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The Role of Corporate Culture in Bad Times: Evidence from the COVID-19 Pandemic

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Abstract

After fitting a topic model to 40,927 COVID-19–related paragraphs in 3,581 earnings calls over the period Jan. 22–Apr. 30, 2020, we obtain firm-level measures of exposure and response related to COVID-19 for 2,894 U.S. firms. We show that despite the large negative impact of COVID-19 on their operations, firms with a strong corporate culture outperform their peers without a strong culture. Moreover, these firms are more likely to support their community, embrace digital transformation, and develop new products than those peers. We conclude that corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise.

> "We are also in the early stages of understanding if and to what extent we may be temporarily impacted by the coronavirus. At this point, we're expecting a 1- to 1.5-week delay in the ramp of Shanghai-built Model 3 due to a government-required factory shutdown. This may slightly impact profitability for the quarter but is limited as the profit contribution from Model 3 Shanghai remains in the early stages."
>
> Zachary Kirkhorn
> Chief Financial Officer (CFO), Tesla, Inc., Jan. 29, 2020

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> "At this point, a broader and more meaningful slowdown in new bookings and an increase in cancellations began to develop for sailings outside of Asia. Since the outbreak began, we have taken several aggressive and proactive measures to assure the safety, security and well-being of our guests and crew by implementing strict embarkation and screening protocols."
>
> Frank J. Del Rio
> President and CEO, Norwegian Cruise Line, Feb. 20, 2020

> "We continue to waive cancellation fees for hotel stays through March 15 for guests with reservations at our hotels in Greater China and for guests from Greater China with reservations at Marriott destinations globally. We began to see the impact of the coronavirus on our business in mid-January with occupancy declines gradually spreading from Wuhan to other markets in the Asia Pacific region. In February, RevPAR at our hotels in Greater China declined almost 90% versus the same period last year. At the end of 2019, we had 375 properties with roughly 122,000 rooms across Greater China, representing 9% of our total global rooms. Around 90 of these properties are currently closed."
>
> Arne M. Sorenson
> President and CEO, Marriott International, Inc., Feb. 27, 2020

> "We have prioritized the health and safety of our teammates, and we have closed our stores. Over the weekend, we drove a strong digital marketing campaign to engage consumers across Europe and across the U.S. to stay healthy and connected while they're at home. And our digital commerce remains open and in growth mode, supported by our teammates in our distribution centers."
>
> John J. Donahoe
> President, CEO, and director, Nike, Inc., Mar. 24, 2020

I. Introduction

Over the past 2 decades, the world has been hit by a number of outbreaks of epidemic diseases, including the severe acute respiratory syndrome (SARS) outbreak of 2002–2004, the swine flu pandemic of 2009–2010, and the Ebola virus epidemic of 2013–2016. By the end of Apr. 2021, the latest, the COVID-19 pandemic, had infected over 150 million people and caused over 3.2 million deaths, and it continues to have a devastating impact on the world economy. Given the extraordinary nature of the current public health crisis, it is imperative for financial economists to study how industries and firms are exposed to an epidemic disease, how they respond, and what makes some firms resilient in the face of heightened uncertainty as the pandemic spreads. In this article, we examine how firms with a strong corporate culture fare amid the COVID-19 outbreak and identify the underlying mechanisms.

Corporate culture is a system of shared beliefs and values within an organization (Cremer (1993), Lazear (1995), and Van den Steen (2010)). In contrast to formal control mechanisms codified in the form of rules and procedures, corporate culture is regulated through peer influence and the social construction of reality (Berger and Luckmann (1967)) and results in positive feelings of solidarity and a greater sense of autonomy among people within an organization (O'Reilly and Chatman (1996)). According to Kreps (1990), corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise. We posit that corporate culture matters even more in a challenging operational environment, such as the COVID-19 pandemic, because a strong culture empowers executives and rank-and-file employees to make consistent decisions and efforts based on long-term perspectives.

To test our hypothesis, we need firm-level measures of exposure and response related to COVID-19 because firms are hit in very different ways and to different degrees by the pandemic (e.g., their employees, customers, suppliers, and/or liquidity; see the first 3 quotes at the start of the article from executives talking about COVID-19 during earnings calls) and also respond differently (e.g., cost cutting and embracing digital transformation; see the fourth quote). In this article, we develop new firm-level measures of exposure and response using earnings calls in which members of senior management discuss business operations and firm performance and answer questions from call participants about firms' prospects, including comments on COVID-19 and its implications. To do so, we use the word-embedding model (Mikolov, Sutskever, Chen, Corrado, and Dean (2013); see Li, Mai, Shen, and Yan (2021) for an application in finance) to create a COVID-19 word list based on 3,581 earnings-call transcripts from 2,894 firms over the period Jan. 22–Apr. 30, 2020. We then tag paragraphs in which any COVID-19–related word appears as COVID-19–related paragraphs. To capture firm-level exposure/response related to COVID-19, we fit a correlated topic model (CTM; Blei and Lafferty (2007)) to the 40,927 COVID-19–related paragraphs. The CTM uncovers underlying topics in a large set of documents (i.e., paragraphs) based on the statistical correlations among words and topics in these documents. The firm-level exposure/response related to COVID-19 is the proportion of text in the firm's COVID-19–related paragraphs devoted to particular topics, and the firm-level overall exposure to COVID-19 is a simple sum of different types of exposure.

We show that there are 6 types of exposure to COVID-19, the top 3 being i) negative demand shocks, ii) supply chain disruption, and iii) employee safety and well-being. The others are lockdown, liquidity and financing, and delays in business operations. There are 4 types of responses to COVID-19: supporting community, cutting costs, embracing digital transformation, and developing new products. At the industry level, the top 3 industries with the greatest exposure to COVID-19 are chemicals and allied products, manufacturing, and consumer durables.

Using a sample of 2,394 U.S. firms with data on corporate culture, COVID-19 exposure/response, and stock returns for the period Jan. 2019–Mar. 2020, we show that firms with a strong culture exhibit better stock market performance during the COVID-19 crisis than their counterparts with a weak culture. A firm is perceived to have a strong culture if its culture score is in the top quartile among all firms (Li et al. (2021)). In terms of economic significance, we show that for a firm with a strong culture, a 1-standard-deviation increase in a firm's overall exposure to COVID-19

(11.28%) reduces its monthly return drop by 0.96 percentage points (or 2.9 percentage points in quarterly returns).

We further show that despite the many different ways in which COVID-19 affects their operations, firms with a strong culture outperform their counterparts with a weak culture. Moreover, we find that firms with a strong culture are more likely to support their community, adopt digital technology, and develop new products, and they are no more likely to engage in cost cutting than their peers without a strong culture. O'Reilly and Chatman (1996) argue that norms of creativity and innovation may be the most effective mechanisms for promoting organizational adaptability amid a major crisis. Our results provide support for their conjecture.

In exploring the channels through which culture makes firms resilient to the pandemic, we find that firms with a strong culture have higher sales per employee, a higher ROA, and a higher profit margin in 2020. Our corporate culture measure is a sum of 5 cultural value scores in innovation, integrity, quality, respect, and teamwork, which can be grouped into a people-oriented cultural dimension comprising integrity, respect, and teamwork and a technology-oriented cultural dimension comprising innovation and quality. We further show that firms strong in either dimension are associated with higher sales per employee, firms strong in the people-oriented cultural dimension are associated with a lower likelihood of employee layoff and a higher ROA, and firms strong in the technology-oriented cultural dimension are associated with a higher profit margin. Edmans (2011) and Oswald, Proto, and Sgroi (2015) show that happy employees are better motivated and more productive. Luo and Bhattacharya (2006), Edmans (2011), and Albuquerque, Koskinen, and Zhang (2019) argue and show that customers are drawn to firms that treat their employees well. We show that happy employees are more productive and that firms with a strong innovation culture are more agile in digital transformation and new-product development, which retain and draw customers, compared with firms without a strong innovation culture during the pandemic. Our results suggest that corporate culture works through the human capital and technology channels to make firms resilient during the pandemic. Taken together, our evidence provides support for the hypothesis that corporate culture is an intangible asset designed to help firms prevail in unforeseen contingencies (Kreps (1990)).

Firms with a strong culture are not the only firms that perform better in 2020. It is worth noting that our main finding remains after controlling for other characteristics known to make firms resilient during this public health crisis, such as financial flexibility, prior epidemic experience, and minimum exposure to China.

Our article contributes to the existing literature in the following ways: First, our article is among the first in the literature, as far as we are aware, to measure firm-level exposure and response related to COVID-19 for a large sample of firms by employing the word-embedding model and the CTM. Our article thus makes an important methodological contribution by highlighting new applications of machine-learning tools in finance.

Second, with more granular data on firm-level exposure/response related to COVID-19, we are able to delineate the channels through which corporate culture matters amid the pandemic. Our article thus contributes to a better understanding of the importance of intangibles in general, and of the role of corporate culture in particular, in enhancing firm value.

Third and finally, given that the COVID-19 pandemic is exogenous to a firm's fundamentals, this unique setting allows us to establish a causal effect of bad times on the culture–value link.

The article proceeds as follows: Section II reviews the literature and develops the hypotheses. We describe our approach to measuring firm-level exposure and response related to COVID-19 using earnings-call transcripts in Section III. Section IV provides a sample overview. Section V presents the main results on the relation between firms with a strong culture and their stock and operating performance during the COVID-19 pandemic and explores the channels. We conduct a large number of robustness checks in Section VI. Section VII concludes.

II. Literature Review and Hypothesis Development

A. Literature Review

Our article is broadly related to one strand of the literature examining the relation between intangibles and firm value. Edmans (2011) shows that firms included in the "100 Best Companies to Work For" list produced annually by the Great Place to Work Institute tend to have higher future abnormal stock returns. Servaes and Tamayo (2013) find that corporate social responsibility (CSR) and firm value are positively related for firms with high customer awareness, as proxied by advertising expenditures. Using advertised values via firms' websites, Guiso, Sapienza, and Zingales (2015) show that proclaimed values are not significantly associated with firm performance; instead, the values perceived by rank-and-file employees shown in the Great Place to Work Institute surveys have performance implications. Lins, Servaes, and Tamayo (2017) find that the trust between a firm and both its stakeholders and investors, built through investments in social capital as measured by CSR, pays off during the 2008–2009 financial crisis. Albuquerque et al. (2019) present a model in which firms with credible environmental and social (ES) policies have a more loyal customer base and face less price-elastic demands for their products, leading to higher firm value. In a recent survey of North American CEOs and CFOs, Graham, Grennan, Harvey, and Rajgopal (2019) note that a majority of senior executives view corporate culture as one of the top 3 factors that affect their firm's value, and over 90% of them believe that improving corporate culture will increase firm value. Li et al. (2021) show that corporate culture correlates with business outcomes, including operational efficiency, risk taking, earnings management, and executive compensation design.

B. Hypothesis Development

In a seminal article, Kreps ((1990), p. 93) takes the view that corporate culture is "how things are done, and how they are meant to be done in the organization." Kreps focuses on situations in which cooperation among employees and their superiors is crucial and discusses two ways to induce cooperation: contracts (e.g., paying efficiency wages[1]) and repeated interaction. However, Kreps notes that both become too costly and/or infeasible when states or actions are not verifiable or are difficult to specify in advance and that establishing a norm to do things (i.e., corporate culture) addresses those challenges.[2] Kreps concludes that corporate culture, as a coordination mechanism, can sustain desirable outcomes in a world with unforeseen contingencies.

Van den Steen (2005), (2010) shows that one way for firms to develop homogeneous beliefs (i.e., corporate culture) is screening: Firms hire employees whose beliefs and work ethos match those of the firm. Henderson and Van den Steen (2015) further establish the linkage between firms having a strong culture and increased profitability because employees having a shared view of the right course of action select into firms with a strong culture, leading to higher effort and lower wages.

Based on the foregoing discussion, we expect that the presence of a strong culture, in which a set of norms and values is widely shared and strongly held throughout an organization (O'Reilly (1989)), will be associated with increased goal alignment and higher levels of motivation among employees and will provide needed controls without resorting to the need to pay above-the-market wages. These effects are more salient in a challenging operational environment like the COVID-19 pandemic, when a strong culture empowers executives and rank-and-file employees to make consistent decisions and exert greater effort based on long-term perspectives. Our first hypothesis is thus as follows:

Hypothesis 1. The positive culture–value link is stronger amid the COVID-19 pandemic.

There are large cross-sectional variations in firm-level exposure to COVID-19 (see, e.g., the first 3 quotes at the beginning of the article). In addition to the detrimental impact of the virus on employee safety and well-being, the lockdown and physical distancing policies reduce revenue and impose additional costs. Pagano, Wagner, and Zechner (2020) show that firms with jobs requiring human contact, for which work-from-home (WFH) policies would be difficult to implement, are more exposed to the pandemic. In contrast, firms in the technology and communication sectors are less affected and even have the opportunity to expand their businesses. Considering this heterogeneity, we hypothesize that the positive association between firms with a strong corporate culture and returns during the pandemic is conditional on firm-level exposure to COVID-19:

Hypothesis 2. The positive culture–value link is stronger for firms with greater exposure to COVID-19.

[1]The basic efficiency wage hypothesis states that workers' productivities depend positively on their wages (Stiglitz (1986), Katz (1986)). The potential benefits to the firm of higher wages include increased effort level and reduced shirking by employees; lower turnover costs; a higher-quality labor force; and improved morale, more easily facilitated teamwork, and greater feelings of loyalty by workers to the firm (Dunlop (1957), Reynolds (1978), chapter 9).

[2]Relatedly, O'Reilly and Chatman (1996) and Bénabou and Tirole (2003) point out the dissonance between the short-run efficacy of explicit motivation (e.g., efficiency wage contracting) on the one hand and the long-run efficacy of implicit motivation (e.g., a strong culture) on the other.

In today's knowledge economy, increased competition worldwide has intensified the demand for process innovation and quality improvement and elevated the significance of human capital in a modern corporation (Zingales (2000)). We posit that one potential channel through which firms with a strong culture outperform their peers with a weak culture in the pandemic is the human capital channel, whereby a strong culture empowers employees to make consistent decisions and exert greater effort based on long-term perspectives, resulting in higher productivity.

Luo and Bhattacharya (2006) establish the link between "corporate abilities," as manifested in terms of innovation capability and product quality, and customer satisfaction, resulting in higher firm value. We posit that another potential channel through which firms with a strong culture outperform their peers with a weak culture in the pandemic is the technology channel, whereby a strong culture instills a long-term orientation and makes firms in the midst of a public health crisis more likely to adopt digital technology and/or introduce new products/services to achieve product differentiation, foster customer loyalty, and command more pricing power.

III. Methodology

In this section, we describe our approach to measuring firm-level exposure and response related to COVID-19 using earnings-call transcripts.

A. Preprocessing the Data

Table 1 lists the steps taken and filters applied to form our sample of 3,581 earnings calls made by 2,894 U.S. firms over the period Jan. 22, 2020–Apr. 30, 2020.

Each call transcript is in PDF format, which we convert to a text file using the Python package *pdfminer* (https://github.com/pdfminer/pdfminer.six). 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.

We use the Stanford CoreNLP package to preprocess and parse the text.[3] We segment text files into sentences and words, 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. Because phrases (collocations) play a crucial role in gathering information from corporate disclosures, we use a 2-step approach to extract both general and corpus-specific phrases. In step 1, we use the dependency parser in the CoreNLP package to identify fixed multiword expressions (e.g., *open up, make sure*) and compound words (e.g., *market volatility* and *growth rate*). These phrases are usually part of the general English vocabulary or can be inferred based on the grammatical relationships between words. We remove punctuation marks, stop words, and single-letter words

[3]The CoreNLP package is an open-source natural language processing (NLP) toolkit for a variety of tasks (Manning, Surdeanu, Bauer, Finkel, Bethard, and McClosky (2014)). We use version 3.9.2, available at https://stanfordnlp.github.io/CoreNLP.

TABLE 1

Sample Formation

Table 1 lists the steps taken to form the sample for regression analysis. We obtain earnings-call transcripts from the Standard & Poor's (S&P) Global Market Intelligence database for the period Jan. 22–Apr. 30, 2020.

	No. of Calls/Firms
All call transcripts from Jan. 22 to Apr. 30, 2020	10,449
Limiting to earnings-call transcripts	8,155
Limiting to firms listed on New York Stock Exchange (NYSE), NASDAQ, or NYSE American (formerly American Stock Exchange (AMEX))	4,140
Matching by	
Tickers	4,083
Compustat company names	9
Manually if no perfect match using above	16
Removing call transcripts by non-U.S. firms	−440
Keeping the most recent call if duplicate entries	−87
No. of calls/firms	3,581/2,894
Corporate culture data available from Li et al. (2021)	2,400
Return and control variables available	2,394
No. of firms	2,394

after identifying and concatenating multiword expressions and compound words.[4] In the second step, we use the *phraser* module of the *gensim* library to find 2- and 3-word phrases that are more specific to the corpus (i.e., words that have statistically significant co-occurrences in the collection of call transcripts).[5] For example, the phrases learned in the second step include *supply chain disruption* and *social distancing measure.* 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 a firm's exposure and response related to COVID-19 are conveyed in calls.

B. The Challenges

The earnings-call examples shown previously illustrate a number of challenges when using calls to measure firm-level exposure/response. First, the goal of earnings calls is to discuss business operations and firm performance. To reduce the number of topics in calls, we need to limit our attention to COVID-19–related paragraphs.

Second, there are many different ways to refer to the COVID-19 pandemic; very often the term *COVID-19* or its variations (e.g., *coronavirus*) are not mentioned, but given the context, the discussion is clearly about COVID-19. For example, discussions of "travel restriction," "self-quarantine," and "shelter-in-place order" undoubtedly relate to the COVID-19 pandemic but have no direct mention of the term. We therefore need an expanded word list to tag COVID-19–related paragraphs in calls.

[4]Our stop words list is a combination of the stopwords-iso list (available at https://github.com/stopwords-iso/stopwords-iso) and words that are often used for facilitating conversations and carry little meaning (see the full list in Table IA1 in the Supplementary Material).

[5]The *gensim* library is an open-source NLP Python package that we use for training the *word2vec* model. We use version 3.7.2, available at https://github.com/RaRe-Technologies/gensim.

Third, different firms may face different challenges and respond differently amid the pandemic, which could potentially shed light on how a strong culture leads to firm resilience. For example, Tesla's January call discusses potential disruption to its supply chain; Norwegian Cruise Line's February call covers the safety of its employees and guests, declines in new bookings, and increases in cancellations; and Marriott's February call is concerned with drastic declines in its Asia Pacific market. In contrast, Nike's March call discusses adopting a digital marketing campaign as a response to the negative demand shock to its stores. We therefore need to develop firm-level measures of exposure and response related to COVID-19.

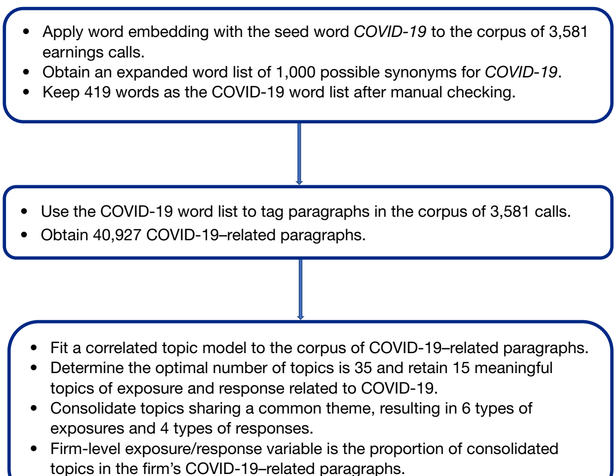
In this article, we offer a machine-learning alternative to address these challenges. Our approach starts with the word-embedding model (specifically, *word2vec*; Mikolov et al. (2013)) to obtain a COVID-19 word list based on each word's proximity to the word *COVID-19* in calls; note that *COVID-19* is the official name for the pandemic from the World Health Organization. Using the word list, we can tag COVID-19–related paragraphs in calls. We then fit a topic model to these paragraphs, and the output is our firm-level measure of exposure and response related to COVID-19. Figure 1 presents the flow chart of our machine-learning approach.[6]

C. Word Embedding and the COVID-19 Word List

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 converts the neighboring word counts of

FIGURE 1

Flow Chart of Our Machine Learning Approach



[6]Code for text processing and model training can be downloaded from our GitHub repository at https://github.com/ssrn3632395/The-Role-of-Corporate-Culture-in-Bad-Times.

a word to a numerical vector, which captures the meaning of the word and supports a synonym search using vector arithmetic. Although there are different variants of the word-embedding model, we use a popular neural-network model, *word2vec* (Mikolov et al. (2013)), to efficiently learn dense and low-dimensional word vectors. 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 output from the process is a vector representation of the word once learning has been completed after a number of iterations through the documents. The vector has a fixed dimension and captures the properties of the original co-occurrence relationship between the word and its neighbors.[7]

We use the *gensim* library in Python to train the *word2vec* model. We set the dimension of word vectors to 300, define 2 words as neighbors if they are no farther apart than 5 words in a sentence, and omit words that appear fewer than 5 times in the corpus. After training, the model converts each of the 73,193 words in the call corpus to a 300-dimensional vector that represents the meaning of that word; we can then compute the cosine similarity between any 2 word vectors to quantify their association.

Using this capability, we construct the COVID-19 word list by associating a set of words gleaned from calls to the word *COVID-19*. We then select the top 1,000 words with the closest associations (i.e., the highest cosine similarity between their word vectors) to the word vector for COVID-19. We do not consider named entities that are recognized automatically by the CoreNLP package. We manually inspect all the words in the auto-generated list and exclude words that do not fit. Most of the excluded words are either too general in meaning (e.g., *unexpected* and *uncertainty*) or too specific in terms of industry context (e.g., *oil demand* and *elective procedure*). Table IA2 in the Supplementary Material provides the word list for COVID-19 ordered by descending similarity to the word *COVID-19*. There are 419 words in the final word list.

With the COVID-19 word list in hand, we tag paragraphs in which any word on the word list appears (i.e., the COVID-19–related paragraphs). There are in total 40,927 COVID-19–related paragraphs in 3,581 calls (representing approximately 11% of all paragraphs) over the period Jan. 22–Apr. 30, 2020, which form the corpus for topic modeling.

D. Correlated Topic Modeling

To measure firm-level exposure/response related to COVID-19, we first need to identify the topics of discussion in relation to COVID-19, then quantify the amount of discussion devoted to each topic. We employ the CTM developed by Blei and Lafferty (2007) and Roberts, Stewart, and Airoldi (2016) for this task.

The CTM represents a substantial improvement to the more rudimentary topic-modeling method, latent Dirichlet allocation (LDA), pioneered by Blei, Ng, and Jordan (2003). Topic modeling has gained increasing popularity for quantifying the

[7]See Li et al. (2021) and their Supplementary Material for a more detailed and technical discussion of the word-embedding model and *word2vec*.

content of firms' textual disclosures, such as earnings calls (Huang, Lehavy, Zhang, and Zheng (2018)). LDA uses a statistical generative model to imitate the process of how a human (e.g., a speaker) composes a document (e.g., a paragraph in a call). Specifically, LDA assumes that each word in a document is generated in two steps. First, assuming the speaker decides that document m is about a specific set of topics that can be described by a distribution θ_m, a topic is randomly drawn based on this topic distribution. Next, assuming the drawn topic k has its own word distribution β_k, a word is randomly drawn from this topic's word distribution. Repeating these 2 steps word by word generates a document. An inference algorithm for LDA discovers the topic distribution for each document and the word distribution for each topic iteratively by fitting this 2-step generative model to the observed words in a collection of documents (i.e., a corpus) until it finds the best set of parameters to describe the topic and word distributions. The fitted model provides i) the topical proportion (i.e., topic prevalence), which tells us how much of a document is devoted to a topic, and ii) the word distribution (i.e., topic content), which provides a list of the words most likely to be related to a given topic.

The CTM is similar to LDA, except that it allows for correlation between topics.[8] The CTM is thus a more realistic generative model than LDA and provides a better model fit (Blei and Lafferty (2007)). Conceptually, the interpretation of estimated parameters of interest from the CTM is nearly identical to that of those parameters from LDA. We can decompose a document into a mixture of topics with their proportions summed to 1, and we can also label those topics by inspecting the word distribution of each topic. We fit a CTM using the *stm* package in R based on the variational expectation-maximization algorithm developed by Roberts et al. (2016).[9]

Choosing the number of topics remains a challenge in topic modeling because no ground truth is available. Chang, Gerrish, Wang, Boyd-Graber, and Blei (2009) note a trade-off between the interpretability of model outcomes and statistical goodness-of-fit. Whereas interpretability usually favors fewer topics, statistical fitness generally favors more. Given that the purpose of our application is to use the CTM to generate interpretable topic clusters (rather than as a predictive model), we choose the number of topics based on the most meaningful topic clustering. We vary the number of topics from 5 to 40 and inspect the results, and we find that 35 topics perform the best in terms of interpretability. As pointed out by Blei (2012), interpretability is a key objective in selecting the best topic model, and careful human inspection is the most common approach.

[8]To generate document m's topic distribution θ_m under the CTM, a vector is first drawn from a multivariate normal distribution that allows correlations among dimensions, and then the vector is mapped to the parameters of a Dirichlet distribution, which produces θ_m. Under LDA, the topic distribution θ_m is drawn from a Dirichlet distribution directly, and correlations among topics are not modeled (and hence not allowed).

[9]The *stm* package in R is written for structural topic models (STMs), another extension to LDA that allows correlations among topics and covariates that can explain the prevalence of topics. In the case of no covariates, the *stm* package reduces to a fast implementation of the CTM, which is what we employ in this article. Importantly, whereas other topic model methods such as LDA may use a randomized algorithm (e.g., Gibbs sampling) for estimation, the CTM model is estimated using a variational expectation-maximization algorithm with a deterministic initialization, thereby producing stable results.

E. Estimating Firm-Level Exposure and Response Related to COVID-19

Because our goal is to estimate firm-level exposure/response related to COVID-19, we exclude general discussions of earnings and performance and fit a topic model only to a set of COVID-19–related paragraphs; we ultimately fit a CTM with 35 topics.

We take a 2-pronged approach to interpret the 35 topics and assign them meaningful labels. First, we rely on the topic-word distributions (i.e., the topic content) from the model output. We look at not only the high-probability words in the vocabulary under a given topic but also the important keywords indicated by three alternative measures: FREX, Lift, and Score.[10] All these measures facilitate interpretation because they highlight keywords that are more exclusive to each topic and discount common words that appear across all topics. Second, for each topic, we inspect representative paragraphs by selecting 10 paragraphs with the highest proportions of discussion on that topic.

To label the economic meanings of those identified topics, and hence different exposures/responses to COVID-19, we make two adjustments in the labeling/interpretation process. First, we drop 20 of the 35 topics because they are either boilerplate comments (e.g., greetings and concluding remarks) or are not about a specific aspect of COVID-19 (e.g., uncertainty and performance). Second, we find that some identified topics share a common theme and can be naturally consolidated (e.g., disruptions to supply chains). This consolidation is expected because the CTM allows topics to be correlated.

We consolidate the remaining 15 topics into 10 broad topics, 6 of which are about firms' exposures to COVID-19, including business operations, demand, employees, liquidity, lockdown, operation, and supply chain, and 4 of which are about firms' responses, including community engagement, cost cutting, digital transformation, and new-product development. Figure 2 presents the word cloud for each topic, and Table IA3 in the Supplementary Material presents the representative paragraphs for each topic.

Our firm-level measure of exposure/response is the average proportion of a firm's discussion on a particular topic in its COVID-19–related paragraphs over the period Jan. 22–Mar. 31, 2020. For a specific firm, we first sum up the product of the proportion of a topic at the paragraph level and the paragraph length, then standardize (divide) by the total length of all COVID-19–related paragraphs, and finally, take an average of the aforementioned ratio across calls if a firm has multiple calls over the 3-month period.[11] Thus, the measure is computed as follows:

$$\text{TOPIC}_{i,k} = \frac{1}{I_i} \sum_{n=1}^{I_i} \frac{\sum_{m=1}^{J_{i,n}} (P_{i,n,m,k} \times L_{i,n,m})}{\sum_{m=1}^{J_{i,n}} L_{i,n,m}}, \tag{1}$$

where $\text{TOPIC}_{i,k}$ is the intensity of topic k for firm i. $P_{i,n,m,k}$ is the proportion of topic k in COVID-related paragraph m in call n of firm i. $L_{i,n,m}$ is the paragraph length, that

[10]We refer readers to Roberts, Stewart, and Tingley (2019) for formal definitions of these measures.

[11]There are three firms (FuelCell Energy Inc., H. B. Fuller Co., and McCormick & Co., Inc.) with 2 calls over the period Jan. 22–Mar. 31, 2020 because they each held their second calls ahead of the regular schedule.

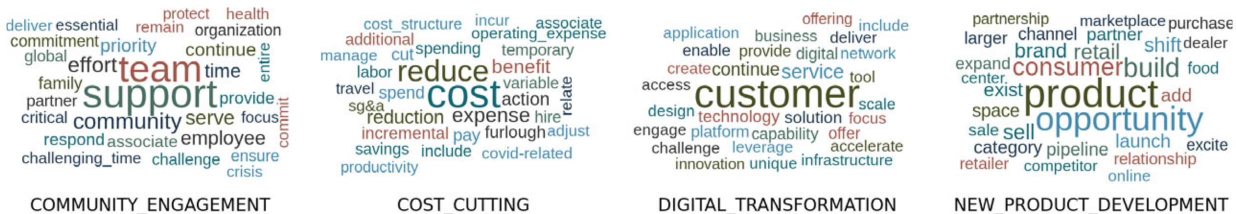
FIGURE 2

Word Clouds for Different Topics

Figure 2 plots the word cloud for each of the 10 topics, 6 of which are about firms' different exposures to COVID-19, including business operations, demand, employees, liquidity, lockdown, and supply chain, and 4 of which are about their responses to COVID-19, including community engagement, cost cutting, digital transformation, and new-product development. For each topic, we generate a word cloud that shows the top words with the highest probabilities. Graph A presents word clouds for the 6 different exposures to COVID-19. Panel B presents word clouds for the 4 different responses to COVID-19.

Graph A. Word Clouds for Different Exposures to COVID-19

Graph B. Word Clouds for Different Responses to COVID-19



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is, the total number of words (a phrase is treated as a single word) in COVID-19–related paragraph m in call n of firm i; $J_{i,n}$ is the number of COVID-19–related paragraphs in call n of firm i; and I_i is the number of calls of firm i in the first quarter of 2020. This measure satisfies the constraint that $\sum_{k=1}^{35}\text{TOPIC}_{i,k}=1$. Throughout the article, we multiply our firm-level measure of COVID-19 exposure/response by 100; thus, the unit of each measure is in percentage points.

Our measure of overall exposure to COVID-19 is the sum of the proportions of discussion on the 6 exposure-related topics. In contrast to prior literature that employs a normalized count of COVID-19–related words as COVID-19 exposure (e.g., Hassan, Hollander, van Lent, Schwedeler, and Tahoun (2020)), our measure has 2 advantages in terms of accuracy and cross-sectional comparability. First, as noted previously, not all topics in COVID-19–related discussions are about types of exposure; some are concerned with other matters, whereas others are simply standard conversational courtesies. Using the word count overstates COVID-19 exposure if firms mainly discuss topics unrelated to exposure. Our measure addresses this concern by only scoring exposure-related discussion. Second, we use the length of COVID-19–related paragraphs to normalize exposure-related discussion, which is cleaner than using the call length because an earnings call contains other discussions unrelated to COVID-19.[12]

Figure 3 presents an overview of firm-level COVID-19 exposure/response based on 40,927 COVID-19–related paragraphs over the period Jan. 22–Apr. 30, 2020. The top 3 types of exposure are demand, supply chain, and employees. The others are lockdown, liquidity and financing, and delays in business operations. The types of response (in descending order of importance) are digital transformation, new-product development, community engagement, and cost cutting.

F. Validating Our Measures of Exposure and Response Related to COVID-19

Given that our method for measuring exposure and response related to COVID-19 is new, it is important to validate our measure using firm (state) characteristics known to make firms (firms in these states) vulnerable to a pandemic. To that end, we employ a number of markers for firms' differential exposure to COVID-19: geographic dispersion in exposure to COVID-19, labor intensity, flexibility for employees to work from home, and exposure to China.

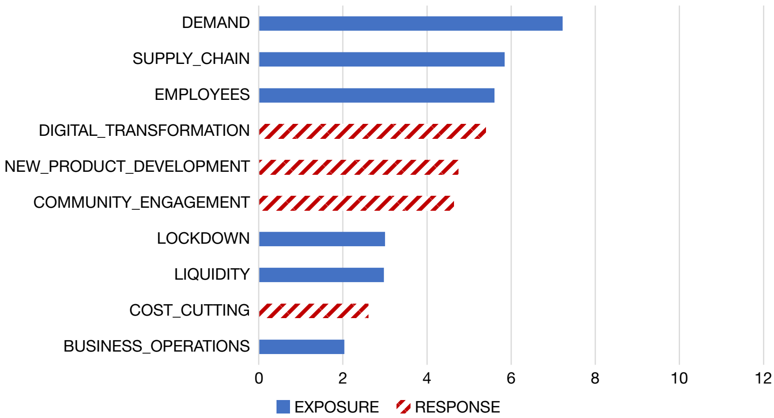
Following Bernile, Kumar, and Sulaeman (2015), we measure a firm's geographic dispersion with the number of unique U.S. states mentioned in its 2019 10-K filing. The relative importance of a particular state for a given firm, the firm-state citation share, is the number of times the state is mentioned in the firm's 10-K divided by the total number of mentions of all U.S. states in the same report. We obtain state-level COVID-19 new (cumulative) cases per 100,000 people

[12]Given that we only employ textual data for the early phase of the pandemic (Jan.–Apr. 2020; i.e., a relatively limited corpus for textual analysis), our measure is subject to noise in the data. Future research might consider applying similar methods to an expanded sample of earnings calls or other corporate disclosures.

FIGURE 3

An Overview of COVID-19 Exposure and Response

Figure 3 plots the average proportion (in percentage points) of each topic across 40,927 COVID-19–relevant paragraphs in earnings calls made over the period Jan. 22–Apr. 30, 2020. The blue bars represent the 6 different exposures to COVID-19, including business operations, demand, employees, liquidity, lockdown, and supply chain. The red bars represent the 4 different responses to COVID-19, including community engagement, cost cutting, digital transformation, and new-product development. The *x*-axis is the average proportion of each topic. Topics on the *y*-axis are ranked by the average proportion in descending order.



from Chetty, Friedman, Hendren, Stepner, and the Opportunity Insights Team (2020). The firm-level exposure to COVID-19, NEW_COVID_CASES (CUMULATIVE_COVID_CASES), is the weighted average of state-level COVID-19 new (cumulative) cases measured right before a firm's quarterly earnings call, with the weight being the firm-state citation share.

Using data from Google's COVID-19 Community Mobility Reports, Chetty et al. (2020) construct a measure of daily time spent at residential locations as changes relative to the median value for the corresponding day of the week during the 5-week period from Jan. 3 to Feb. 6, 2020. The variable GPS_RESIDENTIAL is the weighted average of the state-level change in the amount of time spent at home measured right before a firm's quarterly earnings call, with the weight being the firm-state citation share.

Fahlenbrach, Rageth, and Stulz (2020) show that more labor-intensive firms have high exposure to the pandemic, whereas firms in industries with the flexibility to work from home have less exposure. Following Fahlenbrach et al. (2020), LABOR_INTENSITY is the ratio of the number of employees to sales, and WFH is a firm's industry's fraction of jobs that can be performed at home (Dingel and Neiman (2020)). Ramilli and Wagner (2020) show that firms with exposure to China are more affected by the pandemic. The variable CHINA is a firm-level exposure-to-China measure from Hoberg and Moon (2017) based on 10-K filings.

Table 2 presents the results from our validation tests. We show that our measure of OVERALL_EXPOSURE is positively and significantly associated with NEW_COVID_CASES, CUMULATIVE_COVID_CASES, GPS_RESIDENTIAL, LABOR_INTENSITY, and CHINA and negatively and significantly associated with WFH after controlling for firm characteristics and industry fixed effects.

TABLE 2

Validating Our Measure of Firm-Level Exposure Related to COVID-19

Table 2 validates our measure of firm-level exposure related to COVID-19. OVERALL_EXPOSURE (in percentage points) is from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls in the first 3 months in 2020. We control for the natural logarithm of total assets, leverage, cash holdings, ROA, and book-to-market ratio (B/M). Industry fixed effects are based on Fama–French 48-industry classification. Definitions of variables are provided in the Appendix. Heteroscedasticity-consistent standard errors are presented in parentheses. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

	OVERALL_EXPOSURE					
	1	2	3	4	5	6
NEW_COVID_CASES	0.126**					
	(0.051)					
CUMULATIVE_COVID_CASES		0.003**				
		(0.002)				
GPS_RESIDENTIAL			0.105***			
			(0.038)			
LABOR_INTENSITY				0.724**		
				(0.355)		
WFH					−0.119***	
					(0.026)	
CHINA						3.192***
						(0.582)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,129	2,129	2,129	2,347	2,394	2,394
Adjusted R^2	0.295	0.295	0.296	0.149	0.163	0.165

In additional analysis, we employ a measure of the overall tone in COVID-19–related discussions to validate our measures of exposure (and response). A priori, we expect our measure of exposure to be negatively correlated with the tone and our measures of response to be mostly positively correlated with the tone. We compute the overall tone of each COVID-19–related paragraph as the difference between the share of positive words and the share of negative words using the positive/negative word lists developed by Loughran and McDonald (2011). The firm-level variable TONE is obtained by taking the average of the aforementioned measure across all COVID-19–related paragraphs in a call. Table IA4 in the Supplementary Material presents the results. We show that firms' overall exposure is negatively and significantly associated with TONE, whereas 3 of the 4 responses (i.e., community engagement, digital transformation, and new-product development) are positively and significantly associated with TONE, and one response (i.e., cost cutting) is negatively and significantly associated with TONE. We interpret these results as suggestive evidence that our measures capture what they are intended to capture.

IV. Sample Overview

A. Key Variables

Our firm-level measure of corporate culture, from Li et al. (2021), covers innovation, integrity, quality, respect, and teamwork (Guiso et al. (2015)); the year 2017 is the most recent year with available data. The indicator variable STRONG_CULTURE takes a value of 1 if the sum of a firm's 5 cultural value scores is in the top quartile across all firms in a year, and 0 otherwise.

We obtain stock returns from the Compustat Security Daily Database and accounting information from the Compustat Fundamentals Annual/Quarterly Database. We require a firm's return data to be available from Jan. through Mar. 2020. On Mar. 23, 2020, the Federal Reserve Board announced 2 new facilities to support credit to large corporations, and on Mar. 27, the U.S. government approved a US$ 2 trillion relief bill (Coronavirus Aid, Relief, and Economic Security Act (CARES Act)). A priori, it is not clear whether firms with a strong culture benefit more or less from government bailouts. Given that one goal of our article is to assess the stock market performance of firms with a strong culture, we do not want stock returns contaminated by government interventions. Therefore, CRISIS_PERIOD_RETURN is computed as a buy-and-hold return (in percentage points) from Jan. 2 to Mar. 20, 2020. After merging with firms in the culture data set, we obtain a final sample of 2,394 firms for our baseline regressions.

B. Sample Overview

Table 3 provides the summary statistics of stock and operating-performance variables, strong culture, key firm control variables, and measures of COVID-19 exposure and response.

Figure 4 plots our exposure and response measures related to COVID-19 across 12 Fama–French industries for our final sample of 2,394 firms. In Panel A, we show that in terms of overall exposure, the top 3 industries are chemicals and allied products, manufacturing, and consumer durables. In Panel B, we show that there are large cross-industry variations in terms of the 6 different exposures. In Panel C, we present different responses across industries. In terms of community engagement, the top 3 industries are utilities; telephone and television transmission; and wholesale, retail, and some services (e.g., laundries and repair shops). In terms of cost cutting, the top 3 industries are oil, gas, and coal extraction and products, consumer durables, and utilities. In terms of digital transformation, the top 3 industries are business equipment, utilities, and consumer durables. In terms of new-product development, the top 3 industries are consumer nondurables; wholesale, retail, and some services; and business equipment.

In summary, Table 3 and Figure 4 show wide variations across firms and industries in their exposure and response to COVID-19.

V. Main Results

A. Baseline Results

We estimate regression models of stock returns over the period Jan. 2 to Mar. 20, 2020 (the crisis period) as a function of firms' pre–COVID-19 cultural ratings and a number of control variables. Table 4 presents our baseline regression results. In all models, we include industry fixed effects (defined at the Fama–French 48-industry level) because different industries may promote their organizational culture with different foci (Li et al. (2021)).

Column 1 of Table 4 presents the return regression without any other controls except for industry fixed effects. We show that firms with a strong culture

TABLE 3

Summary Statistics

Table 3 presents sample summary statistics. The sample consists of 2,394 firms in the baseline cross-sectional quarterly return regression in the first quarter of 2020. Panel A provides the summary statistics. Panel B presents the correlation matrix for variables in the baseline regression. Panel C presents correlations among STRONG_CULTURE and firm exposure to COVID-19. Panel D presents correlations among STRONG_CULTURE and firm response to COVID-19. Definitions of variables are provided in the Appendix. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
CRISIS_PERIOD_RETURN	−41.034	20.399	−54.976	−41.401	−28.283
STRONG_CULTURE	0.252	0.434	0.000	0.000	1.000
TOTAL_ASSETS ($millions)	10,079.470	24,849.160	545.118	1,955.709	7,043.412
MARKET_CAP ($millions)	9,267.865	23,769.350	430.674	1,814.735	6,154.253
ln(MARKET_CAP)	7.409	1.989	6.068	7.504	8.725
LEVERAGE	0.328	0.241	0.124	0.317	0.467
CASH_HOLDINGS	0.166	0.212	0.024	0.074	0.213
ROA	−0.029	0.210	−0.020	0.022	0.059
B/M	0.532	0.589	0.187	0.411	0.739
MOMENTUM	21.074	44.748	−3.855	19.587	41.109
OVERALL_EXPOSURE	23.943	13.256	16.065	24.790	32.710
BUSINESS_OPERATIONS	2.143	2.557	0.980	1.459	2.356
DEMAND	7.853	7.671	2.777	5.831	10.647
EMPLOYEES	3.711	4.093	1.382	2.557	4.568
LIQUIDITY	2.184	3.962	0.628	1.049	2.057
LOCKDOWN	2.160	2.366	0.980	1.582	2.508
SUPPLY_CHAIN	5.891	6.092	1.844	3.681	8.357
COMMUNITY_ENGAGEMENT	2.644	3.143	0.937	1.742	3.208
COST_CUTTING	2.019	2.471	0.835	1.318	2.314
DIGITAL_TRANSFORMATION	5.225	5.978	1.956	3.455	6.303
NEW_PRODUCT_DEVELOPMENT	4.637	4.143	2.303	3.690	5.851

(continued on next page)

TABLE 3 (continued)

Summary Statistics

Panel B. Correlation Matrix for Variables in the Baseline Regression

	CRISIS_PERIOD_RETURN	STRONG_CULTURE	ln(MARKET_CAP)	LEVERAGE	CASH_HOLDINGS	ROA	B/M	MOMENTUM
CRISIS_PERIOD_RETURN	1.000							
STRONG_CULTURE	0.155***	1.000						
ln(MARKET_CAP)	0.149***	−0.062***	1.000					
LEVERAGE	−0.196***	−0.131***	0.064***	1.000				
CASH_HOLDINGS	0.214***	0.271***	−0.197***	−0.273***	1.000			
ROA	0.017	−0.118***	0.464***	0.021	−0.487***	1.000		
B/M	−0.203***	−0.171***	−0.301***	−0.133***	−0.232***	−0.011	1.000	
MOMENTUM	0.109***	−0.019	0.257***	−0.016	0.030	0.195***	−0.310***	1.000

Panel C. Correlation Matrix for Strong Culture and Firm Exposure to COVID-19

	STRONG_CULTURE	OVERALL_EXPOSURE	BUSINESS_OPERATIONS	DEMAND	EMPLOYEES	LIQUIDITY	LOCKDOWN	SUPPLY_CHAIN
STRONG_CULTURE	1.000							
OVERALL_EXPOSURE	−0.102***	1.000						
BUSINESS_OPERATIONS	−0.036*	0.373***	1.000					
DEMAND	−0.136***	0.668***	0.062***	1.000				
EMPLOYEES	0.138***	0.313***	0.125***	−0.144***	1.000			
LIQUIDITY	−0.073***	0.327***	0.065***	0.109***	−0.032	1.000		
LOCKDOWN	−0.005	0.401***	0.112***	0.116***	0.185***	0.031	1.000	
SUPPLY_CHAIN	−0.078***	0.599***	0.144***	0.151***	0.087***	−0.094***	0.146***	1.000

Panel D. Correlation Matrix for Strong Culture and Firm Response to COVID-19

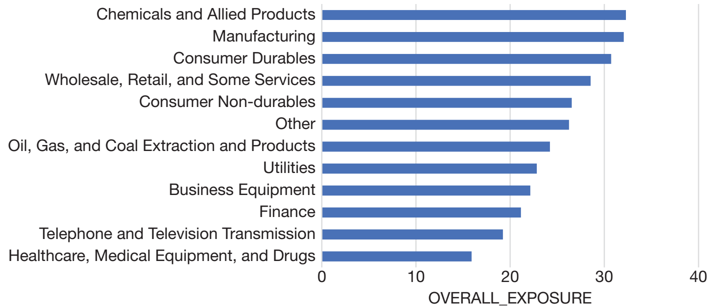
	STRONG_CULTURE	COMMUNITY_ ENGAGEMENT	COST_CUTTING	DIGITAL_TRANSFORMATION	NEW_PRODUCT_DEVELOPMENT
STRONG_CULTURE	1.000				
COMMUNITY_ENGAGEMENT	0.063***	1.000			
COST_CUTTING	−0.052**	0.029	1.000		
DIGITAL_TRANSFORMATION	0.247***	0.302***	−0.008	1.000	
NEW_PRODUCT_DEVELOPMENT	0.102***	0.080***	0.033	0.324***	1.000

FIGURE 4

Exposure and Response Related to COVID-19 Across 12 Fama–French Industries

Figure 4 plots measures of exposure and response related to COVID-19 across 12 Fama–French industries. Graph A plots overall exposure to COVID-19. Graph B plots 6 different exposures to COVID-19, including business operations, demand, employees, liquidity, lockdown, and supply chain. Graph C plots 4 different responses to COVID-19, including community engagement, cost cutting, digital transformation, and new-product development. The *x*-axis is the average exposure/response (in percentage points) across firms within an industry.

Graph A. Overall Exposure to COVID-19 Across 12 Fama–French Industries



Graph B. Different Exposures to COVID-19 Across 12 Fama–French Industries

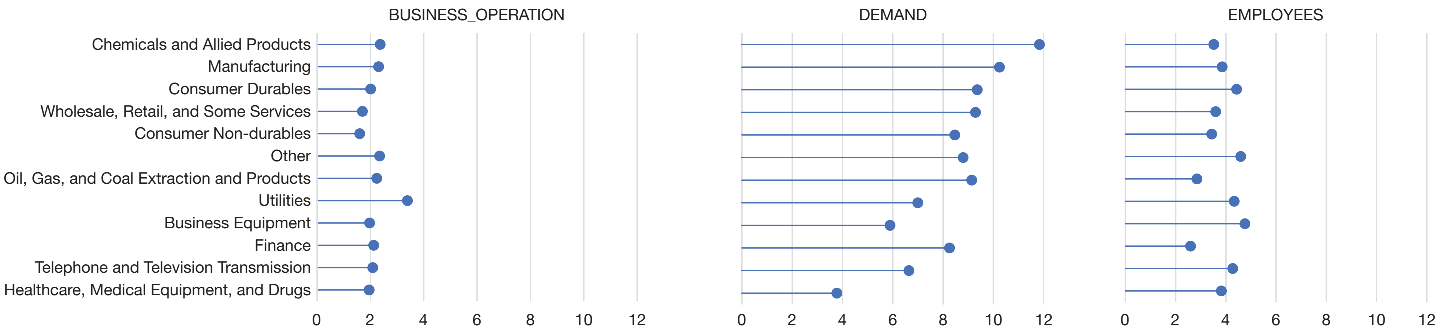


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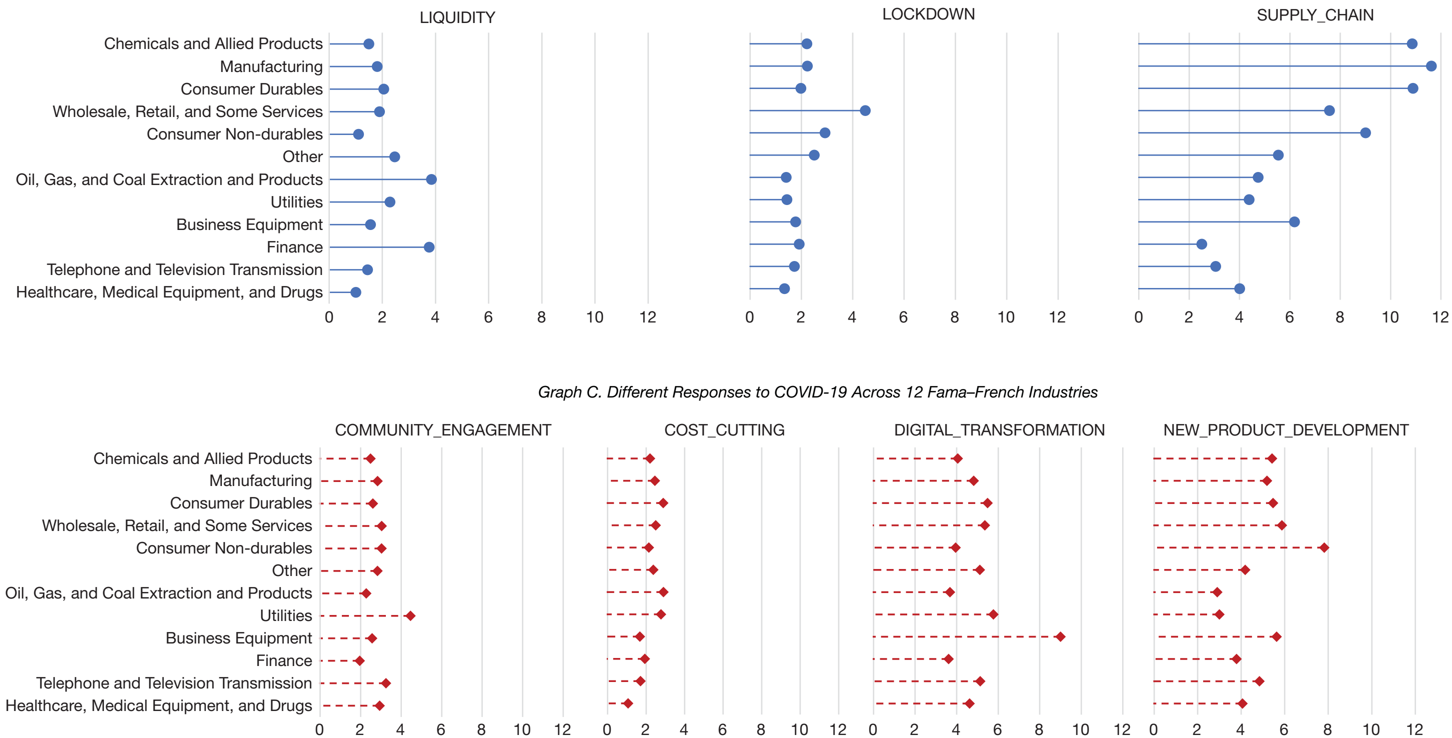
FIGURE 4 (continued)

Exposure and Response Related to COVID-19 Across 12 Fama–French Industries



Graph C. Different Responses to COVID-19 Across 12 Fama–French Industries

TABLE 4

Corporate Culture and Stock Returns in the Crisis Period

Table 4 presents baseline cross-sectional regression estimates of the relation between strong culture and stock returns in the crisis period of Jan. 2–Mar. 20, 2020. Industry fixed effects are based on Fama–French 48-industry classification. Definitions of variables are provided in the Appendix. Heteroscedasticity-consistent standard errors are presented in parentheses. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

	CRISIS_PERIOD_RETURN			
	1	2	3	4
STRONG_CULTURE	4.872***	4.996***	3.862***	3.928***
	(1.081)	(1.063)	(1.064)	(1.070)
ln(MARKET_CAP)			1.216***	0.814***
			(0.241)	(0.256)
LEVERAGE			−13.098***	−11.077***
			(2.057)	(2.069)
CASH_HOLDINGS			7.659**	8.161***
			(3.035)	(3.001)
ROA			8.528***	6.344**
			(3.204)	(3.104)
B/M			−2.709***	−1.514
			(0.971)	(0.981)
MOMENTUM			0.003	0.001
			(0.011)	(0.012)
Constant	−42.272***	−34.012***	−46.361***	−37.563***
	(0.458)	(1.041)	(2.374)	(2.671)
FOUR_FACTOR_LOADINGS	No	Yes	No	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes
No. of obs.	2,394	2,394	2,394	2,394
Adjusted R^2	0.161	0.226	0.218	0.256

performed significantly better during the crisis period. In terms of economic significance, firms with a strong culture were associated with a 4.9-percentage-point increase in returns during the first quarter of 2020. In column 2, we also control for a firm's factor loadings based on the Fama and French 3-factor model plus the momentum factor (Fama and French (1993), Carhart (1997)). We find that the coefficient on STRONG_CULTURE remains positive and significant.

One concern with the specifications in columns 1 and 2 of Table 4 is that the performance of firms with a strong culture during the crisis period may be due to omitted variables that are correlated with corporate culture, rather than due to corporate culture itself. To address this concern, in columns 3 and 4, we control for firm operating performance in the year before the pandemic and other characteristics known to affect stock returns (e.g., Daniel and Titman (1997), Asness, Moskowitz, and Pedersen (2013)). We again show that firms with a strong culture had higher stock returns during the crisis period of 2020. The magnitude of the outperformance by firms with a strong culture is somewhat attenuated after we include additional control variables, but the effect is still economically important. In column 4, we show that firms with a strong culture were associated with a 3.9-percentage-point increase in returns during the first quarter of 2020.

In terms of the control variables, we show that firms that entered the pandemic with higher market capitalization, lower leverage, higher cash holdings, and higher ROA are associated with higher first-quarter stock returns. In terms of economic significance, based on the specification in column 4, a 1-standard-deviation increase in market capitalization (1.989), leverage (0.241), cash holdings (0.212), and ROA (0.210) is associated with a change in the crisis period return of 1.6, 2.7, 1.7, 1.3, and 0.9 percentage points, respectively. Thus, the economic impact of culture during the first quarter of 2020 is 105% of the impact of market capitalization, 64% of the impact of leverage, 99% of the impact of cash holdings, and 128% of the impact of ROA, indicating that corporate culture is important in explaining returns in the first quarter of 2020.

These findings provide some direct evidence of our first hypothesis, that is, that there is a positive association between firms with a strong culture and stock returns during the first quarter of 2020. Next, we employ a time series of returns to directly test our first hypothesis that the culture–value link is stronger during the pandemic.

B. Corporate Culture, COVID-19 Exposure, and Returns

In this section, we investigate whether the positive culture–return link is unique to bad times or is common to most periods, perhaps as a result of some unobservable risk factors that are correlated with culture. Following Lins et al. (2017), we utilize monthly return data before and during the onset of the COVID-19 pandemic. More importantly, the topic model we employ allows us to explore whether this positive association is contingent on firms' differential exposure to COVID-19. To do so, we estimate a panel data regression model interacting culture with a continuous COVID-19 exposure variable (i.e., OVERALL_EXPOSURE) and include firm and month fixed effects:

$$\begin{aligned}(2)\qquad \text{MONTHLY\_RETURN}_{i,t} = \alpha &+ \beta_1 \text{OVERALL\_EXPOSURE}_{i,t} \\ &+ \beta_2 \text{OVERALL\_EXPOSURE}_{i,t} \\ &\times \text{STRONG\_CULTURE}_{i} \\ &+ \beta_3 \text{FIRM\_CHARACTERISTICS}_{i,t} \\ &+ \beta_4 \text{FOUR\_FACTOR\_LOADINGS}_{i,t} \\ &+ \text{FIRM\_FE} + \text{MONTH\_FE} + \varepsilon_{i,t},\end{aligned}$$

where $\text{MONTHLY\_RETURN}_{i,t}$ is the monthly return over the period Jan. 2019 to Mar. 20, 2020. OVERALL_EXPOSURE is the sum of the proportions of discussion on the 6 different exposures to COVID-19 from the output of a CTM for the first quarter in 2020, and 0 for the entire year of 2019. Corporate culture is measured at the end of 2017, 2 years before the onset of the pandemic, to eliminate any concern that firms changed their culture in anticipation of a public health crisis. Firm fixed effects control for time-invariant omitted risk factors, and month fixed effects control for return seasonality. The coefficient on the interaction term OVERALL_EXPOSURE × STRONG_CULTURE captures the differential impact of corporate culture on monthly stock returns during the 3-month period from Jan. 2020 to Mar. 20, 2020, for a given level of overall exposure to COVID-19.

Panel A of Table 5 presents the results.[13] We first show that the coefficient on OVERALL_EXPOSURE is negative and significant. In terms of economic

[13]To help interpret the economic magnitude, Table IA5 in the Supplementary Material provides the summary statistics of the key variables in Table 5.

TABLE 5

Corporate Culture, COVID-19 Exposure, and Stock Returns

Table 5 presents panel data regression estimates of the relation between strong culture and stock returns over the period Jan. 2019–Mar. 2020, contingent on firms' exposure to COVID-19. OVERALL_EXPOSURE and 6 different exposures (in percentage points) are from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls in the first 3 months in 2020, and 0 for the entire year of 2019. Panel A presents the regression results using the overall exposure variable. Panel B presents the regression results using the 6 different exposure variables. Control variables are the same as those in Table 4. Firm fixed effects and month fixed effects are included. Definitions of variables are provided in the Appendix. Heteroscedasticity-consistent standard errors in parentheses are clustered at the firm level. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Strong Culture, Overall Exposure, and Stock Returns

	MONTHLY_RETURN			
	1	2	3	4
OVERALL_EXPOSURE	−0.098***	−0.105***	−0.092***	−0.098***
	(0.015)	(0.015)	(0.014)	(0.015)
OVERALL_EXPOSURE × STRONG_CULTURE	0.109***	0.109***	0.084***	0.085***
	(0.017)	(0.018)	(0.016)	(0.017)
FIRM_CHARACTERISTICS	No	No	Yes	Yes
FOUR_FACTOR_LOADINGS	No	Yes	No	Yes
FIRM_FE	Yes	Yes	Yes	Yes
MONTH_FE	Yes	Yes	Yes	Yes
No. of obs.	35,505	35,505	35,505	35,505
Adjusted R^2	0.407	0.415	0.423	0.429

Panel B. Strong Culture, Different Exposure, and Stock Returns

	MONTHLY_RETURN					
	1	2	3	4	5	6
BUSINESS_OPERATIONS	−0.162*					
	(0.084)					
BUSINESS_OPERATIONS × STRONG_CULTURE	0.573***					
	(0.137)					
DEMAND		−0.145***				
		(0.024)				
DEMAND × STRONG_CULTURE		0.177***				
		(0.047)				
EMPLOYEES			−0.099*			
			(0.053)			
EMPLOYEES × STRONG_CULTURE			0.387***			
			(0.072)			
LIQUIDITY				−0.240***		
				(0.054)		
LIQUIDITY × STRONG_CULTURE				0.355***		
				(0.093)		
LOCKDOWN					−0.512***	
					(0.100)	
LOCKDOWN × STRONG_CULTURE					0.466***	
					(0.124)	
SUPPLY_CHAIN						−0.118***
						(0.032)
SUPPLY_CHAIN × STRONG_CULTURE						0.158***
						(0.055)
FIRM_CHARACTERISTICS	Yes	Yes	Yes	Yes	Yes	Yes
FOUR_FACTOR_LOADINGS	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes
MONTH_FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	35,505	35,505	35,505	35,505	35,505	35,505
Adjusted R^2	0.427	0.428	0.428	0.428	0.428	0.427

significance, based on the specification in column 4, a 1-standard-deviation increase in OVERALL_EXPOSURE (11.28%) is associated with a drop in monthly returns of 1.1 percentage points. We further show that the coefficient on the interaction term OVERALL_EXPOSURE × STRONG_CULTURE is positive and significant, suggesting that firms with a strong culture are associated with a smaller drop in returns. In terms of economic significance, the coefficient of 0.085 on the interaction term indicates that a 1-standard-deviation increase in OVERALL_EXPOSURE for firms with a strong culture is associated with reducing the monthly return drop by 1.0 percentage points during the crisis compared with firms without a strong culture. In combination with the economic effect from the standalone term OVERALL_EXPOSURE, we show that in net, firms with a strong culture are associated with a monthly return drop of only 0.1 percentage points compared with 1.1 percentage points for firms without a strong culture when their exposure to COVID-19 is increased by 1 standard deviation. These results suggest that in the face of a major pandemic, firms with a strong culture experience a significantly smaller drop in returns than their peers without a strong culture.

Panel B of Table 5 presents the results when we decompose the overall exposure measure into its 6 components through topic modeling. We show large heterogeneity in terms of how a strong culture helps firms with different exposures to outperform their peers without a strong culture. LOCKDOWN has the largest standalone effect on returns among different types of exposure. A 1-standard-deviation increase in LOCKDOWN is associated with a drop in monthly returns of 0.7 percentage points. Corporate culture is most effective in alleviating the negative impact of EMPLOYEES. A 1-standard-deviation increase in EMPLOYEES of firms with a strong culture is associated with reducing the return drop by 0.9 percentage points compared with firms without a strong culture. In contrast, corporate culture is least effective in alleviating the negative impact of SUPPLY_CHAIN. A 1-standard-deviation increase in SUPPLY_CHAIN for firms with a strong culture is associated with reducing the return drop by 0.6 percentage points compared with firms without a strong culture.

C. Channels

As discussed earlier, the topic model we employ identifies not only firms' exposure to COVID-19 but also their responses to and strategies for dealing with the pandemic. In this article, we provide one of the first investigations into the relation between firms with a strong culture and their different responses to a public health crisis. Table 6 presents the results.[14]

We first show that firms with a strong culture are more likely to support their community, embrace digital transformation, and develop new products (columns 1, 7, and 10 of Table 6). Moreover, firms with greater exposures to COVID-19 are more likely to support their community, cut costs, embrace digital transformation, and develop new products (columns 2, 5, 8, and 11). Importantly, we show that in the midst of a pandemic, firms with a strong culture are more likely to support their community, embrace digital transformation, and develop new products than their

[14] In Table 6, STRONG_CULTURE takes the value of 0 in 75% of the cases; accordingly, the interaction term (OVERALL_EXPOSURE × STRONG_CULTURE) also takes the value of 0 in those same cases, resulting in the correlation between STRONG_CULTURE and the interaction term being 0.84. In columns 3, 6, 9, and 12 when including the interaction term, we do not include the standalone term STRONG_CULTURE to avoid the multicollinearity problem.

TABLE 6

Corporate Culture and Firm Response in the Crisis Period

Table 6 presents cross-sectional regression estimates of the relation between strong culture and firm response in the crisis period. OVERALL_EXPOSURE and 4 firm responses (in percentage points) are from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls in the first 3 months in 2020. We control for the natural logarithm of total assets, leverage, cash holdings, ROA, and book-to-market ratio (B/M). Industry fixed effects are based on Fama–French 48-industry classification. Definitions of variables are provided in the Appendix. Heteroscedasticity-consistent standard errors are presented in parentheses. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

	COMMUNITY_ENGAGEMENT			COST_CUTTING			DIGITAL_TRANSFORMATION			NEW_PRODUCT_DEVELOPMENT		
	1	2	3	4	5	6	7	8	9	10	11	12
STRONG_CULTURE	0.394***	0.417***		−0.068	−0.003		1.800***	1.834***		0.548**	0.609***	
	(0.148)	(0.147)		(0.104)	(0.098)		(0.326)	(0.325)		(0.213)	(0.209)	
OVERALL_EXPOSURE		0.021***	0.017***		0.059***	0.059***		0.031***	0.018**		0.056***	0.051***
		(0.004)	(0.004)		(0.003)	(0.003)		(0.008)	(0.008)		(0.006)	(0.006)
OVERALL_EXPOSURE × STRONG_CULTURE			0.017***			0.002			0.056***			0.018**
			(0.005)			(0.004)			(0.011)			(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,394	2,394	2,394	2,394	2,394	2,394	2,394	2,394	2,394	2,394	2,394	2,394
Adjusted R^2	0.039	0.046	0.047	0.052	0.161	0.161	0.111	0.116	0.111	0.081	0.112	0.111

peers without a strong culture while being no more likely than those peers to engage in cost cutting (as shown via the interaction term in columns 3, 6, 9, and 12).

According to the human capital channel discussed earlier, firms with a strong culture invest more in their employees during calm times, and well-treated employees are better motivated and more productive. Our finding suggests that firms that have regularly treated their employees well can weather negative economic shocks better; hence, there is no need to engage in aggressive cost cutting. Our finding on cost cutting is consistent with this channel.

According to the technology channel discussed earlier, highly innovative firms are more adaptable to changing environments. Our finding that firms with a strong culture, which includes innovation, are more likely to pivot toward digital technology and new-product development amid a pandemic supports this channel.

We next examine a number of performance and real outcome measures to shed light on the excess returns earned by firms with a strong culture during the crisis period. To gain a better understanding of how a strong culture helps firms in the midst of a pandemic, we group the 5 cultural values underlying a strong culture into STRONG_PEOPLE_CULTURE, comprising integrity, respect, and teamwork, and STRONG_TECHNOLOGY_CULTURE, comprising innovation and quality. The model specification is similar to equation (2). The sample consists of 2,032 firms whose accounting data are available for at least 3 fiscal quarters since the onset of the pandemic and 4 quarters prior from Compustat.

Panel A of Table 7 presents the summary statistics of the key variables examined.[15] Panel B presents the panel data regression results relating strong culture and strong people/technology culture to different performance and real outcome measures.

We first show that the coefficient on the standalone term OVERALL_EXPOSURE is not significant when the dependent variable is SALES_PER_EMPLOYEE (column 1 of Table 7). We further show that the coefficient on the interaction term OVERALL_EXPOSURE × STRONG_CULTURE is positive and significant, indicating that firms with a strong culture exhibit higher employee productivity relative to their peers with a weak culture after the onset of the pandemic. In terms of economic significance, a 1-standard-deviation increase in OVERALL_EXPOSURE for firms with a strong culture is associated with an increase in quarterly sales by about $5,734 per employee compared with firms without a strong culture. For an average-sized firm in our sample (with 16,163 employees), this translates into an increase in quarterly sales of approximately $93 million, which is approximately 6% of the average quarterly sales ($1,588 million) over the estimation period. The size of these effects appears to be economically meaningful. In columns 2 and 3, we show that both STRONG_PEOPLE_CULTURE and STRONG_TECHNOLOGY_CULTURE help raise employee productivity.

[15]Because of the pandemic, there are wide variations in sales among the population of Compustat firms as well as among our sample firms. We opted to winsorize sales at the 5th and 95th percentiles instead. It is worth noting that our main findings remain if we use winsorization at the 1st and 99th percentiles (but resulting in much larger economic effects). For comparability, we multiple the layoff likelihood by 100 when running the linear probability model in Panel B of Table 7.

TABLE 7

Corporate Culture, COVID-19 Exposure, and Performance and Real Outcomes

Table 7 presents panel data regression estimates of the relation between strong culture, its components, and performance and real outcomes, contingent on firms' exposure to COVID-19. The sample consists of 2,032 firms whose accounting data are available for at least 3 fiscal quarters since the onset of the pandemic and 4 quarters prior from Compustat. For the fiscal quarters in 2020, OVERALL_EXPOSURE (in percentage points) is from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls in the first quarter in 2020. For the prior 4 fiscal quarters, OVERALL_EXPOSURE takes the value of 0. Panel A presents the summary statistics. Panel B presents panel data regression estimates of the relation between STRONG_CULTURE, its two components (i.e., STRONG_PEOPLE_CULTURE and STRONG_TECHNOLOGY_CULTURE), and performance and real outcomes, contingent on firms' exposure to COVID-19. Panel C presents panel data regression estimates of the relation between the 5 cultural values (the 3 components of STRONG_PEOPLE_CULTURE, integrity, respect, and teamwork, and the 2 components of STRONG_TECHNOLOGY_CULTURE, innovation and quality) and performance and real outcomes, contingent on firms' exposure to COVID-19. We control for the natural logarithm of total assets, leverage, cash holdings, ROA, and book-to-market ratio (B/M). Firm fixed effects and quarter fixed effects are included. Definitions of variables are provided in the Appendix. Heteroscedasticity-consistent standard errors in parentheses are clustered at the firm level. *, **, and *** correspond to statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics

	N	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
SALES_PER_EMPLOYEE	14,594	148.069	216.737	52.314	82.370	147.457
LAYOFF (%)	14,594	12.697	33.295	0.000	0.000	0.000
MARKET_SHARE (%)	14,594	1.806	4.553	0.036	0.216	1.143
ROA (%)	14,594	1.243	4.594	0.519	2.107	3.436
ROS (%)	14,594	6.875	37.083	3.720	13.203	24.818
OVERALL_EXPOSURE	14,594	11.132	15.010	0.000	0.000	23.983

(continued on next page)

TABLE 7 (continued)

Corporate Culture, COVID-19 Exposure, and Performance and Real Outcomes

Panel B. Strong Culture, Strong People/Technology Culture, Overall Exposure, and Performance and Real Outcomes

	SALES_PER_EMPLOYEE			LAYOFF		
	1	2	3	4	5	6
OVERALL_EXPOSURE	0.028	0.062	0.013	0.207***	0.216***	0.206***
	(0.130)	(0.129)	(0.133)	(0.040)	(0.040)	(0.041)
OVERALL_EXPOSURE × STRONG_CULTURE	0.382***			0.009		
	(0.117)			(0.050)		
OVERALL_EXPOSURE × STRONG_PEOPLE_CULTURE		0.465***			−0.110**	
		(0.129)			(0.055)	
OVERALL_EXPOSURE × STRONG_TECHNOLOGY_CULTURE			0.354***			0.010
			(0.102)			(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes
QUARTER_FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,594	14,594	14,594	14,594	14,594	14,594
Adjusted R^2	0.058	0.058	0.058	0.035	0.036	0.035

	MARKET_SHARE			ROA			ROS		
	7	8	9	10	11	12	13	14	15
OVERALL_EXPOSURE	0.001	0.000	0.001	−0.007*	−0.007*	−0.007*	−0.015	−0.008	−0.018
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.031)	(0.031)	(0.032)
OVERALL_EXPOSURE × STRONG_CULTURE	−0.001			0.008**			0.059**		
	(0.002)			(0.004)			(0.027)		
OVERALL_EXPOSURE × STRONG_PEOPLE_CULTURE		0.000			0.011**			0.041	
		(0.002)			(0.005)			(0.038)	
OVERALL_EXPOSURE × STRONG_TECHNOLOGY_CULTURE			−0.001			0.005			0.057**
			(0.002)			(0.004)			(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QUARTER_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594
Adjusted R^2	0.036	0.036	0.036	0.063	0.063	0.063	0.048	0.048	0.048

(continued on next page)

TABLE 7 (continued)

Corporate Culture, COVID-19 Exposure, and Performance and Real Outcomes

Panel C. Five Cultural Values, Overall Exposure, and Performance and Real Outcomes

	SALES_PER_EMPLOYEE					LAYOFF				
	1	2	3	4	5	6	7	8	9	10
OVERALL_EXPOSURE	0.082 (0.130)	0.041 (0.130)	0.079 (0.129)	0.020 (0.130)	0.006 (0.135)	0.207*** (0.040)	0.212*** (0.040)	0.211*** (0.040)	0.205*** (0.041)	0.225*** (0.041)
OVERALL_EXPOSURE × STRONG_INTEGRITY_CULTURE	0.090 (0.148)					0.015 (0.059)				
OVERALL_EXPOSURE × STRONG_RESPECT_CULTURE		0.324*** (0.112)					−0.020 (0.050)			
OVERALL_EXPOSURE × STRONG_TEAMWORK_CULTURE			0.342** (0.167)					−0.061 (0.058)		
OVERALL_EXPOSURE × STRONG_INNOVATION_CULTURE				0.384*** (0.103)					0.021 (0.047)	
OVERALL_EXPOSURE × STRONG_QUALITY_CULTURE					0.336*** (0.099)					−0.065 (0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QUARTER_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594
Adjusted R^2	0.056	0.057	0.057	0.058	0.057	0.035	0.035	0.035	0.035	0.036

	MARKET_SHARE					ROA				
	11	12	13	14	15	16	17	18	19	20
OVERALL_EXPOSURE	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	−0.007* (0.004)	−0.008** (0.004)	−0.007* (0.004)	−0.007* (0.004)	−0.008** (0.004)
OVERALL_EXPOSURE × STRONG_INTEGRITY_CULTURE	0.001 (0.002)					0.004 (0.004)				
OVERALL_EXPOSURE × STRONG_RESPECT_CULTURE		0.002 (0.002)					0.011*** (0.003)			
OVERALL_EXPOSURE × STRONG_TEAMWORK_CULTURE			−0.001 (0.002)					0.014*** (0.005)		

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TABLE 7 (continued)

Corporate Culture, COVID-19 Exposure, and Performance and Real Outcomes

Panel C. Five Cultural Values, Overall Exposure, and Performance and Real Outcomes (continued)

	MARKET_SHARE					ROA				
	11	12	13	14	15	16	17	18	19	20
OVERALL_EXPOSURE × STRONG_INNOVATION_CULTURE				−0.001 (0.002)					0.005 (0.004)	
OVERALL_EXPOSURE × STRONG_QUALITY_CULTURE					−0.000 (0.001)					0.007** (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
QUARTER_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594	14,594
Adjusted R^2	0.036	0.036	0.036	0.036	0.036	0.063	0.063	0.064	0.063	0.063

	ROS				
	21	22	23	24	25
OVERALL_EXPOSURE	−0.004 (0.031)	−0.018 (0.031)	−0.007 (0.031)	−0.016 (0.032)	−0.023 (0.032)
OVERALL_EXPOSURE × STRONG_INTEGRITY_CULTURE	−0.009 (0.039)				
OVERALL_EXPOSURE × STRONG_RESPECT_CULTURE		0.083*** (0.026)			
OVERALL_EXPOSURE × STRONG_TEAMWORK_CULTURE			0.042 (0.040)		
OVERALL_EXPOSURE × STRONG_INNOVATION_CULTURE				0.058** (0.025)	
OVERALL_EXPOSURE × STRONG_QUALITY_CULTURE					0.071*** (0.023)
Controls	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes
QUARTER_FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,594	14,594	14,594	14,594	14,594
Adjusted R^2	0.047	0.048	0.048	0.048	0.048

Next, we examine whether strong culture helps mitigate the likelihood of employee layoff. We first show that the coefficient on the standalone term OVERALL_EXPOSURE is positive and significant across columns 4–6 of Table 7, indicating that firms with greater exposure to COVID-19 are more likely to experience employee layoffs. We then show that the coefficient on the interaction term OVERALL_EXPOSURE × STRONG_PEOPLE_CULTURE is negative and significant in column 5, indicating that firms with a strong people culture avoid laying off employees. In terms of economic significance, a 1-standard-deviation increase in OVERALL_EXPOSURE for firms with a strong culture is associated with a drop in the likelihood of employee layoff by approximately 2 percentage points compared with firms without a strong culture.

We then show that the effect of OVERALL_EXPOSURE on MARKET_SHARE is insignificant (columns 7–9 of Table 7), indicating that there is no significant change in market structure during the pandemic. Moreover, we do not find any evidence showing that a strong culture could contribute to a firm's strengthening its market position.

Lastly, we examine whether a strong culture could mitigate the effect of COVID-19 on operating performance. We show that firms with a strong culture have a higher ROA and profit margin (return on sales [ROS]) than their peers without a strong culture during the pandemic (columns 10 and 13 of Table 7). In terms of economic significance, a 1-standard-deviation increase in OVERALL_EXPOSURE for firms with a strong culture is associated with an increase of ROA by 0.1 percentage points and an increase of ROS by 0.9 percentage points compared with firms without a strong culture. Inspecting the two dimensions of corporate culture, we find that the driving force for a higher ROA is STRONG_PEOPLE_CULTURE (column 11), whereas the driving force for a higher ROS is STRONG_TECHNOLOGY_CULTURE (column 15).

Panel C of Table 7 presents the results using strong culture indicators based on the 5 cultural values: innovation, integrity, respect, teamwork, and quality. We first show that among the 3 components of STRONG_PEOPLE_CULTURE, both STRONG_RESPECT_CULTURE and STRONG_TEAMWORK_CULTURE are the primary drivers of employee productivity and ROA, and STRONG_RESPECT_CULTURE is the primary driver of ROS. Moreover, both STRONG_INNOVATION_CULTURE and STRONG_QUALITY_CULTURE are the primary drivers of employee productivity and ROS, and STRONG_QUALITY_CULTURE is the primary driver of ROA. Again, our findings support both the human capital and technology channels.

In summary, the results in Table 7 provide supporting evidence for the human capital and technology channels through which corporate culture makes firms resilient to pandemics.

VI. Robustness Checks

In this section, we conduct a large number of robustness checks on our main findings. Table IA6 presents panel data regression estimates of the relation between strong culture, overall exposure to COVID-19, and stock returns (as in Table 5) after controlling for other attributes that may make firms resilient during the COVID-19 pandemic.

Albuquerque, Koskinen, Yang, and Zhang (2020) show that firms with high ES ratings outperform during the first quarter of 2020 compared with other firms. Bae, El Ghoul, Gong, and Guedhami (2021) note that during the COVID-19 crisis period, the relation between CSR and stock returns varies, depending on the data provider of CSR scores. We obtain firms' ES ratings from the Thomson Reuters' Refinitiv Environmental, Social, and Corporate Governance (ESG) (formerly ASSET4) database and firms' summary scores in community, diversity, employee relations, environment, and human rights from the Morgan Stanley Capital International (MSCI) ESG Stats (formerly KLD Stats) database. In columns 1 and 2 of Table IA6, we show that firms with higher CSR scores are associated with a smaller drop in returns. Importantly, we show that after controlling for their CSR practices, firms with a strong corporate culture are associated with higher stock returns than their counterparts without a strong culture. It is worth noting that our finding that firms with a strong corporate culture provide more support to their community during the COVID-19 crisis distinguishes us from prior research using pre-crisis ratings to study the value of CSR during the crisis.

Pagano et al. (2020) show that firms that have flexible work-from-home arrangements significantly outperform those that do not have such arrangements during the COVID-19 outbreak. In column 3 of Table IA6, we control for the feasibility of working from home and show that, indeed, firms with flexible work arrangements outperform their peers without such arrangements during the pandemic. Moreover, our main findings remain.

Using international data, Hassan et al. (2020) show that firms that have experienced SARS or H1N1 are better at dealing with the COVID-19 outbreak. In column 4 of Table IA6, we control for firms' prior experience with other epidemic diseases and show no significant association between U.S. firms' prior exposure and their stock performance during the COVID pandemic. Importantly, our main findings remain.

Ramelli and Wagner (2020) find that firms with lower exposure to China are less affected than other firms. In column 5 of Table IA6, we control for firms' business associations with Chinese firms and show no significant association between firms' exposure to China and their stock performance during the first quarter of 2020. One possible explanation is that by Mar. 2020, China emerges from the pandemic, and any business connection to China becomes an asset. Importantly, our main findings remain.

Table IA7 presents robustness checks on both cross-sectional and panel data regression estimates using two different return windows: i) over the period Jan. 20–Mar. 20, 2020, the combination of outbreak and fever periods following Ramelli and Wagner (2020), and ii) over the period Jan. 2–Mar. 31, 2020. We show that our main findings remain unchanged.

Given that industry affiliation is one of a number of factors shaping corporate culture (Graham et al. (2019)), in our empirical analysis (Tables 4 and 6), we include industry fixed effects throughout. As a robustness check, we construct alternative measures of a strong culture by either using the top quartile with an industry or subtracting industry means before using the top quartile across all firms as the cutoff. Table IA8 in the Supplementary Material replicates the analyses in Table 4 and Panel A of Table 5. We show that our main findings remain.

Finally, we repeat our analysis in Tables 4–7 after removing utilities and financial firms. Table IA9 in the Supplementary Material presents the results. We show that our main findings remain.

In summary, we conclude that firms with a strong culture are associated with a smaller drop in returns than their peers without a strong culture, controlling for their CSR practices, flexibility for employees to work from home, prior pandemic experience, and connections to Chinese businesses. Our main findings remain using different return windows and different ways of defining strong culture and after excluding utilities and financial firms.

VII. Conclusions

After fitting a topic model to 40,927 COVID-19–related paragraphs in 3,581 earnings calls over the period Jan. 22–Apr. 30, 2020, we obtain firm-level measures of exposure and response related to COVID-19 for 2,894 U.S. firms. We show that despite the many different ways in which COVID-19 affects their operations, firms with a strong corporate culture outperform their peers without a strong culture. Moreover, firms with a strong culture are more likely to support their community, embrace digital transformation, and develop new products, and they are no more likely to cut costs than their peers without a strong culture.

To explore the channels through which culture makes firms resilient in the midst of a pandemic, we show that firms with a strong culture have higher sales per employee, a higher ROA, and a higher profit margin. Our results provide support for the hypothesis that corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise (Kreps (1990)).

Appendix. Variable Definitions

Continuous variables, with the exception of COVID-19 exposure/response variables, are winsorized at the 1st and 99th percentiles.

COVID-19 Exposure Variables

BUSINESS_OPERATIONS: The proportion of discussion on delays in business operations (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

DEMAND: The proportion of discussion on demand shocks (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

EMPLOYEES: The proportion of discussion on employee safety and well-being (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

LIQUIDITY: The proportion of discussion on liquidity and financing (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

LOCKDOWN: The proportion of discussion on lockdown and its implications for business operations (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

OVERALL_EXPOSURE: The sum of proportions of discussion on the 6 different exposures to COVID-19 (business operations, demand, employees, liquidity, lockdown, and supply chain) over the period Jan. 22–Mar. 31, 2020.

SUPPLY_CHAIN: The proportion of discussion on supply chain disruptions (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

COVID-19 Response Variables

COMMUNITY_ENGAGEMENT: The proportion of discussion on community engagement (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

COST_CUTTING: The proportion of discussion on cost cutting (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

DIGITAL_TRANSFORMATION: The proportion of discussion on adopting digital technology (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

NEW_PRODUCT_DEVELOPMENT: The proportion of discussion on developing new products (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19–relevant paragraphs in earnings calls. For each firm, we take the average of call-level proportions across all calls over the period Jan. 22–Mar. 31, 2020.

Firm-Level Variables

B/M: Book value of equity divided by market value of equity.

CASH_HOLDINGS: Cash and marketable securities divided by total assets.

CHINA: An indicator variable that takes the value of 1 if a firm mentions China in its annual report in relation to importing and/or exporting activities, and 0 otherwise. Source: Hoberg and Moon (2017).

CRISIS_PERIOD_RETURN: Buy-and-hold return (in percentage points) from Jan. 2 to Mar. 20, 2020.

CSR_ASSET4: A firm's average score in environmental and social practices. Source: Thomson Reuters' Refinitiv ESG (formerly ASSET4) database for the year 2017.

CSR_MSCI: A firm's summary score in community, diversity, employee relations, environment, and human rights (Lins et al. (2017)). Source: MSCI ESG Stats (formerly KLD Stats) database for the year 2017.

CUMULATIVE_COVID_CASES: The weighted average of state-level COVID-19 cumulative cases measured right before a firm's quarterly earnings call (7-day moving average), with the weight being the firm-state citation share (Bernile et al. (2015)).

FOUR_FACTOR_LOADINGS: Factor loadings based on the Fama–French 3-factor model plus the momentum factor, which are estimated over the previous 60-month period. Firms are excluded from the analysis if fewer than 12 months of data are available to estimate factor loadings. For Table 4, factor loadings are estimated over the previous 60-month period ending in Dec. 2019.

GPS_RESIDENTIAL: The weighted average of the state-level change in the amount of time spent at home (in percentage points) measured right before a firm's quarterly earnings call (7-day moving average), with the weight being the firm-state citation share (Bernile et al. (2015)). Time-usage data are from Chetty et al. (2020), where they use Google's COVID-19 Community Mobility Reports to construct a measure of daily time spent at residential locations as changes relative to the median value for the corresponding day of the week during the 5-week period from Jan. 3 to Feb. 6, 2020.

LABOR_INTENSITY: Number of employees divided by sales, multiplied by 100.

LAYOFF: An indicator variable that takes the value of 1 if a firm has employee-layoff–related announcements in a quarter, and 0 otherwise. Source: The data on layoff-related announcements are obtained from RavenPack.

LEVERAGE: Total liabilities divided by total assets.

ln(MARKET_CAP): Natural logarithm of market capitalization.

MARKET_SHARE: The share of sales (in percentage points) among all Compustat firms in the same 2-digit SIC industry.

MOMENTUM: Buy-and-hold return (in percentage points) over months (−12, −2) before the focal month. In Table 4, we use the buy-and-hold return over the period Jan.–Nov. 2019.

MONTHLY_RETURN: Monthly return (in percentage points) from Jan. 2019 to Mar. 2020, where the return for March ends on Mar. 20, 2020.

NEW_COVID_CASES: The weighted average of state-level COVID-19 new cases measured right before a firm's quarterly earnings call (7-day moving average), with the weight being the firm-state citation share. Following Bernile et al. (2015), we measure a firm's geographical dispersion with the number of unique U.S. states mentioned in its 2019 10-K filing. The relative importance of a particular state for a given firm, the firm-state citation share, is the number of times the state is mentioned in the firm's 10-K divided by the total number of mentions of all U.S. states in the same report. State-level COVID-19 new cases per 100,000 people are from Chetty et al. (2020).

PRIOR_EPIDEMIC_EXPERIENCE: An indicator variable that takes the value of 1 if a firm mentions SARS- and/or H1N1-related words in its earnings calls in 2003 and/or 2009, and 0 otherwise. Source: Hassan et al. (2020).

ROA: Operating income before depreciation divided by total assets.

ROS: Operating income before depreciation divided by sales.

SALES_PER_EMPLOYEE: Sales per employee ($thousands).

STRONG_CULTURE: An indicator variable that takes the value of 1 if the sum of a firm's 5 cultural value scores is in the top quartile across all firms in 2017, which is the most recent year with available cultural value data, and 0 otherwise. Corporate culture data are from Li et al. (2021), who compute the scores of the top 5 cultural values proposed by Guiso et al. (2015): innovation, integrity, quality, respect, and teamwork.

STRONG_INNOVATION_CULTURE: An indicator variable that takes the value of 1 if the cultural value score of innovation is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_INTEGRITY_CULTURE: An indicator variable that takes the value of 1 if the cultural value score of integrity is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_PEOPLE_CULTURE: An indicator variable that takes the value of 1 if the sum of a firm's 3 people-oriented cultural value scores (integrity, respect, and teamwork) is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_QUALITY_CULTURE: An indicator variable that takes the value of 1 if the cultural value score of quality is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_RESPECT_CULTURE: An indicator variable that takes the value of 1 if the cultural value score of respect is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_TEAMWORK_CULTURE: An indicator variable that takes the value of 1 if the cultural value score of teamwork is in the top quartile across all firms in a year, and 0 otherwise.

STRONG_TECHNOLOGY_CULTURE: An indicator variable that takes the value of 1 if the sum of a firm's 2 technology-oriented cultural value scores (innovation and quality) is in the top quartile across all firms in a year, and 0 otherwise.

TONE: The average of the overall tone across all COVID-19–related paragraphs in a call. The overall tone of each COVID-19–related paragraph is computed as the difference between the share of positive words and the share of negative words using the positive/negative word lists developed by Loughran and McDonald (2011).

WFH: Share of jobs that can be done from home at the 2-digit NAICS industry level. Source: Dingel and Neiman (2020).

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109021000326.

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