Measuring Corporate Culture Using Machine Learning*

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Abstract

We create a culture dictionary using one of the latest machine learning techniques—the word embedding model—and 209,480 earnings call transcripts. We score the five corporate cultural values of *innovation*, *integrity*, *quality*, *respect*, and *teamwork* for 62,664 firm-year observations over the period 2001–2018. We show that an innovative culture is broader than the usual measures of corporate innovation – R&D expenses and the number of patents. Moreover, we show that corporate culture correlates with business outcomes, including operational efficiency, risk-taking, earnings management, executive compensation design, firm value, and deal making, and that the culture-performance link is more pronounced in bad times. Finally, we present suggestive evidence that corporate culture is shaped by major corporate events, such as mergers and acquisitions. (*JEL* C45, G34)

What is corporate culture? According to O'Reilly and Chatman (1996, p. 160), corporate culture is "a system of shared values (that define what is important) and norms that define appropriate attitudes and behaviors for organizational members (how to feel and behave)." Unlike deeply held national cultural values, corporate culture is path dependent and can be shaped by major corporate events (Weber, Shenkar, and Raveh 1996; Guiso, Sapienza, and Zingales 2015; Graham et al. 2018; Grennan 2018). Corporate culture matters because employees will inevitably face choices that cannot be properly regulated ex ante (O'Reilly 1989; Kreps 1990). Despite the topic's importance, extant literature has limited large sample evidence, possibly because the notion of corporate culture is somewhat nebulous and thus raises numerous measurement issues in empirical research (see the review by Zingales [2015] and interview evidence in Graham et al. [2018]).

In this paper, we propose a semisupervised machine learning approach to measuring corporate culture. Our starting point is the often-mentioned values by the S&P 500 firms on their corporate websites (Guiso, Sapienza, and Zingales 2015): *innovation*, *integrity*, *quality*, *respect*, and *teamwork*, each of which serves as a "value word"; that is, it expresses a core corporate value. We make an important methodological contribution to the finance and accounting literatures by introducing the word embedding model, a novel machine learning method to quantify text (Mikolov et al. 2013; specifically *word2vec*). Using this new method, we first train a neural network model to learn the meanings of all words and phrases in earnings call transcripts based on their respective contexts. We then construct a "culture dictionary" of words and phrases that appear in close association with each cultural value. For example, the method automatically identifies words, such as *alliance* and *ecosystem*, phrases, such as *win-win*, and even idioms, such as *shoulder to shoulder* and *hand in glove*, as part of the culture dictionary in association with the cultural value of *teamwork*. The *teamwork* score of a firm is then based on a weighted-frequency count of those words and phrases in its earnings call transcripts.

We use earnings calls to score corporate culture for the following reasons. First, a firm's current culture is most significantly influenced by its top management (e.g., Guiso, Sapienza, and Zingales 2015; Graham et al. 2019). Guiso, Sapienza, and Zingales (2015) further note that for a particular value to be enforced, corporate leaders must themselves live by the value and share it throughout their companies, thereby leading by example. If managers "walk the talk," we would expect their words in calls to reflect the prevailing values in their organization. Second, unlike a firm's website or its press releases, where it is relatively easy to engage in "cheap talk" to advertise certain values, the primary purpose of earnings calls is not to discuss a firm's values but rather its business operations and performance. We use the extemporaneous question-and-answer (QA) section of a call instead of the scripted management presentation section to measure corporate culture to help mitigate excessive self-promotion. During the QA section, managers have little opportunity to pick discussion topics (Lee 2016). Third and finally, our method empirically determines the most relevant words and phrases in association with a particular value and creates a relatively exhaustive culture dictionary that makes promoting certain values over others much more challenging. Moreover, our method puts lower weights on more frequently occurring words/phrases in calls when scoring corporate culture, which further helps address the concern that we mainly capture "stated" value. In additional analyses, we also remove emotion-laden paragraphs (Larcker and Zakolyukina 2012) before scoring. As Loughran and McDonald (2011) point out, any nontrivial word list like ours applied to the vast number of call transcripts will inevitably misclassify; the issue is to what extent misclassification will occur. In this paper, we try to be as transparent as possible when introducing a new machine learning method to the finance and accounting literatures.

Using 209,480 earnings calls from Thomson Reuters' StreetEvents database over the period 2001–2018, we first train the word embedding model and then obtain corporate cultural values for 7,501 unique firms (62,664 firm-year observations). We validate our corporate culture measure using well-established markers for best practices in corporate innovation, integrity, product quality, respect, and teamwork and show that corporate cultural values are positively and significantly associated with those markers. We also compare our main measure based on the QA section of calls with alternative measures based on (a) the entire call, including the management presentation section and QA section; (b) a simple count of Guiso, Sapienza, and Zingales' (2015) seed words including the value word (e.g., innovation) in the QA section; and (c) applying the word embedding model to the Management's Discussion and Analysis (MD&A) section of annual reports (10-Ks). We show that applying the word embedding model to the QA section of calls represents a significant improvement to alternative approaches to measuring corporate culture based on validation tests.

We next explore the implications of having a strong corporate culture on business outcomes. We show that firms with a strong corporate culture are associated with greater operational efficiency, more corporate risk-taking, less earnings management, an executive compensation design fostering risk-taking and long-term orientation, and higher firm value. Moreover, the culture-performance link is more pronounced in bad times. In another application, we examine the role of corporate culture in mergers and acquisitions (M&As) using a sample of close to 8,000 deals over the period 2003–2018. We first show that firms scoring high on the cultural values of *innovation* and *respect* are more likely to be acquirers, whereas firms scoring high on the cultural values of *integrity* and *quality* are less likely to be acquirers. In terms of merger pairing, we find that firms closer in cultural values are more likely to do a deal together. We further show that post-merger, acquirers' cultural values are positively associated with their target firms' premerger cultural values after controlling for matching cultures between acquirers and their targets, suggesting that corporate culture itself is also shaped by M&As.

Our paper makes an important contribution to the long-standing literature on corporate culture spanning management, accounting, and finance. Despite the topic's importance, prior work exploring the relationship between corporate culture and firm policy mainly employs proxies for the former (e.g., Biggerstaff, Cicero, and Puckett 2015; Davidson, Dey, and Smith 2015) or relies on survey/interview evidence (e.g., Guiso, Sapienza, and Zingales 2015; Graham et al. 2018, 2019). Our paper extends and complements these earlier efforts by using one of the latest machine learning techniques—the word embedding model (Mikolov et al. 2013)—to measure corporate culture that can be easily applied to a large sample of firms over time. We show that an innovative culture is broader than the usual measures of corporate innovation – R&D expenses and the number of patents and that corporate culture correlates with business outcomes in all possible dimensions based on large sample evidence.

Our paper is among the first in the finance and accounting literatures, as far as we are aware, to apply neural network language models, an important part of recent advances in "deep learning" (e.g., LeCun, Bengio, and Hinton 2015), to the analysis of qualitative corporate disclosures.[1] From a methodological perspective, we contribute to the literature in two major ways.

[1] As such, our paper joins the recent surge of research in the fields of economics, finance, and accounting studying the different applications of machine learning tools. A nonexhaustive list includes Hansen, McMahon, and Prat (2018), Huang et al. (2018), Routledge, Sacchetto, and Smith (2018), Bellstam, Bhagat, and Cookson (forthcoming), Chen, Wu, and Yang (2019), Cong, Liang, and Zhang (2019), Erel et al. (2019), Gentzkow, Shapiro, and Taddy (2019), Hanley and Hoberg (2019), Lowry, Michaely, and Volkova (2020), and Li et al. (2020). See also Athey and Imbens (2019) for machine learning applications in general and Gentzkow, Kelly, and Taddy (2019) for methods involving text data.

First, we introduce the word embedding model as a new approach to quantifying the meaning of expressions. As Loughran and McDonald (2016) note, most textual analysis methods only operate at the document level and treat words as independent tokens based on the assumption that their order and context do not matter. This "bag-of-words" assumption is behind applications, such as tone (sentiment) measurement, using manually constructed word lists (e.g., Loughran and McDonald 2011; Henry and Leone 2016), text classification (e.g., Routledge, Sacchetto, and Smith 2018), and topic modeling (e.g., Huang et al. 2018; Lowry, Michaely, and Volkova 2020). The word embedding model (*word2vec*) goes beyond this assumption by using a neural network to deeply parse the immediate contexts of words. As a result, words and phrases are encoded as numeric vectors rather than independent tokens. Such vectorization provides an effective way to quantify the *semantics*, rather than merely the *syntactic*, at the expression level.

Second, we propose a new semisupervised machine learning approach for textual analysis. This approach falls between supervised and unsupervised learning approaches. The former needs a considerable number of labeled observations—usually in the form of firm outcomes—as training examples (e.g., predicting M&As as in Routledge, Sacchetto, and Smith [2018] and director elections as in Erel et al. [2019]); the latter keeps human input to a minimum and lets the data speak for themselves (e.g., topic modeling as in Huang et al. [2018] and Li et al. [2020]). In contrast, our approach does not rely on human-labeled documents, yet we can still provide limited albeit crucial guidance (i.e., cultural values and their seed words) to the algorithm while letting it inductively gather information about corporate culture from earnings calls. Therefore, our method can be applied to measure other predefined firm attributes from corporate disclosures under two conditions: (1) there is a lack of clear firm outcomes or human-labeled data so that supervised learning is not applicable; and (2) these predefined firm attributes are fairly subtle and do not emerge naturally from the data so that topic modeling (e.g., the latent Dirichlet allocation [LDA] method) is not applicable.

Recognizing the challenge of replicating textual analysis, we provide a self-contained technical appendix in the Internet Appendix that describes document parsing and model training step by step. We also provide our code in a public repository for future studies,[2] which is particularly important for the task of measuring corporate culture, as words and phrases pertaining to cultural values may evolve over time.

1. Data, Preprocessing and Parsing, and Learning Phrases

1.1 Using earnings calls to score corporate culture

When top executives were surveyed (Graham et al. 2018) about the most influential factor in building their firm's current culture, more than half identified their current CEO, bypassing the other options of owners, founders, reputation or image in the market place, internal policies and procedures, and difficult times experienced in the past as the most influential factor. Consistent with the survey evidence, prior studies, such as Biggerstaff, Cicero, and Puckett (2015), Davidson, Dey, and Smith (2015), and Guiso, Sapienza, and Zingales (2015), have used CEO attributes and behaviors to proxy for corporate culture. We thus expect earnings calls, as a commonly employed external corporate communication channel involving mostly CEOs and sometimes other top executives speaking to analysts, to reveal the set of values that are important to those corporate leaders and their company; Graham et al. (2018) also recommend earnings calls as the primary avenue for measuring corporate culture.

Admittedly, an important concern for us in using earnings calls as the data source is that managers may attempt to window dress their corporate culture during calls. It is worth

[2] Python code for text processing and model training can be downloaded from our GitHub repository, which is available at https://github.com/MS20190155/Measuring-Corporate-Culture-Using-Machine-Learning.

pointing out that the primary purpose of these calls is to discuss business operations and performance, not to promote corporate culture. Prior research shows that earnings calls provide value-relevant information beyond earnings announcements and that much of these calls' informativeness is attributable to their interactive nature, which allows for more extemporaneous disclosures targeting specific concerns raised by call participants (Frankel, Johnson, and Skinner 1999; Matsumoto, Pronk, and Roelofsen 2011; Lee 2016). As such, our application of using earnings calls to score corporate culture is an unintended consequence of mostly informative discussions on firm operations and performance by top executives. Because management presentation in a call is more likely to be scripted and/or vetted by corporate lawyers and investor relations than the QA section, which is more spontaneous and therefore offers far less of an opportunity for managers to engage in window dressing (Lee 2016), using the latter to measure corporate culture further mitigates the concern that we might simply capture "cheap talk" by managers.

From a methodological perspective, the method we use also helps mitigate the above concern. A reasonable assumption is that managers who engage in "cheap talk" would be more likely to use common words, such as the value words themselves. Our method is capable of learning hundreds or even thousands of words and phrases related to each cultural value. As such, a firm's cultural score is determined by a combination of all these words and phrases, not just the value words that managers are more likely to mention. In addition, because the word embedding method learns the meaning of a word or phrase from adjacent words/phrases, unless managers are able to choreograph their (impromptu) speeches during the QA section by putting a certain buzzword in a context that helps promote the natural meaning of that word, our method will not necessarily include the buzzword in the culture dictionary. Finally, we employ a word weighting scheme that puts lower weights on more frequently occurring words/phrases in calls when scoring corporate culture, which helps address the concern that we mainly capture "stated" value. To further assuage this concern, we will provide supporting evidence on the validity of our measure in Section 4.

Nonetheless, we are well aware that our word lists and measurement are subject to noise, and more future work is called for to improve our method. Our goal in the present study is to offer a new approach to measuring corporate culture based on the best available data source, notwithstanding managers' unobservable intentions.

1.2 Data, preprocessing and parsing, and learning phrases

We obtain earnings call transcripts from Thomson Reuters' StreetEvents (SE) database for the period January 1, 2001, to May 25, 2018. Each file contains the body of a call transcript and the following metadata that help us match the company to the Compustat database: the ticker symbol header, the company name, the title of the event, and the date of the call. After matching, the earnings call data set consists of 209,480 QA sections that can be mapped to 64,511 firm-year observations. We refer readers to Section 1 of the Internet Appendix for our matching procedure. Table 1 lists the steps taken and filters applied to form our final sample.

[Insert Table 1 about here]

We use the Stanford CoreNLP package to preprocess and parse the text.[3] Sections 2 and 3 of the Internet Appendix provide a detailed description of the steps. We segment documents into sentences and words, and then lemmatize words to their base forms. We conduct Named Entity Recognition (NER) to replace named entities, such as locations, times, persons, and company names, with a predefined tag.[4] Most importantly, as Routledge, Sacchetto, and Smith (2018) illustrate, phrases (collocations) play a crucial role in gathering

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[3] The CoreNLP package is an open-source Natural Language Processing (NLP) toolkit for a variety of tasks (Manning et al. 2014). We use version 3.9.2, which is available at https://stanfordnlp.github.io/CoreNLP.
[4] For example, "We repurchased 71.7 million Apple shares" is transformed to "we repurchase [NER:NUMBER] [NER:ORGANIZATION] share." Multiword named entities, such as "Wells Fargo," are also recognized.

information from corporate disclosures. We build upon their work by using a two-step approach to extracting both general and corpus-specific phrases. In step one, we use the dependency parser in the CoreNLP package to identify fixed multiword expressions (e.g., *with respect to*, *rather than*) and compound words (e.g., *intellectual property, healthcare provider*). These phrases are usually part of the general English vocabulary or can be inferred based on the grammatical relationships between words.[5] In the second step, we use the *phraser* module of the *gensim* library to find two- and three-word phrases that are more specific to the corpus (i.e., words that have statistically significant co-occurrences in the collection of QA sections in call transcripts).[6] For example, the phrases learned in the second step include *forward-looking statement* and *beat (a) dead horse*. We concatenate all the phrases using the underscore symbol "_" and treat them as a single word. Our results show that phrases constitute an essential part of how cultural values are conveyed in earnings calls.

2. Word Embedding, *word2vec*, and Model Training

2.1 Why word embedding?

Researchers in finance and accounting are increasingly relying on automated textual analysis to extract information from corporate disclosures. A particularly popular method is counting word occurrences from word lists (dictionaries) that share common meanings. For example, dictionaries, such as Harvard's General Inquirer tag categories, Loughran and McDonald (2011), and Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al. 2015), have been extensively used to measure the tone (sentiment) of documents. However, developing such dictionaries for measuring corporate culture can be a daunting task. As

[5] We remove punctuation marks, stop words, and single-lettered words after identifying and concatenating multiword expressions (MWEs) and compound words. This order is important because some of the stop words are part of MWEs and compound words.
[6] The *gensim* library is an open-sourced NLP Python package that we use for training the *word2vec* model. We use version 3.7.2, which is available at https://github.com/RaRe-Technologies/gensim.

Loughran and McDonald (2016) point out, creating a useful dictionary requires a good grasp of the context of business applications. The conventional solution, as in Loughran and McDonald (2011) and LIWC, is to have experts manually inspect and categorize words that commonly appear in a specific context. Several immediate challenges arise when applying this approach to generating a dictionary for corporate culture.

First, corporate culture is often discussed in a subtle and nuanced fashion. Unlike tones that reflect a general business outlook, culture can be described using less frequent words, abbreviations, phrases, or idioms that make sense only in a particular context. For example, humans can understand that the phrase "two-way street" is related to teamwork during an earnings call, yet it is difficult even for an expert in finance to pick that particular phrase out from millions of isolated words and phrases in call transcripts. Second, corporate culture can be an elusive, multidimensional construct. This inherent complexity means that even once all culture-related words and phrases can be extracted from a set of documents, categorizing them will be a more complicated task compared to tone analysis. It is difficult for humans to categorize each word in a consistent and objective fashion when facing five or more options (e.g., the five cultural values in our setting). Third, it is unrealistic to presume that experts could create and maintain dictionaries capable of adapting to constant paradigm shifts in the business world. Words and phrases enter and drop out of business vocabulary as technologies and industries evolve. For example, a dictionary created in the early 2000s would probably not recognize that "artificial intelligence" would drive corporate innovation some 20 years later; similarly, it would probably overlook "freelancer," given its inevitable inability to anticipate the growing role of freelancers in today's workforce.

In summary, while it is theoretically possible for experts with deep knowledge of various aspects of business operations to understand the rich, nuanced meanings of individual words and phrases based on context, their doing so is often impractical and cost ineffective.

As such, we offer a machine learning alternative to address these challenges. Our proposed approach starts with seed words that define each cultural value and automatically creates a high-quality dictionary from qualitative corporate disclosures. The centerpiece of our approach is the word embedding model, which learns the meaning of a word (phrase) based on its context.[7] Our approach can be used beyond measuring corporate culture to generate dictionaries applicable to other disciplines.

2.2 Word embedding

The goal of word embedding is to represent semantics (i.e., the meaning of a word) using a numeric vector. The word vector, in turn, allows us to determine the relationship between words using simple vector arithmetic. In our application, we rely on the cosine similarity between any two-word vectors to determine whether the two words are synonyms. Based on the learned similarity relationship to seed words describing a particular cultural value, a broad set of words and phrases that describe that cultural value can be identified and can be used to score firms accordingly.

The word embedding model is based on a simple, time-tested concept in linguistics: Words that co-occur with the same neighboring words have similar meanings (Harris 1954); the model thus identifies synonyms from common neighboring words. A naïve way to embed a word is to construct a count vector that tallies the number of times other words appear near (e.g., no more than a certain number of words away from) the focal word in the corpus (Section 4.2 and Table IA1 in the Internet Appendix provide a simple example). Once we construct such a vector for each word by counting its neighbors, we can theoretically compute the association between any pair of words using the cosine similarity of their underlying vectors. In reality, however, the number of combinations of all the words and their

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[7] The method learns the meanings of both words and phrases. For simplicity, we use "word" to indicate either a word or a phrase in our discussion of the methodology.

possible neighboring words is enormous, making the simple count-based word embedding method challenging to implement; hence, a new approach is called for.

2.3 word2vec and implementation

As a breakthrough in natural language processing (NLP), *word2vec* (Mikolov et al. 2013) employs a neural network to efficiently learn dense and low-dimensional vectors that can represent the meaning of words. In essence, *word2vec* "learns" the meaning of a specific word via a neural network that "reads" through the textual documents and thereby learns to predict all its neighboring words. The parameters in the neural network are initialized randomly. As learning progresses, the parameters in the neural network are adjusted via backpropagation (i.e., a standard training algorithm for neural networks) so the network continually improves its ability to predict a word's neighboring words. These parameters become an effective vector representation of the word when learning is completed after a number of iterations through the documents. The vector has a fixed dimension, usually between 50-500, and captures the properties of the original co-occurrence relationship between the word and its neighbors. Levy and Goldberg (2014) show that the vectorization achieved by *word2vec* is similar to a singular value decomposition (i.e., a dimension reduction technique) of the neighboring word count matrix. We refer readers to Section 4.4 in the Internet Appendix for a more technical description of *word2vec*.

We use the *gensim* library in Python to train the *word2vec* model. Other deep learning packages, such as TensorFlow and PyTorch, also can be used for training. We set the dimension of word vectors to 300; we define two words as neighbors if they are no farther apart than five words in a sentence, and we omit words that appear fewer than five times in the corpus. The hyperparameters for training the model are further explained in Section 4.5 of the Internet Appendix.[8] After training, the model converts each of the 764,276 words in the corpus to a 300-dimensional vector that represents the meaning of that word.

3. Measuring Corporate Culture Using *word2vec*

3.1 Seed words

The starting point for us to measure corporate culture is the five most-often mentioned values by the S&P 500 firms on their corporate websites (Guiso, Sapienza, and Zingales 2015): *innovation* (80% of the time), *integrity* (70%), *quality* (60%), *respect* (70%), and *teamwork* (50%). Guiso, Sapienza, and Zingales (2015) also provide units of meaning (i.e., seed words) for each value after checking all other words clustered with a value by each firm and their frequency across firms.[9]

Loughran and McDonald (2011) note that word lists developed for other disciplines misclassify common words in financial text and thus, by extension, word lists culled from companies' websites (Guiso, Sapienza, and Zingales 2015) might not be exactly applicable to our context of using earnings calls to score corporate culture. Therefore, after training the *word2vec* model (so we can get the word vector for each value/seed word), we manually inspect the value/seed words in Guiso, Sapienza, and Zingales (2015) to ensure that each cultural value is clearly defined using a coherent set of seed words, based on the following two criteria:

1. The word or phrase is in the vocabulary of call transcripts. Phrases such as "*do the right thing*" (under integrity) and "*exceed expectations*" (under quality) are excluded for this reason.

[8] Although the parameter choices can be data and task dependent (Caselles-Dupré et al. 2018), we find they have no significant effect on our main findings.

[9] For example, to find the seed words for *integrity*, the authors check all other words clustered with *integrity* by each company and their frequency across companies. They then take words most commonly associated with *integrity*. The word *ethics* is found to be associated with *integrity* in about 34% of companies and is added on the seed word list for *integrity*.

2. The synonyms of a word or phrase (via *word2vec*) indicate that, in the context of the QA section of calls, this particular word or phrase is unambiguously culture related. Words such as "*growth*" (under innovation) and "*diversity*" (under respect) are excluded because their synonyms indicate that "*growth*" is more likely to describe past performance and "*diversity*" is more likely to describe a diversification strategy.

After excluding some value/seed words in Guiso, Sapienza, and Zingales (2015) that do not meet the above criteria, we also add new seed words. These additional words include (1) other forms of the original seed words in Guiso, Sapienza, and Zingales (2015). For example, *cooperative* (adjective) and *cooperate* (verb) are added (under teamwork) based on their synonyms and given that *cooperation* (noun) is on the list; and (2) phrase variations that are more specific than the original seed words in Guiso, Sapienza, and Zingales (2015). For example, instead of *commitment*, we add *customer commitment* (under quality).

Table IA2 in the Internet Appendix lists included seed words in Guiso, Sapienza, and Zingales (2015) with their top synonyms, excluded value/seed words from Guiso, Sapienza, and Zingales (2015) with their top synonyms, and added seed words with their top synonyms.

3.2 Generating the culture dictionary

We use the trained *word2vec* model to develop an expanded, context-specific dictionary for measuring cultural values. As noted earlier, we can compute the cosine similarity between any two word vectors to quantify their association. Using this capability, we construct the culture dictionary by associating a set of words gleaned from earnings calls to seed words defining each cultural value. We use the following example to illustrate the procedure.

The seven seed words for the cultural value of *teamwork* are *collaborate*, *collaboration*, *collaborative*, *cooperate*, *cooperation*, *cooperative*, and *teamwork*. Let the vector representations for the first seed word *collaborate* be $V^{\{1\}} = \left[x_1^{\{1\}}, x_2^{\{1\}}, \dots, x_{300}^{\{1\}}\right]$, and the vector for the second seed word *collaboration* be $V^{\{2\}} = \left[x_1^{\{2\}}, x_2^{\{2\}}, \dots, x_{300}^{\{2\}}\right]$, …and the vector for the last seed word be $V^{\{7\}} = \left[x_1^{\{7\}}, x_2^{\{7\}}, \dots, x_{300}^{\{7\}}\right]$. We first compute the average of the vectors of the seed words, that is, $\overline{V}^{\{teamwork\}} = \frac{1}{7}\sum_{i=1}^{7}\left[x_1^{\{i\}}, x_2^{\{i\}}, \dots, x_{300}^{\{i\}}\right]$. We then compute the cosine similarity between each unique word in earnings calls with $\overline{V}^{\{teamwork\}}$. We select the top-500 words with the closest associations (i.e., the highest cosine similarity between their word vectors) to $\overline{V}^{\{teamwork\}}$ as the dictionary for the cultural value of *teamwork*. We do not consider named entities that are recognized automatically by the CoreNLP package. If a word appears in dictionaries for multiple cultural values, we only include it in the dictionary for the value with the highest cosine similarity to the average of seed word vectors for that value.

Finally, we manually inspect all the words in the auto-generated dictionary and exclude words that do not fit. When considering whether a word should be excluded, we carefully study its context in earnings calls. Most of the excluded words are named entities that the CoreNLP package missed (e.g., *gs1* and *dana-farber*), are too specific in terms of industry context (e.g., *chef* and *pharmacist*), or are too general in meaning (e.g., *importance* and *job*).[10]

Table IA3 in the Internet Appendix lists included and excluded words in the culture dictionary in order by descending similarity to seed words for each cultural value.

3.3 Scoring corporate culture

[10] As robustness checks, we expand the dictionary for each value to include the top-2,000 closest words. We also experiment with a procedure that, instead of relying on manual inspection of each dictionary word, automatically removes words from the dictionary if they are not mentioned by at least 20 firms. Our main findings remain, suggesting that our results are robust to the number of dictionary words for each cultural value and human judgment when excluding words from the dictionary.

After generating the culture dictionary, we measure each of the five cultural values at the firm-fiscal year level. We use the weighted count of the number of words associated with each value divided by the total number of words in the document. The weight is tf.idf, with tf (term frequency) representing the word frequency in the document, and idf (inverse document frequency) denoting the inverse frequency of documents with the word in the corpus. In essence, this weighting scheme accounts for both the importance of a word in a document and the significance of a word within the corpus.[11] Table 2, panel A, lists the 30 most representative words in order by descending similarity to seed words for each cultural value.[12] Panel B lists the 30 most frequently occurring words for each cultural value, with the frequency (%) being the tf.idf weighted word count.

[Insert Table 2 about here]

Table 3 provides an overview of our sample. Our firm-year measures of cultural values are based on 3-year moving averages of annual values. Our final sample consists of 7,501 firms and 62,664 firm-year observations. Panel A presents the summary statistics for corporate cultural value measures and some basic firm characteristics. We find that *innovation* is the most frequently mentioned cultural value, consistent with Guiso, Sapienza, and Zingales (2015), whereas *integrity* is the least frequently mentioned cultural value, based on earnings calls.

Panel B presents the autocorrelation of corporate cultural value measures. We calculate the autocorrelation for firms with more than 15 observations over the sample period. We show that the mean correlation between year t and year t - 1 cultural values ranges from 0.695 for *integrity* and 0.790 for *innovation*, and the mean correlation between year t and year

[11] An ongoing discussion in the literature concerns the applicability of tf.idf weighting. For example, Henry and Leone (2016) evaluate different weighting schemes to quantify the tone of financial disclosures and conclude that using a domain-specific word list and equal-weighted word-frequency measures produce both powerful and replicable results in settings of measuring qualitative information in disclosures for capital markets research.

[12] “sla” in panel A stands for “service-level agreement.”

t - 2 cultural values ranges from 0.361 for *integrity* and 0.512 for *innovation*. By the fifth lagged correlation, the mean values are substantially lower and very often become negative, suggesting that corporate culture evolves slowly over time.

Panel C presents the correlations of corporate cultural values and firm characteristics. We show that among the five cultural values, the correlation between *innovation* and *quality* is the highest, at 0.490, and the correlation between *innovation* and *teamwork* is the second highest, at 0.371, while the correlation between *integrity* and *quality* is the lowest, at 0.023, and the correlation between *innovation* and *integrity* is the second lowest, at 0.109. We further show that both firm size and leverage are negatively and significantly associated with *innovation*, *quality*, *respect*, and *teamwork*. Operating performance (ROA) is negatively and significantly associated with all five cultural values. These negative associations with ROA are consistent with the general observation (e.g., Guiso, Sapienza, and Zingales 2015) that having a strong culture calls for investment in R&D and selling, general, and administrative expenses (SG&A), resulting in forgone short-term profit but long-term benefits (as will be shown later in the paper). Sales growth has little association with any of the five cultural values (in terms of economic significance). Top-5 institutional ownership has mixed moderate associations with all five values.

[Insert Table 3 about here]

Table 4 lists top- and bottom-ranked S&P 500 firms in different corporate cultural values over three subperiods. We first show that a firm's strong culture can change over time. For example, Nvidia Corp. scores high in *innovation* during the two subperiods 2001–2006 and 2007–2012 but drops from the tier of top firms in *innovation* over the subperiod 2013–2018. Moreover, we show that a firm can excel in multiple cultural values. Over the subperiod 2007–2012, Salesforce.com Inc. scores high in *innovation*, *quality*, and *respect*, and over the subperiod 2013–2018, Blackrock Inc. scores high in both *integrity* and *quality*.

Finally, we also see some stability in corporate culture. For example, Lauder (Estee) Cos Inc. and Procter & Gamble Co. (Texas Instruments Inc. and Archer-Daniels-Midland Co.) score high (low) in *innovation*, Emerson Electric Co. scores low in *quality* and *teamwork*, and Tapestry Inc. and Tupperware Brands Corp. score high in *respect* during the entire sample period.[13]

[Insert Table 4 about here]

Figure 1 plots the five cultural values across 12 Fama-French industries over the sample period. We see some interesting patterns. Over time, most industries put more emphasis on technology and innovation and score higher in *innovation*. The healthcare industry stands out by scoring the highest in *integrity* and *teamwork*, and the business equipment industry holds the highest scores in *quality* over the sample period.

[Insert Figure 1 about here]

In summary, Table 4 and Figure 1 show that corporate culture evolves slowly over time.

4. Validating Our Measure of Corporate Culture

4.1 The validation tests

Given that our method for scoring corporate culture is new, it is important to validate our measure using well-established markers for best practices in the corporate world. To that end, we employ a large number of markers for the five cultural values.

[13] It might be surprising to see JCPenney and Kate Spade scoring high in *innovation* during our sample period. We note that in their heyday, both firms were leaders in innovation in their respective spaces, a fact recognized by their peers and the business community (see, e.g., Business Wire 2009; Song 2018). It is thus worth noting that an innovative culture is broader than the usual measures of corporate innovation—R&D expenses and the number of patents—as innovative firms can also have novel/original marketing strategies like Kate Spade or efficient back-office operations like JCPenney.

To validate the cultural value of *innovation*, we use ln(Patent), R&D spending, and innovation strength.[14] ln(Patent) is the natural logarithm of one plus the number of patents filed and eventually granted in a year. The data come from Kogan et al. (2017). R&D spending is R&D expenditures normalized by total assets. Innovation strength is an indicator variable that takes the value of one if a firm is considered to have strengths in innovation and R&D, and zero otherwise. Kinder, Lydenberg & Domini (KLD 2006) defines strength in innovation as "the company is a leader in its industry for research and development (R&D), particularly by bringing notably innovative products to market." The data come from KLD.

To validate the cultural value of *integrity*, we use malfeasance in accounting and backdating executives' option grants (Biggerstaff, Cicero, and Puckett 2015). Restatement is an indicator variable that takes the value of one if a firm later restates its (annual or quarterly) financial statements, and zero otherwise. The data come from Audit Analytics. Backdating is an indicator variable that takes the value of one if option grants to a firm's CEO are backdated, and zero otherwise. To identify backdating, we follow Heron and Lie (2009), whose estimation methodology is based on the assumption that, in the absence of backdating or other types of grant date manipulation, the distributions of stock returns during the month before and after grant dates should be roughly the same.[15] The data on CEOs' option grants come from Thomson Reuters' Insider Filing database.

To validate the cultural value of *quality*, we use product quality, product safety, and top brand. Product quality is an indicator variable that takes the value of one if a firm is considered to have strengths in product quality, and zero otherwise. KLD (2006) defines

[14] In unreported analysis, we also use the number of citations (either the raw count or adjusted for truncation bias) to validate the cultural value of *innovation.* Our main takeaway does not change, which is not surprising given the high correlation between the natural logarithm of one plus the number of patents and the natural logarithm of one plus the number of citations (at 0.881 using the raw count and at 0.882 using the adjusted measure).

[15] We thank Randy Heron for providing us with the SAS code used in Heron and Lie (2009) to identify option grant backdating.

strengths in product quality as "the company has a long-term, well-developed, company-wide quality program, or it has a quality program recognized as exceptional in U.S. industry." Product safety is an indicator variable that takes the value of one if a firm is considered as having no concerns about product safety, and zero otherwise. KLD (2006) defines concerns in product safety as "the company has recently paid substantial fines or civil penalties or is involved in major recent controversies or regulatory actions, relating to the safety of its products and services." The data for both variables come from KLD. Top brand is an indicator variable that takes the value of one if a firm is included in the top-500 list of Brand Finance rankings, and zero otherwise. The list is constructed by Brand Finance (http://brandirectory.com/), and the data range from 2007 to 2017.

To validate the cultural value of *respect*, we use diversity and "best employer" status. The former is the number of diversity strengths minus the number of diversity concerns. The data come from KLD. The latter is an indicator variable that takes the value of one if a firm is included on Fortune's "100 Best Companies to Work for in America" list, and zero otherwise; the main criteria for appearing on the list are job satisfaction, fairness, and camaraderie (for details, see Edmans [2011]; Table A1 in the appendix). Edmans (2011) shows that firms on Fortune's list have greater employee satisfaction than other firms. The list covers data up to 2017.

To validate the cultural value of *teamwork*, we use the level of employee involvement and the number of joint ventures (JVs) and strategic alliances (SAs). The former is an indicator variable that takes the value of one if a firm is considered to have strengths in employee involvement, and zero otherwise. KLD (2006) defines employee involvement as "the company strongly encourages worker involvement and/or ownership through stock options available to a majority of its employees; gain sharing, stock ownership, sharing of financial information, or participation in management decision making." The data come from

KLD. The latter is the number of JVs and SAs formed by a firm in a given year. The data come from Thomson Reuters' SDC database.

Table 5 presents the results of validation tests for our main measure, namely, cultural values based on the QA section of calls. In panel A, we show that the cultural value of *innovation* is positively and significantly associated with all three measures of corporate innovation activities. This positive association remains after controlling for industry and year fixed effects as well as firm size and operating performance. In panel B, we show that the cultural value of *integrity* is negatively and significantly associated with one form of accounting malfeasance: restatement. Moreover, we show that the cultural value of *integrity* is negatively and significantly associated with backdating executives' option grants. In panel C, we further show that the cultural value of *quality* is positively and significantly associated with two out of three measures of product quality, namely, product safety and top brand status. In panel D, we show that the cultural value of *respect* is positively and significantly associated with the diversity score reported by KLD and the best employer ranking by Fortune. Finally, in panel E, we show that the cultural value of *teamwork* is positively and significantly associated with both employee involvement from KLD and the number of JVs/SAs. At the bottom of Table 5, we present incremental R^2 (Pseudo R^2), which gives the increase in model fit from adding the variable of interest (our measure for a particular cultural value) to the regression specification. For example, in panel A, we report an R^2 of 3.6% in column 1 up to an R^2 of 16.6% in column 3, which includes size, ROA, and industry and year fixed effects. The incremental R^2 of the cultural value of *innovation* in these two specifications is 3.0% and 0.75%, respectively. The fact that *innovation* has an incremental

R^2 of 0.75% (out of 16.6%) suggests that it remains an important factor in explaining a firm's number of patents after controlling for various fixed effects.[16]

[Insert Table 5 about here]

As a much higher hurdle of validating our measures as well as to illustrate the positive correlations among all five measures (see Table 3, panel C), we introduce an encompassing specification where we put all five value measures on the right-hand side, while the dependent variables are different markers for each of the five cultural values. Table IA4 in the Internet Appendix presents the results.

Panel A shows that there remains a positive and significant association between the cultural value of *innovation* and any of the three measures for corporate innovation activities, after controlling for all four other cultural values; none of the four other cultural values has consistent positive associations with our three measures of corporate innovation activities. Panel B shows that there remains a negative and significant association between the cultural value of *integrity* and any of the two measures of unethical behaviour in a company, after controlling for all four other cultural values; in contrast, *innovation* and *respect* are positively and significantly associated and *teamwork* is negatively and significantly associated with the two measures of unethical corporate behavior. None of the above positive associations has a compelling economic explanation, unlike that for *integrity*. Panel C shows that with the exception of product quality (columns 1–3), there remains a positive and significant association between the cultural value of *quality* and any of the two other measures of product quality—product safety and top brand—after controlling for all four other cultural values; none of the four other cultural values has consistent positive associations with our

[16] Across Table 5, some of the increases in model fit are small for the following reasons: first, our measure of corporate culture is broader than the markers used (see the earlier examples of JCPenney and Kate Spade); second, our measure captures the fact that corporate culture exhibits important industry differences and moves slowly over time (Figure 1), and thus most of the variation is absorbed by industry and year fixed effects; and third, two-thirds of the markers are binary variables with limited variations.

three measures of product quality. Panel D shows that after controlling for all four other cultural values, the cultural value of *respect* is positively and significantly associated with best employer, while the cultural value of *innovation* is positively and significantly associated with both diversity and best employer, which might not be surprising given the strong positive correlation between *innovation* and *respect* (at 0.321). Panel E shows that there remains a positive and significant association between the cultural value of *teamwork* and any of the two measures of employee engagement and collaboration, after controlling for all four other cultural values; none of the four other cultural values has consistent positive associations with our two measures of employee engagement and collaboration.

In summary, the validation tests in Table 5 and Table IA4 reassure us that our measure of corporate culture is correlated with shared values and practices by employees at large and has performed as expected.

4.2 Corporate culture and its markers

One natural concern from the above validation exercise is that those very markers for the test could make our measure of corporate culture potentially redundant given their high correlations. We believe our corporate culture measure is an important addition to corporate finance research for the following reasons.

First, corporate culture could be an aspiration that has yet to bear fruit in firm policy or performance (Graham et al. 2018, 2019), and a strong corporate culture permeates all aspects of a firm's operations and the behavior of its employees. In this paper, we focus on the five most common cultural values and their markers to keep the analyses manageable.

Second, the set of markers we employ to validate a particular value is typically much narrower than what the value embodies. For example, an innovative culture is manifested beyond R&D expenses and the number of patents, as innovative firms could also have more trade secrets, novel/original marketing strategies, optimized production processes, and efficient back-office operations. Similarly, a culture of integrity is not limited to the two malfeasance markers that we use to validate it.

Third, the data coverage and quality of our corporate culture measure are far better than those for most of the markers. Specifically, we can measure corporate culture for any firms with earnings calls (including private firms registered under the Securities Exchange Act of 1934; Gao, Harford, and Li 2013), whereas most of the markers that we use are only available for public firms. Consider the cultural value of *innovation,* for example; it is a well-known issue that less than 40% of Compustat firms report positive R&D expenses, and about 15% of firms repeatedly deliver patentable innovation output (Bena and Li 2014; Koh et al. 2019). Moreover, our corporate cultural value measures are continuous, whereas many of the markers used for validation tests are binary (with the exceptions of ln(Patent), R&D spending, diversity, and the number of JVs/SAs), and are thus limited in cross-sectional variations.

4.3 Other ways of measuring corporate culture

Our main measure of corporate culture is obtained by applying the culture dictionary to the QA section of calls. Applying the culture dictionary to the full transcript of calls, we generate an alternative set of corporate cultural value measures, and label them with the suffix _full.

Given that we are among the first to apply the word embedding model to quantify culture, the question inevitably arises: How does our approach perform compared to a simple alternative using the list of seed words provided by Guiso, Sapienza, and Zingales (2015) and the specific value word (e.g., *innovation*)? We employ a simple count of the seed words (plus the value word) in the QA section of calls to generate a new alternative set of corporate cultural value measures, and label them with the suffix _seed.[17]

Thus far, we employ earnings calls to score corporate culture. An alternative would be employing the MD&A section of 10-Ks, which are often employed in textual analysis of corporate disclosures. Applying the word embedding model to the MD&A section of 10-Ks over the fiscal year 1993–2017, we generate another alternative set of corporate cultural value measures and label them with the suffix _10k.[18]

Table 6 presents the results of validation tests for these three alternative measures.[19] Compared to Table 5, Table 6 shows that our main measure outperforms all these three alternative measures. The alternative measure based on the full call comes as a close second, and the alternative measure based on a simple count of seed words performs the worst. Overall, Table 6 shows that while our method is applicable to other types of qualitative disclosures, using the QA section of calls is the better alternative for measuring corporate culture.

[Insert Table 6 about here]

Finally, we also consider two other possibilities for scoring corporate culture. The first is to apply the word embedding model to employee reviews, such as Glassdoor.com.

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[17] For consistency, the value/seed word list in Guiso, Sapienza, and Zingales (2015) is updated after applying *word2vec* to our corpus to learn the meanings of those words (as we did in obtaining our main measure of corporate culture).

[18] Table IA5 in the Internet Appendix presents the summary statistics of all alternative measures and their correlations with our main measure based on the QA section of calls. We show that the correlations between the alternative measure based on the full call and our main measure are the highest, ranging from 0.847 for *quality* to 0.934 for *teamwork*. Such high correlations are expected because the tf.idf weighting scheme dampens the effect of the most frequent words when scoring, which also would be the words with the greatest difference between the QA section and the management presentation section of a call. The correlations between the alternative measure based on a simple count of seed words and our main measure are the second highest, ranging from 0.458 for *teamwork* to 0.520 for *innovation*. The correlations between the alternative measure based on 10-Ks and our main measure are the lowest.

[19] Table IA6 in the Internet Appendix employs an encompassing specification where we put all four cultural value measures on the right-hand side. With the exception of *integrity*, we show that our main measure outperforms all three alternative measures. One caveat to this analysis is that some of the regressions potentially suffer from multicollinearity due to some high correlations among different measures as noted above.

Although these reviews are a sensible source for learning corporate culture (Graham et al. 2018; Grennan 2018), the data are not publicly available. In addition, data from employee review sites have limited temporal coverage and many firms have very few reviews.[20] The second alternative is to apply topic modeling tools like LDA to earnings calls. However, because LDA is an unsupervised learning model, there is no guarantee that the topics uncovered will be related to corporate culture. Huang et al. (2018) find that most topics extracted from earnings calls are either industry specific or performance related. We apply LDA to the QA section of earnings calls; Table IA7 in the Internet Appendix lists different top topics from this exercise. Consistent with Huang et al. (2018), we show that none of these topics is closely related to corporate cultural values.

In summary, both validation tests and horse races between our main measure of corporate culture and a number of alternatives suggest that the word embedding model generates a high-quality culture dictionary useful for scoring corporate cultural values.

4.4 Addressing self-promotion in calls

One could be concerned that managers may be engaging in excessive self-promotion during calls and that our approach does not therefore fully capture corporate culture. In this section, we check whether our measure is susceptible to managers' responses laden with emotion words.

We use Linguistic Inquiry and Word Count (LIWC) to capture positive and negative emotions in each paragraph of the QA section of calls. LIWC is a computer program developed for studying the various emotional components that present in individuals' verbal and written speeches (Tausczik and Pennebaker 2010). Larcker and Zakolyukina (2012)

[20] We note that the median number of reviews for a public firm in a year is only five based on Glassdoor.com, which limits our ability to obtain firm-year observations of cultural values.

provide an accounting application in which they use LIWC to detect highly emotional discussions in calls.

To implement this robustness check, for each transcript we remove the top quartile of those paragraphs with the greatest positive (negative) emotion scores. We then recompute our measure using the modified corpora. The correlations between the new measure and our original measure at the firm-year level range from 0.909 (*quality*) to 0.961 (*teamwork*) when we exclude positive emotion-laden paragraphs, and from 0.898 (*quality*) to 0.942 (*teamwork*) when we exclude negative emotion-laden paragraphs.

As an additional investigation, we repeat the above analysis using an alternative word list developed by Larcker and Zakolyukina (2012) to capture only extremely positive emotions, which the authors identify as important markers for deceptive speeches by CEOs during calls. The correlations between the new measure and our original measure range from 0.880 (*integrity*) to 0.927 (*teamwork*). Overall, these high correlations suggest that management's self-promotion in calls does not play a significant role in our approach to measuring corporate culture.

4.5 Words with multiple senses

One limitation of the word embedding model is that multiple senses (meanings) of a word are combined into a single vector. Because our corpus is from a very specific domain—earnings call transcripts—the meaning of a word derived from such a corpus is less likely to be ambiguous compared to a more general corpus like Wikipedia (Magnini et al. 2002; Henry and Leone 2016). Nonetheless, we conduct a robustness check by examining the correlation between cultural values used in our main analysis and those same cultural values measured using a dictionary in which words with multiple senses are removed.

We use an algorithm developed by Pelevina et al. (2016) to learn word senses from embedding vectors. The intuition of the algorithm is that for each focal word in the dictionary, we first find its top synonyms using the trained *word2vec* model. The algorithm then groups the synonyms into different clusters based on how similar they are to each other. Multiple clusters among its synonyms would imply that the focal word has multiple senses.[21]

We find that only a small fraction of the words (12%, or 212 words) in our dictionary has more than one sense. We compute the cultural values at the firm-year level using the same method on the QA section, but remove those multisensed words from the dictionary. The correlation between the measures with and without the multisensed words is high, ranging from 0.868 (*quality*) to 0.939 (*teamwork*) among the five values, suggesting that words with multiple senses are of limited significance in our setting. Given the high correlations and the specific domain of our corpus, we opt to keep the multisensed words in the dictionary.

5. Implications of Corporate Culture

In a recent survey of North American CEOs and Chief Financial Officers (CFOs), over half of senior executives view corporate culture as one of the top-three factors that affect their firm's value, and over 90% of them believe that improving corporate culture will increase firm value. Cultural fit in M&As is so important that about half of executives would walk away from a culturally misaligned target (Graham et al. 2019). By applying *word2vec* to earnings calls to score corporate cultural values, our paper provides a rare opportunity to examine the implications of having a strong corporate culture based on large sample evidence.

5.1 Corporate culture and business outcomes

[21] For example, the algorithm finds that the word *caring*, which is in our culture dictionary for the cultural value of *respect*, has two senses in the transcript corpus. The first sense is captured by a cluster of thematically related words, including *passion*, *meritocracy*, and *dignity*. The second sense is captured by another cluster of thematically related words, including *healthcare*, *mental health,* and *medication management*.

According to Graham et al. (2018), corporate executives characterize culture as "a belief system," "a coordination mechanism," and "an invisible hand," and they generally believe that corporate culture affects all aspects of a firm's operations. In this section, we explore the role of corporate culture in operational efficiency, risk-taking, the incentive to manage earnings, executive compensation design, and firm value, motivated by survey/interview evidence in Graham et al. (2018, 2019).

A priori, it is difficult to say which cultural value is more conducive to business operations. Moreover, there are strong positive correlations among all five values as shown earlier. Following Graham et al. (2019), we use a summary measure to capture firms with strong corporate cultures. Strong culture is an indicator variable that takes the value of one if the sum of a firm's five cultural values is in the top quartile across all Compustat firms in a year, and zero otherwise. Table 7, panel A, presents the lead-lag associations between having a strong corporate culture and firm outcomes.

Consistent with interview evidence in Graham et al. (2018), we find a positive association between firms with a strong culture and their operational efficiency as measured by assets turnover and inventory turnover. The survey evidence in Graham et al. (2019) provides examples of how effective culture facilitates risk-taking. We show a positive association between firms with a strong culture and a summary measure of corporate risk-taking as captured by the standard deviation of monthly stock returns.

According to Graham et al. (2019), interviewed executives consistently made connections between effective culture and managerial and employee focus on long-term objectives, which would have implications for incentives to manage short-term earnings and executive compensation design. Using discretionary accruals to proxy for earnings management, we show a negative association between firms with a strong culture and discretionary accruals. If the board is attuned to the same culture, we expect executive compensation will be set in a way consistent with the values in place and will foster risk-taking and long-term orientation. Consistent with this conjecture, we show a positive association between firms with a strong culture and CEO wealth-performance sensitivity (delta), between firms with a strong culture and the sensitivity of CEO wealth to stock volatility (vega, Coles, Daniel, and Naveen 2006), and between firms with a strong culture and CEO pay duration (Gopalan et al. 2014).

Given that a strong corporate culture helps improve efficiency, encourage risk-taking, and instill long-term orientation, we expect firms with a strong culture to have higher firm value. Panel A, column 8, shows a positive association between firms with a strong culture and Tobin's q. It is worth noting that when we use different lead-lag specifications up to 5 years apart, the strong association between corporate culture and business outcomes remains.

[Insert Table 7 about here]

5.2 Corporate culture in bad times

According to Graham et al. (2018), interviewed executives believe the culture-performance link is more apparent in a challenging operational environment, because a strong culture empowers executives and rank-and-file employees to make consistent decisions and effort based on long-term perspectives.

To examine the performance implications of corporate culture in bad times, we focus on the effects of the financial crisis on companies in the financial industry (based on the Fama-French 48 industry classification, these companies are in banking, insurance, real estate, and trading); and on the effects of British Petroleum's (BP) Deepwater Horizon oil spill on oil companies. The specification for the financial crisis-related tests largely follows Lins, Servaes, and Tamayo (2017). The sample period is from 2007 to 2010, and the financial crisis period is from August 2008, preceding the September 2008 Lehman Brothers' bankruptcy, to March 2019, when the S&P 500 hit its lowest point of the crisis. The sample period for BP's oil spill-related tests is from 2009 to 2012, and the oil spill period is from May 2010 to February 2011.

Table 7, panel B, presents the results using market-model adjusted monthly returns.[22] Column 1 includes year fixed effects and shows that firms with a strong culture exhibit superior performance during the crisis period. Column 2 includes firm and year fixed effects and our main findings remain. In terms of economic significance, the coefficient of 0.024 on the interaction term *Strong culture* × *Financial crisis* indicates that firms with a strong culture are associated with a 2.4-percentage-point higher monthly return during the crisis period than their counterparts without a strong culture. Columns 3 and 4 present the results related to the effect of BP's oil spill on oil companies. We show that oil companies with a strong culture exhibit superior performance during the industry crisis period. In terms of economic significance, the coefficient of 0.018 on the interaction term *Strong culture* × *BP oil spill* in column 4 indicates that oil companies with a strong culture are associated with a 1.8-percentage-point higher monthly return during the industry crisis period than their counterparts without a strong culture.

In summary, consistent with ample survey/interview evidence in prior work (e.g., Guiso, Sapienza, and Zingales 2015; Graham et al. 2018, 2019), we show that corporate culture correlates with all aspects of business operations, including operational efficiency, risk-taking, earnings management, executive compensation design, and firm value, and the culture-performance link is more pronounced in bad times. We are mindful that there is no perfect identification scheme when relating corporate culture to business outcomes, so most of the findings above are mere associations.

[22] It is worth noting that our main findings remain if we hold our measure of a strong culture constant as of the 2006 year-end, before the onset of the crisis, for the financial crisis-related tests (the 2008 year-end for BP's oil spill-related tests).

5.3 Corporate culture and M&As

M&As are a setting in which employees of the merging firms with possibly conflicting values and preferences must work together to achieve synergies. If they do not share similar beliefs about the best ways of conducting business, impediments, such as mismatched corporate goals, mistrust, poor morale, and high employee stress and turnover, could hinder teamwork and coordination, thereby making post-merger integration difficult and lowering productivity. For example, in firms with a strong culture in *innovation*, creating future opportunities in the marketplace through innovation is the ultimate goal, while in firms with a strong culture in *quality*, creating value through internal improvements in efficiency and the implementation of better processes and quality enhancements is the long-range goal. Anticipating that the costs of integrating two culturally distant firms will erode or even overwhelm potential synergistic gains, we expect to see fewer deals between firms with conflicting corporate cultures. The cultural fit hypothesis thus suggests that differences in corporate cultures of firm-pairs are a key determinant of deal incidence.

On the other hand, corporate culture may play a limited role in M&As for a number of reasons. First, unlike deeply held national cultural values, corporate culture is path dependent and potentially can be shaped by major corporate events (Weber, Shenkar, and Raveh 1996). Nahavandi and Malekzadeh (1988) and Cartwright and Cooper (1993) highlight the process of cultural adaptation and acculturation in M&As whereby post-merger integration leads to some degree of change in merging firms' cultures and practices. Second, a shorter cultural distance between firm pairs does not necessarily imply cultural congruence, as congruence also can be achieved by complementarity, and not always via similarity; compatible culture does not mean similar culture (Weber, Shenkar, and Raveh 1996; Krishnan, Miller, and Judge 1997). Finally, according to the *q*-theory of mergers (Jovanovic and Rousseau 2002), contracts, economic incentives, and takeovers might fully resolve any organizational differences, leaving no role for corporate culture in M&As. The acculturation hypothesis thus predicts that merging firms with different cultures will develop a jointly determined culture.

5.3.1 Measures of cultural fit and/or conflict.

We employ two commonly used summary measures of cultural distance. *Cultural similarity* is the cosine similarity between two five-by-one vectors capturing the cultural values of a firm-pair. The higher the value of this summary measure, the closer corporate culture is between a firm-pair. *Cultural distance* is the square root of the sum of squared differences between a firm-pair across all five cultural values (i.e., the Euclidean distance). The lower the value of this summary measure, the closer corporate culture is between a firm-pair.

5.3.2 Corporate cultural values and acquisitiveness.

Our sample comprises all U.S. deals completed from January 1, 2003, to December 31, 2018, and reported in Thomson Reuters' SDC database.[23]

Table 8, panel A, presents coefficient estimates from a linear probability model (LPM) and a conditional logit model (Clogit) to predict acquirers using three different samples: the entire Compustat population of firm-years with cultural values; acquirers and their industry- and size-matched control firms;[24] and acquirers and their industry-, size-, and B/M-matched control firms.

Across different specifications, we find that firms scoring high on the cultural values of *innovation* and *respect* are more likely to be acquirers, whereas firms scoring high on the

[23] Table IA8 in the Internet Appendix presents an overview of the acquirer sample and the pair sample used in the deal incidence and merger pairing analysis, respectively. Table IA9 presents the summary statistics for the acquirer sample and the pair sample.

[24] First, to form the industry- and size-matched control firms, for each acquirer of a deal announced in year t, we find up to five matching acquirers by industry—where the industry definitions are based on the narrowest SIC grouping that includes at least five firms—and by size from Compustat/CRSP in year $t-1$ for firms that were neither an acquirer nor a target firm in the 3-year period prior to the deal. We further require that control firms' size be within [0.5, 1.5] times that of the event firm. In the end, 50% (17%) acquirers are matched at the four-digit (three-digit) SIC industry level, 53% (17%) target firms are matched at the four-digit (three-digit) SIC industry level, and the remainder are at the two-digit SIC industry level.

cultural values of *integrity* and *quality* are less likely to be acquirers (with the exception of columns 2 and 3 for *innovation*). In terms of economic significance, using the specification in column 4, we find that when the cultural value of *innovation* (*respect*) increases by one standard deviation, the likelihood of a firm becoming an acquirer increases by 0.68% (2.38%), whereas when the cultural value of *integrity* (*quality*) increases by one standard deviation, the likelihood of a firm becoming an acquirer decreases by 2.34% (1.13%). In contrast, when the value of leverage (past return) increases by one standard deviation, the likelihood of a firm becoming an acquirer decreases (increases) by 2.67% (1.57%). The effect of cultural values is clearly economically significant.[25]

Other findings not directly related to corporate culture are nonetheless consistent with prior work in M&As (e.g., Moeller, Schlingemann, and Stulz 2004; Li, Qiu, and Shen 2018). In particular, we show that firms with better operating performance, faster sales growth, stronger prior year returns, and higher institutional ownership are more likely, whereas firms with higher leverage are less likely, to be acquirers.

[Insert Table 8 about here]

5.3.3 Cultural fit and merger pairing.

Table 8, panel B, presents coefficient estimates from a conditional logit model to predict merger pairs.[26] We find that firms closer in cultural values are more likely to do a deal together, whereas firms farther apart in cultural values are less likely to do so, which supports our cultural fit hypothesis. We further find that firms headquartered in the same state or sharing similar product descriptions in 10-K filings (*HP similarity* as defined in Hoberg and Phillips [2016]) are more likely to do deals together.[27] In terms of economic significance,

[25] Given that no solid theory, to our knowledge, currently explains these findings, we opt to be descriptive in the paper; we leave it to future work to interpret the link between corporate cultural values and acquisitiveness.
[26] Results using the LPM are largely similar to those reported using the conditional logit model.
[27] Because of using control firms matched by industry, we do not include the indicator *Same industry* in the conditional logit model.

using the specifications in column 3 (4), we find that when the measure of *cultural similarity* (*distance*) increases by one standard deviation, the likelihood of a firm-pair becoming an acquirer-target increases (decreases) by 3.18% (4.10%). In contrast, when the two firms have their headquarters in the same state instead of different states, the likelihood of a firm-pair becoming an acquirer-target increases by 9.59%; and when the measure of product description similarity increases by one standard deviation, the likelihood of a firm-pair becoming an acquirer-target increases by 13.12%.[28] The effect of cultural similarity is clearly economically significant.

Overall, Table 8, panel B, provides strong evidence in support of our cultural fit hypothesis that firms sharing similar corporate culture are more likely to do deals together.

5.3.4 Post-merger acculturation.

In the field of anthropology and cross-cultural psychology, acculturation is generally defined as "changes induced in (two cultural) systems as a result of the diffusion of cultural elements in both directions" (Berry 1980, p. 215). We conjecture that a successful merger will also involve members of the acquirer and the target firm adapting to each other and resolving emergent conflicts; thus, the merger itself could also shape corporate culture.

To explore acculturation, we require that acquirers not engage in any other significant deals for 1 year (3 years) after the focal deal's completion. The sample consists of 492 (335) deals 1 year (3 years) after deal completion. As suggested by Table 8, panel B, and noted above, acquirers' cultural values are positively associated with those of their target firms' premerger. To extract a target-specific culture distinct from that of its acquirer in such a corporate culture match, we run an ordinary least squares (OLS) regression where a specific cultural value of the target in the year prior to the deal announcement is the dependent

[28] The conditional logit model does not allow us to calculate the marginal effects. For deal probability, we estimate an equivalent (unconditional) logit model with deal fixed effects and compute the economic magnitude using the average marginal effect of the independent variable multiplied by the standard deviation of the variable (if continuous) or by one (if binary).

variable, and the corresponding cultural value of the acquirer and acquirer characteristics in the year prior to the deal announcement are the explanatory variables. The residual is the target-specific cultural value after controlling for cultural congruency between the acquirer and its target. If corporate events like M&As also shape corporate culture, we expect the culture of the combined firm to be significantly associated with the premerger target-specific culture.

Table 8, panel C, provides some suggestive evidence. We show that within either the 1-year or the 3-year period after deal completion, the acquirer's cultural values are significantly related to both the acquirer's and the target's premerger cultural values, after controlling for acquirer-target matching in cultural values. We conclude that mergers help acquirers create a new jointly determined culture, consistent with our acculturation hypothesis.

6. Conclusions

This paper shows that word embedding (Mikolov et al. 2013), a natural language model based on artificial neural networks, can learn the context-specific meanings of words and phrases. Using this model, we propose a new semisupervised machine learning approach to generating a culture dictionary and quantifying corporate disclosures. We apply our method to 209,480 earnings call transcripts and obtain scores for the top-five corporate cultural values proposed by Guiso, Sapienza, and Zingales (2015)—*innovation*, *integrity*, *quality*, *respect*, and *teamwork*—for 62,664 firm-year observations over the period 2001–2018. We conduct a large number of tests to validate our measure and demonstrate the advantages of our method over several alternative approaches. We show that corporate culture correlates with business outcomes, including operational efficiency, risk-taking, earnings management, executive compensation design, and firm value. The culture-performance link is more pronounced in bad times. Finally, we show that corporate culture plays an important role in deal incidence and merger pairing, and that post-merger, acquirers' cultural values are positively associated with their target firms' premerger cultural values, suggesting that corporate culture is shaped by major corporate events, such as M&As. We conclude that machine learning is useful for measuring corporate culture and holds promise for more applications in social sciences.

Appendix
Table A1. Variable definitions

Variable	Definition
Culture variables	
Innovation	Weighted-frequency count of innovation-related words in the QA section of earnings calls averaged over a 3-year window
Integrity	Weighted-frequency count of integrity-related words in the QA section of earnings calls averaged over a 3-year window
Quality	Weighted-frequency count of quality-related words in the QA section of earnings calls averaged over a 3-year window
Respect	Weighted-frequency count of respect-related words in the QA section of earnings calls averaged over a 3-year window
Teamwork	Weighted-frequency count of teamwork-related words in the QA section of earnings calls averaged over a 3-year window
[Cultural value]_full	Weighted-frequency count of [cultural value]-related words in earnings calls averaged over a 3-year window
[Cultural value]_seed	Weighted-frequency count of [cultural value]-related seed words and the [Cultural value] word based on a simple count in the QA section of earnings calls averaged over a 3-year window
[Cultural value]_10K	Weighted-frequency count of [cultural value]-related words in the MD&A section of 10-K averaged over a 3-year window
Strong culture	An indicator variable that takes the value of one if the sum of a firm's five cultural values is in the top quartile across all Compustat firms in a year, and zero otherwise
Cultural similarity	Cosine similarity between firm *a* and firm *b*'s culture vectors [$innovation_a$, $integrity_a$, $quality_a$, $respect_a$, $teamwork_a$] and [$innovation_b$, $integrity_b$, $quality_b$, $respect_b$, $teamwork_b$]. A higher value indicates similar cultures
Cultural distance	Euclidean distance between firm *a* and firm *b*'s culture vectors [$innovation_a$, $integrity_a$, $quality_a$, $respect_a$, $teamwork_a$] and [$innovation_b$, $integrity_b$, $quality_b$, $respect_b$, $teamwork_b$]. The culture scores are first standardized by subtracting the mean and dividing by the standard deviation of each year. A lower value indicates similar cultures
Validation variables	
Backdating	An indicator variable that takes the value of one if option grants to a firm's CEO are backdated, and zero otherwise. To identify backdating, we follow Heron and Lie (2009), whose estimation methodology rests on the assumption that, in the absence of backdating or other types of grant date manipulation, the distributions of stock returns during the month before and after grant dates should be roughly the same, implying that the distribution of return differences should be centered on zero. The data on option grants to CEOs come from Thomson Reuters' Insider Filing database
Best employer	An indicator variable that takes the value of one if a firm is included in "100 Best Companies to Work for in America" list, and zero otherwise. Fortune compiles the ranking based on the following methodology (Edmans 2011). Two-thirds of the score comes from employee responses to a 57-question survey created by the Great Place to Work Institute in San Francisco, which covers a variety of topics, such as attitudes toward management, job satisfaction, fairness, and camaraderie. The remaining one-third of the score comes from the Institute's evaluation of firm factors, such as a firm's demographic makeup, pay and benefits programs, and culture. The final score covers four areas: credibility (communication to employees), respect (opportunities and benefits), fairness (compensation, diversity), and pride/camaraderie (teamwork, philanthropy, celebrations). The list is available until 2017
Diversity	The number of diversity strengths minus the number of diversity concerns as reported by KLD database. The last year of data availability is 2016

Employee involvement	An indicator variable that takes the value of one if a firm is considered to have strengths in employee involvement, and zero otherwise. KLD (2006) defines employee involvement as "the company strongly encourages worker involvement and/or ownership through stock options available to a majority of its employees; gain sharing, stock ownership, sharing of financial information, or participation in management decision making." The last year of data availability is 2016
Innovation strength	An indicator variable that takes the value of one if a firm is considered to have strengths in innovation and R&D, and zero otherwise. KLD (2006) defines strength in innovation as "the company is a leader in its industry for research and development (R&D), particularly by bringing notably innovative products to market." The last year of data availability is 2016
ln(Patent)	Natural logarithm of one plus the number of patents filed and eventually granted in a year. The data come from Kogan et al. (2017), and the last year of data availability is 2010 (https://iu.app.box.com/v/patents)
Product quality	An indicator variable that takes the value of one if a firm is considered to have strengths in product quality, and zero otherwise. KLD (2006) defines strength in product quality as "the company has a long-term, well-developed, company-wide quality program, or it has a quality program recognized as exceptional in U.S. industry." The last year of data availability is 2016
Product safety	An indicator variable that takes the value of one if a firm is not considered to have concerns in product safety, and zero otherwise. KLD (2006) defines concerns in product safety as "the company has recently paid substantial fines or civil penalties, or is involved in major recent controversies or regulatory actions, relating to the safety of its products and services." The last year of data availability is 2016
R&D spending	R&D expenses divided by total assets
Restatement	An indicator variable that takes the value of one if a firm later restates its (annual or quarterly) financial statements, and zero otherwise. The data come from Audit Analytics
Top brand	An indicator variable that takes the value of one if a firm is included in the top 500 list of Brand Finance rankings, and zero otherwise. The list is constructed by Brand Finance (http://brandirectory.com/) and is available from 2007 to 2017
Number of JVs/SAs	The number of joint ventures (JV) or strategic alliances (SA) established in a year. The data come from Thomson Reuters' SDC database and available until 2018
Implication variables	
Assets turnover	Sales divided by total assets
Inventory turnover	Cost of goods sold divided by inventory
Stock return volatility	Standard deviation of monthly stock returns in a year
Discretionary accrual	Estimated using modified Jones' (1991) model. In each year, we run the following regression within each two-digit SIC industry: $$\frac{Accrual}{TA} = \alpha + \beta \times \frac{1}{TA} + \gamma \times \frac{\Delta Sales}{TA} + \theta \times \frac{PPE}{TA}$$ $Accrual$ is net income minus net operating cash flow, TA is total assets, $\Delta Sales$ is change in sales from year t - 1 to year t, and PPE is gross amount of property, plant and equipment at the beginning of year t. Discretionary accruals is calculated as the residual of the estimation
ln(Delta)	Natural logarithm of the change in the dollar value of a CEO's stock and option portfolio with respect to a 1% change in stock price
ln(Vega)	Natural logarithm of the change in the dollar value of a CEO's stock and option portfolio with respect to a 1% change in the annualized standard deviation of stock returns, following Coles, Daniel, and Naveen (2006)
CEO pay duration	Weighted average duration of four components of a CEO's annual compensation: salary, bonus, restricted stocks, and stock options, following Gopalan et al. (2014)
Tobin's q	Sum of market value of equity and book value of debt divided by total assets
Abnormal returns	Market-model adjusted monthly stock return
Financial crisis	An indicator variable that takes the value of one for the months between August 2008 and March 2009, and zero otherwise

BP oil spill	An indicator variable that takes the value of one for the months between May 2010 and February 2011, and zero otherwise
Firm characteristics	
Firm size	Natural logarithm of total assets
Book-to-market (B/M)	Book value of equity divided by market value of equity
Leverage	Book value of debt divided by the sum of market value of equity and book value of debt
ROA	Income before extraordinary items divided by total assets
Sales growth	Growth rate of sales, calculated as (sales in year t – sales in year t - 1)/sales in year t - 1
Past return	Buy-and-hold stock return in the year prior to deal announcement
Top-5 institutions	Fraction of shares outstanding held by the five largest institutional investors prior to deal announcement
Deal characteristics	
Same industry	An indicator variable that takes the value of one if an acquirer is from the same Fama-French 12 industry as its target firm, and zero otherwise
Same state	An indicator variable that takes the value of one if an acquirer's and its target's headquarters are in the same state, and zero otherwise
HP similarity	Acquirer-target pairwise similarity scores from Hoberg and Phillips (2016)

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Figure 1
Cultural values across 12 Fama-French industries over time

This figure plots the five cultural values across 12 Fama-French industries over time. The *y*-axis represents the average cultural value across firms within each industry. The *x*-axis represents the years over the period from 2001 to 2018.

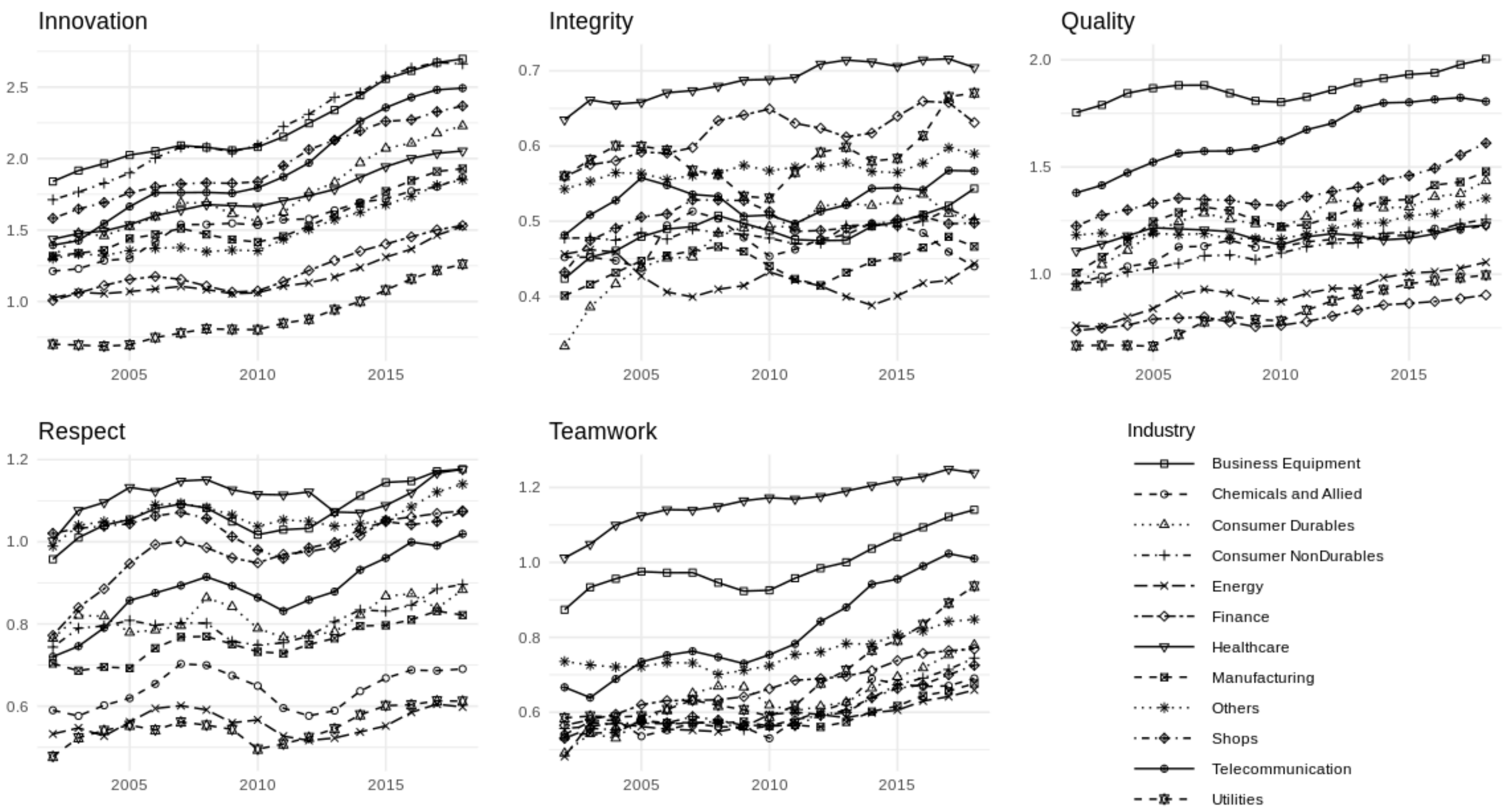

Table 1
Sample formation

This table reports the impact of various matching steps and data filters on the initial conference call transcript sample. Numbers in boldface indicate the number of observations remaining at each major matching stage. We obtain conference call transcripts from Thomson Reuters' StreetEvents (SE) database for the period January 1, 2001, to May 25, 2018.

	# firm-year obs.		# firm-year obs. removed	# transcripts	# transcripts removed
Match company names in call transcripts to GVKEY					
All conference call transcripts				391,091	
Earnings call transcripts				270,879	120,212
Transcripts matched with GVKEY	**66,371**			**221,209**	49,670
Including					
Perfect match with CRSP company name		21,627			
Perfect match with Compustat company name		7,355			
Perfect match with Compustat-CRSP merged		1,238			
Ticker matching if not subject to backfilling		559			
Manual matching if no perfect match		35,075			
Nonduplicated company name in brief files		517			
Transcripts without the QA section	65,247		1,124	214,295	6,914
Transcripts with fewer than 200 words in the QA section	**64,511**		736	**209,480**	4,815
Sample formation for Table 3					
After applying 3-year rolling average	84,144				
After imposing fiscal year ≤ 2018	76,232		7,912		
After matching with financial data	62,664		13,568		
Final sample	**62,664**				

Table 2
Thirty most representative and most frequently occurring words in the culture dictionary

Panel A lists the 30 most representative words in order by descending similarity to seed words for each cultural value. Panel B lists the 30 most frequently occurring words for each cultural value, with the frequency (%) being the tf.idf weighted word count.

A. Thirty most representative words for each cultural value in the culture dictionary

Innovation	Integrity	Quality	Respect	Teamwork
Creativity	Accountability	Dedicated	Talented	Collaborate
Innovative	Ethic	Quality	Talent	Cooperation
Innovate	Integrity	Dedication	Empower	Collaboration
Innovation	Responsibility	Customer_service	Team_member	Collaborative
Creative	Transparency	Customer	Employee	Cooperative
Excellence	Accountable	Dedicate	Team	Partnership
Passion	Governance	Service_level	Leadership	Cooperate
World-class	Ethical	Mission	Leadership_team	Collaboratively
Technology	Transparent	Service_delivery	Culture	Partner
Operational_excellence	Trust	Customer_satisfaction	Teammate	Co-operation
Passionate	Responsible	Service	Organization	Coordination
Product_innovation	Oversight	Reliability	Entrepreneurial	Engage
Capability	Independence	Commitment	Skill	Jointly
Customer_experience	Objectivity	Customer_need	Executive	Coordinate
Thought_leadership	Moral	Customer_support	Empowerment	Teamwork
Expertise	Trustworthy	High-quality	Management_team	Business_partner
Agility	Fairness	Ensure	Best_brightest	Alliance
Efficient	Hold_accountable	Customer_relationship	Professionalism	Team_up
Technology_innovation	Corporate_governance	Quality_service	Staff	Technology_partner
Competency	Autonomy	Product_quality	Highly_skilled	Joint
Know-how	Core_value	Quality_product	Skill_set	Cooperatively
Cutting-edge	Assure	Capable	Technologist	Relationship
Agile	Stakeholder	Service_quality	Competent	Collaborator
Creatively	Fiduciary_responsibility	End_user	Entrepreneur	Interaction
Customer-centric	Continuity	Quality_level	Experienced	Working_relationship
Enable	Credibility	Customer_expectation	Energize	Co-operate
Value_proposition	Honesty	Service_capability	Entrepreneurial_spirit	Technology_partnership
Reinvent	Privacy	Client	High-caliber	Association
Focus	Fiduciary_duty	Customer_requirement	Manager	Dialogue

Innovation_capability	Rigor	Sla	Leadership_skill	Dialog

B. Thirty most frequently occurring words for each cultural value in the culture dictionary

Innovation			Integrity			Quality			Respect			Teamwork		
Word	%	Cum. %	Word	%	Cum. %	Word	%	Cum. %	Word	%	Cum. %	Word	%	Cum.%
Brand	4.24	4.24	Control	5.81	5.81	Customer	9.22	9.22	People	5.91	5.91	Partner	6.01	9.22
Technology	3.08	7.32	Management	4.93	10.74	Product	8.09	17.31	Team	5.10	11.00	Relationship	5.36	17.31
Focus	3.02	10.34	Careful	3.46	14.19	Client	5.99	23.30	Company	5.00	16.00	Discussion	5.22	23.30
Great	2.73	13.08	Honestly	2.71	16.90	Service	4.72	28.02	Hire	3.78	19.78	Together	4.61	28.02
Platform	2.53	15.61	Regulator	2.68	19.58	Build	4.09	32.11	Folk	3.61	23.39	Integrate	4.07	32.11
Ability	2.41	18.02	Honest	2.43	22.01	Deliver	3.42	35.54	Organization	3.39	26.78	Involve	3.77	35.54
Best	2.37	20.39	Safety	2.09	24.10	Network	3.30	38.84	Resource	3.11	29.89	Conversation	3.73	38.84
Design	2.19	22.58	Assure	2.01	26.11	Support	3.12	41.96	Employee	2.96	32.86	Integration	3.24	41.96
Create	2.18	24.76	Compliance	1.88	27.98	Quality	2.40	44.36	Management_team	1.91	34.77	Partnership	3.17	44.36
Solution	2.16	26.92	Trust	1.87	29.86	Sales_force	2.31	46.68	Train	1.88	36.65	Engage	2.65	46.68
Develop	2.12	29.04	Disciplined	1.82	31.68	Infrastructure	2.27	48.94	Training	1.81	38.46	Align	2.07	48.94
Success	2.00	31.04	Responsible	1.71	33.39	Supplier	2.21	51.16	Senior	1.80	40.26	Explore	1.79	51.16
Content	1.99	33.03	Proper	1.62	35.01	Serve	2.15	53.31	Staff	1.80	42.06	Communication	1.77	53.31
Capability	1.97	35.00	Responsibility	1.61	36.62	Commit	2.10	55.41	Member	1.79	43.85	Dialogue	1.67	55.41
Effort	1.92	36.92	Thoughtful	1.55	38.17	Field	2.09	57.51	Leader	1.63	45.48	Engagement	1.61	57.51
Successful	1.80	38.72	Convince	1.50	39.67	Commitment	1.95	59.46	Person	1.53	47.01	Contact	1.49	59.46
Efficiency	1.67	40.39	Seriously	1.48	41.15	Delivery	1.90	61.36	Proud	1.44	48.45	Conduct	1.41	61.36
Productivity	1.64	42.03	Transparent	1.48	42.63	Vendor	1.85	63.21	Talent	1.41	49.86	On_behalf_of	1.38	63.21
Learn	1.56	43.59	Expert	1.45	44.08	Customer_base	1.80	65.01	Leadership	1.38	51.24	Joint	1.16	65.01
Unique	1.49	45.08	Consistency	1.41	45.50	Supply_chain	1.65	66.66	Manager	1.34	52.58	Collaboration	1.12	66.66
Tool	1.42	46.50	Candidly	1.40	46.90	Critical	1.47	68.13	CEO	1.31	53.89	Sponsor	1.09	68.13
Innovation	1.42	47.92	Transparency	1.39	48.29	Requirement	1.46	69.59	Knowledge	1.28	55.17	Conjunction	1.01	69.59
Efficient	1.39	49.31	Authority	1.17	49.46	Ensure	1.37	70.96	Engineer	1.23	56.41	Supportive	1.00	70.96
Terrific	1.35	50.66	Responsive	1.12	50.57	Speed	1.30	72.26	Recruit	1.20	57.61	Alliance	0.96	72.26
Execution	1.30	51.96	Truth	1.10	51.68	Desire	1.07	73.33	Salespeople	1.16	58.76	Merge	0.91	73.33
Exciting	1.29	53.24	Principle	1.06	52.74	Productive	1.06	74.39	Sales_team	1.11	59.87	Interaction	0.90	74.39
Enhance	1.24	54.48	Comply	1.00	53.74	Guest	0.92	75.31	Consultant	1.00	60.87	Put_together	0.86	75.31
Business_model	1.18	55.66	Board_director	0.95	54.69	Service_provider	0.88	76.19	Culture	0.93	61.80	Organize	0.85	76.19
Enable	1.13	56.79	Thorough	0.92	55.61	Capable	0.81	77.00	Sales_organization	0.89	62.69	Embrace	0.84	77.00
Discipline	1.12	57.91	Conflict	0.86	56.47	Functionality	0.80	77.80	Advisor	0.88	63.57	Assist	0.83	77.80

Table 3
Summary statistics for corporate cultural values

The sample consists of 62,664 firm-year observations (7,501 firms) with earnings calls over the period 2001–2018. Panel A provides the summary statistics. Panel B presents the autocorrelations of corporate cultural values. We calculate the autocorrelation for each firm with more than 15 observations over the sample period. We report the mean, median (in brackets), and standard deviation (in parentheses) of autocorrelations across firms. Panel C presents the correlations between corporate cultural values and firm characteristics. Table A1 in the appendix defines the variables. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Summary statistics for corporate cultural values and firm characteristics

Variable	Obs.	Mean	10th percentile	Median	90th percentile	SD
Innovation	62,664	1.737	0.692	1.488	3.141	1.029
Integrity	62,664	0.584	0.198	0.504	1.077	0.381
Quality	62,664	1.323	0.499	1.155	2.384	0.777
Respect	62,664	1.005	0.306	0.793	1.983	0.754
Teamwork	62,664	0.864	0.286	0.688	1.689	0.635
Total assets	62,664	12289	69.525	1133.0	20660	44449
Leverage	62,664	0.251	0.000	0.186	0.623	0.246
ROA	62,664	-0.027	-0.216	0.025	0.113	0.218
Sales growth	62,664	0.041	-0.201	0.067	0.311	0.320
Top-5 institutions	62,664	0.203	0.000	0.224	0.402	0.166

B. Autocorrelations of corporate cultural values

Variable in year *t*	Obs.	Year *t*-1	Year *t*-2	Year *t*-3	Year *t*-4	Year *t*-5
		0.790	0.512	0.190	0.090	0.045
Innovation	1,971	[0.828]	[0.559]	[0.203]	[0.071]	[0.031]
		(0.151)	(0.301)	(0.441)	(0.475)	(0.500)
		0.695	0.361	-0.037	-0.085	-0.103
Integrity	1,971	[0.728]	[0.378]	[-0.071]	[-0.141]	[-0.160]
		(0.179)	(0.292)	(0.397)	(0.405)	(0.434)
		0.738	0.417	0.052	-0.023	-0.051
Quality	1,971	[0.776]	[0.442]	[0.029]	[-0.082]	[-0.116]
		(0.169)	(0.311)	(0.427)	(0.442)	(0.479)
		0.709	0.370	-0.020	-0.090	-0.121
Respect	1,971	[0.744]	[0.393]	[-0.049]	[-0.146]	[-0.194]
		(0.173)	(0.300)	(0.401)	(0.413)	(0.445)
		0.728	0.405	0.033	-0.047	-0.081
Teamwork	1,971	[0.758]	[0.423]	[0.004]	[-0.103]	[-0.126]
		(0.166)	(0.296)	(0.411)	(0.426)	(0.451)

C. The correlation matrix

	Innovation	Integrity	Quality	Respect	Teamwork	Firm size	Leverage	ROA	Sales growth	Top-5 institutions
Innovation	1.000									
Integrity	0.109***	1.000								
Quality	0.490***	0.023***	1.000							
Respect	0.321***	0.269***	0.317***	1.000						
Teamwork	0.371***	0.276***	0.271***	0.258***	1.000					
Firm size	-0.186***	-0.010**	-0.261***	-0.255***	-0.309***	1.000				
Leverage	-0.282***	0.024	-0.276***	-0.170***	-0.199***	0.360***	1.000			
ROA	-0.105***	-0.130***	-0.069***	-0.093***	-0.352***	0.403***	-0.035***	1.000		
Sales growth	0.008*	-0.047***	0.017***	0.033***	-0.025***	0.057***	-0.076***	0.222***	1.000	
Top-5 institutions	0.059***	-0.096***	0.018***	0.033***	-0.081***	0.027***	-0.084***	0.145***	0.050***	1.000

Table 4
Top- and bottom-ranked S&P 500 firms by corporate cultural values

This table presents a snapshot of top- and bottom-ranked S&P 500 firms by corporate cultural values. Panel A presents the top- and bottom-ranked S&P 500 firms over the period 2001–2006. Panel B presents the top- and bottom-ranked S&P 500 firms over the period 2007–2012. Panel C presents the top- and bottom-ranked S&P 500 firms over the period 2013–2018.

A. Top- and bottom-ranked S&P 500 firms, 2001–2006

Innovation	Integrity	Quality	Respect	Teamwork
		Top		
Procter & Gamble Co	Fannie Mae	Cognizant Tech Solutions	Cognizant Tech Solutions	First Data Corp
Nvidia Corp	Franklin Resources Inc	Juniper Networks Inc	Tapestry Inc	Silicon Graphics Inc
Gap Inc	Kate Spade & Co	Paychex Inc	Aflac Inc	McKesson Corp
Lauder (Estee) Cos Inc	Encompass Health Corp	Akamai Technologies Inc	Tupperware Brands Corp	Northwest Airlines Corp
PTC Inc	Synovus Financial Corp	Convergys Corp	Monster Worldwide Inc	Altaba Inc
Penney (JC) Co	Northwest Airlines Corp	IMS Health Holdings Inc	Robert Half Intl Inc	GenOn Energy Inc
Harman International Inds	EMCOR Group Inc	Ryder System Inc	Health Management Assoc	American Airlines Group Inc
Home Depot Inc	Exelon Corp	C H Robinson Worldwide Inc	Paychex Inc	Novell Inc
Kate Spade & Co	Service Corp International	PTC Inc	Sapient Corp	Express Scripts Holding Co
BroadVision Inc	Compuware Corp	AutoZone Inc	Encompass Health Corp	Kate Spade & Co
		Bottom		
Luby’s Inc	VF Corp	Tribune Media Co	Calpine Corp	Agilent Technologies Inc
Genuine Parts Co	Luby’s Inc	Emerson Electric Co	Target Corp	Intel Corp
Univision Communications	M & T Bank Corp	Northrop Grumman Corp	Lennar Corp	Emerson Electric Co
Patterson Cos Inc	Amazon.Com Inc	eBay Inc	Vulcan Materials Co	Vulcan Materials Co
Archer-Daniels-Midland Co	TECO Energy Inc	Disney (Walt) Co	Plum Creek Timber Co Inc	Microchip Technology Inc
Tyson Foods Inc	Bristol-Myers Squibb Co	SanDisk Corp	Loews Corp	Calpine Corp
Automatic Data Processing	Bausch & Lomb Hldgs	Calpine Corp	Genuine Parts Co	Bausch & Lomb Hldgs
Texas Instruments Inc	Regions Financial Corp	Danaher Corp	M & T Bank Corp	Corning Inc
Tribune Media Co	Citigroup Inc	GameStop Corp	Weyerhaeuser Co	Luby’s Inc
CenturyLink Inc	Equity Residential	Charming Shoppes Inc	HSBC Finance Corp	Abbott Laboratories

B. Top- and bottom-ranked S&P 500 firms, 2007–2012

Innovation	Integrity	Quality	Respect	Teamwork
		Top		
Nvidia Corp	Tribune Media Co	Express Scripts Holding Co	Tupperware Brands Corp	American Airlines Group Inc
Procter & Gamble Co	Wynn Resorts Ltd	Juniper Networks Inc	Salesforce.com Inc	Avaya Inc
Adobe Inc	Beam Inc	Convergys Corp	Chipotle Mexican Grill Inc	Express Scripts Holding Co
Discovery Inc	Ambac Financial Group Inc	Akamai Technologies Inc	Janus Capital Group Inc	Intercontinental Exchange
Lauder (Estee) Cos Inc	Intercontinental Exchange	Cognizant Tech Solutions	Tapestry Inc	Novell Inc
Netflix Inc	Lockheed Martin Corp	Paychex Inc	Fastenal Co	Genentech Inc
Salesforce.com Inc	Exelon Corp	Salesforce.com Inc	Humana Inc	Steel Excel Inc
VF Corp	American Electric Power Co	Palm Inc	Adtalem Global Education Inc	Red Hat Inc
Fossil Group Inc	Kate Spade & Co	FedEx Corp	BMC Software Inc	United Airlines Holdings Inc
Kate Spade & Co	Lorillard Inc	IMS Health Holdings Inc	Robert Half Intl Inc	Medco Health Solutions Inc
		Bottom		
Genuine Parts Co	Bausch & Lomb Hldgs	Twenty-First Century Fox Inc	Ross Stores Inc	Bausch & Lomb Hldgs
CVS Health Corp	Public Storage	First Data Corp	Plum Creek Timber Co Inc	Emerson Electric Co
Univision Communications	Sigma-Aldrich Corp	Emerson Electric Co	Centex Corp	Lexmark Intl Inc
Archer-Daniels-Midland Co	Wyndham Destinations Inc	Danaher Corp	National City Corp	Centex Corp
American Greetings	VF Corp	DXC Technology Co	AES Corp (The)	Intel Corp
Texas Instruments Inc	Equity Residential	EW Scripps	Vulcan Materials Co	Molex Inc
Ryerson Holding Corp	Winn-Dixie Stores Inc	CBS Corp	Bausch & Lomb Hldgs	Automatic Data Processing
DXC Technology Co	Host Hotels & Resorts Inc	Micron Technology Inc	Fannie Mae	Ross Stores Inc
Patterson Cos Inc	Spire Inc	Disney (Walt) Co	Micron Technology Inc	Stryker Corp
Cintas Corp	Luby's Inc	Univision Communications	Rohm and Haas Co	QLogic Corp

C. Top- and bottom-ranked S&P 500 firms, 2013–2018

Innovation	**Integrity**	**Quality**	**Respect**	**Teamwork**
		Top		
Netflix Inc	Blackrock Inc	Blackrock Inc	Salesforce.com Inc	Cigna Corp
Fossil Group Inc	Wynn Resorts Ltd	Target Corp	Tupperware Brands Corp	Twitter Inc
Nike Inc	Ambac Financial Group Inc	Paychex Inc	Gartner Inc	Facebook Inc
Lauder (Estee) Cos Inc	Big Lots Inc	Ulta Beauty Inc	Raymond James Financial	Blackrock Inc
Procter & Gamble Co	Intercontinental Exchange	Donnelley (R R) & Sons Co	Primerica Inc	Salesforce.com Inc
Adobe Inc	Gap Inc	MSCI Inc	Tapestry Inc	Quest Diagnostics Inc
Salesforce.com Inc	Genworth Financial Inc	Equinix Inc	Under Armour Inc	Activision Blizzard Inc
Acuity Brands Inc	U.S. Bancorp	Interpublic Group of Cos	Chipotle Mexican Grill Inc	Citrix Systems Inc
Twitter Inc	News Corp	FedEx Corp	Advance Auto Parts Inc	Global Payments Inc
Facebook Inc	United States Steel Corp	Digital Realty Trust Inc	Ameriprise Financial Inc	Freeport-McMoRan Inc
		Bottom		
Archer-Daniels-Midland Co	National Fuel Gas Co	AMETEK Inc	Ross Stores Inc	Emerson Electric Co
Genuine Parts Co	Idexx Labs Inc	CBS Corp	Micron Technology Inc	Mettler-Toledo Intl Inc
FleetCor Technologies Inc	Cooper Cos Inc (The)	EW Scripps	Texas Instruments Inc	AMETEK Inc
Univision Communications	SBA Communications Corp	Emerson Electric Co	Avis Budget Group Inc	Texas Instruments Inc
LKQ Corp	IDACORP Inc	Tribune Media Co	Maxim Integrated Products	Cooper Cos Inc (The)
Philip Morris International	ONEOK Inc	Raytheon Co	Home Depot Inc	Hologic Inc
Cintas Corp	Ryder System Inc	Danaher Corp	Prologis Inc	Henry (Jack) & Associates
Costco Wholesale Corp	CenterPoint Energy Inc	Costco Wholesale Corp	Citigroup Inc	Boston Scientific Corp
Emerson Electric Co	Williams Cos Inc	TransDigm Group Inc	Teradyne Inc	Edwards Lifesciences Corp
Texas Instruments Inc	Public Storage	eBay Inc	Crown Castle Intl Corp	Ryder System Inc

Table 5
Validating our main measure of corporate cultural values

This table validates our main measure of corporate cultural values based on the QA section of calls. In panel A, ln(Patent), R&D spending, and innovation strength are used to validate the cultural value of innovation. In panel B, restatement and backdating are used to validate the cultural value of integrity. In panel C, product quality, product safety, and top brand are used to validate the cultural value of quality. In panel D, diversity and best employer are used to validate the cultural value of respect. In panel E, employee involvement and the number of JVs/SAs are used to validate the cultural value of teamwork. Ordinary least squares (OLS) regressions are used when the dependent variables are ln(Patent), R&D spending, diversity, and the number of JVs/SAs, and probit regressions are used for all other validating variables. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Incremental R^2/pseudo R^2 gives the increase in model fit from adding the variable of interest (our measure for a particular cultural value) to the regression specification. Table A1 in the appendix defines the variables. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm level. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Validating the cultural value of innovation

	ln(Patent) (1)	ln(Patent) (2)	ln(Patent) (3)	R&D spending (4)	R&D spending (5)	R&D spending (6)	Innovation strength (7)	Innovation strength (8)	Innovation strength (9)
Innovation	0.183***	0.183***	0.098***	0.015***	0.013***	0.008***	0.194***	0.191***	0.131*
	(0.018)	(0.018)	(0.017)	(0.001)	(0.001)	(0.001)	(0.051)	(0.051)	(0.076)
Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes	No	No	Yes
Ind FE/yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,298	25,298	25,298	62,584	62,584	62,584	11,500	11,500	7,676
R^2/pseudo R^2	.036	.036	.166	.211	.459	.571	.035	.038	.154
Incremental R^2	.0301	.0303	.0075	.0170	.0133	.0038			
Incremental pseudo R^2							.0173	.0166	.0053

B. Validating the cultural value of integrity

	Restatement (1)	Restatement (2)	Restatement (3)	Backdating (4)	Backdating (5)	Backdating (6)
Integrity	-0.105***	-0.098***	-0.060*	-0.237***	-0.206***	-0.228***
	(0.031)	(0.031)	(0.031)	(0.049)	(0.049)	(0.050)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/yr FE	No	No	Yes	No	No	Yes

Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	50,452	50,452	50,452	17,671	17,671	17,671
Pseudo R^2	.001	.001	.022	.014	.019	.042
Incremental pseudo R^2	.0008	.0006	.0002	.0037	.0027	.0030

C. Validating the cultural value of quality

	Product quality	Product quality	Product quality	Product safety	Product safety	Product safety	Top brand	Top brand	Top brand
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quality	0.009	0.003	-0.068	0.153***	0.174***	0.262***	0.399***	0.369***	0.207***
	(0.033)	(0.033)	(0.052)	(0.039)	(0.040)	(0.063)	(0.044)	(0.044)	(0.057)
Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Ind FE/yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,285	18,285	18,285	21,341	21,341	21,341	40,917	40,917	40,917
Pseudo R^2	0078	.079	.235	.109	.117	.232	.437	.452	.498
Incremental pseudo R^2	.0000	.0000	.0005	.0040	.0049	.0063	.0205	.0163	.0033

D. Validating the cultural value of respect

	Diversity	Diversity	Diversity	Best employer	Best employer	Best employer
	(1)	(2)	(3)	(4)	(5)	(6)
Respect	0.098***	0.098***	0.092***	0.212***	0.221***	0.205***
	(0.023)	(0.023)	(0.023)	(0.055)	(0.060)	(0.064)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/yr FE	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,385	19,385	19,385	54,603	54,603	52,930
R^2/pseudo R^2	.168	.168	.308	.091	135	.196
Incremental R^2	.0025	.0025	.0020			
Incremental pseudo R^2				.0136	.0139	.0100

E. Validating the cultural value of teamwork

	Employee involvement (1)	Employee involvement (2)	Employee involvement (3)	Number of JV/SA (4)	Number of JVs/SAs (5)	Number of JVs/SAs (6)
Teamwork	0.340***	0.360***	0.188***	0.009***	0.008***	0.010***
	(0.043)	(0.046)	(0.052)	(0.001)	(0.001)	(0.001)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/yr FE	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,262	17,262	17,262	62,584	62,584	62,584
R^2/pseudo R^2	.055	.056	.127	.021	.021	.029
Incremental R^2				.0011	.0008	.0011
Incremental pseudo R^2	.0159	.0164	.0034			

Table 6
Validating alternative measures of corporate cultural values

This table validates alternative measures of corporate cultural values. The suffix _full refers to the measure based on the entire call (i.e., including both management presentation and QA sections). The suffix _seed refers to the measure based on a simple count of the seed words (including the value word) in the QA section of calls. The suffix _10k refers to the measure based on applying the word embedding model to the MD&A section of 10-Ks. In panel A, ln(Patent), R&D spending, and innovation strength are used to validate the cultural value of innovation. In panel B, restatement and backdating are used to validate the cultural value of integrity. In panel C, product quality, product safety, and top brand are used to validate the cultural value of quality. In panel D, diversity and best employer are used to validate the cultural value of respect. In panel E, employee involvement and the number of JVs/SAs are used to validate the cultural value of teamwork. OLS regressions are used when the dependent variables are ln(Patent), R&D spending, diversity, and the number of JVs/SAs, and probit regressions are used for all other validating variables. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Incremental R^2/pseudo R^2 gives the increase in model fit from adding the variable of interest (our measure for a particular cultural value) to the regression specification. Table A1 in the appendix defines the variables. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm level. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Validating alternative measures for innovation

Variable	ln(Patent) (1)	R&D spending (2)	Innovation strength (3)	ln(Patent) (4)	R&D spending (5)	Innovation strength (6)	ln(Patent) (7)	R&D spending (8)	Innovation strength (9)
Innovation_full	0.004	0.007***	0.169						
	(0.023)	(0.001)	(0.147)						
Innovation_seed				0.257*	-0.033***	-0.140			
				(0.142)	(0.008)	(0.790)			
Innovation_10k							0.073**	0.003*	0.164
							(0.033)	(0.002)	(0.120)
Size/ROA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,298	62,584	7,676	25,298	62,584	7,676	17,820	44,474	6,629
R^2/pseudo R^2	.159	.568	.151	.159	.568	.149	.214	.574	.151
Incremental R^2	.0000	.0012		.0005	.0007		.0013	.0002	
Incr. pseudo R^2			.0025			.0001			.0037

B. Validating alternative measures for integrity

Variable	Restatement (1)	Backdating (2)	Restatement (3)	Backdating (4)	Restatement (5)	Backdating (6)
Integrity_full	-0.115***	-0.569***				
	(0.040)	(0.066)				
Integrity_seed			-0.004	-0.228		
			(0.142)	(0.237)		
Integrity_10k					0.038	-0.086
					(0.036)	(0.073)
Size/ROA	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	50,452	17,671	50,452	17,671	35,823	12,427
Pseudo R^2	.022	.051	.021	.039	.023	.058
Incremental pseudo R^2	.0005	.0114	.0000	.0001	.0001	.0005

C. Validating alternative measures for quality

Variable	Product quality (1)	Product safety (2)	Top brand (3)	Product quality (4)	Product safety (5)	Top brand (6)	Product quality (7)	Product safety (8)	Top brand (9)
Quality_full	-0.157	0.362***	0.262**						
	(0.096)	(0.121)	(0.117)						
Quality_seed				0.219	0.961	1.180			
				(0.523)	(0.758)	(0.746)			
Quality_10k							-0.124	0.268***	0.358***
							(0.085)	(0.094)	(0.106)
Size/ROA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,285	21,341	40,917	18,285	21,341	40,917	15,905	18,530	29,234
Pseudo R^2	.235	.229	.496	.235	.227	.495	.234	.215	.476
Incr. pseudo R^2	.0007	.0032	.0013	.0000	.0007	.0007	.0007	.0031	.0045

D. Validating alternative measures for respect

Variable	Diversity (1)	Best employer (2)	Diversity (3)	Best employer (4)	Diversity (5)	Best employer (6)
Respect_full	0.098***	0.200*				
	(0.035)	(0.106)				
Respect_seed			0.389	2.461***		
			(0.296)	(0.690)		
Respect_10k					0.211***	0.275**
					(0.054)	(0.136)
Size/ROA	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,385	52,930	19,385	52,930	16,679	37,719
R^2/pseudo R^2	.307	.189	.306	.192	.293	.219
Incremental R^2	.0008		.0001		.0026	
Incremental pseudo R^2		.0030		.0068		.0037

E. Validating alternative measures for teamwork

Variable	Employee involvement (1)	Number of JVs/SAs (2)	Employee involvement (3)	Number of JVs/SAs (4)	Employee involvement (5)	Number of JVs/SAs (6)
Teamwork_full	0.060	0.019***				
	(0.077)	(0.003)				
Teamwork_seed			1.347**	0.085***		
			(0.529)	(0.024)		
Teamwork_10k					0.255***	0.007***
					(0.059)	(0.002)
Size/ROA	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,262	62,584	17,262	62,584	14,908	44,474
R^2/pseudo R^2	.124	.029	.125	.028	.131	.022
Incremental R^2		.0009		.0003		.0002
Incremental pseudo R^2	.0001		.0012		.0048	

Table 7
Implications of a strong corporate culture

This table examines the implications of having a strong corporate culture. Strong culture is an indicator variable that takes the value of one if the sum of a firm's five cultural values is in the top quartile across all Compustat firms in a year, and zero otherwise. In panel A, the dependent variables are different business outcomes including operational efficiency, risk-taking, earnings management, executive compensation design, and firm value. We present the OLS regression results where our measure of a strong culture is lagged 1, 3, and 5 years. In panel B, we examine the implications of having a strong corporate culture in bad times. Specifically, we examine the stock market performance of financial firms around the financial crisis and oil firms around BP's oil spill. The dependent variable is market-model-adjusted monthly returns. The financial and oil firms are identified using the Fama-French 48-industry classification. The sample period for the financial crisis-related tests is from 2007 to 2010. Financial crisis is an indicator variable that takes the value of one for the months between August 2008 and March 2009, and zero otherwise, following Lins, Servaes, and Tamayo (2017). The sample period for BP's oil spill-related tests is from 2009 to 2012. BP oil spill is an indicator variable that takes the value of one for the months between May 2010 and February 2011, and zero otherwise. OLS regressions are used in all regressions. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Table A1 in the appendix defines the variables. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm level. **p* < .1; ***p* < .05; ****p* < .01.

A. The implications of having a strong culture on business outcomes

	Assets turnover (1)	Inventory turnover (2)	Stock return volatility (3)	Discretionary accrual (4)	ln(Delta) (5)	ln(Vega) (6)	CEO pay duration (7)	Tobin's q (8)
Strong culture$_{(t-1)}$	0.052***	6.741***	0.005***	-0.917**	0.080**	0.202***	1.037***	0.043***
	(0.014)	(1.582)	(0.001)	(0.404)	(0.040)	(0.045)	(0.349)	(0.009)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	48,763	35,197	48,614	39,206	23,804	19,714	14,349	48,750
R^2	.445	.054	.429	.007	.355	.343	.135	.687
Strong culture$_{(t-3)}$	0.055***	6.316***	0.004***	-1.150**	0.133***	0.219***	0.945**	0.048***
	(0.015)	(1.708)	(0.001)	(0.506)	(0.044)	(0.051)	(0.378)	(0.009)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	36,962	27,158	36,851	29,353	19,921	16,184	11,849	36,954
R^2	.457	.056	.436	.008	.353	.325	.123	.712
Strong culture$_{(t-5)}$	0.060***	5.479***	0.005***	-1.696**	0.150***	0.209***	0.777*	0.053***

	(0.017)	(1.895)	(0.001)	(0.663)	(0.047)	(0.059)	(0.423)	(0.010)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	27,307	20,376	27,219	21,532	16,012	12,630	9,520	27,302
R^2	.467	.056	.426	.010	.345	.309	.112	.726

B. The implications of having a strong culture in bad times

	Abnormal return (1)	Abnormal return (2)	Abnormal return (3)	Abnormal return (4)
Strong culture	-0.012***	-0.004	-0.006*	0.000
	(0.003)	(0.004)	(0.003)	(0.007)
Strong culture × Financial crisis	0.028***	0.024***		
	(0.005)	(0.005)		
Strong culture × BP oil spill			0.017***	0.018***
			(0.005)	(0.005)
Firm-level controls	Yes	Yes	Yes	Yes
FF3 factor loadings	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	22,092	22,091	6,524	6,523
R^2	.018	.021	.026	.043

Table 8
Acquisitiveness, merger pairing, and post-merger acculturation

This table examines the relations between corporate cultural values and acquisitiveness and between cultural fit and merger pairing, and acculturation after deal completion. Panel A examines the relation between a firm's cultural values and its probability of being an acquirer. The dependent variable is equal to one for the acquirer, and zero for other firm-years in the full Compustat sample or matched acquirers that form the control group. The acquirer sample consists of 7,773 completed deals over the period 2003–2018 from Thomson Reuters' SDC database. The coefficients are estimated from linear probability models (LPM) and conditional logit models (Clogit). Panel B examines the relation between cultural fit and acquirer-target firm pairing. The dependent variable is equal to one for the acquirer-target firm pair, and zero for the control firm pairs. The acquirer-target sample consists of 594 completed deals where both the acquirer and its target firms are public with available control firms. The coefficients are estimated from conditional logit models (Clogit). Panel C examines acculturation after deal completion using OLS regressions. We require that acquirers not engage in any other significant deals in the year (3 years) after deal completion. The sample consists of 492 (335) deals 1 year (3 years) after deal completion. Target-specific innovation/integrity/quality/respect/teamwork is obtained by regressing each target cultural value on corresponding acquirer cultural value and acquirer characteristics in the year prior to deal announcement and keeping the residual. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Table A1 in the appendix defines the variables. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the acquirer level. *$p < .1$; **$p < .05$; ***$p < .01$.

A. Corporate cultural values and acquisitiveness

Variable	Full sample	Industry and size-matched		Industry, size, and B/M-matched	
	LPM	LPM	Clogit	LPM	Clogit
	(1)	(2)	(3)	(4)	(5)
Innovation	0.004**	0.005	0.028	0.007**	0.044**
	(0.002)	(0.003)	(0.020)	(0.003)	(0.020)
Integrity	-0.045***	-0.053***	-0.330***	-0.059***	-0.368***
	(0.005)	(0.008)	(0.047)	(0.008)	(0.047)
Quality	-0.008***	-0.014***	-0.083***	-0.014***	-0.084***
	(0.003)	(0.004)	(0.024)	(0.004)	(0.025)
Respect	0.015***	0.032***	0.183***	0.033***	0.191***
	(0.002)	(0.004)	(0.022)	(0.004)	(0.023)
Teamwork	-0.000	-0.001	-0.010	-0.003	-0.021
	(0.003)	(0.005)	(0.032)	(0.005)	(0.033)
Firm size	-0.002**	0.359***	2.133***	0.344***	2.042***
	(0.001)	(0.012)	(0.044)	(0.012)	(0.044)
Leverage	-0.028***	-0.128***	-0.824***	-0.116***	-0.736***
	(0.008)	(0.014)	(0.081)	(0.015)	(0.086)
ROA	0.137***	0.060***	0.452***	0.041*	0.312**
	(0.009)	(0.021)	(0.130)	(0.024)	(0.145)

Sales growth	0.054***	0.071***	0.402***	0.066***	0.369***
	(0.004)	(0.007)	(0.035)	(0.007)	(0.035)
Past return	0.023***	0.027***	0.162***	0.030***	0.178***
	(0.003)	(0.005)	(0.028)	(0.005)	(0.029)
Top-5 institutions	0.169***	0.268***	1.686***	0.287***	1.805***
	(0.011)	(0.018)	(0.103)	(0.019)	(0.107)
Ind FE/yr FE	Yes	No	No	No	No
Deal FE	No	Yes	Yes	Yes	Yes
Intercept	Yes	Yes		Yes	
Obs.	53,545	39,669	39,664	38,512	38,507
R^2/pseudo R^2	.047	.065	.063	.066	.063

B. Cultural fit and merger pairing

	Industry and size-matched		Industry, size, and B/M-matched	
	Clogit	Clogit	Clogit	Clogit
Variable	(1)	(2)	(3)	(4)
Cultural similarity	4.305***		4.210***	
	(0.902)		(0.943)	
Cultural distance		-0.496***		-0.515***
		(0.075)		(0.075)
Acquirer characteristics				
Firm size	2.634***	2.680***	2.695***	2.719***
	(0.210)	(0.210)	(0.217)	(0.219)
Leverage	-1.062***	-1.153***	-1.260***	-1.365***
	(0.342)	(0.350)	(0.374)	(0.384)
ROA	-0.077	-0.223	-0.427	-0.587
	(0.566)	(0.581)	(0.650)	(0.637)
Sales growth	0.355**	0.398**	0.361**	0.415**
	(0.169)	(0.168)	(0.175)	(0.179)
Past return	0.164	0.153	0.166	0.157
	(0.142)	(0.147)	(0.161)	(0.166)
Top-5 institutions	1.645***	1.665***	1.800***	1.852***

	(1)	(2)	(3)	(4)
	(0.442)	(0.432)	(0.479)	(0.471)
Target characteristics				
Firm size	2.090***	2.064***	2.060***	2.071***
	(0.299)	(0.300)	(0.280)	(0.289)
Leverage	0.062	-0.113	0.295	0.087
	(0.307)	(0.307)	(0.336)	(0.343)
ROA	-0.585*	-0.605**	-0.855***	-0.908***
	(0.308)	(0.306)	(0.320)	(0.317)
Sales growth	0.321**	0.323**	0.328***	0.331***
	(0.141)	(0.141)	(0.117)	(0.117)
Past return	-0.053	-0.035	-0.017	0.003
	(0.092)	(0.095)	(0.095)	(0.098)
Top-5 institutions	2.783***	2.818***	3.059***	3.137***
	(0.379)	(0.381)	(0.387)	(0.386)
Deal characteristics				
Same state	0.928***	0.925***	0.855***	0.853***
	(0.147)	(0.148)	(0.150)	(0.153)
HP similarity	26.551***	26.661***	27.044***	27.140***
	(2.058)	(2.035)	(2.164)	(2.158)
Deal FE	Yes	Yes	Yes	Yes
Obs.	5,682	5,682	5,497	5,497
Pseudo R^2	.295	.300	.302	.309

C. Post-merger acculturation

	Innovation_{t+1}	Innovation_{t+3}	Integrity_{t+1}	Integrity_{t+3}	Quality_{t+1}	Quality_{t+3}	Respect_{t+1}	Respect_{t+3}	Teamwork_{t+1}	Teamwork_{t+3}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Acquirer innovation	0.854***	0.905***	0.030**	0.042**	0.026	0.059	0.049*	0.043	0.035*	0.072***
	(0.039)	(0.053)	(0.014)	(0.020)	(0.028)	(0.041)	(0.027)	(0.036)	(0.021)	(0.025)
Target-specific innovation	0.108***	0.108**	0.003	0.022	-0.010	-0.049	-0.022	-0.028	-0.002	-0.014
	(0.034)	(0.052)	(0.014)	(0.021)	(0.025)	(0.038)	(0.023)	(0.033)	(0.018)	(0.027)
Acquirer integrity	0.027	-0.050	0.552***	0.506***	-0.038	-0.077	0.073	0.026	0.043	-0.047
	(0.107)	(0.161)	(0.051)	(0.063)	(0.077)	(0.101)	(0.073)	(0.096)	(0.063)	(0.079)

Target-specific integrity	-0.038	-0.043	0.069*	0.112*	-0.002	0.040	0.074	0.065	0.045	0.067
	(0.086)	(0.132)	(0.041)	(0.058)	(0.070)	(0.100)	(0.061)	(0.101)	(0.048)	(0.068)
Acquirer quality	0.074	0.067	0.041*	0.044	0.841***	0.790***	0.077***	0.108**	0.073***	0.090**
	(0.048)	(0.083)	(0.022)	(0.033)	(0.032)	(0.048)	(0.029)	(0.053)	(0.026)	(0.037)
Target-specific quality	-0.001	0.064	-0.008	-0.003	0.099***	0.154***	-0.034	-0.034	0.015	0.027
	(0.035)	(0.052)	(0.016)	(0.023)	(0.028)	(0.041)	(0.026)	(0.037)	(0.020)	(0.030)
Acquirer respect	-0.104**	-0.196**	0.002	-0.001	0.035	0.014	0.766***	0.685***	-0.013	0.006
	(0.052)	(0.077)	(0.022)	(0.033)	(0.044)	(0.060)	(0.040)	(0.064)	(0.033)	(0.044)
Target-specific respect	0.085**	-0.012	-0.036*	-0.068**	0.024	0.044	0.094***	0.092**	0.025	-0.039
	(0.043)	(0.064)	(0.021)	(0.031)	(0.033)	(0.053)	(0.029)	(0.046)	(0.023)	(0.033)
Acquirer teamwork	0.064	0.079	-0.003	-0.038	-0.025	-0.036	-0.013	-0.071	0.684***	0.562***
	(0.076)	(0.105)	(0.031)	(0.042)	(0.044)	(0.067)	(0.051)	(0.082)	(0.042)	(0.049)
Target-specific teamwork	-0.071	-0.135*	0.029	-0.020	-0.001	-0.001	-0.016	-0.054	0.081***	0.200***
	(0.044)	(0.069)	(0.021)	(0.032)	(0.034)	(0.058)	(0.031)	(0.051)	(0.025)	(0.044)
Acquirer/target/deal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE/yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	492	335	492	335	492	335	492	335	492	335
R^2	.806	.780	.538	.472	.807	.761	.746	.707	.717	.679

Internet Appendix for "Measuring Corporate Culture Using Machine Learning"

In this technical appendix, we describe how we process earnings call transcripts and train the *word2vec* model. Python codes for text processing and model training can be downloaded from our GitHub repository (https://github.com/MS20190155/Measuring-Corporate-Culture-Using-Machine-Learning).

1. Matching company names in earnings calls to GVKEY

We obtain earnings call transcripts from Thomson Reuters' StreetEvents (SE) database for the period January 1, 2001 to May 25, 2018. The database consists of two folders of XML (i.e., extensible markup language) files: 1) the full transcript folder that includes both the management presentation and QA sections of a call, and 2) the brief transcript folder that contains a brief summary of the management presentation and the full QA section of a call.[1]

Apart from the body of a call transcript, each XML file contains the following meta-data that help us match the company to the COMPUSTAT database: the ticker symbol header, the company name, the title of the event, and the date of the call. We use the xml package in Python to extract these fields and the main body of the call.

We note that when a company changes its name or ticker, or is acquired, Thomson Reuters backfills with the new company name and the new ticker, or replaces a target firm's name and ticker with those of its acquirer, which inevitably complicates the matching process between companies in calls and Compustat firms. Fortunately, the company name in the event title still is the original company name. Hence, we extract the company name and fiscal year or quarter from the event title at the end of a call (e.g., "Q4 2012 Venoco, Inc. Earnings Conference Call") for the vast majority of the calls. For the remainder (less than 2% of the calls), the event title is not organized; we therefore use various heuristics rules to infer the company name and fiscal year.[2]

To maximize matching between SE's company name to GVKEY, we employ a multipronged approach. First, we use the fuzzy matching function SPEDIS in SAS to match the first 25 characters of a company's name extracted from the event title of a call to a company's name from CSRP. We obtain PERMNO in this step and then match PERMNO to obtain GVKEY using the CRSP-Compustat link table. Second, we use the same SAS function to match company names from SE to company names from Compustat. Third, we also use another fuzzy matching function, COMPGED in SAS, to match a company's full name extracted from the event title of a call to a company's name from CRSP/Compustat Merged File.[3] A perfectly matched pair would be the case with exactly the same company name from SE and CRSP in order to get PERMNO (or Compustat to get GVKEY, or CRSP/Compustat Merged File to get GVKEY), and the distance score from SAS would be zero. Fourth, for less than perfect matching cases based on the company name (i.e., the distance score is greater than zero), if a company's name provided by SE (subject to backfilling) is the same as the name extracted from the event title (without backfilling), i.e., the company name and ticker symbol are accurate (not subject to backfilling), we use both the ticker and fiscal year to match with CRSP in order to get PERMNO and then GVKEY. Fifth and finally, the rest of the calls, along with company

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[1] As far as we can tell, these two folders are non-overlapping in terms of their coverage of firms, so we use the QA section of both folders in our analysis.

[2] For example, we use regular expressions to extract years 2012 and 2005 and company names from the event titles "AT&T's 4Q12 Earnings Conference Call" and "PMC-Sierra Third Quarter 2005 Conference Call", respectively.

[3] The reason we use company names provided by CRSP, Compustat, and CRSP/Compustat Merged File for matching is because occasional small variations in company names occur across these three databases. Relying on multiple sources helps us capture as many matches as possible before starting manual checking.

names in the brief folder that are not matched in the above steps, are manually checked and matched to GVKEY. Table 1 provides the steps taken and filters applied to form our final sample.

2. Preprocessing and parsing the QA section

The QA section of a call is marked by "\nQUESTIONS AND ANSWERS\n". Here "\n" is a line breaker. We include both the questions and answers, but not the speakers and their titles, from the QA section. The speaker and their titles (see an example below) are removed using the regular expression pattern ".+\[\d+\]$".

```
--------------------------------------------------------------------------------
 Robert W. Cremin,  Esterline Technologies   [3]
--------------------------------------------------------------------------------
```

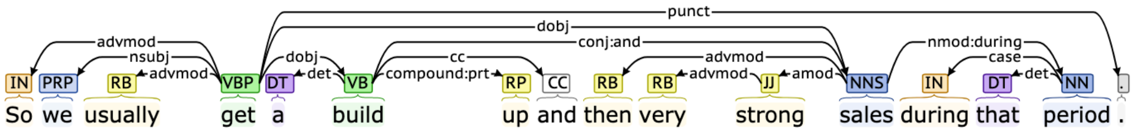
We use the Stanford CoreNLP package (https://stanfordnlp.github.io/CoreNLP/) version 3.9.2 (released on 2018-10-05) to parse the text. The CoreNLP package is an open-source Natural Language Processing (NLP) toolkit for a variety of tasks (Manning et al. 2014). The most relevant modules for our purpose are the following:

1. Sentence segmentation and tokenization: Since the *word2vec* model operates at the sentence level, we use the sentence segmentation and tokenization model to split a QA section into sentences, with each sentence in its own line, and individual sentences broken down into words separated by white spaces.

2. Lemmatization: Words are returned to their base forms in lower cases. For example, *jumped* -> *jump*, *are* -> *be*. Note that lemmatization (compared with stemming) is a relatively non-aggressive way of returning words to base forms. For example, words such as *creatively* will not be transformed to *creative*.

3. Named Entity Recognition (NER): We replace named entities such as locations, times, persons, and company names with a predefined tag.[4] For example, "*We repurchased 71.7 million Apple shares*" is transformed to "*we repurchase [NER:NUMBER] [NER:ORGANIZATION] share*". Multi-word named entities, such as *Wells Fargo,* are also recognized. The reason to replace named entities with generic tags, rather than removing them, is that these tags may allow us to learn semantic information about the neighboring words.

4. Dependency parsing: This step learns grammatical relationships in a sentence and provides syntactic clues to learn the meaning of a word. The following diagram shows the parsed dependency relationship for the sentence "*So we usually get a build up and then very strong sales during that period.*"



The most important implication of the above step is that we can identify collocations (i.e., a group of words that have different or additional meaning when they are used together). We use the CoreNLP package to identify the following two types of collocations. Both types are

[4] Version 3.9.2 of the CoreNLP package recognizes the following classes of named entities: PERSON, LOCATION, ORGANIZATION, MISC, MONEY, NUMBER, ORDINAL, PERCENT, DATE, TIME, DURATION, and SET. See https://stanfordnlp.github.io/CoreNLP/ner.html for a full description.

defined in the Universal Dependencies annotations, a collaborative project that defines the syntactic structure for all human languages (Nivre et al. 2016):

- Multi-word expression (MWE): MWEs are fixed expressions that behave like function words (Sag et al. 2002). They are largely immutable and carry little meaning by themselves. Examples include: *as well as, with respect to, because of, rather than, de facto.*

- Compounds: Compounds can be either noun compounds or verb compounds. When used together, they usually carry fixed meanings. Examples include: *attorney general, intellectual property, put up, energy level, chicken wing, healthcare provider*.

We concatenate the MWEs and compounds in the text using the symbol _ and treat them as single words (*as well as* -> *as_well_as*). It is important to note that while the accuracy of the CoreNLP package is impressive and constantly improving, none of the above steps is perfect. The reason for using these modules – rather than our own parsing rules – to process the text is two-fold. First, we can rely on language models trained by linguistic experts using massive amounts of external data. Second, we use standardized annotations such as Universal Dependencies to denote the objective of parsing, which facilitates replication by other scholars. The disadvantages of doing so include the imprecision associated with those modules and extra computational time.[5]

3. Cleaning parsed text and learning phrases

After parsing, we remove punctuation marks, stop words, and single-letter words. We use their Generic Stopwords list that includes 121 words such as *and*, *the*, and *of*.[6] Removing isolated stop words only after parsing is crucial, because some of them could potentially be part of MWEs and compounds.

We use the *phraser* module of the *gensim* library to find collocations that are specific to our corpus (i.e., the entire collection of QA sections in call transcripts). We use *phrases* to denote these collections of terms that have statistically significant co-occurrences because of conventions and real-world events, not because of linguistic rules (Sag et al. 2002). We use the learning algorithm by Mikolov et al. (2013) to learn two- and three-word phrases. Specifically, the algorithm calculates a score for every bigram (every two consecutive words w_i and w_j) using the formula: $score(w_i, w_j) = \frac{(count(w_i w_j) - \delta) \times |V|}{count(w_i) \times count(w_j)}$, where δ is the minimum frequency for the phrase to be considered ($\delta = 50$ in our algorithm), and $|V|$ is the size of vocabulary. If the score for any two words is greater than 10 (the default), we consider these two words to be a phrase, concatenate them using the underscore symbol _, and treat them as a single word (e.g., *cash flow*).[7] We then run the algorithm again to learn three-word phrases. For example, some of the phrases learned are: *private equity fund, forward-looking statement, beat (a) dead horse.*

[5] The parsing of all transcripts takes about 400 CPU hours, or about 2 days with a 2 × E5-2670 workstation with parallelization.

[6] Available at https://sraf.nd.edu/textual-analysis/resources/#StopWords.

[7] As an example, the phrase *cash_flow* is included because count(*cash flow*) = 362,938, the vocabulary size is 11 million, count(*cash*) = 532,240, and count(*flow*) = 192,208. The formula gives (362,938 – 50) × 11 million / (532,240 × 192,208) = 39, which is above the threshold 10.

4. Word embedding, *word2vec*, and model training

4.1. Why word embedding?

Researchers in finance and accounting are increasingly relying on automated textual analysis to extract information from corporate qualitative disclosures. A particularly popular method is counting word occurrences from word lists (dictionaries) that share common meanings. For example, dictionaries such as Harvard's General Inquirer tag categories, Henry (2008), and Loughran and McDonald (2011) have been extensively used to measure the tone (sentiment) of documents. However, developing such dictionaries for measuring corporate culture can be a daunting task. As Loughran and McDonald (2016) point out, creating a useful dictionary requires a good grasp of the context of business applications. The conventional solution, as in Henry (2008) and Loughran and McDonald (2011), is to have experts manually inspect and categorize words that commonly appear in a specific context. Several immediate challenges arise when applying this approach to generating a dictionary for corporate culture.

First, corporate culture is usually discussed in a subtle and nuanced fashion. Unlike tones that reflect a general business outlook, culture can be described using less frequent words, abbreviations, phrases, or idioms that make sense only in a particular context. For example, humans can understand that the phrase "two-way street" is related to teamwork during an earnings call, yet it is difficult even for an expert in corporate finance to pick that particular phrase out from millions of isolated words and phrases in call transcripts.

Second, corporate culture can be an elusive, multidimensional construct. This inherit complexity means that even once all culture-related words and phrases can be extracted from a set of documents, categorizing them will be a more complicated task compared to tone analysis. It is difficult for humans to categorize each word in a consistent and objective fashion when facing five or more options (e.g., the five cultural values in our setting).

Third, it is unrealistic to presume that experts could create and maintain dictionaries capable of adapting to constant paradigm shifts in the business world. Words and phrases enter and drop out of the business vocabulary as industries and technologies evolve. For example, a dictionary created in the early 2000s would probably not recognize that "artificial intelligence" would drive corporate innovation some twenty years later; similarly, it would probably overlook "freelancer", given its inevitable inability to anticipate the growing role of freelancers in today's workforce.

In summary, while it is theoretically possible for experts with deep knowledge of various aspects of business operations to understand the rich, nuanced meanings of individual words and phrases based on context, their doing so is often impractical and cost ineffective. As such, we offer a machine learning alternative to address these challenges. Our proposed approach starts with seed words that define each cultural value and automatically creates a high-quality dictionary from qualitative corporate disclosures. The centerpiece of our approach is the word embedding model, which learns the meaning of a word (phrase) based on its context.[8] Our approach can be used beyond measuring corporate culture to generate dictionaries applicable to other disciplines.

4.2. Word embedding

The goal of word embedding is to represent the semantics—the meaning of a word—using a numeric vector. The word vector, in turn, allows us to determine the relationship between words using simple vector arithmetic. In our application, we rely on the cosine similarity between any two word vectors to determine if the two words are synonyms. Based on the learned similarity relationship to seed words describing a particular cultural value, a broad set of words and phrases that describe that cultural value can be identified and can be used to score firms accordingly.

[8] The method learns the meanings of both words and phrases. For simplicity, we use "word" to indicate either a word or a phrase in our discussion of the methodology.

The word embedding model is based on a simple, time-tested concept in linguistics: Words that co-occur with the same neighboring words have similar meanings (Harris 1954); the model thus identifies synonyms from common neighboring words. To illustrate, suppose we want to examine the relationship between three words: *collective, partnership*, and *governance*. We can start by counting how many times any neighboring words appear near these three specific words in a collection of documents. We find that *share, fruitful,* and *joint* tend to appear most often near *collective* and *partnership*; and *oversight* and *proper* tend to appear most often near *governance*. We record the number of times those five words – *share, fruitful, joint, oversight,* and *proper* – appear in a vector for each of these three words. In this case, we can use a vector [4, 5, 5, 0, 1] to represent *collective* where 4 is the number of times the word *share* appears close to the word *collective*, and 5 is the number of times the word *fruitful* appears close to the word *collective*, etc. Similarly, we can use a vector [3, 6, 7, 0, 0] to represent *partnership*, and a vector [0, 0, 1, 10, 9] to represent *governance*. Table IA1 in the Internet Appendix provides an illustration of the above example in a matrix format.

Such vector representation of a word allows us to compute the association between any pair of words using the cosine similarity of their underlying vectors. The cosine similarity between *collective* and *partnership* is 0.97 and the cosine similarity between *collective* and *governance* is 0.13.[9] We conclude that *collective* and *partnership* are semantically closer to each other than *collective* and *governance*. Thus, word embedding can identify that *partnership* is a closer synonym than *governance* to *collective* based on the textual context, which is defined by the neighboring words.

4.3. Overview of word2vec

In the above example, the vectors are only five components long because we list only five neighboring words. In reality, however, the number of combinations of all the words and their possible neighboring words is enormous, making the simple count-based word embedding method challenging to implement. We would need to maintain a table that has $|V|$ rows and $|V|$ columns, where $|V|$ is the number of unique words in the vocabulary. Further, the count-based method assumes that the dimensions defined by different neighboring words are orthogonal (e.g., there is no relationship between *share* and *joint* in the above example). This assumption leads to unnecessarily sparse (i.e., many zeros) and high-dimensional neighboring-word count vectors.

As a breakthrough in natural language processing (NLP), *word2vec* (Mikolov et al. 2013) employs a neural network to efficiently learn dense and low-dimensional vectors that can represent the meaning of words. In essence, *word2vec* "learns" the meaning of a specific word via a neural network that "reads" through the textual documents and thereby learns to predict all its neighboring words. The parameters in the neural network are initialized randomly. As learning progresses, the parameters in the neural network are adjusted via backpropagation (i.e., a standard training algorithm for neural networks) so the network continually improves its ability to predict a word's neighboring words. These parameters become an effective vector representation of the word when learning is completed after a number of iterations through the documents. The vector has a fixed dimension, usually between 50-500, and captures the properties of the original co-occurrence relationship between the word and its neighbors. Levy and Goldberg (2014) show that the vectorization achieved by *word2vec* is similar to a singular value decomposition (i.e., a dimension reduction technique) of Table IA1.[10]

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[9] The cosine similarity between two word vectors $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ is defined as follows: $\text{cosine}(\boldsymbol{w}_1, \boldsymbol{w}_2) = \frac{\boldsymbol{w}_1 \cdot \boldsymbol{w}_2}{|\boldsymbol{w}_1||\boldsymbol{w}_2|} = \frac{\sum_{i=1}^{d} w_{1,i} w_{2,i}}{\sqrt{\sum_{i=1}^{d} w_{1,i}}^2 \sqrt{\sum_{i=1}^{d} w_{2,i}}^2}$. where $w_{1,i}$ is the ith element in vector $\boldsymbol{w}_1$, and d is the dimension or length of the vector. A high degree of similarity between two word vectors indicates the two words are semantically close.

[10] The neural network can be interpreted as performing dimension reduction (e.g., principal component analysis) on the matrix of neighboring word frequency counts; see Table IA1. For each term, the original dimensions (columns) in Table IA1 are the frequencies of observing neighboring words: *share*, *fruitful*, *joint*…. The frequencies in each row vector capture the semantic meaning of the term. The word embedding model reduces dimensions in Table IA1 using a neural network and creates new dimensions that are, roughly speaking, linear combinations of the original dimensions in Table IA1. For example, after word embedding, dimension (column)

4.4. Technical details on word2vec

We now describe the neural network behind *word2vec* in detail. Figure A1 provides an illustration of the model. The model is a feed-forward neural network – given an input word, the neural network outputs neighboring context words. Predicting each word's neighboring words is equivalent to maximizing the log probability:

$$\frac{1}{|V|}\sum_{t=1}^{|V|}\sum_{-k\le j\le k, j\ne 0}\log p(w_{t+j}\,|w_t),$$

where k is the "window size" of the context (5 words in our case), w_t is a word at location t, and $|V|$ is the size of the vocabulary. At the left of Figure A1, each word is naturally represented using a $|V|$ dimensional one-hot row vector.[11] A single-hidden-layer neural network, parameterized by a $|V| \times d$ weight matrix W, first projects an input word w to a vector v_w in $\mathbb{R}^d$, where v_w is simply the corresponding row in W.[12] The network's output softmax layer, parameterized by a second $d \times |V|$ weight matrix W_c, uses the v_w as the input to predict the probability of observing each context word *c* in the context of *w*. The corresponding column in W_c is denoted as v_c. That is:

$$p(c|w) = \frac{\exp(v_c^{\mathrm{T}} v_w)}{\sum_{c'\in V}\exp(v_{c'}^{\mathrm{T}} v_w)}.$$

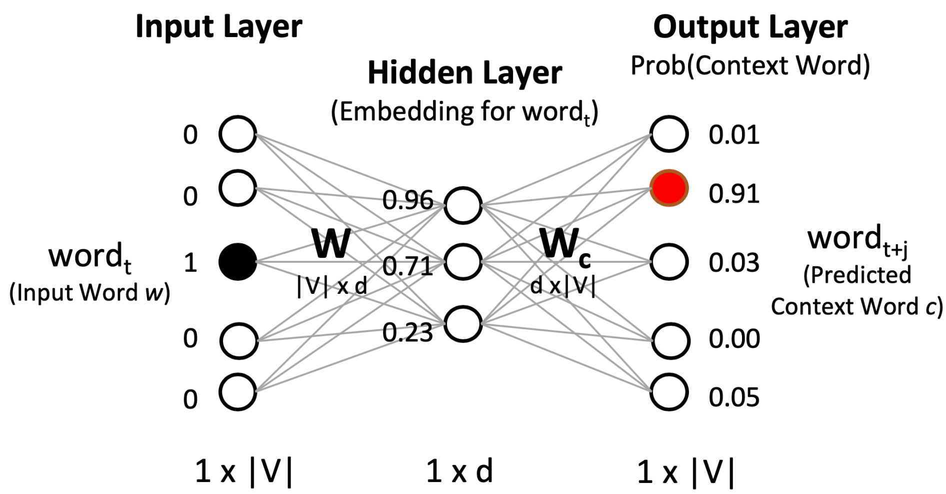

Figure A1. Illustration of the neural network for word embedding

In combination, the best parameters should maximize the likelihood of the entire model by combining all (w, c) pairs:

$$\arg\max_{W,W_c} \prod_{w\in V}\prod_{c\in c(w)} p(c|w;\ W,\ W_c),$$

where $c \in c(w)$ is the set of all context words for word w.

The above neural network can be viewed as two layers of regressions concatenated, with the first layer of the regressions' output becoming another layer's input. The first layer contains *d* linear regressions, each taking the same input, the one-hot vector (|V| dimensional) of a word [0, 0, 0, 1, …, 0], and outputs a single number. Together the output of the first layer is the vector $[x_1, x_2, \ldots, x_d]$.

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1 is no longer how often we observe the word *share* near a term (let *n_share* denote the count), but may be 0.3**n_share* + 0.2**n_fruitful* + 0.5**n_joint* + …, a new composite variable constructed from the frequencies of the original neighboring words.

[11] A one-hot vector is a vector with a single 1 and the others 0. Since there are $|V|$ unique words, each word can be represented using a one-hot vector with a unique entry being 1. For example, *a* is [1, 0, 0, 0, …], *ability* is [0, 1, 0, 0, 0, …], *able* is [0, 0, 1, 0, …] , *zoo* is [0, 0, 0, …,0, 1].

[12] A one-hot row vector with the *w*th entry being 1 multiplying *W* outputs the *w*th row of *W*.

This output of the first layer is then used as the input of a multinomial logistic regression of |V| classes, and the final output is the probabilities of neighboring words.

The learning of word vectors $v_w{}'$s is achieved when the log-likelihood is maximized; i.e., the neural network is trained using a collection of documents (training corpus). For such a feed-forward neural network, the W and W_c can be initialized randomly. As the neural network passes through the text word by word, it continually predicts surrounding words for each focal word. The neural network will make mistakes, and a backpropagation algorithm can adjust W and W_c by learning from those mistakes. After several passes through the entire text collection, the neural network becomes adept at the task. The training is now complete, and *word2vec* uses the average of $v_w{}'$s and (rows of W) and v_c's (columns of W_c) as our final d-dimension vector representation of each word.

Negative sampling provides an efficient way to learn the parameters W and W_c. Instead of asking the neural network to predict neighboring words, which is a multi-class classification problem, negative sampling reduces the problem to binary classification (similar to logistic regression). The neural network now tries to predict the probability $P(Y = 1|w, c;\ W,\ W_c)$, where $Y = 1$ if a focal word-neighboring word pair (w, c) comes from the training corpus, and $Y = 0$ otherwise. The model learns by passing through the training corpus to gather the (w, c)'s that are actually observed (positive samples), and distinguishing them from the randomly generated (w, c) word pairs that are unlikely to come from the training corpus (negative samples). Formally, the solution is

$$\underset{W, W_c}{\arg\max} \prod\nolimits_{(w,c)\in D} P(Y = 1|w, c; W, W_c) \prod\nolimits_{(w,c)\in D'} P(Y = 0|w, c; W, W_c),$$

where D are the positive samples, D' are the negative samples, and $P(Y = 1|w, c;\ W,\ W_c) = \frac{\exp(v_c^{\mathrm{T}} v_w)}{1+\exp(v_c^{\mathrm{T}} v_w)}$; i.e., the logistic function that takes the dot product $v_c^{\mathrm{T}} v_w$ as input.

4.5. Training the word2vec model

We use the *gensim* library in Python and the following parameters to train our *word2vec* model:[13]

- Window size = 5: This parameter determines the maximum distance between the focal word and its neighboring words. The algorithm is trained to use the focal word in the center to predict the five words to its left and the five words to its right. The default number is 5.

- Dimension of the word vector = 300: This parameter is the size of the vector we use to represent a word. Typical values are between 50-500. Studies show that word vectors with a dimension greater than 300 offer little improvement in quality, as evaluated by how well word vectors can be used to solve word analogy problems (Pennington et al. 2014).

- Number of iterations over the corpus = 20: Twenty is the number of times the algorithm goes through the corpus to train the parameters. More iterations would take a longer time but may improve model performance. We increase the number of iterations from 5 (the default) to 20.

- Min word count = 5: We ignore words that appear fewer than five times in the corpus.

- Training method = Negative sampling: Mikolov et al. (2013) discuss two ways to accelerate the training of *word2vec* for a large corpus. We use the skip-gram with negative-sampling method (SGNS).[14] Recall that *word2vec* trains a model to predict neighboring words given a focal word. The main idea of SGNS is to first randomly generate focal-word-neighboring-

[13] Although the parameter choices can be data and task dependent (Caselles-Dupré et al. 2018), we find they have no significant effect on our main findings.

[14] The alternative method is hierarchical softmax. Mikolov et al. (2013) show that its performance is worse than the SGNS method.

word pairs that are not observed in the corpus as negative samples. The model then learns to discriminate between negative samples and focal-word-neighboring-word pairs that are actually in the corpus.

After training, the *word2vec* model converts each of the 764,276 words in the corpus to a 300-dimensional vector representing the meaning of that word. Other deep learning packages such as TensorFlow and PyTorch can also be used for training.

5. Seed words

The starting point for us to measure corporate culture is the five most-often mentioned values by the S&P 500 firms on their corporate Web sites (Guiso, Sapienza, and Zingales 2015): *innovation* (80% of the time), *integrity* (70%), *quality* (60%), *respect* (70%), and *teamwork* (50%). Guiso et al. (2015) also provide units of meaning (i.e., seed words) for each value after checking all other words clustered with a value by each firm and their frequency across firms.[15] Although it is possible to generate the dictionary using only the value words (e.g., *innovation*), several cultural values identified by Guiso et al. (2015) encompass meanings beyond their value words. For example, the cultural value of *respect* includes the meaning of respecting diversity as well as empowering employees. Using the set of seed words as listed in Guiso et al. (2015) allows us to capture the broader meanings of different cultural values.

Loughran and McDonald (2011) note that word lists developed for other disciplines misclassify common words in financial text and thus, by extension, word lists culled from companies' websites (Guiso et al. 2015) might not be exactly applicable to our context of using earnings calls to score corporate culture.

Therefore, after training the *word2vec* model (so we can get the word vector for each value/seed word), we manually inspect the value/seed words in Guiso et al. (2015) to ensure that each cultural value is clearly defined using a coherent set of seed words, based on the following two criteria:

1) The word or phrase is in the vocabulary of call transcripts. Phrases such as "*do the right thing*" (under integrity) and "*exceed expectations*" (under quality) are excluded from our seed word list for this reason.

2) The synonyms of a word or phrase (via *word2vec*) indicate that, in the context of the QA section of calls, this particular word or phrase is unambiguously culture related. Words such as "*growth*" (under innovation) and "*diversity*" (under respect) are excluded because their synonyms indicate that "*growth*" is more likely to describe past performance and "*diversity*" is more likely to describe a diversification strategy.

After excluding some value/seed words in Guiso et al. (2015) that do not meet the above criteria, we also add new seed words to help score corporate culture. These additional words include: 1) other forms of the original seed words in Guiso et al. (2015). For example, *cooperative* (adjective) and *cooperate* (verb) are added (under teamwork) based on their synonyms and given that *cooperation* (noun) is on the list; and 2) phrase variations that are more specific than the original seed words in Guiso et al. For example, instead of *commitment*, we add *customer commitment* (under quality).

[15] For example, to find the seed words for *integrity*, the authors check all other words clustered with *integrity* by each company and their frequency across companies. They then take words most commonly associated with *integrity*. The word *ethics* is shown to be associated with *integrity* in about 34% of companies and is added on the seed word list for *integrity*.

Table IA2 in the Internet Appendix provides the list of included seed words in Guiso et al. (2015) with their top synonyms, the list of excluded value/seed words from Guiso et al. (2015) with their top synonyms, and the list of added seed words with their top synonyms.

6. Generating the culture dictionary

We use the trained *word2vec* model to develop an expanded, context-specific dictionary for measuring cultural values. As noted earlier, we can compute the cosine similarity between any two word vectors to quantify their association. Using this capability, we construct the culture dictionary by associating a set of words gleaned from earnings calls to seed words defining each cultural value. Such a procedure, known as bootstrapping, is common in information retrieval literature for learning new semantic lexicons (Riloff and Jones 1999). We use the following example to illustrate the procedure.

The seven seed words for the cultural value of *teamwork* are: *collaborate*, *collaboration*, *collaborative*, *cooperate*, *cooperation*, *cooperative*, and *teamwork*. Let the vector representations for the first seed word *collaborate* be $V^{\{1\}} = \left[x_1^{\{1\}}, x_2^{\{1\}}, \ldots, x_{300}^{\{1\}}\right]$, and the vector for the second seed word *collaboration* be $V^{\{2\}} = \left[x_1^{\{2\}}, x_2^{\{2\}}, \ldots, x_{300}^{\{2\}}\right]$, …and the vector for the last seed word be $V^{\{7\}} = \left[x_1^{\{7\}}, x_2^{\{7\}}, \ldots, x_{300}^{\{7\}}\right]$. We first compute the average of the vectors of the seed words, i.e., $\overline{V}^{\{teamwork\}} = \frac{1}{7}\sum_{i=1}^{7}\left[x_1^{\{i\}}, x_2^{\{i\}}, \ldots, x_{300}^{\{i\}}\right]$. We then compute the cosine similarity between each unique word in earnings calls with $\overline{V}^{\{teamwork\}}$. We select the top 500 words with the closest associations (i.e., the highest cosine similarity between their word vectors) to $\overline{V}^{\{teamwork\}}$ as the expanded dictionary for the cultural value of *teamwork*.[16] We do not consider named entities that are recognized automatically by the CoreNLP package. If a word appears in dictionaries for multiple cultural values, we only include it in the dictionary for the value with the highest cosine similarity to the average of seed word vectors for that value.

Finally, we manually inspect all the words in the auto-generated dictionary and exclude words that do not fit. When considering whether a word should be excluded, we carefully study its context in earnings calls. Most of the excluded words are named entities that the CoreNLP package missed (e.g., *gs1* and *dana-farber*), are too specific in terms of industry context (e.g., *chef* and *pharmacist*), or are too general in meaning (e.g., *importance* and *job*).

Table IA3 in the Internet Appendix provides a list of included and excluded words in the culture dictionary ordered by descending similarity to seed words for each cultural value.[17]

7. Scoring corporate culture

After generating the culture dictionary, we measure each of the five cultural values at the firm-fiscal year level. For each transcript, we use the weighted count of the number of words associated with each value divided by the total number of words in the document. If there are multiple transcripts within the fiscal year, we aggregate scores by taking the average. This step is similar to the use in prior literature that employs word lists to score documents. We experiment with different weighting methods. While our results are robust to the different weights we used, we choose tf.idf (term

[16] As robustness checks, we expand the dictionary for each value to include the top 2,000 closest words. We also experiment with a procedure that, instead of relying on manual inspection of each dictionary word, automatically removes words from the dictionary if they are not mentioned by at least 20 firms. Our main findings remain, suggesting that our results are robust to the number of dictionary words for each cultural value and human judgment when excluding words from the dictionary.

[17] The acronyms "sla", "isv", and "crada" in the table stand for "service-level agreement", "independent software vendor partner", and "cooperative research and development agreement", respectively.

frequency-inverse document frequency) as advocated by Loughran and McDonald (2011). Such a weighting scheme puts lower weights on terms that appear more frequently across the documents.[18] As a result, more frequent words have a smaller influence on the scoring of cultural value compared with equal term frequency weighting (tf). The methods that we assess are (all scores are adjusted by document length):

- tf: Equal term frequency weighting where we simply count the number of words for each value in the document and give them equal weight.

- tf.idf (Log): The count for word *i* in document *d* is first weighted using $(1 + \mathrm{Log}(tf_{i,d}))$, and then multiplied by the idf weight of Log(N/df), where N is the total number of documents and df is the number of documents with the word *i* in it.

- tf.idf: The count for word *i* in document *d* is the raw count $tf_{i,d}$ multiplied by the idf weight Log (N/df).

- tf.idf (Log) with similarity weights: The tf.idf weight is further adjusted by how similar each dictionary word is to the seed words. Specifically, the dictionary words for each value are ranked by similarity, and their similarity weights are 1/Log(1 + rank). For example, *creativity* is the first dictionary word for *innovation*, and its weight is the tf.idf weight multiplied by 1/Log(1+1) = 1.44; *usability* is the 300th dictionary word for *innovation*, and its weight is the wf.idf weight multiplied by 1/Log(1+300) = 0.175.

- tf.idf with similarity weights: The tf.idf weight is further adjusted by how similar each dictionary word is to the seed words.

Table 2 Panel A lists the thirty most representative words, ordered by descending similarity to seed words for each cultural value. Panel B lists the thirty most frequently occurring words for each cultural value, with the frequency (%) being the tf.idf weighted word count.

[18] There is ongoing discussion on the applicability of tf.idf weighting in the literature. For example, Henry and Leone (2016) evaluate different weighting schemes to quantify the tone of financial disclosures and conclude that using a domain-specific word list and equal-weighted word-frequency measures produce both powerful and replicable results in settings of measuring qualitative information in disclosures for capital markets research.

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Table IA1
An example on terms and neighboring word counts

This table provides an illustration of the simple example discussed in Section 4.2 in the Internet Appendix.

	Neighboring Word Counts				
Terms	*share*	*fruitful*	*joint*	*oversight*	*proper*
collective	4	5	5	0	1
partnership	3	6	7	0	0
governance	0	0	1	10	9

Table IA2
Included/excluded/added seed words in Guiso et al. (2015)

This table lists corporate cultural value and seed words in Guiso et al. (2015) together with their top synonyms by applying the *word2vec* method to the corpus of earnings call transcripts (the QA section only). Panel A lists the included seed words in Guiso et al. (2015). Panel B listed the excluded seed/value words in Guiso et al. (2015). Two phrases, "do the right thing" and "exceed expectations" are removed due to their rare usage during calls. Panel C lists the added seed words, largely based on inflections of the original seed words in Guiso et al. (2015).

Panel A: Included seed words in Guiso et al. (2005) with their top synonyms

Culture value	*Seed words*	*Synonyms*
Innovation	creativity	creative, passion, innovation, professionalism, ingenuity, inspiration, entrepreneurship, storytelling, teamwork, innovative
	efficiency	cost_efficiency, productivity, operating_efficiency, efficiency_gain, productivity_improvement, efficiency_improvement, process_improvement, productivity_gain, process_efficiency, manufacturing_efficiency
	excellence	operational_excellence, world-class, service_excellence, competence, execution_excellence, center_excellence, leadership, competency, professionalism, excellence_initiative
	innovation	product_innovation, innovate, technology_innovation, innovative, product_development, innovation_pipeline, creativity, product_technology, technology, innovation_capability
	passion	passionate, dedication, creativity, professionalism, enthusiasm, excitement, teamwork, culture, inspire, work_ethic
	pride	reputation, proud, passion, admiration, admire, hallmark, culture, work_ethic, testament, track_record
Integrity	accountability	responsibility, accountable, empowerment, alignment, empower, hold_accountable, transparency, p&l_responsibility, teamwork, organization
	ethic	ethical, culture, moral, integrity, governance, business_conduct, code_ethic, value_system, core_value, corporate_governance
	fairness	honesty, respectful, candor, frustrate, courtesy, acknowledge, deference, honest, candid, transparency
	honesty	candor, fairness, honest, perfectly_honest, candid, frankness, truth, humility, sincerity, candidly
	integrity	ethic, ensure, continuity, reliability, quality, independence, safety, ethical, core_value, professionalism
	responsibility	responsible, accountability, oversight, management_responsibility, oversee, leadership_role, leadership, mission, role, supervision
	transparency	transparent, accountability, clarity, predictability, certainty, disclosure, openness, consistency, governance, credibility
	trust	credibility, reputation, identity, trustworthy, entrust, credentials, loyalty, advisor_relationship, integrity, business_partner
Quality	customer	client, customer_base, vendor, end_customer, end_user, enterprise_customer, consumer, user, supplier, channel_partner
	dedication	passion, tireless, perseverance, professionalism, hard-working, team_member, devotion, teammate, gratitude, tirelessly
	quality	product_quality, reliability, quality_level, high-quality, quality_product, service_quality, customer_service, service_level, customer_satisfaction, customer_experience
Respect	dignity	caring, entrepreneurial_spirit, admiration, empathy, kindness, elder, uhs, work_ethic, affection, compassion

	employee	team_member, worker, employee_base, teammate, staff, member, staff_member, executive, workforce, crew_member
	empowerment	empower, accountability, entrepreneurship, autonomy, teamwork, agility, passion, meritocracy, p&l_responsibility, business_leader
	talent	skill, skill_set, engineering_talent, talent_pool, management_talent, sale_talent, competency, leadership, talented, expertise
Teamwork	collaboration	partnership, alliance, cooperation, collaborate, partner, collaborator, collaborative, partnering, technology_partnership, co-development
	cooperation	co-operation, collaboration, partnership, collaborate, coordination, alliance, involvement, cooperate, working_relationship, relationship
	teamwork	camaraderie, passion, work_ethic, team_work, culture, professionalism, team_effort, entrepreneurship, creativity, leadership

Panel B: Excluded seed/value words from Guiso et al. (2005) with their top synonyms

Culture value	*Seed words*	*Synonyms*
Innovation	growth	revenue_growth, growth_rate, volume_growth, sale_growth, top_line_growth, topline_growth, growth_momentum, growth_trend, market_share_growth, share_growth
	leadership	leadership, leadership_team, leader, team, management_team, talent, sale_leadership, leadership_position, organization, executive_team, culture
	performance	sale_performance, operating_performance, revenue_performance, margin_performance, volume_performance, top_line_performance, profit_performance, result, business_performance, growth_performance
	result	operating_result, performance, operating_performance, sale_result, earnings_result, business_result, outcome, effect, consequence, sale_performance
Integrity	do the right thing	
	ownership	ownership_interest, shareholding, ownership_position, equity_ownership, ownership_stake, stake, ownership_structure, equity_stake, ownership_percentage, majority_ownership
Quality	commitment	committment, commit, obligation, capital_commitment, customer_commitment, contractual_obligation, desire, promise, contract_commitment, committed
	exceed expectations	
	value	value_proposition, value_creation, customer_value, shareholder_value. intrinsic_value, market_value, equity_value, value-add, service_value, value_equation
Respect	development	development_activity, development_program, development_effort, development_project, development_work, technology_development, development_area, commercialization, project_development, exploration
	diversity	diversification, breadth, diverse, diversified, geographic_diversity, breadth_depth, diversify, depth_breadth, product_diversity, uniqueness
	inclusion	incorporation, include, exclusion, deconsolidation, removal, exclude, incorporate, inclusive, elimination, discontinuation
	respect	with_regard_to, regard, with_respect_to, relation, relate, as_for, pertain, vis-a-vi, related, apart_from
Teamwork	improvement	deterioration, margin_improvement, operating_improvement, cost_improvement, performance_improvement, profitability_improvement, revenue_improvement, earnings_improvement, volume_improvement, sale_improvement

Panel C: Added seed words with their top synonyms

Culture value	*Seed words*	*Synonyms*
Innovation	create	creation, bring, find, build, enable, unlock, enhance, capture, maximize, attract
	creative	innovative, creativity, creatively, clever, artistic, imaginative, innovate, entrepreneurial, interactive, marketer
	efficient	efficiently, cost-effective, cost-efficient, productive, effective, streamlined, inefficient, optimize, efficiency, smarter
	innovate	innovative, innovation, reinvent, differentiate, product_innovation, iterate, drive_innovation, innovator, technology_innovation, technology
	innovative	innovate, creative, innovation, differentiate, cutting-edge, novel, innovator, product_innovation, technology, distinctive
	passionate	passion, energize, passionately, inspiring, loyal, knowledgeable, enthusiastic, motivated, excited, engaging
Integrity	accountable	hold_accountable, responsible, accountability, empower, responsibility, incentivize, incent, business_unit_manager, motivate, delegate
	ethical	ethic, moral, ethically, unethical, integrity, corporate_governance, science-based, socially_responsible, governance, anti-competitive
	honest	honestly, candid, perfectly_honest, candidly, truth, frankly, honesty, truthfully, blunt, truthful
	honestly	candidly, frankly, honest, candid, truthfully, truth, perfectly_honest, personally, honesty, frank
	responsible	oversee, responsibility, accountable, supervise, coordinate, in-charge, govern, empower, competent, chief
	transparent	forthright, transparency, communicative, transparently, candid, clear, disclosive, concise, respectful, straightforward
Quality	customer_commitment	delivery_commitment, contract_commitment, customer_requirement, delivery_requirement, customer_demand, customer_obligation, commitment, production_need, contract_requirement, customer_delivery
	customer_expectation	consumer_expectation, guest_expectation, client_expectation, customer_demand, customer_requirement, customer_need, quality_expectation, market_requirement, client_requirement, customer_delivery
	dedicate	dedicated, devote, devoted, specialize, focus, redirect, allocate, commit, concentrate
	dedicated	dedicate, specialize, specialized, full-time, specialist, support_team, system_engineer, focused, non-dedicated, devoted
Respect	empower	empowerment, interact, motivate, accountability, embrace, energize, passionate, entrepreneurial, organize, educate
	respectful	cognizant, mindful, appreciative, attentive, thoughtful, friendly, abide, act_responsibly, transparent, reassure
	talented	experienced, highly_skilled, competent, high-caliber, talent, team, seasoned_experienced, deep_bench, well-experienced, top-flight
Teamwork	collaborate	collaboration, collaboratively, engage, collaborative, jointly, interact, cooperation, partner, coordinate, team_up
	collaborative	collaborate, collaboration, cooperative, collaboratively, consultative, coordinate, collegial, engage, joint, partnership

	cooperate	co-operate, collaborate, cooperative, cooperation, engage, co-operation, cooperatively, investigate, collaboratively, supportive
	cooperative	collaborative, cooperate, collegial, supportive, co-operative, collaboratively, cooperation, cooperatively, collaborate, mutually_beneficial

Table IA3
Included and excluded words in the culture dictionary

This table lists the included and excluded words in the culture dictionary after we apply the *word2vec* method to the corpus of earnings call transcripts (the QA section only). Panel A lists the included words. Panel B lists the excluded words after manual checking.

Panel A: Included words in the culture dictionary

Culture values	*Included words*
Innovation	creativity, innovative, innovate, innovation, creative, excellence, passion, world-class, technology, operational_excellence, passionate, product_innovation, capability, customer_experience, thought_leadership, expertise, agility, efficient, technology_innovation, competency, know-how, cutting-edge, agile, creatively, customer-centric, enable, value_proposition, reinvent, focus, innovation_capability, efficiency, customer_value, customer_intimacy, competence, user_experience, create, storytelling, pride, core_competency, ingenuity, technology_platform, consumer_experience, product_technology, engineering_team, differentiate, powerful, inspiring, innovation_process, transform, product_team, inspiration, innovation_team, technology_team, best-in-class, r&d_team, loyalty, truly, technological, differentiation, technology_capability, intellect, focused, design_capability, product_development, solve_customer_problem, customer_focus, inspire, branding, cut_edge, business_process, brand, personalization, distinctive, cost-effective, automation, world_class, harness, efficiently, domain_expertise, product_development_capability, cost-efficient, core_capability, consumer_insight, platform, engaging, delight, mass_customization, uniqueness, product_leadership, customer_success, specialization, innovation_engine, invent, guest_experience, innovator, tool, design_team, craftsmanship, seamlessness, intellectual_property, solve_problem, incredible, go-to-market, service_experience, enhance, technology_standpoint, sophistication, excitement, innovatively, great, business_model, world-leading, innovation_lab, fanatical_support, brand_management, service_model, go-to-market_capability, customer_insight, authentic, discipline, nimble, effectiveness, customer-oriented, design_thinking, execution, mobile-first, knowhow, product_idea, relentless, r&d_capability, importantly, product_development_team, customer-focused, product_design, showcase, innovation_standpoint, core_competence, ai_technology, excel, develop, effort, responsiveness, process_excellence, building_capability, technology_solution, product_capability, execution_capability, critically_important, solution, heritage, simplicity, cohesive, scalability, intelligent, curation, process_improvement, intimacy, user_interface, r&d_organization, best-in-breed, core_technology, analytic, domain_knowledge, creativeness, client_experience, technology_perspective, invention, cost_efficiency, technologically, core_strength, award-winning, learn, merchandising, marketing_team, ethos, optimize, awareness, technology_leadership, game_team, leadership_position, engineering_capability, leverage_technology, feature_functionality, brand_equity, smarter, enabler, dna, operating_platform, computer_graphic, service_excellence, marketing_idea, service_delivery_platform, artistic, product_development_process, ability, reimagine, platform_capability, democratize, end-to-end, forefront, connectedness, customer_interface, datum_analytic, innovation_perspective, r&d_department, take_cost_out, reengineer, workflow, center_excellence, marketing_technology, relevancy, unparalleled, content, successful, smart, technology_architecture, process_innovation, authenticity, scalable, vision, marketer, visual_merchandising, brand_experience, productivity, technology-enabled, terrific, easy-to-use, product_experience, coherence, product_management, machine_learning_ai, leadership_product, industry_leadership, simplify, science, versatility, artificial_intelligence, packaging_solution, intellectual, datum_science, best-of-breed, attract, adaptability, r&d_group, drive_innovation, delivery_platform, succeed, modern, state-of-the-art, immersive, information_technology, engineering_skill, r&d_community, transformation, ease-of-use, design, category_management, technology_base, business_system, unique, application_expertise, video_technology, product_creation, breakthrough_technology, teaching, innovation_technology, delivery_system, breadth_depth, architecture,

	marketing_capability, visual, world_class_product, technology-driven, internally_externally, delivery_model, consumer_engagement, success, rapid_prototyping, customer_centricity, information-based, problem_solver, delivery_organization, video_experience, globalize, product_excellence, problem-solving, machine_learning, product_offering, marketing_expertise, social_media, customer_loyalty, design_expertise, personalized, unique_selling_proposition, marketing_skill, enablement, product_developer, service_leader, engineering_organization, usability, technology_development, manufacturing_engineering, innovativeness, leadership_model, technology_organization, entertainment_experience, imaginative, product_differentiation, resourceful, search_capability, consumer-centric, creator, brand_recognition, shopping_experience, innovation_center, breakthrough_innovation, knowledge-based, design_standpoint, knowledge_management, content_creation, secret_sauce, core_business_process, multi-channel, software_team, software_engineering, distinctiveness, store_environment, imperative, compelling, globalization, customer_relationship_management, product_development_system, core_value_proposition, product_functionality, operation_excellence, prowess, resonate, fabulous, technology-based, process_management, newness, exciting, clever, restaurant_experience, recipe, marketing_tool, supply_chain_approach, technology_differentiation, proven, storyteller, devops, inventive, architect, product_solution, deep_domain_expertise, technology_leader, engineering_expertise, amazing, solution_capability, engineering_talent, innovation_side, application_knowledge, consumer_understanding, experiential, solve_business_problem, fantastic, brand_name, service_culture, brand_building, search_technology, testament, unifying, organizations, workspace, foundation, brand_identity, inventiveness, brand_positioning, integrated, wonderful, fanatical, best, messaging, mastery, fun, self-expression, store_experience, first-rate, elegance, marketing_excellence, content_experience, beautiful, consulting_expertise, operating_skill, brain_power, taste, inspirational, hallmark, superb
Integrity	accountability, ethic, integrity, responsibility, transparency, accountable, governance, ethical, transparent, trust, responsible, oversight, independence, objectivity, moral, trustworthy, fairness, hold_accountable, corporate_governance, autonomy, core_value, assure, stakeholder, fiduciary_responsibility, continuity, credibility, honesty, privacy, fiduciary_duty, rigor, empathy, ethic_integrity, egalitarian, fiduciary, utmost, code_ethic, faith, passionately, impartial, compliance, honorable, socially_responsible, ethically, company_culture, solidarity, democracy, stewardship, identity, constituent, governance_model, citizen, scrupulous, society, governance_structure, safety_soundness, humility, decency, meritocracy, reassure, exemplary, business_ethic, act_responsibly, advocacy, controllership, diligent, sincerity, satisfaction, supervision, consistency, value_system, delegate, advocate, fiduciary_obligation, philanthropy, risk_control, empathetic, advice, safety_culture, risk_management, business_conduct, unbiased, principled, rigorous, candid, principle, humble, eat_cooking, banking_supervision, risk_oversight, condone, correctness, science-based, skin_game, equality, preach, compassion, adhere, management_style, consumer_protection, religious, credo, citizenship, governance_standpoint, management, executive_committee, seriousness, probity, executive_board, governance_process, sincere, management_board, counsel, rigor_discipline, safety_environment, assurance, candor, compliance_team, well-informed, elect_official, corrupt, mindset, pragmatic, anonymity, onus, business_practice, thoughtful, board_oversight, evidence-based, meticulous, crime, patient_safety, committee, risk_committee, finance_department, traceability, mission_statement, spirit, paternalistic, freedom, governance_rule, high-integrity, quality_assurance, policymaker, risk_organization, credible, audit_committee, quality_management_system, shareholder_community, policy_maker, governance_perspective, custodian, governance_system, faithful, instruct, well-intended, supervise, communication_style, regulator, instil, authorship, paramount_importance, compliance_program, convince, unwavering_commitment, honest, institutionalize, courage, insist, governance_practice, community_member, governance_framework, nonpartisan, proper, honor, secrecy, bureaucrat,

	risk_management_function, abide, frugality, performance_culture, safeguard, community_standard, steadfast, level_playing_field, conformity, forthright, deserve, thoughtfulness, board_director, decentralize, control, moral_obligation, finance_team, instill, sovereignty, well-intentioned, comply, convincing, misconduct, zeal, applaud, democratic, quality_organization, fact-based, frustration, decision_rights, harm, constitutionally, oversight_responsibility, conscience, government_regulator, authority, bureaucracy, responsibly, unethical, trustworthiness, esteem, safety, supervisory, journalism, council, expert, mantra, audit_function, genuinely, adhering, responsive, govern_body, hands-off, decentralized, diligence, disinterested, conflict-free, disciplined, confidentiality, oversight_committee, company_management, adherence, motivation, quality_care, governance_standard, in-charge, business-like, dishonest, caretaker, compliance_department, paramount, employee_engagement, core_principle, judiciary, management_discipline, team-oriented, suitability, thoroughness, information_flow, management_approach, compliance_function, impeccable, overseer, thorough, unequivocally, nondiscrimination, politician, harmonized, strict, embarrassment, board_function, enforce, business_principle, steward, operation_council, compliance_aspect, vested_interest, governance_issue, prescriptive, attentive, risk_manager, subcommittee, inculcate, resolute, reproach, safety-first, risk_management_group, management_committee, nominating_committee, safety_management, unequivocal, management_philosophy, reputable, keen, reputational_risk, individualistic, metrics-driven, authoritative, governmental_agency, wisdom, procurement_department, demonize, insistence, law-abiding, resourcefulness, proprietor, money_laundering, ingrained, harassment, customer_champion, brand_champion, communicative, franchisor, bureaucratic, advice_counsel, stakeholder_management, entrust, shareholder_interest, police, unselfish, suasion, courteous, vouch, visionary, intellectually_honest, derelict, sincerely, corruption, conflict, remuneration_committee, legitimacy, prudence, acutely_aware, legislator, informed, investment_community, wholeheartedly, ombudsman, dictatorship, core_responsibility, unanimously, ego, sympathetic, journalistic, careful, illegality, conscientious, obsessive, stand_up, governing_council, litigator, renown, seriously, honestly, partisan, truth, humbly, reprehensible, praise, disrespect, let_you_down, criticism, irresponsible, arrogant, candidly
Quality	dedicated, quality, dedication, customer_service, customer, dedicate, service_level, mission, service_delivery, customer_satisfaction, service, reliability, commitment, customer_need, customer_support, high-quality, ensure, customer_relationship, quality_service, product_quality, quality_product, capable, service_quality, end_user, quality_level, customer_expectation, service_capability, client, customer_requirement, sla, support, customer_commitment, vendor_partner, service_standard, service_team, operation_team, quality_standard, mission-critical, customer_care, customer_solution, deliver, customer_engagement, support_team, service_level_agreement, connectivity, customer_demand, system_engineer, commit, service_offering, service_support, service_organization, channel_partner, product, service_product, customer_base, vendor, service_management, supplier, network, service_requirement, brand_promise, customer_team, specialize, application_solution, serve, customer_service_organization, end_customer, customer_support_people, speed, it_team, service_people, field, delivery_people, quality_control, delivery_capability, desire, delivery_team, customer_contact, customer-facing, account_team, top-quality, customize, customization, specification, guest, customer_service_level, support_capability, it_department, skill_building, high-touch, help_desk, support_organization, end-user, service_commitment, engineering_support, critical, enterprise-class, implementation_team, field_technician, service_proposition, high-value, it_governance, service_personnel, supply_chain, solution_set, application_engineer, service_representative, security_operation_center, quality_management, tailor, professional_service_team, product_management_team, breadth, workload, service_provider, infrastructure, customer_interaction, build, sale_support, work_flow, specialized, project_management, customer_site, quality_delivery, application_support, consulting_organization, functionality, high-performance, friendliness, brand_partner, customer_relation, shop_floor, field_application_engineer, service_aspect, uptime, classroom_experience, on-time_delivery, sale_engineering_team, customer_training, devotion,

	program_management, professional_service_organization, quality_work, task, tireless, deployment_team, call_center_agent, application_people, specialist, end-user_customer, enterprise-grade, solution_center, service_engineer, security_specialist, engineering_resource, deliver_it_out, customer_service_rep, field_service_engineer, delivery_performance, customer_service_experience, service_need, quality_aspect, product_spec, requirement, field_sale_organization, sale_management, maintenance_team, customer_request, application_engineering, supplier_quality, end-to-end_solution, service_automation, sale_floor, bandwidth, productive, locally, sale_machine, seamless, it_capability, selling_skill, war_fighter, installation_team, relationship_management, carrier_partner, proficiency, sale_engineer, logistics, product_specialist, system_requirement, back_they_up, client_interface, account_management, quality_system, application_integration, customer_orientation, automation_capability, sale_force, customer_delivery, essential, product_service, project_team, turnkey_solution, product_training, mission_critical_application, custom_solution, field_application, service_element, solution_team, retrain, on-site, r&d_people, sale_effort, implementation_capability, customer_engineer, service_specialist, customer_application, customer_service_solution, business_outcome, assemble, customer_service_group, network_team, devoted, delivery, engineering_department, tech_support, mission_critical, management_support, business_team, quality_expectation, business_need, manpower, client_service_team, work_type, support_structure, aftermarket_support, system_engineering, it_infrastructure, manufacturing_team, quality_support, it_solution, manufacturing_capability, certification_program, mobility_solution, deliverable, architecture_team, fulfillment, process_capability, customer_spec, supply_chain_logistics, partner_enablement, it_operation, project_management_skill, integration_service, market_requirement, support_infrastructure, market-facing, manufacturing_organization, market_need, meeting_customer, service_reliability, system_support, technology_requirement, guest_need, supply_chain_requirement, client_requirement, engineering_requirement, client_need, reliability_requirement, guest_expectation
Respect	talented, talent, empower, team_member, employee, team, leadership, leadership_team, culture, teammate, organization, entrepreneurial, skill, executive, empowerment, management_team, best_brightest, professionalism, staff, highly_skilled, skill_set, technologist, competent, entrepreneur, experienced, energize, entrepreneurial_spirit, high-caliber, manager, leadership_skill, management_group, motivated, executive_team, senior_executive, deep_bench, employee_base, leader, business_acumen, career_path, sale_professional, motivate, management_people, human_resource_department, dignity, entrepreneurship, quality_people, senior-level, talent_pool, scientist, work_ethic, it_professional, leadership_talent, well-trained, technology_people, athlete, veteran, workforce, highly_motivate, field_organization, it_people, talent_base, personality, recruit, knowledgeable, hard-working, top-notch, business_leader, leadership_level, co-worker, stylist, management_skill, mentore, management_talent, store_manager, ambassador, reputation, culturally, faculty, professionally, branch_staff, leadership_group, bench_strength, designer, career_opportunity, organisation, sale_executive, subject_matter_expert, skillset, subject_matter_expertise, people, relationship_manager, frontline_employee, top-flight, team_approach, proud, domain_expert, investment_professional, senior_leadership_team, salespeople, sale_leader, caliber, project_manager, sale_team, mentorship, founder, business_people, respectful, sale_organization, operating_team, development_team, work_force, industry_expertise, re-skill, sale_people, energetic, business_professional, credentials, relationship_management_team, workplace, core_team, coach, datum_scientist, team_player, work_environment, nurture, senior_officer, hardworking, trainer, company_employee, caring, team_leader, folk, account_management_team, practice_leader, coaching, camaraderie, morale, software_developer, staff_member, consultant, skilled, sale_associate, trained, coworker, admire, brand_ambassador, cultural, fellow, railroader, executive_talent, training, servant, officer, field_people, highly-skilled, training_program, health_enthusiast, seasoned_experienced, mentoring, store_team, store_manager_district_manager, client_service, field_team, train_they_up, leadership_development, editorial_team, department_head, finance_organization,

	marketing_manager, well-skilled, cast_member, executive_level, field_leader, sale_management_team, management_staff, client-facing, well-educated, member, director-level, hire, managing_director, relationship_banker, adviser, crew_member, educate, sale_folk, assistant, teacher, c_suite, leadership_standpoint, branch_manager, cultural_fit, respected, train, banker, grateful, well-experienced, advisor, product_manager, program_manager, district_manager, accomplished, selling_organization, sale_skill, compliance_officer, recruiting_organization, investment_team, long-tenured, technician, talent_people, leadership_capability, highly-talented, decision_maker, skill_level, person, cadre, army, operation_staff, district_sale_manager, labor_leader, communication_skill, leadership_role, caregiver, senior, field_sale_people, marketing_person, proven_track_record, project_leader, management_organization, people_development, appreciative, salesforce, insurance_professional, field_leadership, cio, business_experience, business_development_people, recruiting_team, recruiting, service_professional, aptitude, profession, privilege, product_knowledge, field_leadership_team, thankful, champion, account_manager, engineer, full-time, engineering_people, general_managers, platform_president, knowledge_base, businesspeople, seasoned_executive, c-level, vp_level, interior_designer, customer_service_team, resource, leadership_quality, bring_people_in, investment_talent, teach, store_employee, technology_folk, accenture, plant_manager, vice_presidents, board_member, product_people, service_mentality, sale_manager, tribute, team_building, management_member, hands-on, marketing_people, work_experience, field_manager, acumen, account_executive, datum_analyst, mid-career, lieutenant, front_line_employee, director, supervisor, spokespeople, charismatic, knowledge_worker, marketing_staff, well-respected, staff_people, field-based, credential, young, filmmaker, train_up, country_manager, account_representative, marketing_organization, executive_leadership, engineering_school, community_leader, freelancer, results-oriented, compliance_organization, restaurant_manager, reward, company, business_development_folk, development_organization, hard-charging, crewmember, administrator, succession_planning, decision-maker, executive_management_team, ceo, cross-trained, employee_group, c-suite, researcher, client_team, team_structure, people_business, knowledge_transfer, senior_management, employer, inspired, career_pathing, it_organization, senior_management_group, country_management, customer_organization, team_effort, regional_vice_president, compliment, customer_service_department, director_level, leadership_style, evangelist, rapport, customer_service_representative, brand_manager, business_culture, engineering_community, mentor, spiritual, customer_service_people, store_organization, marketing_consultant, network_engineer, sales-oriented, executive_management, security_professional, reskill, product_expert, people_skill, business_analyst, business_executive, selling_team, loyal, educator, line_manager, bless, planner, restaurant_general_manager, ceo_level, employee_team, sale_department, training_group, first-class, field_management, high-performing, operating_committee, mid-management, distributor_organization, line_people, deal_maker, ceo_cfo, people_culture, invaluable, advisory_council, store_director, bank_manager, health_care_professional, town_hall, operating_manager, rank-and-file, can-do, family_member, values-based, well-versed, constituency, knowledge, team-based, indoctrinate, immerse, train_master, business_manager, gender_equality, mission-driven, training_organization, customer_community, boardroom, esprit_de_corps, business_community, comradery, motivational, rewarding, fellow_board_member, role_model, oversee, kindness, admiration, channel_organization, grown-up
Teamwork	collaborate, cooperation, collaboration, collaborative, cooperative, partnership, cooperate, collaboratively, partner, co-operation, coordination, engage, jointly, coordinate, teamwork, business_partner, alliance, team_up, technology_partner, joint, cooperatively, relationship, collaborator, interaction, working_relationship, co-operate, technology_partnership, association, dialogue, dialog, collegial, information_sharing, co-selling, business_relationship, partnering, involvement, mutually_beneficial, unite, organize, partnership_way, cross-functional, interact, embrace, win-win, alignment, co-market, join_up, joint_development_committee, mutually, technology_provider,

	consortium, bring_together, reach_out, work_relationship, marketing_partner, joint_steering_committee, communication, partner_up, academic_collaborator, openness, co-develop, industry_partner, interface, collegiality, constructive_dialogue, collaboration_partner, harmonious, partnership_relationship, actively_engage, co-marketing, federation, ecosystem, co-development, interoperability, like-minded, co-creation, link_up, consortia, outreach, engagement, co-operative, ecosystem_partner, co-development_relationship, supportive, trade_association, co-sell, industry_organization, standard_body, integrate, partnership_approach, technology_collaboration, foster, development_partner, development_relationship, development_partnership, win/win, symbiotic_relationship, contact, group_file, partnership_basis, co-work, assist, technology_exchange, supplier_partner, co-create, cooperation_agreement, building_relationship, research_institute, engagement_model, innovation_group, research_organization, pioneering, government_partner, constructive_dialog, technology_sharing, together_with, implementation_partner, consultation, collaboration_model, application_provider, think_tank, business_agreement, business_collaboration, brainstorm, key_opinion_leader, service_partner, auspices, co-venture, distribution_partnership, technology_relationship, tripartite, isv_partner, partnership_arrangement, sharing, liaison, dealings, study_group, codevelopment, datum_exchange, commercialization_partner, open_source_community, joint_development_agreement, long-standing_relationship, platform_partner, funding_organization, umbrella_organization, technology_vendor, steer_committee, unify, knowledge_sharing, consultative, mutual, constructively, system_integrator, research_institutes, supply_partner, federate, multi-stakeholder, involve, technology_transfer, facilitator, advocacy_group, sit_down, orchestrate, revenue_integration, collaboration_program, unified, media_partner, coalition, patient_advocacy_group, crada, sponsor, alliance_partner, self-trafficking, marketing_partnership, thought_leader, interoperate, alliance_management, partnership_opportunity, explore, innovation_partner, interoperable, collaboration_agreement, core_partner, co-innovate, partner_company, antitrust_immunity, instrumental, regulatory_authority, system_integration_partner, team_work, comarketing, union_leadership, marriage, standardize, partner_organization, co-development_project, research_laboratory, device_partner, mutually-beneficial, worker_representative, cross-business-unit, software_partner, exchange_information, technology_agreement, co-development_arrangement, pioneer, discussion, codevelop, align, licensor, venture_organization, commercialization_deal, information_exchange, psychiatry_division, cross-fertilization, academic_institution, union, marketing_relationship, put_together, program_office, game_developer, platform_technology, partner_community, ad_hoc_type, collaboration_effort, endorsement, merge, distribution_partner, management_consulting_firm, partnering_relationship, development_group, help_each_other_out, concert, engagement_process, partnership_kind, demonstration, investigate, shoulder_shoulder, forward-thinking, contract_research_organization, government_agency, engineering_level, trade_group, engineering_group, work_along, labor_organization, supply_chain_partner, research_center, formalize, pharma_partner, platform_partnership, cultivate, ministry, integration, transition_team, implementer, co-development_partner, platform_provider, symbiosis, comarket, integrative, ownership_relationship, sister_company, regulatory_body, integration_team, technology_integration, opendaylight, solution_partner, industry_partnership, symbiotic, two-way_street, aboriginal, cooperation_partner, open-sourcing, developer_framework, cross-functionally, developer_partner, device_manufacturer, go-to-market_partnership, community_group, content_owner, formal_informal, business_arrangement, collaboration_opportunity, marketeer, friendship, customer_relationship_model, facilitate, co-promotion, co-fund, industry_association, real_estate_partner, cordial, corroboration, operationalize, marketing_alliance, co-chair, renowned, provider_community, integrator, university, technology_alliance, infrastructure_provider, co-share, pathology_group, document_management_solution, private-public, coordinator, probe_audit, integration_partner, home_infusion_provider, consortium_member, integrator_partner, software_provider, partner_team, world-renowned, harmonize, government_official, alliance_relationship, fruitfully, conduct,

	joint_venture_relationship, intimately_involve, assistance, sale_partner, co-prime, co-partner, collaboration_basis, system_integration_community, group_affiliate, fruitful, co-opetition, validation, together, idea_generation, corporation_agreement, health_authority, deepen_relationship, partnership_relation, research_agreement, one-stop-shop, task_force, on_behalf_of, enlist, individualism, leadership_potential, delivery_system_model, conjunction, business_partnership, technology_firm, chipset_vendor, newspaper_consortium, conversation, engagement_team, content_provider, partnership_work, investigator, lead_vendor, marketing_agreement, collaborate_on, base_band_partner, patient_organization, arm_length, cross_pollinate, harmony, independently, signing_agreement, worker_council, hand_glove, confrontation, utility_partner, amicable

Panel B: Excluded words from the culture dictionary

Culture values	*Excluded words*
Innovation	really, bring, value, invest, find, panera
Integrity	emotional, company_director, incitec_pivot, personally, frustrate, sure, h_shareholder, underwriter, euro_group, emotion, priest, wall_street
Quality	need, autozoners, so_that, in_order, able, importance, mammo_workstation
Respect	manger, job, chef, pharmacist
Teamwork	work, gs1, crispr_therapeutics, health_discovery, fluxys, lfb, shyft, halozyme, nanoimprint_technology, dena, 3lp, az, mhlw, dana-farber, xiaomi, bristol-myers_squibb, sloan-kettering, qihoo, memorial_sloan-kettering, zjx, tttech, astellas, si_partner, servicesource, mobileye, appnexus, cloudera, macrogenics, nanthealth, behalf, biontech, work_on, hhs, pricing_authority, snai, security_agency

Table IA4
Validating our main measure of corporate cultural values: Including all five values

This table validates our main measure of corporate cultural values. We extend Table 5 by including all five cultural values in each regression. In Panel A, LnPatent, R&D spending, and innovation strength are used to validate the cultural value of innovation. In Panel B, restatement and backdating are used to validate the cultural value of integrity. In Panel C, product quality, product safety, and top brand are used to validate the cultural value of quality. In Panel D, diversity and best employer are used to validate the cultural value of respect. In Panel E, employee involvement and the number of JVs/SAs are used to validate the cultural value of teamwork. OLS regressions are used when the dependent variables are LnPatent, R&D spending, diversity, and the number of JVs/SAs, and probit regressions are used for all other validating variables. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Validating the cultural value of *innovation*

	LnPatent (1)	LnPatent (2)	LnPatent (3)	R&D spending (4)	R&D spending (5)	R&D spending (6)	Innovation strength (7)	Innovation strength (8)	Innovation strength (9)
Innovation	0.186***	0.186***	0.150***	0.007***	0.008***	0.007***	0.144**	0.140**	0.165**
	(0.019)	(0.019)	(0.018)	(0.001)	(0.001)	(0.001)	(0.059)	(0.059)	(0.082)
Integrity	-0.291***	-0.291***	-0.197***	0.005*	-0.007***	-0.003*	-0.218	-0.208	0.022
	(0.025)	(0.025)	(0.022)	(0.003)	(0.002)	(0.002)	(0.207)	(0.205)	(0.220)
Quality	0.099***	0.099***	-0.015	-0.004**	0.003**	-0.001	0.273***	0.266***	0.076
	(0.017)	(0.017)	(0.017)	(0.001)	(0.001)	(0.001)	(0.087)	(0.089)	(0.122)
Respect	-0.130***	-0.130***	-0.072***	-0.024***	-0.019***	-0.017***	-0.167*	-0.173*	-0.045
	(0.012)	(0.012)	(0.012)	(0.001)	(0.001)	(0.001)	(0.096)	(0.096)	(0.102)
Teamwork	-0.001	-0.001	-0.078***	0.068***	0.044***	0.027***	-0.016	0.012	-0.226
	(0.015)	(0.016)	(0.017)	(0.002)	(0.002)	(0.002)	(0.112)	(0.118)	(0.146)
Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes	No	No	Yes
Ind FE/Yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,298	25,298	25,298	62,584	62,584	62,584	11,500	11,500	7,676
R^2/Pseudo R^2	0.071	0.071	0.182	0.339	0.511	0.594	0.059	0.061	0.158

Panel B: Validating the cultural value of *integrity*

	Restatement	Restatement	Restatement	Backdating	Backdating	Backdating
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.036**	0.036**	0.037**	0.183***	0.182***	0.203***
	(0.014)	(0.014)	(0.015)	(0.028)	(0.028)	(0.031)
Integrity	-0.076**	-0.077**	-0.058*	-0.286***	-0.273***	-0.297***
	(0.033)	(0.033)	(0.033)	(0.053)	(0.053)	(0.054)
Quality	-0.001	-0.001	-0.025	-0.091***	-0.100***	-0.061*
	(0.018)	(0.018)	(0.019)	(0.030)	(0.030)	(0.033)
Respect	0.041**	0.041**	0.042**	0.161***	0.154***	0.133***
	(0.017)	(0.017)	(0.018)	(0.031)	(0.031)	(0.032)
Teamwork	-0.128***	-0.129***	-0.090***	-0.170***	-0.131***	-0.155***
	(0.021)	(0.022)	(0.023)	(0.034)	(0.035)	(0.038)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/Yr FE	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	50,452	50,452	50,452	17,671	17,671	17,671
Pseudo R^2	0.003	0.003	0.023	0.030	0.032	0.056

Panel C: Validating the cultural value of *quality*

	Product quality	Product quality	Product quality	Product safety	Product safety	Product safety	Top brand	Top brand	Top brand
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Innovation	0.177***	0.173***	0.036	-0.146***	-0.127***	-0.053	0.327***	0.290***	0.215***
	(0.026)	(0.026)	(0.034)	(0.033)	(0.032)	(0.042)	(0.041)	(0.041)	(0.048)
Integrity	-0.148*	-0.142*	-0.214**	-0.145*	-0.160*	-0.287***	-0.189*	-0.175*	-0.008
	(0.084)	(0.083)	(0.103)	(0.085)	(0.085)	(0.092)	(0.104)	(0.104)	(0.107)
Quality	-0.092**	-0.097**	-0.015	0.186***	0.200***	0.266***	0.199***	0.187***	0.032
	(0.042)	(0.043)	(0.056)	(0.051)	(0.052)	(0.068)	(0.059)	(0.059)	(0.069)
Respect	-0.059	-0.062	-0.027	0.163***	0.164***	0.062	-0.021	-0.006	0.142**
	(0.039)	(0.039)	(0.045)	(0.049)	(0.049)	(0.056)	(0.063)	(0.063)	(0.069)
Teamwork	0.018	0.037	-0.249***	0.176**	0.128*	0.123	-0.088	-0.044	0.009
	(0.054)	(0.056)	(0.070)	(0.071)	(0.075)	(0.080)	(0.088)	(0.090)	(0.097)

Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Ind FE/Yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,285	18,285	18,285	21,341	21,341	21,341	40,917	40,917	40,917
Pseudo R^2	0.090	0.090	0.241	0.119	0.124	0.235	0.463	0.471	0.509

Panel D: Validating the cultural value of *respect*

	Diversity (1)	Diversity (2)	Diversity (3)	Best employer (4)	Best employer (5)	Best employer (6)
Innovation	0.215***	0.215***	0.209***	0.187***	0.153***	0.185***
	(0.029)	(0.029)	(0.027)	(0.041)	(0.043)	(0.048)
Integrity	-0.017	-0.018	-0.027	-0.603***	-0.609***	-0.554***
	(0.051)	(0.051)	(0.047)	(0.140)	(0.139)	(0.144)
Quality	0.005	0.006	-0.004	0.035	0.014	-0.049
	(0.030)	(0.030)	(0.031)	(0.066)	(0.066)	(0.075)
Respect	0.026	0.026	0.024	0.216***	0.233***	0.224***
	(0.024)	(0.024)	(0.024)	(0.058)	(0.060)	(0.068)
Teamwork	0.049	0.048	0.028	-0.084	-0.008	-0.059
	(0.031)	(0.032)	(0.031)	(0.082)	(0.086)	(0.082)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/Yr FE	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,385	19,385	19,385	54,603	54,603	52,930
R^2/Pseudo R^2	0.189	0.189	0.322	0.129	0.164	0.215

Panel E: Validating the cultural value of *teamwork*

	Employee involvement	Employee involvement	Employee involvement	Number of JVs/SAs	Number of JVs/SAs	Number of JVs/SAs
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.106***	0.107***	0.032	0.001	0.001	0.001
	(0.030)	(0.030)	(0.034)	(0.001)	(0.001)	(0.001)
Integrity	-0.323***	-0.327***	-0.184**	-0.002	-0.003	0.001
	(0.082)	(0.081)	(0.080)	(0.002)	(0.002)	(0.002)
Quality	0.238***	0.241***	0.132***	-0.002*	-0.002	-0.004***
	(0.041)	(0.042)	(0.050)	(0.001)	(0.001)	(0.001)
Respect	-0.068	-0.067	-0.008	-0.004***	-0.003***	-0.001
	(0.044)	(0.044)	(0.045)	(0.001)	(0.001)	(0.001)
Teamwork	0.269***	0.261***	0.154***	0.010***	0.009***	0.010***
	(0.053)	(0.056)	(0.059)	(0.001)	(0.001)	(0.001)
Size	Yes	Yes	Yes	Yes	Yes	Yes
ROA	No	Yes	Yes	No	Yes	Yes
Ind FE/Yr FE	No	No	Yes	No	No	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,262	17,262	17,262	62,584	62,584	62,584
R^2/Pseudo R^2	0.085	0.085	0.131	0.021	0.022	0.029

Table IA5
Summary statistics of alternative measures of corporate cultural values

This table presents an overview of alternative measures of corporate cultural values. The suffix _full refers to the measure based on the entire call (i.e., including both management presentation and QA sections). The suffix _seed refers to the measure based on a simple count of the seed words (including the value word) in the QA section of calls. The suffix _10k refers to the measure based on applying the word embedding model to the MD&A section of 10-Ks. Panel A presents the summary statistics. Panel B presents the correlations between our main and alternative measures of the cultural value of innovation. Panel C presents the correlations between our main and alternative measures of the cultural value of integrity. Panel D presents the correlations between our main and alternative measures of the cultural value of quality. Panel E presents the correlations between our main and alternative measures of the cultural value of respect. Panel F presents the correlations between our main and alternative measures of the cultural value of respect.

Panel A: Summary statistics for alternative measures of corporate cultural values

Variable	Obs.	Mean	10th Percentile	Median	90th Percentile	SD
Innovation_full	62,664	1.149	0.469	0.981	2.088	0.673
Integrity_full	62,664	0.447	0.149	0.378	0.845	0.296
Quality_full	62,664	0.775	0.314	0.662	1.407	0.452
Respect_full	62,664	0.679	0.200	0.530	1.377	0.509
Teamwork_full	62,664	0.617	0.202	0.483	1.234	0.455
Innovation_seed	62,664	0.105	0.011	0.082	0.225	0.091
Integrity_seed	62,664	0.071	0.000	0.051	0.170	0.076
Quality_seed	62,664	0.085	0.015	0.071	0.170	0.067
Respect_seed	62,664	0.038	0.000	0.019	0.104	0.052
Teamwork_seed	62,664	0.023	0.000	0.000	0.070	0.052
Innovation_10k	44,745	0.586	0.045	0.427	1.340	0.548
Integrity_10k	44,745	0.358	0.000	0.268	0.789	0.355
Quality_10k	44,745	0.500	0.078	0.391	1.085	0.420
Respect_10k	44,745	0.317	0.000	0.208	0.770	0.346
Teamwork_10k	44,745	0.328	0.000	0.147	0.808	0.529

Panel B: Correlations between our main and alternative measures of *innovation*

	Innovation	Innovation_full	Innovation_seed	Innovation_10k
Innovation	1.000			
Innovation_full	0.879***	1.000		
Innovation_seed	0.520***	0.507***	1.000	
Innovation_10k	0.385***	0.363***	0.179***	1.000

Panel C: Correlations between our main and alternative measures of *integrity*

	Integrity	Integrity_full	Integrity_seed	Integrity_10k
Integrity	1.000			
Integrity_full	0.931***	1.000		
Integrity_seed	0.475***	0.461***	1.000	
Integrity_10k	0.142***	0.116***	0.068***	1.000

Panel D: Correlations between our main and alternative measures of *quality*

	Quality	Quality_full	Quality_seed	Quality_10k
Quality	1.000			
Quality_full	0.847***	1.000		
Quality_seed	0.479***	0.559***	1.000	
Quality_10k	0.438***	0.416***	0.261***	1.000

Panel E: Correlations between our main and alternative measures of *respect*

	Respect	Respect_full	Respect_seed	Respect_10k
Respect	1.000			
Respect_full	0.927***	1.000		
Respect_seed	0.470***	0.465***	1.000	
Respect_10k	0.381***	0.380***	0.163***	1.000

Panel F: Correlations between our main and alternative measures of *teamwork*

	Teamwork	Teamwork_full	Teamwork_seed	Teamwork_10k
Teamwork	1.000			
Teamwork_full	0.934***	1.000		
Teamwork_seed	0.458***	0.443***	1.000	
Teamwork_10k	0.498***	0.480***	0.410***	1.000

Table IA6
Horse race between our main and alternative measures of corporate cultural values

This table extends Table 6 and compares our main measure with alternative measures altogether. These alternative measures are based on: i) the entire call (_full); 2) a simple count of the seed words (including the value word) in the QA section of calls (_seed); and iii) applying the word embedding model to the MD&A section of 10-Ks (_10k). In Panel A, LnPatent, R&D spending, and innovation strength are used to validate the cultural value of innovation. In Panel B, restatement and backdating are used to validate the cultural value of integrity. In Panel C, product quality, product safety, and top brand are used to validate the cultural value of quality. In Panel D, diversity and best employer are used to validate the cultural value of respect. In Panel E, employee involvement and the number of JVs/SAs are used to validate the cultural value of teamwork. OLS regressions are used when the dependent variables are LnPatent, R&D spending, diversity, and the number of JVs/SAs, and probit regressions are used for all other validating variables. Industry fixed effects (FE) are based on the Fama-French 12-industry classification. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Horse race between innovation, innovation_full, innovation_seed, and innovation_10k

	LnPatent (1)	R&D spending (2)	Innovation strength (3)
Innovation	0.335***	0.024***	0.205
	(0.044)	(0.002)	(0.127)
Innovation_full	-0.478***	-0.020***	-0.175
	(0.065)	(0.003)	(0.303)
Innovation_seed	0.257	-0.090***	-1.499
	(0.167)	(0.010)	(0.948)
Innovation_10k	0.039	-0.000	0.166
	(0.033)	(0.002)	(0.122)
Size & ROA	Yes	Yes	Yes
Ind FE/Yr FE	Yes	Yes	Yes
Intercept	Yes	Yes	Yes
Obs.	17,820	44,474	6,629
R^2/Pseudo R^2	0.234	0.584	0.156

Panel B: Horse race between integrity, integrity_full, integrity_seed, and integrity_10k

	Restatement (1)	Backdating (2)
Integrity	-0.017	0.641***
	(0.109)	(0.218)
Integrity_full	0.004	-0.890***
	(0.141)	(0.282)
Integrity_seed	0.009	0.343
	(0.186)	(0.355)
Integrity_10k	0.039	-0.095
	(0.036)	(0.073)
Size & ROA	Yes	Yes
Ind FE/Yr FE	Yes	Yes
Intercept	Yes	Yes
Obs.	35,823	12,427
Pseudo R^2	0.023	0.061

Panel C: Horse race between quality, quality_full, quality_seed, and quality_10k

	Product quality (1)	Product safety (2)	Top brand (3)
Quality	0.005	0.374***	0.017
	(0.078)	(0.098)	(0.109)
Quality_full	-0.166	-0.141	0.060
	(0.163)	(0.192)	(0.263)
Quality_seed	0.845	-0.236	0.492
	(0.656)	(0.884)	(1.220)

Quality_10k	-0.108	0.159	0.334***
	(0.088)	(0.099)	(0.108)
Size & ROA	Yes	Yes	Yes
Ind FE/Yr FE	Yes	Yes	Yes
Intercept	Yes	Yes	Yes
Obs.	15,905	18,530	29,234
Pseudo R^2	0.234	0.223	0.476

Panel D: Horse race between respect, respect_full, respect_seed, and respect_10k

	Diversity (1)	Best employer (2)
Respect	0.257***	0.364**
	(0.063)	(0.147)
Respect_full	-0.336***	-0.452*
	(0.096)	(0.232)
Respect_seed	0.048	1.651**
	(0.342)	(0.802)
Respect_10k	0.170***	0.145
	(0.054)	(0.134)
Size & ROA	Yes	Yes
Ind FE/Yr FE	Yes	Yes
Intercept	Yes	Yes
Obs.	16,679	37,719
R^2/Pseudo R^2	0.296	0.231

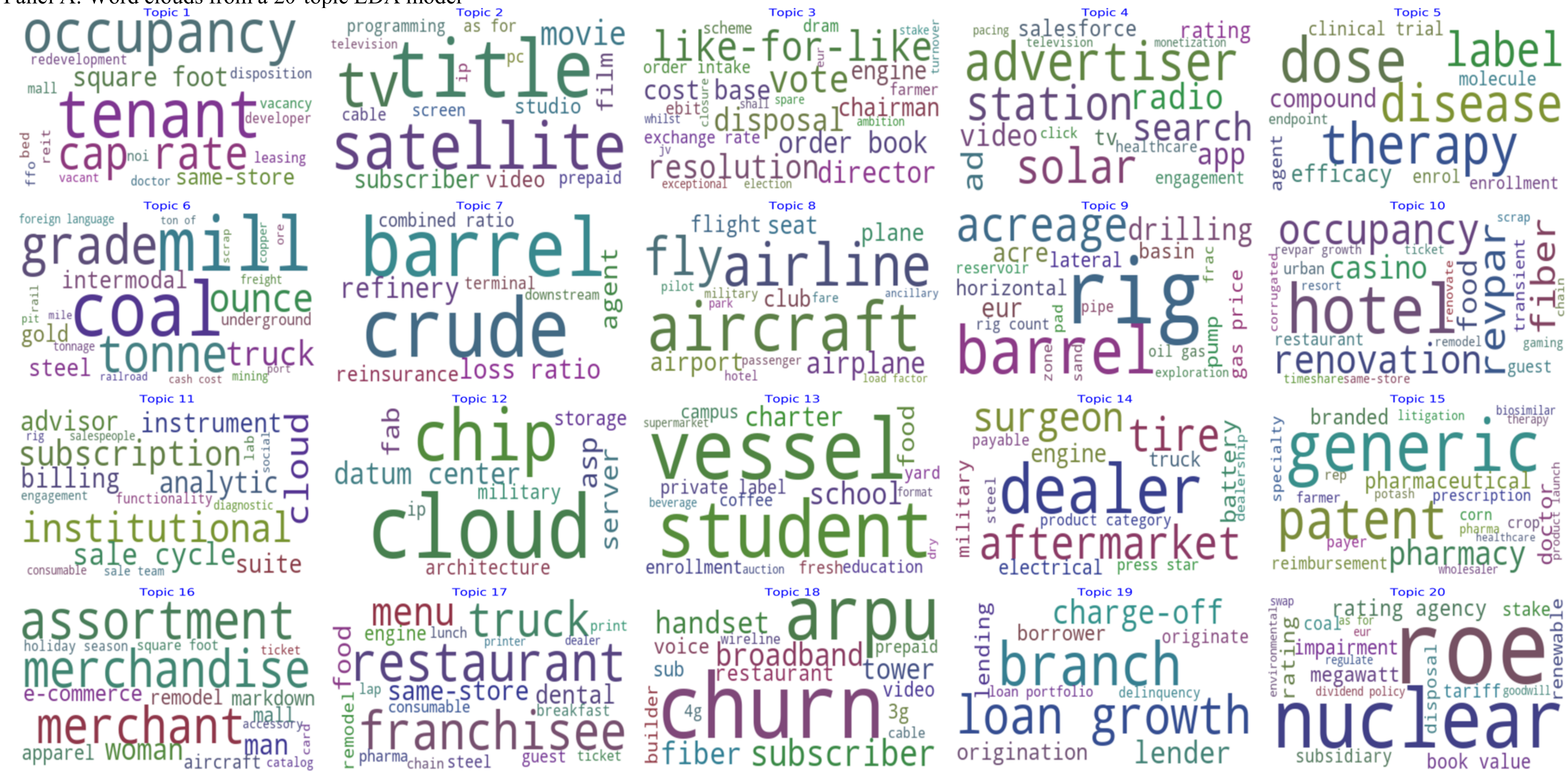
Panel E: Horse race between teamwork, teamwork_full, teamwork_seed, and teamwork_10k

	Employee involvement (1)	Number of JVs/SAs (2)
Teamwork	0.668***	0.017***
	(0.122)	(0.007)
Teamwork_full	-1.004***	-0.007
	(0.194)	(0.009)
Teamwork_seed	0.477	-0.026
	(0.669)	(0.024)
Teamwork_10k	0.196***	0.003
	(0.065)	(0.002)
Size & ROA	Yes	Yes
Ind FE/Yr FE	Yes	Yes
Intercept	Yes	Yes
Obs.	14,908	44,474
R^2/Pseudo R^2	0.140	0.023

Table IA7
Results from topic modeling

This table presents the results from LDA, a topic modeling method, applied to the QA section of calls. Before fitting LDA models, we pre-process the data by removing numerical digits, less frequent words (n < 5) and top 2,000 common words. We fit two different LDA models, with the number of topics being 20 and 100. For each topic, we generate word clouds that show the top words with the highest probabilities. Panel A presents the word clouds from a 20-topic LDA model. Panel B presents the 20 randomly chosen word clouds from a 100-topic LDA model.

Panel A: Word clouds from a 20-topic LDA model



Panel B: Twenty randomly chosen word clouds from a 100-topic LDA model

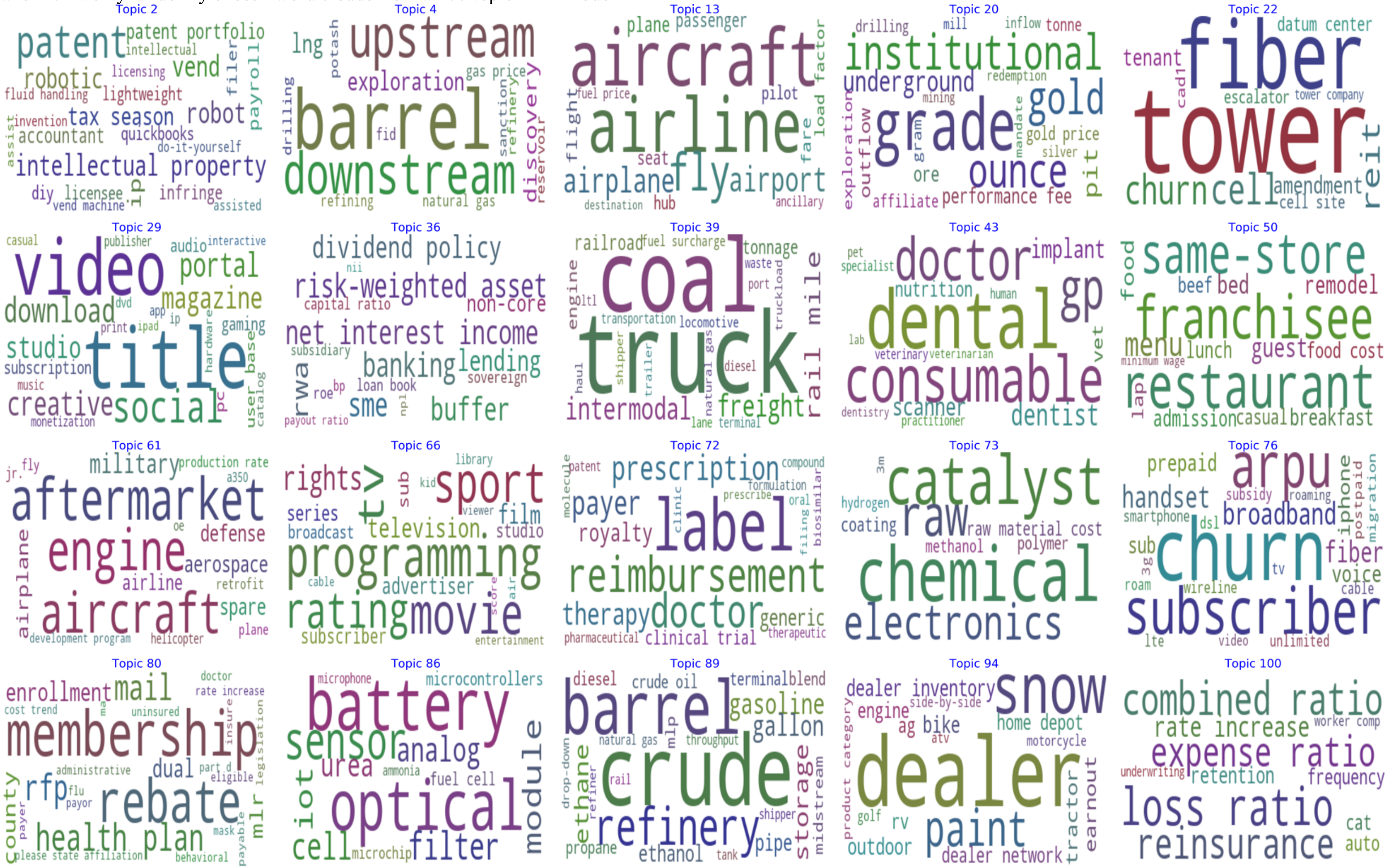


Table IA8
M&A sample overview

The acquirer sample consists of 7,773 completed deals over the period 2003–2018 from Thomson Reuters' SDC database. The sample is formed as the intersection of the Compustat database, Thomson Reuters' SDC database, and the earnings call data set. The pair sample consists of 594 completed deals where both the acquirer and its target firm are public and with available control firms. The sample selection criteria are as follows: 1) the deal is classified as "Acquisition of Assets (AA)", "Acquisition of Majority Interest (AM)," or "Merger (M)" by the data provider; 2) the acquirer is a U.S. public firm listed on the AMEX, NYSE, or NASDAQ; 3) the acquirer holds less than 50% of the shares of the target firm before deal announcement and ends up owning 100% of the shares of the target firm through the deal; 4) the deal value is at least $1 million (in 1995 dollar value); 5) the relative size of the deal (i.e., the ratio of transaction value over book value of acquirer total assets) is at least 1%; 6) the target firm is domiciled in the U.S.; 7) the target firm is a public firm, a private firm, or a subsidiary; 8) multiple deals announced by the same acquirer on the same day are excluded; 9) basic financial and stock return information is available for the acquirer; and 10) culture variables are available for the acquirer (as well as for the target for the pair sample).

Year	Acquirer sample	Pair sample
2003	402	25
2004	520	45
2005	597	50
2006	648	47
2007	613	46
2008	428	31
2009	313	36
2010	460	42
2011	476	21
2012	542	31
2013	515	38
2014	602	49
2015	529	54
2016	452	52
2017	357	14
2018	319	13
Total	7,773	594

Table IA9
Summary statistics of the acquirer and pair samples for acquisitiveness and merger pairing analysis

The acquirer sample consists of 7,773 completed deals over the period 2003–2018. The pair sample consists of 594 completed deals where both the acquirer and its target firm are public with available control firms. Panel A presents the summary statistics of acquirers. Panel B presents the summary statistics of the pair sample. Panel C presents the correlations between corporate culture variables and acquirer characteristics. Panel D presents the correlations between cultural similarity and other similarity measures. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics of the acquirer sample

Variable	Obs.	Mean	10th Percentile	Median	90th Percentile	SD
Innovation	7,773	1.704	0.722	1.460	3.005	0.959
Integrity	7,773	0.520	0.191	0.459	0.933	0.311
Quality	7,773	1.306	0.455	1.123	2.420	0.798
Respect	7,773	1.037	0.341	0.831	1.991	0.738
Teamwork	7,773	0.807	0.302	0.685	1.486	0.510
Total assets	7,773	7.124	4.997	7.084	9.258	1.644
Leverage	7,773	0.210	0	0.167	0.494	0.195
ROA	7,773	0.0350	-0.0322	0.0399	0.115	0.0808
Sales growth	7,773	0.206	-0.0695	0.120	0.525	0.388
Past return	7,773	0.225	-0.260	0.158	0.735	0.474
Top5 institutions	7,773	0.276	0.114	0.284	0.417	0.122
Same industry	7,773	0.704	0	1	1	0.457
Same state	7,773	0.218	0	0	1	0.413
HP similarity	7,773	0.00886	0	0	0	0.0441

Panel B: Summary statistics of the pair sample for merger pairing analysis

	Obs.	Mean	10th Percentile	Median	90th Percentile	SD	Mean	10th Percentile	Median	90th Percentile	SD
				Acquirers					Target Firms		
Innovation	594	1.824	0.866	1.669	2.967	0.916	1.849	0.808	1.686	3.128	0.973
Integrity	594	0.513	0.212	0.467	0.866	0.278	0.529	0.190	0.470	0.966	0.317
Quality	594	1.406	0.615	1.277	2.382	0.718	1.543	0.565	1.366	2.842	0.864
Respect	594	0.919	0.336	0.759	1.622	0.627	1.050	0.322	0.877	1.987	0.705
Teamwork	594	0.841	0.355	0.730	1.489	0.504	0.953	0.334	0.786	1.830	0.646

Firm size	594	8.411	6.050	8.419	10.784	1.858	6.483	4.234	6.409	9.004	1.799
Leverage	594	0.198	0.000	0.142	0.480	0.190	0.198	0.000	0.125	0.544	0.221
ROA	594	0.039	-0.025	0.047	0.127	0.109	-0.042	-0.235	0.022	0.105	0.291
Sales growth	594	0.369	-0.087	0.095	0.462	4.733	0.167	-0.149	0.074	0.441	0.756
Past return	594	0.194	-0.292	0.154	0.617	0.461	0.157	-0.463	0.057	0.816	0.709
Top5 institutions	594	0.266	0.143	0.269	0.379	0.104	0.309	0.167	0.303	0.454	0.120
Acquirer-Target Firm Pairs											
Cultural similarity	594	0.927	0.840	0.951	0.987	0.075					
Cultural distance	594	1.411	0.536	1.240	2.576	0.804					

Panel C: Correlation between cultural values and firm characteristics of the acquirer sample

	Innovation	Integrity	Quality	Respect	Teamwork	Firm size	Leverage	ROA	Sales growth	Past return	Top5 institutions
Innovation	1.000										
Integrity	0.141***	1.000									
Quality	0.546***	0.064***	1.000								
Respect	0.325***	0.301***	0.332***	1.000							
Teamwork	0.459***	0.253***	0.376***	0.331***	1.000						
Firm size	-0.103***	-0.028**	-0.238***	-0.246***	-0.205***	1.000					
Leverage	-0.328***	0.001	-0.410***	-0.220***	-0.210***	0.325***	1.000				
ROA	-0.054***	-0.055***	-0.039***	-0.058***	-0.152***	0.171***	-0.187***	1.000			
Sales growth	-0.038***	-0.017	-0.059***	0.029**	0.083***	-0.098***	0.010	0.025**	1.000		
Past return	0.026**	0.005	0.016	0.028**	0.006	-0.065***	-0.089***	0.073***	0.086***	1.000	
Top5 institutions	0.036***	-0.007	0.045***	0.047***	0.005	-0.027**	-0.012	0.008	-0.093***	-0.060***	1.000

Panel D: Correlations between culture similarity and other similarity measures of the pair sample

	Cultural similarity	Cultural distance	Same industry	Same state	HP similarity
Cultural similarity	1.000				
Cultural distance	-0.410***	1.000			
Same industry	0.017	-0.110***	1.000		
Same state	-0.016	-0.010	0.056	1.000	
HP similarity	-0.035	-0.148***	0.085**	0.213***	1.000