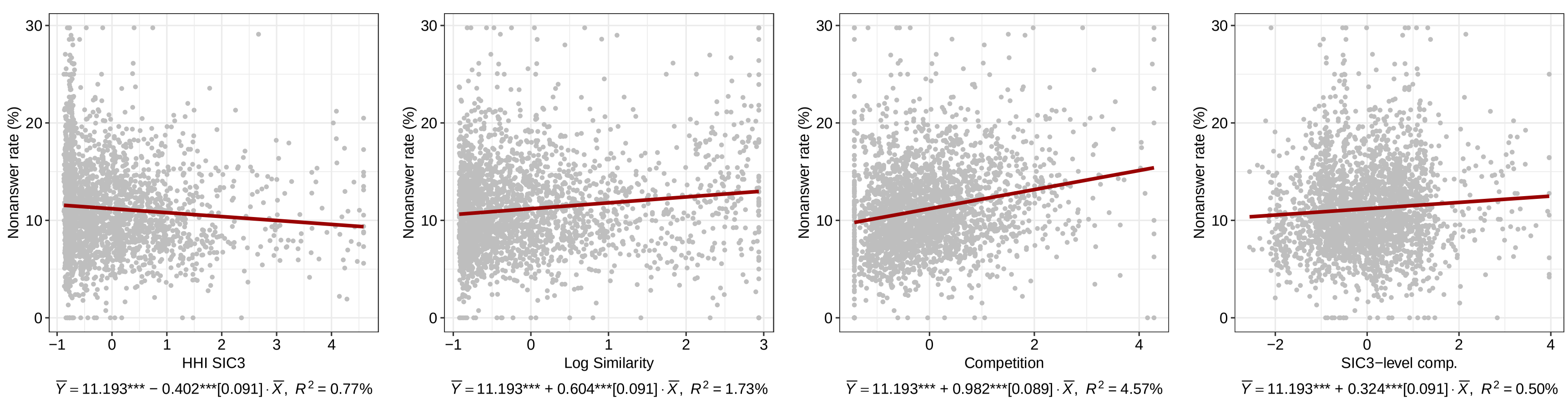


Figure 4: **Imports from China to the U.S. and non-U.S.**

This figure plots aggregate imports from China to the U.S. and non-U.S. for manufacturing industries (in 2000 $trillion). The non-U.S. set of countries is defined as eight high-income countries as in Autor et al. (2014): Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

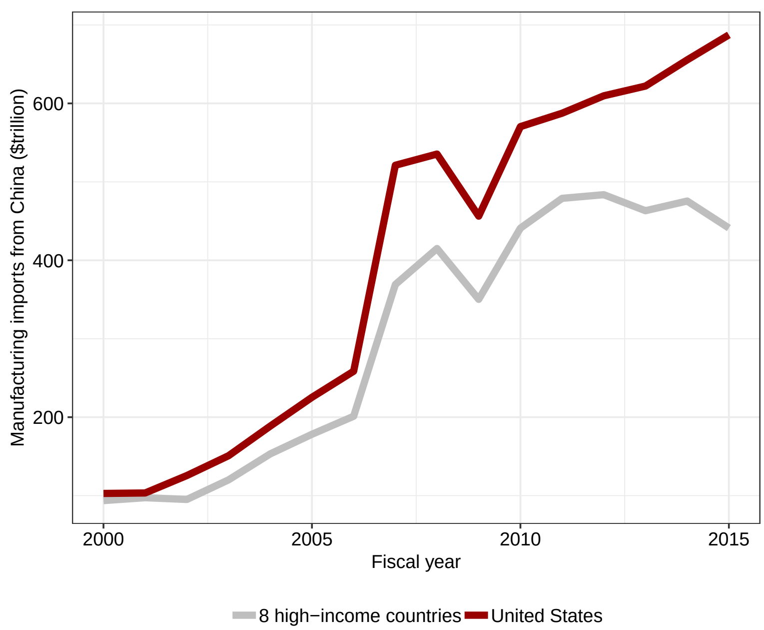
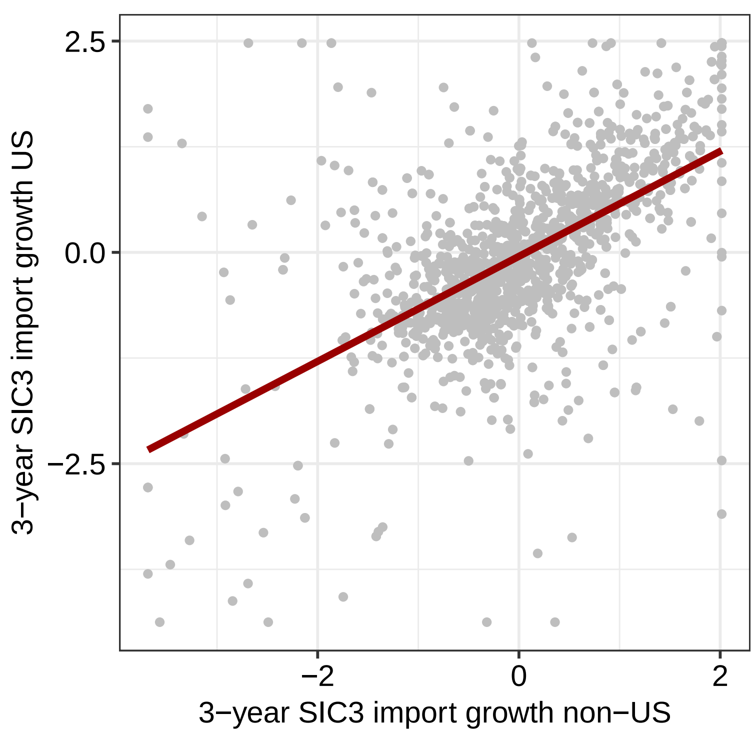


Figure 5: **Growth in imports from China to the U.S. and non-U.S.**

This figure depicts the scatterplot and the regression line of the three-year growth rates in imports from China to the U.S. against non-U.S. for three-digit SIC manufacturing industries. The non-U.S. set of countries is defined as eight high-income countries as in Autor et al. (2014): Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Growth rates are standardized to zero mean and unit standard deviation. Standard errors are in parentheses.



$Y = -0.047^{**} + 0.621^{***}[0.023] \cdot X,\ \ R^2 = 33.24\%$

Table 1:
Summary statistics

This table presents descriptive statistics for the variables used in estimation. The sample is based on Equilar, StreetEvents, Hoberg-Phillips data library, Compustat, Capital IQ, and the UN Comtrade database. Panel A presents data for the firm-year sample. Panel B presents data for the question-answer-level sample. These samples cover the period from 2002 to 2015. Firm characteristics are from Compustat. Compustat data codes are in parentheses. In Panel A, for each conference call, we first compute the rate of answers that contain non-answer phrases as described in Section 3. We then average these rates for all conference calls for the fiscal year to obtain *Non-answer*, *Refuse*, *Unable*, and *After-call*. *HHI SIC3* is the Herfindahl-Hirschman Index computed using sales for 3-digit SIC industries. *Similarity* is the product market similarity measure from Hoberg and Phillips (2016). *Competition* is the competition intensity measure computed using conference call transcripts similar to Li et al. (2013). *SIC3-level comp.* is the average of *Competition* over firms in the same 3-digit SIC industry, excluding the firm itself. *3-year SIC3 import growth US(t-1)* is import growth from China to the U.S. as described in Section 4. *3-year SIC3 import growth non-US(t-1)* is import growth from China to the non-U.S. as described in Section 4. These growth rates have the advantage of being bounded within $[-2; 2]$. The non-U.S. set includes eight high-income countries from Autor et al. (2014). *Debt due in 1-year-to-cash* is the ratio of debt due in 1 year (DD1) to cash holdings (CHE). *Equity offering* is the amount of equity issued (SSTK) divided by lagged market capitalization (CSHO*PRCC_F) at the time of equity issuance. Equity issuance events are identified from Capital IQ using event types "Follow-on Equity Offerings" or "IPOs." *Debt offering* is the amount of debt issued (DLTIS) divided by lagged market capitalization (CSHO*PRCC_F) at the time of debt issuance. Debt issuance events are identified from Capital IQ using event types "Fixed Income Offerings." *Private placement* is the sum of equity issued (SSTK) and debt issued (DLTIS) divided by lagged market capitalization (CSHO*PRCC_F) at the time of private placement. Private placement events are identified from Capital IQ using event types "Private Placements." *P(Fail)* is the probability of failure computed using Campbell et al. (2008) model as described in Section 5.2.3. *Total assets* is assets total (AT). *Sales* is sales revenue (SALE). *Market value* is the product of common shares outstanding (CSHO) and fiscal-year closing price (PRCC_F). *Leverage* is total debt (DD1 + DLTT) divided by total assets (AT). *Return on assets* is income before extraordinary items (IB) divided by lagged total assets (AT). *Return* is stock return over the specified period. *Market-to-book* is the sum of market value and total assets minus book value of equity divided by total assets. *Volatility* is annualized stock return volatility over the specified period. *Future profitability* is the *Return on assets* averaged over fiscal years $t + 1$, $t + 2$, and $t + 3$. CEO characteristics are from Equilar. *Shares held* is the value of CEOs' stock holdings. *Equity compensation* is the ratio of CEO's equity compensation to total compensation. In Panel B, *Non-answer* is an indicator variable that equals 1 if an answer contains a non-answer phrase, and 0 if not. *Refuse*, *Unable*, and *After-call* are defined similarly. *Product-related* is an indicator variable that equals 1 if a question contains a named entity classified as a product or organization by the Stanford Named Entity Recognizer as described in Section 3, and 0 if not. *Future perf.-related* is an indicator variable that equals 1 if a question contains a forward-looking phrase from Bozanic et al. (2018) and a finance term from Matsumoto et al. (2011) as described in Section 3, and 0 if not. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year.

Table 1: —*Continued*

Panel A: Firm-year data

	Obs.	Mean	Std.Dev	p5	p25	p50	p75	p95
Non-answers								
Non-answers	18,112	0.112	0.057	0.033	0.072	0.104	0.143	0.219
Refuse	18,112	0.082	0.049	0.017	0.048	0.074	0.108	0.176
Unable	18,112	0.036	0.030	0.000	0.015	0.030	0.051	0.096
After-call	18,112	0.002	0.005	0.000	0.000	0.000	0.000	0.011
Competition								
HHI SIC3	18,112	0.150	0.133	0.038	0.055	0.103	0.193	0.406
Similarity	18,112	4.105	5.739	1.046	1.260	1.921	3.767	18.572
Competition	18,112	0.032	0.028	0.000	0.012	0.026	0.046	0.088
SIC3-level comp.	18,112	0.032	0.013	0.013	0.023	0.032	0.040	0.053
Chinese import to the U.S. and other developed countries								
3-year SIC3 import growth US(t-1)	10,042	0.421	0.441	-0.330	0.206	0.426	0.666	1.041
3-year SIC3 import growth non-US(t-1)	10,042	0.406	0.445	-0.317	0.174	0.419	0.698	1.090
Capital markets								
Debt due in 1-year-to-cash	18,112	0.389	1.233	0.000	0.000	0.013	0.195	1.873
Equity offering	18,112	0.018	0.070	0.000	0.000	0.000	0.000	0.144
Debt offering	18,112	0.051	0.195	0.000	0.000	0.000	0.000	0.316
Private placement	18,112	0.015	0.078	0.000	0.000	0.000	0.000	0.026
Probability of failure during credit crisis								
P(Fail)	2,422	0.003	0.021	0.000	0.000	0.001	0.001	0.010
Firm characteristics								
Total assets ($bn)	18,112	4.609	11.882	0.040	0.233	0.826	3.120	22.578
Sales ($bn)	18,112	4.061	10.409	0.019	0.193	0.764	2.741	19.058
Market value ($bn)	18,112	5.255	14.058	0.047	0.276	0.911	3.251	24.828
Leverage	18,112	0.203	0.210	0.000	0.005	0.163	0.313	0.615
Return on assets	18,112	-0.003	0.190	-0.388	-0.024	0.043	0.088	0.188
Return, 12-month	18,112	0.161	0.586	-0.615	-0.189	0.083	0.377	1.211
Market-to-book	18,112	2.062	1.392	0.863	1.194	1.602	2.385	4.986
Volatility, 12-month	18,112	0.476	0.237	0.199	0.305	0.420	0.584	0.950
Future profitability	18,112	-0.006	0.176	-0.361	-0.031	0.039	0.081	0.164
Equity compensation	18,112	0.459	0.269	0.000	0.262	0.503	0.670	0.851
Shares held ($mm)	18,112	30.370	99.471	0.000	0.926	4.569	16.145	122.681

Panel B: Question-answer-level data

	Obs.	Mean	Std.Dev	p5	p25	p50	p75	p95
Non-answer	2,017,404	0.107	0.309	0.000	0.000	0.000	0.000	1.000
Refuse	2,017,404	0.077	0.267	0.000	0.000	0.000	0.000	1.000
Unable	2,017,404	0.037	0.188	0.000	0.000	0.000	0.000	0.000
After-call	2,017,404	0.002	0.041	0.000	0.000	0.000	0.000	0.000
Product-related	2,017,404	0.117	0.321	0.000	0.000	0.000	0.000	1.000
Future perf.-related	2,017,404	0.061	0.240	0.000	0.000	0.000	0.000	1.000

Table 2:
Non-answers and competition

This table reports estimates of the linear regressions of non-answers on future profitability, competition measures, and control variables for the firm-year sample. The variables are defined in Table 1. Non-answers are in percentage points. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-answers (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Future profitability	−0.232***	−0.215**	−0.076	−0.142	−0.393***	−0.275***	−0.302***	−0.254**
	(0.079)	(0.106)	(0.083)	(0.109)	(0.079)	(0.102)	(0.079)	(0.104)
HHI SIC3	−0.388***	−0.320***						
	(0.081)	(0.083)						
Log Similarity			0.591***	0.405***				
			(0.098)	(0.098)				
Competition					1.001***	0.929***		
					(0.072)	(0.066)		
SIC3-level comp.							0.359***	0.380***
							(0.087)	(0.083)
Log Total assets		0.906***		0.873***		0.795***		0.921***
		(0.140)		(0.141)		(0.132)		(0.140)
Leverage		−0.186**		−0.195**		−0.167**		−0.191**
		(0.083)		(0.082)		(0.081)		(0.083)
Return on assets		−0.223**		−0.186*		−0.254***		−0.232**
		(0.097)		(0.097)		(0.095)		(0.096)
Return, 12-month		−0.244***		−0.243***		−0.203***		−0.245***
		(0.084)		(0.084)		(0.079)		(0.083)
Market-to-book		0.671***		0.618***		0.676***		0.713***
		(0.084)		(0.089)		(0.084)		(0.084)
Volatility, 12-month		0.286***		0.268***		0.331***		0.325***
		(0.106)		(0.102)		(0.104)		(0.111)
Equity compensation		0.086		0.068		0.080		0.101
		(0.064)		(0.064)		(0.063)		(0.065)
Log Value of shares held		0.003		−0.008		0.009		−0.002
		(0.060)		(0.062)		(0.061)		(0.061)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.013	0.037	0.018	0.038	0.038	0.060	0.012	0.038
Obs.	18,112	18,112	18,112	18,112	18,112	18,112	18,112	18,112

Table 3:
Product-related questions, non-answers, and competition

This table reports estimates of the linear probability models of non-answers on an indicator variable for a product-related question, an interaction term between the indicator and competition measures, and *call* fixed effects. The variables are defined in Table 1. As described in Section 3, product-related questions are identified using NER for organizations, which corresponds to products or organizations. Non-answers are in percentage points, that is, 0 or 100. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-answer (%)				
	(1)	(2)	(3)	(4)	(5)
Product-related	6.517***	6.503***	6.486***	6.486***	6.504***
	(0.110)	(0.110)	(0.109)	(0.109)	(0.109)
Product-related × HHI SIC3		−0.213**			
		(0.105)			
Product-related × Log Similarity			0.370***		
			(0.111)		
Product-related × Comp.				0.538***	
				(0.100)	
Product-related × SIC3 comp.					0.255***
					(0.093)
Call FE	Yes	Yes	Yes	Yes	Yes
R^2	0.053	0.053	0.053	0.053	0.053
Obs.	2×10^6	2×10^6	2×10^6	2×10^6	2×10^6

Table 4:
Non-answers and growth in imports from China

This table reports results of the instrumental variable estimation. Panel A reports results of the regressions of the 3-year growth in imports from China to the U.S. on the 3-year growth in imports from China to non-U.S. and controls from Table 2. Panel B reports results of the regressions of non-answers on instrumented lagged 3-year growth in imports from China to the U.S. and controls from Table 2. The variables are defined in Table 1. The sample is restricted to the firms in manufacturing industries (based on 3-digit SIC codes). All variables are winsorized at the 1st and 99th percentiles by fiscal year. Independent variables are normalized to unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: First stage

	3-year SIC3 import growth US(t-1)	
	(1)	(2)
3-year SIC3 import growth non-US$_{t-1}$	1.433***	1.434***
	(0.189)	(0.187)
Controls	No	Yes
Year FE	Yes	Yes
F-Stat (1st Stage)	57.70	58.88
R^2	0.538	0.539
Obs.	10,042	10,042

Panel B: Second stage

	Non-answers (%)	
	(1)	(2)
3-year SIC3 import growth US$_{t-1}$	0.630***	0.666***
	(0.220)	(0.211)
Controls	No	Yes
Year FE	Yes	Yes
R^2	0.007	0.039
Obs.	10,042	10,042

Table 5:
Non-answers and capital issuance

This table reports estimates of the linear regressions of non-answers on future profitability, debt due in 1-year, issuance of equity or debt, and control variables for the firm-year sample. The variables are defined in Table 1. Non-answers are in percentage points. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-answers (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Future profitability	−0.280***	−0.231**	−0.333***	−0.271***	−0.287***	−0.235**	−0.324***	−0.253**
	(0.079)	(0.105)	(0.075)	(0.099)	(0.079)	(0.105)	(0.083)	(0.107)
Debt due in 1-year-to-cash	−0.180***	−0.107**						
	(0.055)	(0.053)						
Equtiy offering			0.025	−0.031				
			(0.042)	(0.049)				
Equity offering$_{t+1}$			−0.172***	−0.189***				
			(0.040)	(0.042)				
Debt offering					0.014	0.012		
					(0.046)	(0.043)		
Debt offering$_{t+1}$					−0.057*	−0.094***		
					(0.033)	(0.028)		
Private placement							0.019	0.026
							(0.050)	(0.050)
Private placement$_{t+1}$							−0.167***	−0.149***
							(0.052)	(0.048)
Log Total assets		0.892***		0.894***		0.910***		0.894***
		(0.142)		(0.140)		(0.143)		(0.141)
Leverage		−0.169**		−0.178**		−0.177**		−0.184**
		(0.083)		(0.084)		(0.084)		(0.085)
Return on assets		−0.230**		−0.260**		−0.230**		−0.239**
		(0.098)		(0.103)		(0.098)		(0.097)
Return, 12-month		−0.252***		−0.241***		−0.252***		−0.261***
		(0.085)		(0.087)		(0.085)		(0.085)
Market-to-book		0.698***		0.717***		0.703***		0.707***
		(0.084)		(0.084)		(0.084)		(0.084)
Volatility, 12-month		0.314***		0.334***		0.326***		0.321***
		(0.110)		(0.111)		(0.111)		(0.113)
Equity compensation		0.110*		0.115*		0.115*		0.112*
		(0.064)		(0.064)		(0.064)		(0.064)
Log Value of shares held		0.003		0.000		−0.001		−0.002
		(0.060)		(0.061)		(0.061)		(0.060)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.009	0.035	0.009	0.035	0.008	0.034	0.009	0.035
Obs.	18,112	18,112	18,112	18,112	18,112	18,112	18,112	18,112

Table 6:
Future-performance-related questions, non-answers, and capital issuance

This table reports estimates of the linear probability models of non-answers on an indicator variable for a future-performance-related question, an interaction term between the indicator and capital issuance measures, and *call* fixed effects. The variables are defined in Table 1. As described in Section 3, future-performance-related questions are identified using forward-looking statements from Bozanic et al. (2018) and finance terms from Matsumoto et al. (2011). In contrast to Table 5, all capital issuance variables are dummy variables taking the value of 1 if the company issues capital and 0 otherwise. Non-answers are in percentage points, that is, 0 or 100. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-answer (%)				
	(1)	(2)	(3)	(4)	(5)
Future perf.-related	6.110***	6.113***	6.104***	5.915***	6.089***
	(0.131)	(0.131)	(0.138)	(0.149)	(0.134)
Future perf.-related × Debt due in 1-year-to-cash		−0.240**			
		(0.107)			
Future perf.-related × Equity offering			−0.823*		
			(0.443)		
Future perf.-related × Equity offering$_{t+1}$			1.092**		
			(0.467)		
Future perf.-related × Debt offering				−0.102	
				(0.300)	
Future perf.-related × Debt offering$_{t+1}$				1.077***	
				(0.315)	
Future perf.-related × Private placement					0.068
					(0.602)
Future perf.-related × Private placement$_{t+1}$					0.538
					(0.593)
Call FE	Yes	Yes	Yes	Yes	Yes
R^2	0.051	0.051	0.051	0.051	0.051
Obs.	2×10^6	2×10^6	2×10^6	2×10^6	2×10^6

Table 7:
Credit crisis, probability of failure, and non-answers

This table reports estimates of the linear regressions of non-answers on the extreme quantiles of the probability of failure. Extreme quantiles are defined as the probability of failure being above 85th, that is, Above P_{85}(Fail), 90th, that is, Above P_{90}(Fail), and 95th percentiles, that is, Above P_{95}(Fail). Pre-period includes calls over 6-months period from March 31, 2008, until September 30, 2008. Post-period includes calls over the six-month period from October 1, 2008, until March 31, 2009. *Post* is an indicator variable that equals 1 in the post-period and 0 in the pre-preiod. The probability of failure is computed as described in Section 5.2.3 using data as of September 30, 2008. The variable definitions are similar for years 2007 and 2009. Non-answers are in percentage points. Continuous independent variables are standardized to zero mean and unit standard deviation. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-answers (%)								
	Pre-/Post- September 30, 2008			Pre-/Post- September 30, 2007			Pre-/Post- September 30, 2009		
Post	0.729***	0.641***	0.588***	0.035	0.086	−0.027	0.289	0.310	0.371*
	(0.206)	(0.201)	(0.200)	(0.210)	(0.204)	(0.203)	(0.194)	(0.193)	(0.191)
Above P_{85}(Fail)	0.951			1.070*			−0.473		
	(0.585)			(0.622)			(0.489)		
Post × Above P_{85}(Fail)	−1.746***			−0.710			0.827		
	(0.664)			(0.670)			(0.608)		
Above P_{90}(Fail)		1.706**			1.976**			−0.767	
		(0.755)			(0.771)			(0.609)	
Post × Above P_{90}(Fail)		−1.732**			−1.573*			1.026	
		(0.857)			(0.860)			(0.696)	
Above P_{95}(Fail)			1.673*			1.231			−0.820
			(0.968)			(1.018)			(0.810)
Post × Above P_{95}(Fail)			−2.423**			−0.892			0.834
			(1.208)			(1.206)			(0.903)
R^2	0.004	0.005	0.003	0.002	0.005	0.001	0.002	0.002	0.002
Obs.	2,422	2,422	2,422	2,234	2,234	2,234	2,514	2,514	2,514

Table 8:
Refusals to answer and competition

This table reports estimates of the linear regressions of refusals to answer on future profitability, competition measures, and control variables for the firm-year sample. The variables are defined in Table 1. Refusals to answer are in percentage points. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Refuse (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Future profitability	−0.382***	−0.284***	−0.231***	−0.216**	−0.528***	−0.338***	−0.449***	−0.323***
	(0.069)	(0.090)	(0.071)	(0.092)	(0.069)	(0.086)	(0.070)	(0.088)
HHI SIC3	−0.353***	−0.268***						
	(0.065)	(0.065)						
Log Similarity			0.562***	0.372***				
			(0.084)	(0.087)				
Competition					0.904***	0.842***		
					(0.061)	(0.058)		
SIC3-level comp.							0.404***	0.416***
							(0.071)	(0.069)
Log Total assets		0.745***		0.715***		0.645***		0.763***
		(0.124)		(0.126)		(0.117)		(0.123)
Leverage		−0.264***		−0.271***		−0.247***		−0.268***
		(0.074)		(0.072)		(0.071)		(0.073)
Return on assets		−0.241***		−0.206***		−0.269***		−0.248***
		(0.073)		(0.071)		(0.073)		(0.072)
Return, 12-month		−0.221***		−0.219***		−0.183**		−0.219***
		(0.081)		(0.079)		(0.074)		(0.079)
Market-to-book		0.609***		0.556***		0.610***		0.644***
		(0.073)		(0.076)		(0.072)		(0.073)
Volatility, 12-month		0.291***		0.272***		0.330***		0.326***
		(0.097)		(0.095)		(0.091)		(0.097)
Equity compensation		0.197***		0.178***		0.190***		0.205***
		(0.061)		(0.062)		(0.060)		(0.062)
Log Value of shares held		−0.095*		−0.105**		−0.089*		−0.100**
		(0.050)		(0.052)		(0.050)		(0.051)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.020	0.049	0.027	0.050	0.049	0.074	0.022	0.053
Obs.	18,112	18,112	18,112	18,112	18,112	18,112	18,112	18,112

Table 9:
Product-related questions, refusals to answer, and competition

This table reports estimates of the linear probability models of refusals to answer on an indicator variable for a product-related question, an interaction term between the indicator and competition measures, and *call* fixed effects. The variables are defined in Table 1. As described in Section 3, product-related questions are identified using NER for organizations, which corresponds to products or organizations. Refusals to answer are in percentage points, that is, 0 or 100. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Refuse (%)				
	(1)	(2)	(3)	(4)	(5)
Product-related	4.915***	4.909***	4.889***	4.892***	4.902***
	(0.096)	(0.096)	(0.095)	(0.095)	(0.095)
Product-related × HHI SIC3		−0.105			
		(0.091)			
Product-related × Log Similarity			0.314***		
			(0.096)		
Product-related × Comp.				0.402***	
				(0.088)	
Product-related × SIC3 comp.					0.258***
					(0.082)
Call FE	Yes	Yes	Yes	Yes	Yes
R^2	0.052	0.052	0.052	0.052	0.052
Obs.	2×10^6	2×10^6	2×10^6	2×10^6	2×10^6

Table 10:
Refusals to answer and growth in import from China

This table reports results of the instrumental variable estimation. Panel A reports results of the regressions of the three-year growth in import from China to the U.S. on the three-year growth in imports from China to non-U.S. and controls from Table 2. Panel B reports results of the regressions of refusals to answer on instrumented lagged three-year growth in imports from China to the U.S. and controls from Table 2. The variables are defined in Table 1. The sample is restricted to the firms in the 3-digit SIC manufacturing industries. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Independent variables are normalized to unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: First stage

	3-year SIC3 import growth US(t-1)	
	(1)	(2)
3-year SIC3 import growth non-US$_{t-1}$	1.433***	1.434***
	(0.189)	(0.187)
Controls	No	Yes
Year FE	Yes	Yes
F-Stat (1st Stage)	57.70	58.88
R^2	0.538	0.539
Obs.	10,042	10,042

Panel B: Second stage

	Refuse (%)	
	(1)	(2)
3-year SIC3 import growth US$_{t-1}$	0.687***	0.692***
	(0.224)	(0.206)
Controls	No	Yes
Year FE	Yes	Yes
R^2	0.008	0.051
Obs.	10,042	10,042

Table 11:
Refusals to answer and capital issuance

This table reports estimates of the linear regressions of refusals to answer on future profitability, debt due in 1-year, issuance of equity or debt, and control variables for the firm-year sample. The variables are defined in Table 1. Refusals to answer are in percentage points. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Refuse (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Future profitability	−0.422***	−0.297***	−0.473***	−0.333***	−0.430***	−0.305***	−0.470***	−0.319***
	(0.069)	(0.090)	(0.064)	(0.084)	(0.070)	(0.090)	(0.071)	(0.089)
Debt due in 1-year-to-cash	−0.253***	−0.157***						
	(0.049)	(0.049)						
Equtiy offering			−0.010	−0.077**				
			(0.037)	(0.038)				
Equity offering$_{t+1}$			−0.124***	−0.140***				
			(0.033)	(0.035)				
Debt offering					−0.060	−0.034		
					(0.039)	(0.033)		
Debt offering$_{t+1}$					−0.094***	−0.108***		
					(0.034)	(0.028)		
Private placement							−0.007	−0.004
							(0.047)	(0.046)
Private placement$_{t+1}$							−0.151***	−0.132***
							(0.050)	(0.048)
Log Total assets		0.730***		0.737***		0.757***		0.734***
		(0.126)		(0.124)		(0.125)		(0.125)
Leverage		−0.235***		−0.259***		−0.239***		−0.260***
		(0.074)		(0.074)		(0.073)		(0.075)
Return on assets		−0.245***		−0.283***		−0.246***		−0.259***
		(0.073)		(0.077)		(0.073)		(0.074)
Return, 12-month		−0.227***		−0.207***		−0.222***		−0.232***
		(0.080)		(0.080)		(0.081)		(0.080)
Market-to-book		0.625***		0.647***		0.629***		0.638***
		(0.073)		(0.073)		(0.073)		(0.073)
Volatility, 12-month		0.313***		0.335***		0.331***		0.322***
		(0.098)		(0.101)		(0.101)		(0.103)
Equity compensation		0.214***		0.222***		0.221***		0.218***
		(0.060)		(0.061)		(0.061)		(0.061)
Log Value of shares held		−0.093*		−0.097*		−0.099*		−0.099**
		(0.051)		(0.051)		(0.051)		(0.051)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.018	0.047	0.016	0.047	0.016	0.046	0.016	0.047
Obs.	18,112	18,112	18,112	18,112	18,112	18,112	18,112	18,112

Table 12:
Future-performance-related questions, refusals, and capital issuance

This table reports estimates of the linear probability models of refusals to answer on an indicator variable for a future-performance-related question, an interaction term between the indicator and capital issuance measures, and *call* fixed effects. The variables are defined in Table 1. As described in Section 3, future-performance-related questions are identified using forward-looking statements from Bozanic et al. (2018) and finance terms from Matsumoto et al. (2011). In contrast to Table 11, all capital issuance variables are dummy variables taking the value of 1 if the company issues capital, and 0 otherwise. Refusals to answer are in percentage points, that is, 0 or 100. We exclude financial firms and utilities. All variables are winsorized at the 1st and 99th percentiles by fiscal year. Continuous independent variables are standardized to zero mean and unit standard deviation. Robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Refuse (%)				
	(1)	(2)	(3)	(4)	(5)
Future perf.-related	5.368***	5.370***	5.386***	5.232***	5.342***
	(0.118)	(0.118)	(0.125)	(0.132)	(0.121)
Future perf.-related × Debt due in 1-year-to-cash		−0.182*			
		(0.101)			
Future perf.-related × Equity offering			−1.011**		
			(0.409)		
Future perf.-related × Equity offering$_{t+1}$			0.970**		
			(0.404)		
Future perf.-related × Debt offering				−0.259	
				(0.273)	
Future perf.-related × Debt offering$_{t+1}$				0.933***	
				(0.288)	
Future perf.-related × Private placement					0.117
					(0.545)
Future perf.-related × Private placement$_{t+1}$					0.601
					(0.570)
Call FE	Yes	Yes	Yes	Yes	Yes
R^2	0.051	0.051	0.051	0.051	0.051
Obs.	2×10^6	2×10^6	2×10^6	2×10^6	2×10^6