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Tarek Alexander Hassan
Stephan Hollander
Laurence van Lent
Markus Schwedeler
Ahmed Tahoun

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ABSTRACT

We introduce a new word pattern-based method to automatically classify firms' primary concerns related to the spread of epidemic diseases raised in their quarterly earnings conference calls. We construct text-based measures of the costs, benefits, and risks listed firms in the US and over 80 other countries associate with the spread of Covid-19 and other epidemic diseases. We identify which firms and sectors expect to lose/gain from a given epidemic and which are most affected by the associated uncertainty. Our new automatic pattern-based method shows how firms' primary concerns (varying from the collapse in demand and disruptions in their production facilities or supply chain, to financing concerns) are changing over time and varying geographically as epidemics spread regionally and globally. We find that the Covid-crisis manifests itself at the firm-level as a simultaneous shock to both demand and supply. In prior epidemics, in contrast, firm discussions center more on shortfalls in demand. In 2020, supply and financing-related concerns are relatively more salient in regions where the spread of Covid-19 is less contained.

Tarek Alexander Hassan
Department of Economics
Boston University
270 Bay State Road
Boston, MA 02215
and NBER
thassan@bu.edu

Stephan Hollander
Tilburg University
Warandelaan 2
5037 AB Tilburg
the Netherlands
s.hollander@tilburguniversity.edu

Laurence van Lent
Frankfurt School of Finance and Management
Adickesallee 32-34
60322 Frankfurt am Main
Germany
l.vanlent@fs.de

Markus Schwedeler
Boston University
270 Bay State Road
Boston, MA 02215
mschwed@bu.edu

Ahmed Tahoun
London Business School
26 Sussex plc, Regent's Park
NW1 4SA London
atahoun@london.edu

Data is available at www.firmlevelrisk.com

"[D]o you want to touch on cancellations and just the whole hype around coronavirus?"
—Colin V. Reed, Chairman and CEO, Ryman Hospitality Properties, February 25, 2020

When the World Health Organization declared the outbreak of the COVID-19 virus a pandemic on March 11, 2020, the disease had already wreaked havoc in large swathes of China and in Northern Italy. What started as a new illness in a middling city in China, had grown within a few months to a global public health crisis the likes of which had been unseen for a century. Stock markets around the world crashed.[1] Even though governments rushed in equal measure to stem the further spread of the virus, locking down entire regions, as well as to support a suddenly wobbling economy, it became quickly clear that the shock would leave few untouched.

While perhaps a singular event, the COVID-19 pandemic offers a unique opportunity to study more generally how firms are *affected by* and *respond to* large aggregate, unexpected "shocks." Those wishing to avail themselves of this opportunity, however, immediately face three fundamental challenges related to measurement: How to identify which firm is affected? How to quantify the intensity of a firm's exposure to the shock? And finally, how to determine the nature of the shock that a firm faces; for example, whether the shock results in a firm's demand contraction, supply disruption, or credit tightening?[2] Such a granular understanding of the microeconomic impacts of large (macro) shocks is essential for formulating an effective policy response. For example, while well-targeted monetary and fiscal policy can compensate for shortfalls in demand, they may be much less effective in addressing the economic fallout of supply shocks.[3]

To meet these challenges, we have two objectives in this paper: (1) measure and classify the firm-level impact of epidemic diseases as an example of such a macro shock, and (2) use

[1]See Davis et al. (2021); Baker et al. (2020) and Ramelli and Wagner (2020) for an early discussion of the stock market response to COVID-19.

[2]Barrero et al. (2021) use data from a survey to underpin their conclusion that COVID-19 is a persistent reallocation shock, shifting employment growth to industries with a capacity for employees to work from home.

[3]See, for example, the debate in the literature about whether the Great Recession was demand-driven or due to a drop in productivity, see Mian et al. (2013) and Kaplan et al. (2020).

these measures to examine firms' responses to such a shock. Specifically, we construct a firm-level, time-varying measure of exposure to epidemic diseases, and decompose this exposure into demand, supply or other concerns. We then use these granular measures to examine at the micro level the relative importance of demand and supply factors in explaining changes in stock valuation and other economic outcomes during the COVID-19 crisis. We believe these efforts to be timely given the concern in the literature that the extraordinary nature of the current COVID-19 crisis might have rendered existing models and policy remedies ineffective (Adda, 2016; Barro et al., 2020). Beyond the COVID-19 emergency, however, we believe that our approach offers opportunities for studying the economic consequences of large shocks in general.

The measure we introduce is based on a text-classification method and proceeds in two steps. First, we identify the exposure of firms to the outbreak of COVID-19 by counting the number of times, if any, the disease is mentioned in the quarterly earnings conference call that publicly-listed firms in the United States and over 80 other countries host with market participants. This approach has been validated in recent work by Hassan et al. (2019, 2020) in the context of measuring a firm's exposure to political risk, Brexit, and to shocks such as the Fukushima nuclear disaster.[4] Second, once we identify those firms exposed to COVID-19 at a given point in time, we can then turn to the details of the conversation in their transcripts to systematically categorize the perceived firm-level impact of the shock.

For this purpose, we introduce a new automatic pattern-based method for classifying the content of discussions in conference calls related to COVID-19 and use it to produce evidence on the topics firms around the globe discuss when their managers talk about the coronavirus outbreak. Guided by the results of an extensive pilot study, we classify COVID-

[4]Intuitively, the idea of constructing a measure of firm-level exposure to a particular shock from transcripts of periodic earnings calls rests on the observation that these conference calls are a venue in which senior management has to respond *directly* to questions from market participants regarding the firm's future prospects. Not only are these disclosures therefore *timely*, but as earnings calls consist of a management presentation and, importantly, a Q&A session, they also require management to comment on matters they might not otherwise have voluntarily proffered. In most countries in our sample, earnings conference calls are held quarterly, which allows us to track changes in firm-level disease exposure over time.

19 related discussions into five topics: (1) demand impacts, (2) supply impacts, (3) cost reductions, (4) financial adjustments, and (5) government assistance. While the first two topics represent the direct impacts of the pandemic on the firm's demand and supply, the latter three represent endogenous responses in the form of cost savings programs, financial adjustments, and the take-up of government assistance programs.

We further refine the exposures to epidemic diseases by constructing—using tools developed in our earlier work (Hassan et al., 2019, 2020)—measures of epidemic diseases' overall impact on the mean (sentiment) and the variance (risk) of the firm's prospects. Doing so allows us to identify expected winners and losers from a shock (as the linguistic "tone" of the discussion of the shock in an earnings call is either positive or negative), and the extent of risks and uncertainty the firm associates with a given outbreak.

Finally, we use these firm-level, topic-specific measures to study micro-level consequences of a large macro-level shock. Specifically, we examine the stock market valuation effects of a firm's overall exposure to a pandemic-induced shock as well to the shock's demand and supply components. We also examine the role these shocks play in affecting firms' subsequent investment and hiring decisions.

Based on our new firm-level epidemic disease (topic-)exposure measures, we document a set of empirical facts about the impact of epidemic outbreaks on firms in 84 countries, the most important of which are as follows. First, the COVID-19 crisis is truly unprecedented in the breadth and intensity of its firm-level impact, even when compared to the most virulent prior epidemics in our sample, for which we generate similar empirical measures. While discussions of prior outbreaks such as SARS and H1N1 were confined to firms in specific regions and sectors, and never occupied more than 20 percent of the firms in our sample at the same time, COVID-19 is at present a major topic of discussion for virtually all firms in all parts of the world. In the second and third quarters of 2020, a remarkable three percent of sentences in earnings conference calls mention COVID-19.

Second, on average, firms expect and report overwhelmingly negative impacts from the spread of COVID-19 on their businesses, while also attributing a large increase in risks to the spread of the disease. In this sense, COVID-19 represents a shock both to the mean and the variance of firms' fortunes. After a peak in pessimism associated with COVID-19 in June of 2020, the tone of discussion recovered in the third and fourth quarters of 2020, lead by an uptick in optimism among Asian firms.

Third, underlying these overwhelmingly negative aggregate trends, significant heterogeneity across firms and sectors exists. For example, as for the tone of COVID-19 related discussions, firms are most pessimistic in the transportation sector, consistent with that industry being hit hard by cancelled air routes and closed borders. In contrast, technology firms are the least pessimistic, perhaps buoyed by the working-from-home orders issued by many governments and the accompanying needed investments in software and hardware solutions. In fact, some tech firms such as Apple, Intel, Microsoft, and Netflix, on average, discuss the impact of COVID-19 with a markedly positive, rather than negative, tone.

Moving beyond these important descriptive statistics, we examine valuation effects of the COVID-19 shock. Using quarterly stock returns in 2020, the first-quarter return of 2020 (that includes the February-March 2020 stock market crash induced by the COVID-19 pandemic (Giglio et al., 2021)), as well as the three-day return centered around the date of the earnings call, we find negative valuation effects for firms with more exposure to COVID-19. Decomposing COVID-19 exposure into risk and sentiment components, suggests that negative sentiment related to the COVID-19 outbreak is the prevalent factor explaining returns, although COVID-19 risk also has a significantly negative effect on stock returns in some of our specifications.

Fourth, probing deeper into the specific concerns firms associate with COVID-19, we find that the pandemic manifests itself at the firm-level as a simultaneous supply and demand shock, with supply concerns meaningfully larger during the COVID-19 crisis than in earlier pandemics. Indeed, during the COVID-19 crisis, firms appear concerned about the supply and demand-related impacts of the pandemic in almost equal measure. In the early days of the pandemic, many firms highlighted concerns relating to their supply chains. Later earnings calls, held in the second and third quarter of 2020, instead emphasize concerns relating to their production and operations with relatively higher frequency. In regions of the world where the outbreak is more virulent, supply impacts tend to be relatively more significant (perhaps due to stricter lockdown measures or other public health restrictions).

Finally, using our deeper understanding of the concerns firms voice over COVID-19, we isolate from these concerns the extent to which a firm is exposed to exogenous COVID-19 demand and supply shocks and examine the degree to which the documented valuation effects can be attributed to each of these two shocks. We show that supply and demand impacts of COVID-19 are about equally important in explaining variation in stock returns in 2020. For example, a one standard deviation increase in the pandemic's negative supply impacts on a given firm is associated with a 1.8 percentage point lower stock market valuation in the cross-section. Similarly, contractions in both supply and demand appear to have driven a drop in employment among large listed firms in the United States which were not eligible for government subsidies for maintaining jobs. By contrast, negative demand impacts appear the driving force behind the significant decline in firm-level investment: a one standard deviation increase in the pandemic's negative demand shock is associated with a 3.7 percent decrease in the firm's investment.

Stepping back, we hope that a deeper understanding of the various ways in which an epidemic affects firms may facilitate developing effective government and/or corporate intervention policies. Clearly, supply-side disruptions should be met with a substantially different toolkit than what is appropriate for demand or finance-related shocks. More fundamentally, however, our methodological innovation, in which we use word-based patterns to determine whether a COVID-19 related text fragment discusses a given topic, has broader applications and can be readily adapted for a range of tasks involving automatic classification of text in conference call transcripts and other firm disclosures.

Related literature. Distinguishing empirically between supply, demand, and financial impacts of specific shocks has long been an open question in macroeconomics (e.g., Blanchard and Quah, 1989). Data on prices and quantities have been used in macroeconomics to test theories about how these variables move in response to shocks, but identification is often challenging and primitive assumptions (e.g., about beliefs) are hard to test. The methods we develop here should aid in this identification effort and inform the broader debate. We offer a way to measure the differential exposure of firms to an aggregate shock and are able to pinpoint whether a given shock is related to supply, demand, or other concerns. As such, we learn about the origins of shocks, as perceived by corporate managers and non-corporate participants in the call. These perceptions are important given recent work on how managerial expectations explain important corporate policies (Gennaioli and Shleifer, 2018; Gennaioli et al., 2016) as well as work on how personal experiences affect expectations about aggregate economic outcomes, such as the severity of a recession (Kuchler and Zafar, 2019).

The fields of natural language processing and computational linguistics in particular have made significant strides in (automated) topic classification.[5] We build on these advances by integrating automated computational linguistic techniques with carefully circumscribed human judgment to meet the specifics of our textual source material (i.e., earnings conference call transcripts) and of our analysis task (i.e., identifying the origins of shocks as perceived by call participants).[6]

We illustrate our method using the setting of the coronavirus pandemic, and consequently, the paper also contributes to a fast-growing literature on the economics and finance of COVID-19.[7] The discussion in these studies centers around understanding whether the

[5] Despite this progress, many applications in the economics and finance literatures rely on Latent Dirichlet Allocation (LDA). While useful, LDA has been criticized for the significant discretion researchers need to exercise when identifying the main topic(s) of a text. Compounding this issue, LDA is non-deterministic inasmuch as repeating the same procedure multiple times may generate different topic word lists.

[6] Consequently, compared with LDA, our method of automatic topic classification limits the researcher judgment needed, precisely traces its consequences on the outcome, and allows us to scale the insights gleaned from human judgement to process systematically a very large number of text documents.

[7] In addition, there is a large literature in development and health economics studying pandemics, either in general or on specific diseases, including papers like Fogli and Veldkamp (2020); Greenwood et al. (2019); Philipson (1999).

economic consequences of COVID-19 are best understood as the pandemic causing a demand shock or a supply shock (Guerrieri et al., 2020; Baqaee and Farhi, 2020; Bekaert et al., 2020; Fornaro and Wolf, 2020; Faria-e Castro, 2020). Depending on the answer to this question, the optimal policy response of governments varies. A particularly interesting proposal is made in studies such as Atkeson (2020) and Eichenbaum et al. (2020), who argue for integrating epidemic models of the spread of a disease with conventional macroeconomic models to study the effect of policy interventions in this context.[8]

In finance, several studies highlight the credit market access and liquidity consequences of the COVID-19 pandemic (Au et al., 2020; Ferrando, 2020; Kargar et al., 2020; Ma et al., 2020; Ozik et al., 2020). For example, Greenwald et al. (2020) argue, and show, that credit lines are central to the transmission of macroeconomic shocks to firm credit, at both the aggregate level and in the cross-section. Closer related to our work are studies on the impact and transmission of COVID-19 on the cross-section of equity returns (Alfaro et al., 2020; Bretscher et al., 2020). The consensus emerging from these studies is that, at the onset of the COVID-19 pandemic, stock prices on average plunged, but since then have regained much of their value. This general pattern, however, potentially masks important heterogeneity across firms. To examine firm-level variation in COVID-19-induced stock returns, Ding et al. (2020) use data on COVID-19 cases from the John Hopkins University Coronavirus COVID-19 Global Cases database, to measure changes in the economy's exposure to the pandemic.

Closely related to our own work, Davis et al. (2020), rely on risk factor discussions in firms' pre-pandemic financial disclosures (Form 10-K filings) to characterize firm-level risk exposures and Croce et al. (2020) who use high-frequency data from Twitter to measure

[8]Important other studies that investigate the policy response (and its economic impact) to the COVID-19 pandemic include work that examines social distancing rules (Barro et al., 2020), lockdowns (Alon et al., 2020; Arnon et al., 2020; Kaplan et al., 2020; Moser and Yared, 2020), and the Paycheck Protecton Program (Joaquim and Netto, 2020).

epidemic contagion risk in financial markets.[9]

Our approach lends itself to quantifying firms' current exposure to COVID-19. Having a firm-level synchronous measure, as opposed to a historic or aggregate measure, is especially important in view of the wide-ranging experiences of firms dealing with the pandemic as suggested in the aforementioned studies. Despite the recovery in aggregate stock prices, we find that exposure to COVID-19 accounts for large-scale variation in the cross-section of stock returns. More importantly, as we identify whether the firm-level exposure is related to demand or supply shocks (or both), we show that the aggregate valuation effect can be attributed about equally to these two different types of shocks.

In sum, we provide new data and evidence on the extent to which epidemic diseases (and in particular the COVID-19 outbreak) affect the corporate world. The data show that the scale of exposure to the coronavirus is unprecedented by earlier outbreaks, spans all major economies, and is pervasive across all industries. Using a new method to automatically distinguish between supply- and demand-related impacts, we show the over-time development in these concerns. Taking a step back, in this paper we show how our text-based approach allows researchers, more generally, to investigate how corporations are affected by large, unexpected macro shocks.

1. Data

We use transcripts of quarterly earnings conference calls held by publicly-listed firms to construct our measures of firm-level exposure to epidemic diseases. These transcripts are available from the Refinitiv Eikon database and we collect the complete set of 333,626 English-language transcripts from January 1, 2002 to December 31, 2020 for 12,952 firms headquar-

[9]More broadly, we also add to the growing literature in finance and related fields using text as data (Gentzkow et al., 2019). A number of other recent papers use firm-level texts to measure firm-level political and non-political risk (Hassan et al., 2019), overall risk (Handley and Li, 2018), climate change exposure (Sautner et al., 2020), cyber risk (Jamilov et al., 2021), and trade policy risk (Caldara et al., 2019; Kost, 2019). Others have used newspapers and FOMC minutes to measure economic policy uncertainty (Baker et al., 2016), the state of the economy (Bybee et al., 2019), and analyze news about monetary policy (Hansen et al., 2017).

tered in 82 countries.[10] Earnings calls are key corporate events on the investor relations agenda, and allow financial analysts and other market participants to listen to senior management presenting their views on the company's state of affairs, ask these company officials questions about the firm's financial performance over the past quarter and, more broadly, discuss current developments (Hollander et al., 2010). As epidemic diseases potentially have a global impact, it is important that our data covers a significant proportion of firms around the globe. Appendix Table 1 presents the details of the extensive global coverage of listed firms in our sample.

We also use financial statement data from Compustat North America and Global, including data on firms' total assets, revenue, and investment rate; we use the location of the firm's headquarters from Refinitiv Eikon.[11] We convert all non-USD denominated variables into USD. Stock return data are from Refinitiv Eikon. Summary statistics for all our variables are provided in Table 1.

2. Measuring Firm-Level Exposure to Epidemic Diseases

Our ultimate aim is to construct a firm-level measure of exposure to demand and supply shocks related to COVID-19. We achieve this aim in two steps. First, we identify whether the corona pandemic is discussed in a quarterly earnings call, and use the extent of this discussion as a measure of firm-level exposure to COVID-19; this is similar to the method described in (Hassan et al., 2019, 2020). Second, we characterize the content of the discussion related to COVID-19 with a new automatic pattern-based approach designed to isolate and typify firms' specific concerns relating to the disease.

[10] This description applies at the moment of writing this paper. The publicly available dataset on www.firmlevelrisk.com is continuously updated as new transcripts become available.

[11] Note that this latter variable is meant to measure the location of the *operational* headquarters rather than the country of incorporation, which is often distorted by tax avoidance strategies.

2.1. *Step 1: Isolating discussions of epidemic diseases*

The computational linguistic algorithm we use for this step involves a simple count of word combinations in earnings call transcripts to measure a given firm's exposure to COVID-19 and other epidemic diseases (cf., Hassan et al., 2019, 2020). To identify keywords informative about the discussion of the corona pandemic and other epidemic diseases, we begin by identifying the epidemic disease outbreaks that occur within our sample period (which starts in 2002) from the list of pandemic and epidemic diseases maintained by the World Health Organization (WHO).[12] We then further restrict the list to diseases that, in our judgement, attracted sufficient international audience and potentially were a concern to investors. This restriction eliminates outbreaks such as the 2019 Chikungunya episode in Congo and the 2018 Monkeypox in Nigeria.

For the remaining list of outbreaks, we identify the most common synonyms for each disease in online resources and in newspaper articles at the time of the event. We also perform a human audit on a limited sample of earnings call transcripts to verify that we are using the disease word (combinations) that were in use during each of these outbreaks. Finally, we verify that disease words (combinations) have no alternate meaning, such as, for example, is the case for MERS and the "Malaysian Emergency Response Services 999." Appendix Table 2 lists the words (combinations) used per disease.

Having thus compiled our disease word (combination) list, our time-varying measure of a given firm's *exposure* to epidemic disease d, denoted $DiseaseExposure^d$, is constructed by counting the number of times the synonyms from Appendix Table 2 associated with each disease d are used. We then divide this number by the total number of words in the transcript to account for differences in transcript length:

$$DiseaseExposure_{it}^{d} = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} 1[b \in \mathcal{D}_d], \tag{1}$$

[12] www.who.int/emergencies/diseases/en/

where $b = 0, 1, ...B_{it}$ index the words contained in the transcript of firm i in quarter t, B_{it} is the total number of words in the transcript, and $\mathcal{D}_d$ is the set of disease words or word combinations of disease d.

2.2. Step 2: Typifying the disease exposure at the firm-level

While our algorithm to measure firm-level exposure to epidemic diseases centers on counting synonyms for each disease in earnings-call transcripts, having a call's full conversation available, allows us to probe deeper into the underlying concerns of management and market participants to understand *how* a disease impacts corporate policies and performance.

Doing so in a systematic way, for all firms in our sample, presents a challenge, however, because of the sheer volume of text fragments that need to be processed and classified to identify the issues discussed by participants on a call. Indeed, focusing only on the 2020 coronavirus outbreak, 14,765 earnings call transcripts mention a COVID-19 synonym and, when we single out all text fragments within a given transcript that include these synonyms, we find 174,582 sentence triples.[13] Therefore, rather than relying on a human reading of these snippets, we develop a word pattern based algorithm tbelow, human judgement is limited to just two instances in the two-step process.

In the first step, we determine the set of topics that companies discuss when mentioning a synonym for COVID-19. We randomly select COVID-19-related sentence triples with the objective of finding broad categories that are simultaneously economically meaningful *and* capture as many of the coronavirus-related discussions as possible. Further, the categories should also be sufficiently sharply delineated to minimize classification ambiguity in our automated reading of the sentence triples in the second step, as discussed next. Following this procedure, we identify five key topics: (1) demand impacts, (2) supply impacts (which includes discussions related to supply chain and production and operations), (3) cost

[13]We define a sentence triple as a set of three consecutive sentences, if available, by the same speaker such that the middle sentence contains a COVID-19 synonym. We use this sentence triple as the unit of analysis for our topic classification because doing so provides more context from which to infer the topic associated with the mention of the COVID-19 synonym.

reductions, (4) financing adjustments, and (5) government assistance.

In the second step, we automatically classify all sentence triples into these five key topics and a residual category that collects all other mentions of a disease, in particular those that are unspecific as to the actual impact on the firm (e.g., "There is no doubt that COVID-19 is impacting our business"). It is worth noting that this can be a difficult task even for the human reader, let alone for a computer algorithm, because the way in which conference call participants discuss each topic varies considerably. For example, there are subtle variations in how corporate managers may discuss disruptions of their supply chains. Rather than mentioning supply chains explicitly, they might instead mention that a health crisis impacts their ability to source components. The challenge of this second step, therefore, is to do justice to such subtle variations.[14] To meet this challenge, we develop an iterative procedure that combines limited human judgement with data-driven decisions to identify a word pattern for each of our five specific topics.

Specifically, the target of our iterative procedure is to develop what we call a topic-specific *word pattern*. When applied to a text, such word pattern should be able to reliably identify whether the text is about the word pattern's topic *and* transparently justify its classification by providing the words that lead to the match. We define it to consist of two components: (1) a set of phrases (contiguous groupings of words) that are directly related to a given topic, and (2) a set of (possibly non-contiguous) word combinations that, when used together within a sentence triple, indicate the topic is discussed. For example, for a sentence triple to be assigned to the "supply chain" topic category, we require it to either include a directly-related phrase such as "supply chain" or, for example, the combination of the words "component" and "impact." In addition, we require a word pattern to satisfy topic-specific constraints in order for its match to be considered valid. For example, a pattern may specify that the word "demand" is only valid if it is used as a noun as opposed to as a verb.

To obtain such word patterns for each of the five topics we read and hand-label 600

[14] With a sufficiently large labeled training dataset, one could train a neural network, which tend to perform well with supervised classification tasks. However, this would require hand-labeling thousands of sentences.

randomly selected sentence-triples that mention COVID-19 from our conference call transcripts, 437 of which we can unambiguously assign to at least one of our five topics. This is our training dataset. For each topic, we then iteratively devise a word pattern with the goal of balancing correctly predicting the labels of these hand-labeled sentence triples (training dataset) with accurately predicting the content of previously unseen sentence triples (validation dataset). Balancing the predictive performance on these two datasets helps us to prevent overfitting on the training dataset.

More specifically, we start by defining the word pattern as a small set of phrases that frequently occur in a given topic's training dataset and that are economically closely linked to the topic (e.g., "stimulus" for the "government assistance" topic category). We then check the fit of the pattern in our training dataset. By examining false positives and false negatives, we update the pattern (e.g., expand the set of phrases) such that it improves the in-sample fit.[15] We continue this process until the pattern predicts the labels in our training dataset with no more than 10 false positives and negatives. Once this threshold is met, we audit the pattern with a validation dataset, created by randomly drawing 30 sentence triples from the population of sentence triples mentioning COVID-19 in our sample of parsed earnings-call transcripts. We read these text excerpts and classify them as true or false positive matches to the predicted topic. If this audit produces fewer than 8 false positives, we stop and save the pattern. If not, we adjust the pattern such that its predictive performance on the validation set meets the threshold, before going back to examining the updated pattern's performance on our training dataset and, if needed, iterating and auditing again with another validation dataset. Once we have arrived at a pattern that meets both criteria the iteration ceases.

Table 2 shows our final word patterns for each of the five topics, separating out the "supply chain" and "production and operations" sub-categories in the "supply impacts." (These two aspects of supply disruptions arose naturally in our classification and seemed

[15]To expedite this process of improving in-sample fit we found it useful to use embedding vectors trained on conference calls as well as lexical databases to identify closely-related words that often co-occur with words in the pattern.

sufficiently distinct to warrant separate measurement.) To make the table easier to read we abstract from stemming, although our algorithm allows for it, so that, for example the word 'challenge' also allows for 'challenges' and 'challenging,' and all nouns apply both in singular and plural. In addition to the words and phrases listed in the table, each topic comes with a list of exclusions (reported in detail in Appendix Table 3), which are, admittedly, somewhat more tedious to read. Table 2 confirms that the word patterns are intuitive, inasmuch as for example the "Production and Operations" category features discussions of (government) permits, productivity, throughput, closures, and shutdowns in conjunction with a mention of a synonym for COVID-19 or other epidemic disease.

Appendix Figure 1 uses "confusion matrices" to report our algorithm's fit to the training dataset for each of our topics after the final iteration (again separating out the "supply chain" and "production and operations" sub-categories within the "supply impacts" topic). Each matrix shows the number of true positives, false positives, true negatives, and false negatives of each pattern. For example, Panel A shows that the algorithm correctly labels 134 sentence triples as related to demand, while producing six false positives and seven false negatives. 290 sentence triples relating to one of the other topics are correctly identified as not relating to demand. Appendix Table 4 shows results of the last manual audit performed in our iterative process. All but one topic are near or below five false positives; the highest number of false positives is eight for the category "Production and Operations."

Based on the 174,582 sentence triples in our sample that mention COVID-19, we define each firm-quarter's exposure to a given COVID-19-related topic as

$$\textit{COVID-19TopicExposure}_{it}^{T} = \frac{1}{S_{it}} \sum_{s=1}^{S_{it}} \left\{ 1[s \in \mathbb{P}^{T}] \right\},$$

where S_{it} is now the total number of sentence triples in the transcript of firm i in quarter t, and $\mathbb{P}^T$ is the set of patterns associated with one of the five topic categories T.

Recall that our objective is to obtain measures of the firm's exposure to a macro event.

A further challenge is identifying whether the discussion for a given topic captures the firm's (direct) exposure to a shock or its attempts to manage its consequences. Firms might respond to the pandemic by cutting costs or guaranteeing access to credit lines in an effort of management to minimize the fallout of the virus for their company. When it is important to separate the firm's exposure to the *exogenous* event from the firm's *endogenous* response to the same, we exclude the topic categories related to cost reductions, financial adjustments, and government assistance from consideration. To see why, consider the examples of sentence triples provided in Table 3. When Floor & Decor Holdings discusses the Coronavirus pandemic on 30 April 2020, their senior management says: " ... we made the difficult decision to resize our store and store support center payroll costs in anticipation that sales could continue to decline." Clearly rather than identifying a shock, this triple describes management's response to the shock: to reduce the workforce and cut costs. Based on a systematic reading of triples across the finance, cost, and government categories, we conclude that the discussions herein are, in general, responses to the shock rather than descriptions of the firm's exogenous exposure to the shock. If we wish to measure the latter, we limit our analysis to the demand and supply impacts, which we discuss in detail below.

2.3. Measuring risk and sentiment associated with discussions of each epidemic disease

Building on our epidemic disease *exposure* measure, we also construct metrics of *risk* and *sentiment*, denoted $DiseaseRisk^d$ and $DiseaseSentiment^d$, respectively (Hassan et al., 2019, 2020).

First, we augment $DiseaseExposure^d$ by conditioning on the proximity to synonyms for risk or uncertainty and define $DiseaseRisk^d$ as the count of words (word combinations) related to a specific disease that are used in the neighborhood of 10 words before and after such a synonym. We obtain a list of synonyms for "risk" and "uncertainty" from the Oxford English Dictionary.[16]

[16]See Appendix Table 5 for a list of these synonyms.

Second, to gauge whether a disease outbreak is considered good or bad news to the firm, we construct a measure of shocks to the firm's prospects.[17] Accordingly, the construction of epidemic disease *sentiment*, denoted $DiseaseSentiment^d$, closely follows the procedure for $DiseaseRisk^d$ in that it counts the words associated with disease d; however, instead of conditioning on the proximity to words associated with risk, this time we condition on positive- or negative-tone words to capture the first moment. These positive- and negative-tone words are obtained from Loughran and McDonald (2011).[18] (Positive words include 'good,' 'strong,' 'great,' while negative words include 'loss,' 'decline,' and 'difficult.'[19,20]) Appendix Table 6 shows the most frequently used tone words in our corpus. As might be expected, descriptive statistics suggest that disease-related discussions in earnings-call transcripts are dominated by negative-tone words. Accordingly, in subsequent analysis, we sometimes bifurcate $DiseaseSentiment^d$ into $DiseaseNegativeSentiment^d$ and $DiseasePositiveSentiment^d$, simply by conditioning on either negative or positive sentiment words, respectively.

3. Exposure to Epidemic Diseases

3.1. Descriptive evidence

In this and the next section, we use our newly developed measures of firm-level exposure to epidemic diseases to document several stylized facts, before in Sections 5 and 6 we will unpack the specific concerns voiced in a firm's earnings call about how shocks affect the firm.

[17] Having such a measure is also helpful to address the issue that innovations to the variance of shocks (risk) are likely correlated with innovations to the conditional mean. Thus, teasing out the effects of disease-related uncertainty on a firm's actions also requires controlling for the effect of the disease event on the conditional mean of the firm's future earnings.

[18] Thirteen of the synonyms for risk or uncertainty used in our sample earnings calls also have negative tone according to this definition. Examples include 'exposed,' 'threat,' 'doubt,' and 'fear.' Our measures thus explicitly allow speakers to simultaneously convey risk and negative sentiment.

[19] We choose to sum across positive and negative sentiment words rather than simply conditioning on their presence to allow multiple positive words to outweigh the use of one negative word, and vice versa.

[20] One potential concern that has been raised with this kind of sentiment analysis is the use of negation, such as 'not good' or 'not terrible' (Loughran and McDonald, 2016). However, we have found that the use of such negation is not common in our sample, so we chose not to complicate the construction of our measures by explicitly allowing for it.

Our emphasis is on the firm-level exposure to the 2020 coronavirus pandemic, but we have occasion to present some findings on the earlier epidemic diseases in our sample period too.

Indeed, Figure 1 depicts the time-series of the percentage of transcripts in which a given disease is mentioned in a quarter separately for COVID-19, SARS, H1N1, Ebola, Zika, and MERS, respectively (moving from the top panel to the bottom).[21] Reassuringly, these patterns closely follow the infection rates for each of the diseases in the population. For example, SARS, according to the WHO, was first recognized in February 2003 (although the outbreak was later traced back to November 2002), and the epidemic ended in July 2003. Accordingly, discussions of SARS in earnings conference calls peak in the first quarter of 2003 and quickly trail off after the epidemic ends. Finally, SARS, a disease likewise caused by a coronavirus, returns as a subject in earnings calls in the first quarter of 2020, when it becomes clear that COVID-19 shares some commonalities with the former outbreak.

The figure highlights once more how exceptional COVID-19 is. Indeed, forty percent of transcripts discuss the outbreak in the first quarter of 2020, and then almost 100 percent of transcripts thereafter: a much larger proportion than in any of the previous outbreaks (with SARS as the closest "competitor" at just over 20 percent). In Appendix Figure 2, we provide additional detail for the separate cases of China, the United States, and Europe (including the UK). Interestingly, SARS was a pervasive topic of discussion in China (at levels similar to COVID-19), whereas the Ebola-virus did not feature at all in earnings calls of firms headquartered in China.

In Figure 2, we zoom in on the first few months in which a given disease occurs and compare by region in which a firm is headquartered, the weekly average corporate exposure to COVID-19, SARS, and H1N1. One immediate takeaway that follows from comparing the plots is that COVID-19 prevails in discussions in earnings calls. The "peak"—i.e., the maximum value of frequency—is much higher than for any of the previous outbreaks: during Q3 of 2020, more than three percent of all sentences in our sample transcripts contain

[21] Our sample currently ends with calls held on December 31, 2020.

discussion of COVID-19. (For comparison, only 0.7 percent of sentences in the average transcript in our sample mention 'competition,' 'competitive,' 'compete,' 'competing,' or 'competitor.') What's more, the exposure to diseases during their epidemic episode is much less synchronised for SARS and H1N1 than for COVID-19, which is rising simultaneously in all parts of the world. The saw-tooth patterns in the cases of SARS and H1N1 signify that earnings call discussions of the disease peaked sequentially in different regions around the world during these outbreaks, with early peaks representing regions in which the disease was first discovered. In contrast, COVID-19 exposure grows rapidly between April and May 2020 in all regions except China, and remains high thereafter. For companies headquartered in China, much of the acceleration in exposure occurs before April, consistent with the outbreak affecting the country hard in the first months of the year. Firm-level exposure to SARS and H1N1, again consistent with the development of infection rates in the population, climbs first in Asia and Mexico respectively (the putative origin regions of the two diseases).

To assess the firm-level impact of exposure to COVID-19 in the opening months of 2020, we plot the weekly average COVID-19 risk and sentiment scores in Figure 3. We observe relatively low COVID-19 risk and slightly negative sentiment in January and February, but by March, weekly average COVID-19 risk climbs quickly and reaches a maximum in early May. These developments are mirrored in the weekly average sentiment during the same period, which declines precipitously from March to early July. From June onward, COVID-19 risk remains high (although never reaching the levels of May again) until the end of the sample period. In contrast, COVID-19 sentiment improves markedly during Q3 of 2020, albeit that sentiment remains negative overall.[22] In this sense, for the average firm, COVID-19 is not only bad news but also exposes management to a significant increase in uncertainty.[23]

[22]In Appendix Figure 3, we document that the improvement in sentiment after the first quarter is driven mainly by a more positive outlook among Asian firms.

[23]Intuitively, the extent to which a population is exposed to a disease in a region should be associated with the exposure of firms to the same. Thus, infection rates should be correlated with our firm-level exposure measures. We explore this relationship in Appendix Table 7. In short, we find that infection and mortality rates in a country are positively associated with $\textit{COVID-19 NegativeSentiment}_{i,t}$, implying that more infections go hand in hand with negatively toned discussions about the coronavirus in the earnings calls. As expected, $\textit{COVID-19 Exposure}_{i,t}$ is also positively associated with infection rates.

These aggregate patterns are important and interesting in their own right, but mask considerable variation at the sector level, as shown in Panel A of Figure 4. High COVID-19 risk is found in sectors such as basic materials and healthcare, but also in technology, whereas perceived risk associated with COVID-19 is noticeably lower for energy and utilities. Importantly, the average sentiment is negative across all sectors, but at the same time, outlooks are much less negative in the technology, healthcare, and consumer non-cyclicals sectors, than in the transportation and energy and utilities sectors. These patterns make intuitive sense: While the crisis severely decreased travel by air and train, and the demand for oil, some supermarkets and tech firms actually saw their businesses expand, as people increasingly work and dine at home. At the same time, healthcare, in particular, faces tremendous changes and volatility as COVID-19 puts into question the ability to deliver these services in person (high risk).

These by-sector figures, while documenting extensive variation in outlook across different parts of the economy, are not completely successful in showcasing the broad range of exposures firms report. We illustrate this point by contrasting text fragments from negatively-toned earnings-call discussions in the transportation sector with much more optimistically-toned discussions in the technology sector. For example, United Airlines Holdings mentions in its May 2020 earnings call: "... we became the first airline to respond to the coronavirus by planning for a capacity cut drastically reducing capex for ..." and "as a strong quarter quickly deteriorated as the spread of covid disrupted travel as well as the lives of everyone around." Likewise, Delta, in its July 2020 earnings call, reports: "... loss that we just posted reflects the severe impact that covid is having on our company and our industry this June." The negative sentiment is not limited to only airline companies, however. The freight-hauling railroad Union Pacific records in the same month "... finally food and beverage was down primarily driven by covid related production challenges for import beer and supply chain shifts."

In contrast, consider the sentiment expressed by senior management in the technology sector, such as in the case of Intel in its April 2020 earnings call: "... some innovative solutions that are helping the medical community tackle covid. One example is medical informatics sickbay platform powered by Intel." Apple, likewise, offered a rosy view with comments such as: "... Apple products and offerings to successfully navigate their business through covid in health care we are seeing rapid acceleration of telehealth to ..." As a final example, ServiceNow, which develops a cloud computing platform to facilitate digital workflows for companies, emphasizes in July that they had a "strong quarter for servicenow despite the macroeconomic headwinds created by covid. We exceeded the high end of our subscription revenues and ..."

These illustrations do not only underpin our finding that COVID-19 exposure, risk and sentiment vary across sectors, but, also, hint at significant variation, even across firms within a given sector. Furthermore, they also hint at the driving factors behind the firm-level variation in COVID-19 exposure scores and outlooks. Indeed, Union Pacific's executives highlight production challenges and disruptions of the supply chain; United reports severe impacts of a dramatic drop in demand; and Apple and ServiceNow experience increased demand for their products. We exploit these possibilities systematically in our topic-based analysis below.

4. Valuation effects of firm-level COVID-19 exposure

We next ask whether COVID-19 exposure, sentiment, and/or risk can account for variation in stock price changes as measured by (1) the quarterly stock return in each of the four quarters of 2020 or (2) over a short (three-day) window centered on the earnings call date (using earnings calls for all four quarters of 2020). Intuitively, standard asset pricing models suggest that a change in stock price occurs when investors, in aggregate, revise their views on expected future cash flows and/or on the expected discount rate. Thus, a more positive sentiment about an epidemic disease should be associated with an increase in returns, whereas a higher perceived risk is expected to be negatively associated with the selfsame.

Exposure, on the other hand, does not have an ex ante clear prediction with stock returns, but given that the shock appears to have increased uncertainty and worsened the outlook for the average firm, most likely is negatively associated with returns.

We test these predictions using the following regression:

$$Ret_{i,t} = \alpha_0 + \delta_t + \delta_j + \delta_c + \beta \, COVID\text{-}19\ X_{i,t} + Z_i^{'}\nu + \epsilon_{i,t}, \tag{2}$$

where $Ret_{i,t}$ is either the (annualized) quarterly return or the cumulative return over a three-day (-1,1) window around the date of the earnings call; *COVID-19* $X_{i,t}$, is either our coronavirus *Exposure*, *Sentiment*, or *Risk* score; and the vector Z includes our standard set of control variables. We also split *COVID-19 Sentiment*$_{i,t}$ into a negative and positive sentiment variable, to document the association between positive (negative) COVID-19 news and returns.

The vector Z_i contains the natural logarithm of the firm's assets, as a control for the size of the firm, and the stock return beta, calculated by regressing daily returns in 2018 for firm i on the S&P 500 index (to measure the firm's exposure to the US capital market).[24] Where possible, we include both quarter (δ_t) and two-digit SIC sector (δ_s) fixed effects, as well as headquarters country fixed effects (δ_c) when we do not focus specifically on the sample of US-headquartered firms. In all regressions, standard errors are clustered at the firm level.

Table 4, Panel A presents our estimation results at the firm-quarter level using quarterly returns over the four quarters of 2020 as the dependent variable, which we detail for the full sample (columns 1-3) and separately for the US (columns 4-6). We document a significantly negative association between a firm's coronavirus *Exposure* and its stock return (in columns 1 and 3). Thus, firms with more extensive discussions in their earnings call about the COVID-19 outbreak experience a greater stock price decline than firms with less exposure; and this holds even more so true for the US sample. For example, in column 1, a one standard

[24] Summary statistics for all variables are reported in Table 1. For ease of interpretation, we standardize all firm-level exposure, sentiment, and risk variables by their standard deviation in the panel.

deviation increase in *COVID-19 Exposure*$_{i,t}$ is associated with a 8.9 percentage point lower annualized return in the quarter of the conference call. Next we consider whether this return response derives from investors revising their expectations of future cash flows, as measured by *COVID-19 Sentiment*$_{i,t}$, or their expectations of the firm's risk, as captured by *COVID-19 Risk*$_{i,t}$.

When regressing each of these variables onto returns, results show that both explain variation therein (columns 2 and 5). Note, however, that when we separate out positive and negative sentiment in columns 3 and 6, only the association between *COVID-19 negative sentiment*$_{i,t}$ and returns remains consistently negative and significant for both the full and US samples (the magnitude of the coefficients tends to remain stable across specifications). For example, in column 3, a one standard deviation increase in negative COVID-19 sentiment is associated with a 5.9 percentage point decrease in stock returns.[25]

In Panel B, we examine the short-window returns surrounding the date of the earnings call in which COVID-19 is discussed. We use earnings calls from all four quarters of 2020. Both in the full sample and in the US sample, we document a significant negative association between *COVID-19 Exposure*$_{i,t}$ and three-day earnings-call returns (columns 1 and 4), consistent with the view that earnings conference calls reveal some incremental information about firms' COVID-19 exposure. In column 1, the estimated coefficient implies that a one standard deviation increase in *COVID-19 Exposure*$_{i,t}$ is associated with a 0.3 percentage point lower return in this narrow window around the conference call. As in Panel B, we find, both in the full sample and the US sample, that the short-window returns are significantly associated with *COVID-19 Sentiment*$_{i,t}$ but not with *COVID-19 Risk*$_{i,t}$ (columns 2 and 5), though even the latter retains the predicted sign. Indeed, per columns 3 and 6, it is the negative sentiment about COVID-19, in particular, that is driving returns around the earnings call date.

Across Table 4, the conclusion emerges that our measures of COVID-19 risk and sentiment indeed contain information relevant to firms' fortunes during the coronavirus pandemic, and

[25]See, e.g., Giglio et al. (2021) for how stock returns changed during the February-March 2020 stock market crash induced by the COVID-19 pandemic.

that some of this information may in fact be originally transmitted to markets through earnings conference calls (Panel B). The fall and subsequent recovery in aggregate stock prices in Q1 and Q3 of 2020, however, mask significant COVID-19-induced heterogeneity in the cross-section of firms. We aim to systematically exploit the discussions of how firms are affected by the pandemic in the next section, in which we identify specific COVID-19-related concerns, as voiced in the earnings call transcripts, and use this to shed light on how the valuation effects documented in this section are related to the type of shocks to which firms are exposed.

5. The Supply, Demand, and Other Impacts of Epidemic Diseases

Figure 5 presents the findings from our automated pattern-based classification method of the full sample of coronavirus sentence triples. For this sample, we assess the frequency of occurrence of a topic category (i.e., supply impacts [supply chain and production and operations], cost reductions, financial adjustments, government assistance, demand impacts) by computing the percentage of COVID-19 related sentence triples with a given topic label among all COVID-19 related sentence triples in our corpus.[26] We then plot the relative share of each topic over time, such that for each month in 2020, the figure depicts the proportion of COVID-19 centered discussion that is devoted to each topic. As shown, the sudden change in demand is the most commonly voiced concern when the discussion turns to the possible impact of the pandemic on the firm. Indeed, 41.53 percent of all sentence triples mention *demand*. The attention for demand abates somewhat after the first quarter, but remains the dominant topic of concern throughout 2020.

Conference call participants also discuss concerns about disruptions to the *supply chain* (5.69 percent) and *operations*, or the closure of a given firm's own *production* facilities and stores (26.70 percent). Supply chain concerns peaked in the first two months of 2020 and decreased quickly thereafter. At the same time, discussions about production and operations

[26] An overview of the topics with example sentence triples is provided in Appendix Table 8.

(including forced closures of sites and stores) increased from March and remained at about the same level after Q3.

Higher costs, and the imposition of cost-saving measures, due to COVID-19 represent a further concern. These discussions represent mostly managerial responses to the pandemic shock inasmuch as managers, observing the negative consequences of Covid for their firm, cut costs and take other efficiency measures. Throughout 2020, cost topics are discussed in 11.22 percent of the sentence triples. Turning to *financial adjustments*, a concern that becomes more prominent from the second quarter of 2020, we classify 13.30 percent of sentence triples in this category. Financing concerns are relatively infrequent in the first quarter, but represent a meaningful category afterwards, only slightly easing in the final month of 2020.

A relatively small percentage of triples (viz., 1.57 percent) discusses issues regarding *government* interventions to support the economy or counter the adverse economic effects of the pandemic. Thus, when call participants discuss programs such as the CARES Act or the Paycheck Protection Program, this counts towards their government topic score.[27]

Overall, summarizing the trends discernible in Figure 5: at least three findings are noteworthy. First, throughout the sample period, demand-side, supply-side (i.e., the combination of supply chain and production and operations concerns), and cost issues are discussed the foremost, with the remaining topics trailing considerably in the attention garnered in earnings calls. Second, costs and supply-side, on the one hand, and demand-side concerns, on the other, remain about equally balanced throughout the sample, although concerns relating to supply chains, specifically, diminish over time, as discussions shift more towards concerns about costs induced by the pandemic. Third, financing issues become more pronounced in the second quarter and remain stable thereafter.

Appendix Figure 4 shows the same graph, but now also includes the share of other or unspecified COVID-19 discussions that can *not* be specifically attributed to one of our five

[27] One possible reason for the relative absence of discussions of government assistance is that some programs were targeted at smaller firms, so that many of the listed firms in our sample were ineligible.

topic categories. One takeaway from this figure is that the first quarter features relatively more conversations about COVID-19 without touching on specific concerns; rather, during this period, call participants typically voice generic uncertainty about what will happen next. As the impact of the pandemic unfolds over the following quarters, this "unspecified" category shrinks as more and more discussions are tied directly to one of our topics. By the end of our sample, we can allocate about 60 percent of sentence triples to a specific topic, up from around 40 percent at the beginning of the pandemic.

Once again, drilling drown into these aggregate findings offers additional insights. In Figure 6, we examine, by geography and by sector, respectively, the relative importance of (1) demand versus supply exposure (Panel A) and (2) finance versus non-finance exposure (Panel B).[28] Demand exposure is simply a given firm's exposure to the "Demand" topic category, as previously defined. Supply exposure equals the sum of the firm's exposure to the "Supply chain" and "Production and operations" topic categories. Similarly, non-finance exposure is defined as the firm's exposure to the "Supply chain," "Cost," "Production and operations," "Government," and "Demand" topic categories, whereas Finance exposure is as previously described. Values larger than unity on the scale denote that demand exposure exceeds supply exposure in the first panel. Financing exposure is always lower than exposure to the other four non-financing topic categories and, hence, the scale marks only values below 1.

The balance between supply and demand concerns appears roughly similar across regions of the world. In Asia, and to a lesser extent in Europe, COVID-19 exposure is slightly more demand-related. In contrast, in North America and other regions of the world, supply and demand exposure are more balanced.

At the sector level, in the basic materials, healthcare, and energy and utilities sectors, supply exposure is a prominent force, likely reflecting increased difficulty of production and sourcing in these industries. By contrast, for the technology sector demand exposure is

[28]For additional details for each sector and region please refer to Appendix Figure 5.

relatively more important: consistent with the view that the pandemic has accelerated the trend towards digital solutions in many areas, such as remote work and online retail.

Financing exposure plays a much larger role in Europe and the rest of the world than in Asia or in China. Interestingly, whereas the healthcare and energy and utilities sectors have similar relative supply exposure, they are on opposite ends with regard to their exposure to financing. In the healthcare sector, few firms' transcripts feature concerns about access to credit or liquidity constraints, whereas the conversation turns to these issues much more for the energy and utilities, academic services, and transportation sectors.

These by-sector figures, while documenting extensive variation in how the COVID-19 pandemic affects different parts of the economy, still masks substantial heterogeneity between firms *within* a given sector. We illustrate this point in Figure 7, which plots the variation of relative demand and supply exposure (in Panel A) and relative finance and non-finance exposure (in Panel B) for S&P 500 firms. In Panel A, while there is significant clustering around unity, consistent with the observation that the COVID-19 pandemic provides a shock to demand *and* supply, some firms still stand out. Linking back to the individual snippets used to compile the relative exposure scores, provides further details. For example, Kinder Morgan's executives, in the April 2020 earnings call, answer the following to a financial analyst's question: "I mean this is certainly different, unprecedented when you put the combination of 2 things, the OPEC Plus falling apart on March 6 together with COVID crushing demand." Or Archer Daniels Midland, in July 2020, looks back on the previous months as follows: "... we see that the worst of the demand destruction due to COVID was behind us." Another early example of a pertinent analyst question is in Coca Cola's January 2020 earnings call: "I realize it is still early, but any kind of thoughts of how coronavirus changes your plans in China, be it just current sales or plans to roll out Costa ..." These are all examples of firms with relatively high demand exposure; moving to the opposite of the scale shows firms coping with supply exposure. Deere & Co's management, for example, in the February 2020 earnings call, discusses how they "are monitoring the coronavirus situation and working closely with the Chinese provincial authorities primarily focused on the well-being of our employees and a safe return to production. In terms of overall exposure, the biggest potential impact to Deere is in relation to the supply base that serves our international operations. And the result of those 2 things will certainly impact what we're able to produce and ship during the month."

Panel B of Figure 7 hones in on the relative finance exposure of S&P 500 companies. Discussions in earnings conference calls vary from a simple statement by Delta in April: "The call today will focus on our response to Covid 19, with Ed giving an overview of our priorities and Paul giving an extensive liquidity update" to Coca Cola in the same month discussing the position of bottling partners: "I know they are proactively taking steps to preserve cash, strengthening their balance sheets and manage their P&Ls. Currently, we don't have any major concerns surrounding our bottling partners from a liquidity perspective, and we are working closely with them to anticipate and deal effectively with a scenario where the coronavirus situation is longer and more severe than currently anticipated." General Motors reassures analysts in July as follows: "And obviously, you're going to see on a quarter-to-quarter some volatility associated with their production or working capital assumption or sales allowances and so on." By November 2020, Marathon Oil starts discussing the company's dividend policy again: "We would also be well positioned for incremental return of capital to shareholders beyond our base dividend. Rest assured, we will continue to manage COVID-19 risk diligently through our business continuity and emergency response plans. In a low growth ... environment, capital efficiency ... are the competitive differentiators." At the low end of the scale, the manufacturer of private label over-the-counter pharmaceuticals Perrigo, had a denominator boost due to their ability to quickly manufacture hand sanitizer in the first quarter of 2020.

It is instructive to compare the relative demand, supply and financing exposure due to COVID-19 with other outbreaks. Figure 8 offers such a comparison between COVID-19, Ebola, SARS, H1N1, Zika, and MERS. We constrain the comparison to the first three quarters after the initial outbreak of each disease. Two observations are striking. For COVID-19, demand and supply concerns receive about the same attention, justifying the view that the 2020 pandemic represents a shock to both supply and demand. The remaining outbreaks mention relatively fewer supply-related concerns and tend to skew more towards demand-side impacts. Interestingly, the outbreaks rank roughly in the order of their severity. Comparing with Figure 1, we find that larger aggregate firm-level exposure (where COVID-19 is discussed relatively more frequently than SARS, H1N1, Zika, and MERS, respectively) correlates with relatively more severe supply-side impacts. The only disease apparently breaking this pattern is Ebola, which is not discussed as frequently as SARS and H1N1 but nevertheless has relatively more discussion of supply-side impacts.[29]

6. Valuation implications of demand and supply shocks

6.1. Isolating demand and supply shocks

So far, our focus has been to summarize our results in topic fractions, showing, in the aggregate, how supply, demand, governmental, and financing concerns vary for firms across countries, in different sectors, and over time. We also hinted at much more variation in these concerns masked when emphasizing aggregate trends. In what follows, we take the logical next step and exploit the unique feature of our method that reveals, *at the firm level*, whether COVID-19 is a shock to the supply side or to the demand side of the firm. This undertaking is important as it shows how our approach can help inform theories about

[29] The comparison with earlier diseases is important for another reason, as revealed by our systematic analysis of snippets: these earlier outbreaks are frequently invoked when discussing the impact of COVID-19. For example, in its January 2020 call, as mentioned above, Coca Cola's executives continue as follows: "... to roll out Costa? And also maybe any update or reminder of kind of what SARS did to numbers, if anything, 10 years ago or 15 years ago?" Or, consider HCA Healthcare which opens its earnings call in January 2020 with the assessment that "[h]istorically, SARS or MERS, which are members of the coronavirus family but far more toxic than the current novel coronavirus, did not affect our emergency department volumes." Similarly, analysts ask Prudential Financial: "As we look back to SARS over 15 years ago in light of the coronavirus, do you see any increased demand for your products on the benefit side to note." In sum, the discussions between analysts and executives about their firms' exposure to COVID-19 suggest that firms might have learned from their earlier experience with outbreaks of infectious diseases. This experience could plausibly add to their resilience in face of the new shock.

how demand and supply factors explain changes in stock valuations and in other first-order economic quantities, such as investments and hiring.

In our setting, we need to implement an important further refinements before we can attempt such an investigation. Recognizing that COVID-19 was a boon for some firms and a bane to others, we must "sign" the shock inasmuch as we identify whether the pandemic improved or deteriorated demand for the firm. This signing can be done for other topic categories too, but practically speaking, few firms experienced positive supply shocks, and hence we will only consider negative shocks in what follows for this topic category.

We accomplish this task by simply using our sentiment dictionary to determine whether negative- or positive-tone words are used in conjunction with discussions of COVID-19's effect on demand. Specifically, for COVID-19-related sentence triples, we count positive minus negative tone words in the sentence that identifies the topic, and average this across all sentence triples about the topic within an earnings call transcript. Thus, the COVID-19 related net demand shock for a given firm in a given quarter is

$$\textit{COVID-19 Net demand shock}_{i,t} = \frac{1}{S_{it}} \sum_{s=1}^{S_{it}} \{1[s \in \mathbb{P}^{Demand}] \times Tone(s)\}, \tag{3}$$

where $Tone(s)$ (again, using Loughran and McDonald (2011)'s sentiment dictionary) maps a sentence's sentiment words into integer counts. In particular, $Tone(s)$ returns the sum of positive words if the sentence contains positive but not negative words; it returns the negative of the sum of negative words if the sentence contains negative but not positive words; and it returns zero if the sentence contains both positive and negative words. We define $\textit{COVID-19 Negative supply shock}_{i,t}$ similarly but with $Tone(s)$ only returning the integer count of negative sentiment words if the sentence that identifies the supply topic contains negative but not positive sentiment words.[30]

Table 5 shows how this process works by providing annotated examples of the sentence

[30] Recall that we define a supply topic as word patterns related to either "Supply Chain" or "Production and Operations."

that identifies the topic within a sentence triple whose middle sentence discusses the coronavirus crisis. Take, for instance, the snippet from the Yokogawa Electric Corp's earnings call transcript, held on 12 May 2020, that is identified as a negative demand shock. Highlighted in blue are the words used to identify the topic category (in this case "Demand"). Highlighted in red are the sentiment words ("decline", "suffered") that indicate that Yokogawa experienced a negative (demand) shock. The table also contains examples for positive demand and negative supply shocks.

Figure 10 demonstrates, at the sector level, the variation in the extent to which firms exhibit negative *net* demand (Panel A) and negative supply shocks (Panel B). As perhaps expected by the large-scale restrictions imposed on travel, the largest negative net demand shock is in the transportation sector, while healthcare and academic and educational services sectors, on average, experience much lower negative net demand shocks. Similarly, the real estate sector and the financial undustry exhibit low negative supply shocks, compared to the healthcare and industrial goods and services sectors.

6.2. Valuation effect of demand and supply shocks

Having signed the demand and supply topic categories, we examine to what extent the stock market response we document in Section 4 can be attributed to demand and/or to supply shocks respectively. We report regression estimates of annualized quarterly stock returns (in the four quarters of 2020) onto two independent variables: *COVID-19 Net demand* $shock_{i,t}$, which is the firm-level *net* exposure score to positive and negative demand shocks, and *COVID-19 Negative supply* $shock_{i,t}$, which is the firm-level exposure score to negative supply shocks associated with the COVID-19 pandemic. Both independent variables are standardized to ease the interpretation of the coefficients. As before, we control for a firm's log of assets in 2019 and its market beta in 2018. What's more, we include quarter and sector fixed effects. We estimate these regressions for the full sample of firms and, separately, for US firms and large US firms only (as measured by having more than 500 employees).

Table 6 presents the findings. In the full sample, in column 1, we find a positive and statistically significant effect of the net COVID-19 demand shock. A one standard deviation increase in exposure to the demand shock increases (annualized) quarterly returns by 2 percentage points, consistent with the view that a contraction in the firm's demand due to COVID-19 lowers its market valuation. When firms are exposed to a negative COVID-19 supply shock, however, we find a negative effect on quarterly returns (-0.010, s.e.=0.005), as expected.

Moving from the full sample to our sample of US firms, we find this basic pattern repeated. Comparing the magnitudes of the coefficient estimates for the full and the US sample (in columns 1 and 2, respectively), for both the demand and the negative supply shocks, reveals a somewhat stronger relation between stock returns and *supply* shocks in the US than internationally.[31] This pattern, however, results from smaller sample firms as large US sample firms (for which we report estimates in column 3) have coefficient estimates closer to the full sample.

We investigate the heterogeneity of the valuation effect of the COVID-19 demand and supply shocks further in Figure 9, in which we visualize the results of estimating the same regression but now for each industry in the US sample, separately. The figure shows that the valuation effects in the Transportation and Real Estate sectors are driven predominantly by the demand shock, whereas valuation in other sectors like Healthcare and Energy & Utilities appear more affected by the impact of supply shocks associated with the pandemic.

Validation check. Our exercise to attribute the valuation effects of COVID-19 to demand and/or supply shocks hinges on the condition that our approach to "sign" the shocks is successful. We probe our ability to do so by offering evidence from a "difference-in-differences" design in which we think of each firm's intensity of the COVID-19 demand and supply shock as a continuous firm-level treatment and relate this to changes in sales

[31] We use the standard deviation in the panel of all firms for economic effects size computations.

revenues:

$$(4)\quad log(Revenues_{i,t}) = \beta \times \overline{COVID\text{-}19\ Net\ demand\ shock}_{i,t} \times Time_t + Z'_{i,t}\nu + Time_t + \delta_i + \epsilon_{i,t},$$

where $log(Revenues_{i,t})$ represent the log of sales revenues, $Time_t$ is an indicator variable equal to one in 2020 and zero in 2019, $\overline{COVID\text{-}19\ Net\ demand\ shock}_{i,t}$ is the average exposure to the COVID-19 demand shock in 2020, δ_i captures firm fixed effects, and $Z'_{i,t}$ contains the interaction of the log of assets in 2019 and $Time_t$.

Table 7 presents estimates of equation 4. In column 1, we find that the association between $\overline{COVID\text{-}19\ Net\ demand\ shock}_{i,t}$ and revenues is significantly stronger for firms more intensely hit by COVID-19 demand shocks (0.032, s.e.=0.005). More importantly, in column 2, where we distinguish positive and negative COVID-19 demand shocks, we find a significant positive coefficient (0.012, s.e.= 0.006) for the former and a negative coefficient (-0.021, s.e. = 0.005) for the latter. Thus, firms exhibiting stronger positive COVID-19 demand shocks have higher revenues, whereas firms with stronger negative demand shocks have lower revenues.[32]

6.3. Firm outcomes after demand and/or supply shocks

Having shown that our text-based method to identify a firm's exposure to demand and supply shocks is useful to understanding valuation effects of the COVID-19 pandemic, we take one further step and document the importance of demand and supply factors to explain changes in firms' investment and hiring during the COVID-19 crisis. We return to the difference-in-differences set up introduced in Equation 4 but now replace the dependent variable $log(Revenues_{i,t})$ with the average investment rate $(i_{i,t}/k_{i,t})$ of firm i in year t, calculated according to the inventory method detailed in Stein and Stone (2013), and with $employment_{i,t}$, which is the log of the number of employees (in thousands). We report results for the full sample and for the sample of US firms separately in Table 8. In Panel A, we

[32] Ideally, we would like to follow a similar approach to validate the identification of negative supply shocks, but in the absence of a compelling dependent variable that could capture the economic consequences on the firm's supply-side from the COVID-19 event, we defer following up on this idea.

detail the estimation results using the investment rate as the dependent variable, whereas Panel B reports the findings for employment.

We find that the intensity of a firm's COVID-19 net demand shock in 2020 has a significant positive effect on its investments, again consistent with the view that firms that suffer a negative demand shock due to COVID-19 invest less. In column 1, for the full sample, the estimated coefficient equals 0.037 (s.e. = 0.013), implying that a one standard deviation decrease in a firm's COVID-19 net demand shock decreases the firm's investment by 3.7 percent. Columns 2 in Panel A suggest that for US firms, the impact of the pandemic on investments is almost twice as strong compared to the full sample (presumably because the US sample also includes smaller firms that suffered larger declines in their investment). Column 3 instead focuses on large US firms, for which we obtain a coefficient estimate that is very similar to the full sample (0.033, s.e.=0.016). In contrast, the firm's exposure to supply shocks does not seem to have had a noticeable differential effect on investment when comparing 2019 and 2020. This is true for the full sample as well as for US firms only.

When, in Panel B, we consider employment, we again find a positive, albeit not statistically significant effect of the net demand shock in the full sample, and a negative marginally significant effect of the negative supply shock, implying that firms affected by the negative supply shock hire less. In column 2, for the full sample of US firms both coefficients of interest are statistically indistinguishable from zero. However, in column 3, for large US firms, we find significant effects of both the demand and the supply shock, where a one standard deviation negative demand and supply shock lower employment at these large firms by 1.9% and 1% respectively.

This pattern is particularly interesting because the US Paycheck Protection Program paid small but not large firms to leave to preserve jobs throughout the pandemic. The differential pattern between small and large firms may thus reflect the effects of this program cutoff.

Taking a step back, the fact that we find significant effects of the COVID-19 demand shock on firm-level stock market valuations, investment, and (to a lesser extent) hiring has important implications for ongoing policy debates. In particular, our results suggest that policy measures designed to support demand for goods and services (such as loose monetary and fiscal policy) can at least mitigate those adverse firm-level impacts of the COVID-19 pandemic that stem from a contraction in demand. By contrast, adverse affects stemming from supply-side impacts may be harder to address.

We show in Appendix Figure 6 evidence consistent with the parallel trends assumption for these results. The figure shows, for the specification in column 3, the percentage change in the investment rate (employment) associated with firms facing a one standard deviation higher COVID-19 demand shock on the vertical axis in Panel A (Panel B). We find no significant coefficient estimates in any year (starting from 2016) *before* 2020. In that year, however, we estimate significant coefficients for both the investment rate and employment.

7. Conclusions

The economic fallout from the worldwide spread of COVID-19 has made clear the need to better understand in real-time the firm-level impact of such large economic shocks. Data on how firms, sectors, and regions are affected by the pandemic is key, not just for effective policy responses, but also for understanding how its indirect effects propagate through supply chains and across borders.

In this paper, we provide measures of the exposure of individual firms to epidemic diseases, including the firm's exposure, sentiment, and risk related to the coronavirus pandemic. We do so based on the quarterly earnings conference calls of a global sample of firms, during which managers discuss with market participants the release of their earnings numbers. Using these earnings-call transcripts, we can not only measure each firm's exposure to the disease, but we also introduce a new automated text-based pattern discovery method to systematically extract information about the exact nature of the cardinal issues firms face as they respond to the challenges of the pandemic. Ultimately, we can, for each firm, measure their exposure to *demand* and/or *supply* shocks associated with epidemic diseases.

Our main findings include, first, even compared to other large-scale epidemics, COVID-19 is unique inasmuch as it affected virtually all firms in all parts of the word at once (with 100 percent of firms discussing its impact in their calls). Second, on aggregate, COVID-19 simultaneously increases firm-level uncertainty and worsens the business outlook of the vast majority of firms. Third, untwining the aggregate of the time-series patterns of Covid exposure, risk and sentiment in 2020, large differences exists between geographical regions, industries, and across firms. For example, many firms in the Tech sector appear to anticipate large positive effects of the pandemic on their businesses, while those in the Transportation sector suffer an unprecedented collapse in demand. Fourth, COVID-19, in contrast to earlier epidemics (in which demand shocks dominate), presents a simultaneous shock to both demand and supply for most sectors.

We are able to pinpoint, for each firm, the relative importance of demand and supply shocks related to the coronavirus and this additional detail, together with the timely measurement of the firm's exposure (as firms host these calls every quarter), renders the data potentially well-suited for testing theories in finance where identification otherwise is often challenging. As we learn about the origin of shocks, as perceived by managers, we gain power to attribute valuation effects to demand and supply factors. What's more, we document how these factors explain important firm outcomes such as their investments and hiring. Thus, our methodological advance provides a versatile way forward to produce new granular data that can inform on issues of key importance to policy makers and fundamental researchers alike.

One key takeaway from this analysis is that demand shocks stemming from the COVID-19 pandemic have significantly depressed firm valuations, their investment activities, and (to a lesser extent) their employment. Part of the economic crisis in the wake of the pandemic is thus clearly attributable to shortfalls in demand, which can be addressed with appropriate monetary and fiscal policy.

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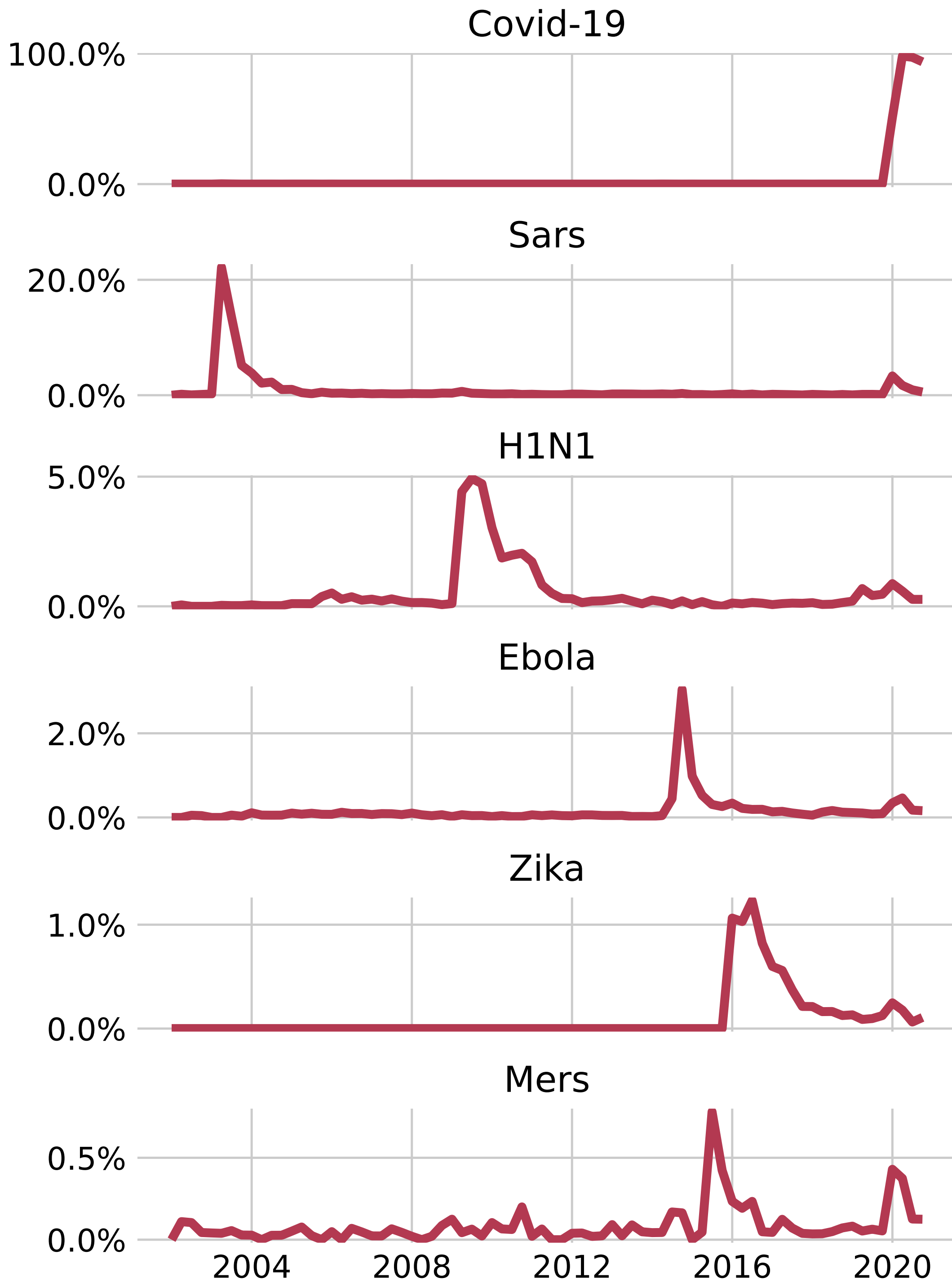
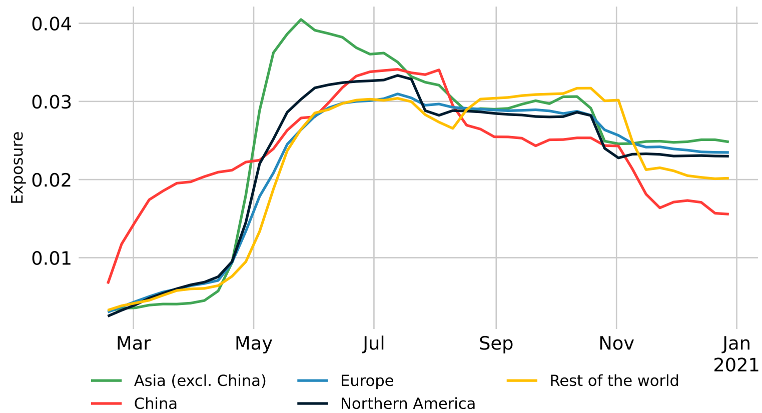
Figure 1: Percentage of earnings calls discussing epidemic diseases



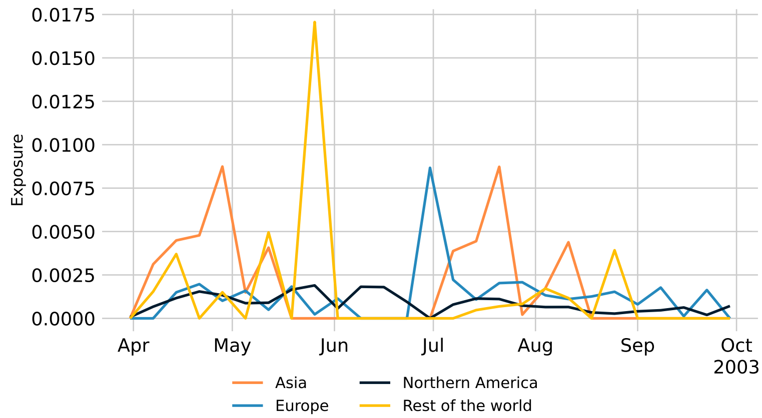
Notes: This figure plots the percentage of earnings calls discussing epidemic diseases (COVID-19, SARS, H1N1, Ebola, Zika, and MERS) by quarter from January 2002 through December 2020.

Figure 2: Discussion of COVID-19, SARS, and H1N1 in earnings calls by region

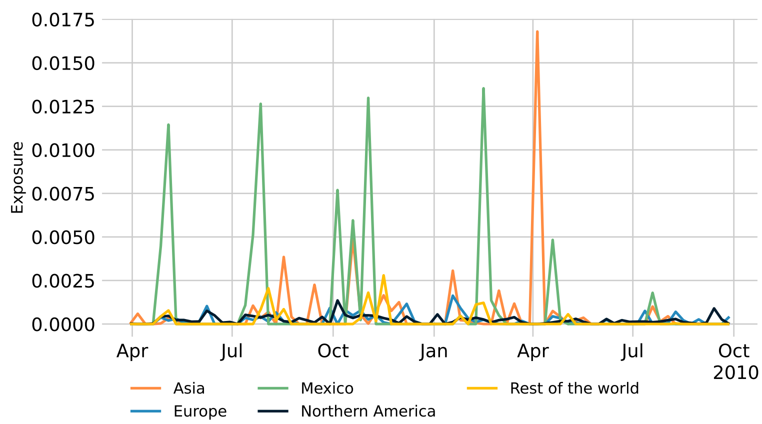
(a) Average *COVID-19* $Exposure_{i,t}$ by region



(b) Average *SARS* $Exposure_{i,t}$ by region



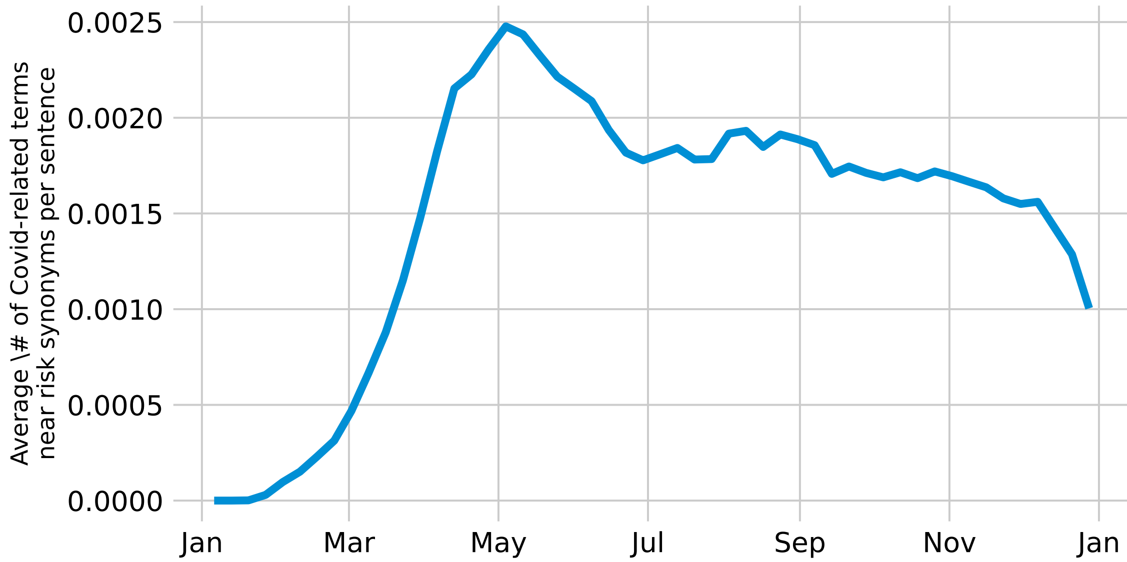
(c) Average *H1N1* $Exposure_{i,t}$ by region



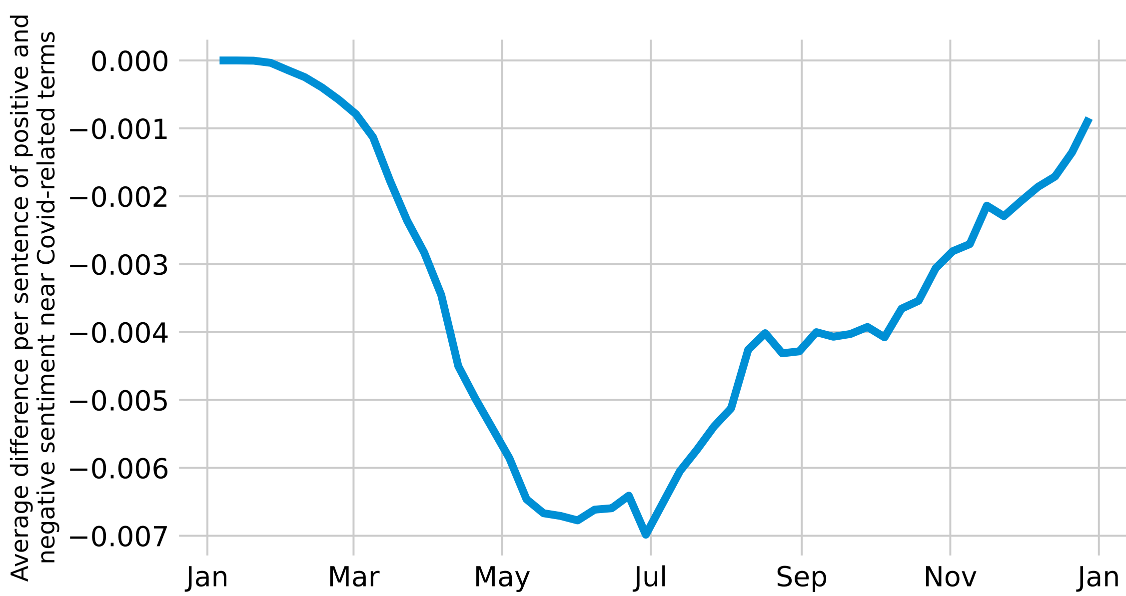
Notes: This figure plots the weekly average of *COVID-19* $Exposure_{i,t}$, *SARS* $Exposure_{i,t}$, and *H1N1* $Exposure_{i,t}$ for firms headquartered in the indicated region for the first 7+ months after the initial outbreak. Exposure measures are scaled by the number of sentences in the transcript. The time series in Panel (a) are smoothed with a weighted moving-average using the last 12 weeks with the number of earnings calls as weights.

Figure 3: Weekly average of *COVID-19 Risk*$_{i,t}$ and *COVID-19 Sentiment*$_{i,t}$

(a) Weekly average of *COVID-19 Risk*



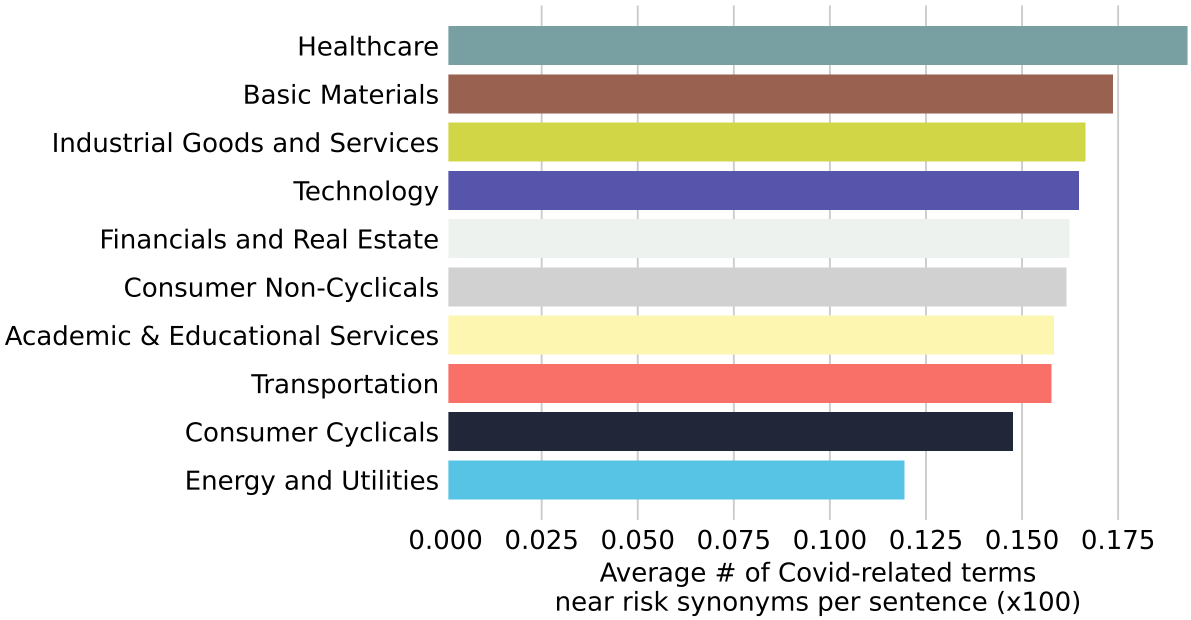
(b) Weekly average of *COVID-19 Sentiment*



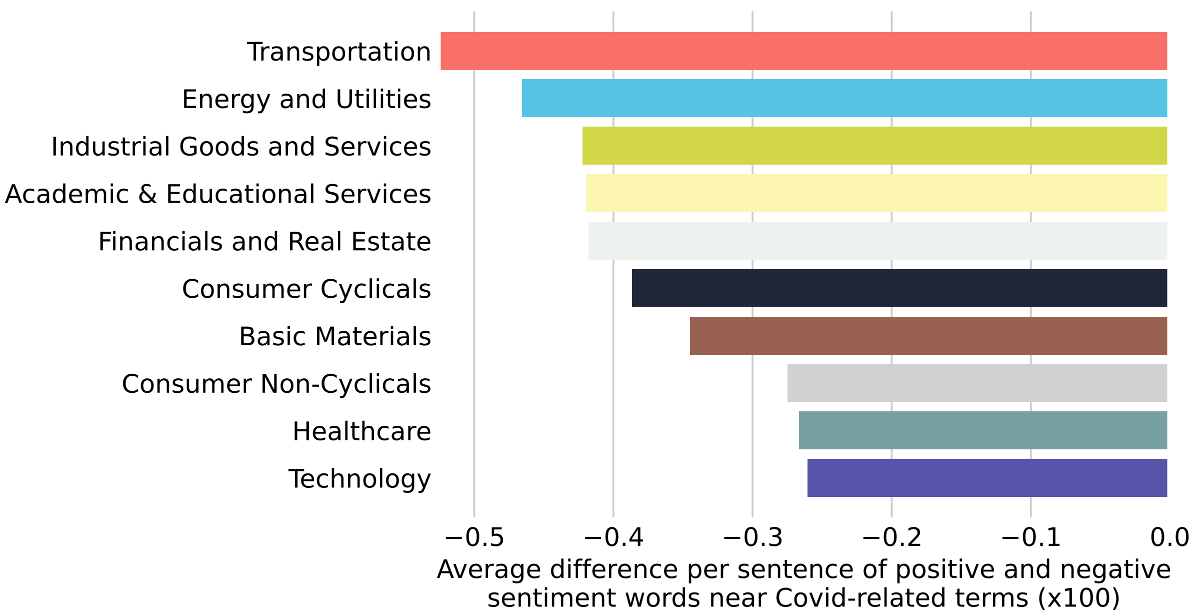
Notes: This figure plots the weekly average of *COVID-19 Risk*$_{i,t}$ and *COVID-19 Sentiment*$_{i,t}$ across all earnings calls held from January through December 2020. The time series are smoothed with a moving-average using the last 6 weeks with equal weighting.

Figure 4: Average *COVID-19 Sentiment*$_{i,t}$ and *COVID-19 Risk*$_{i,t}$ by sector

(a) Average of *COVID-19 Risk*$_{i,t}$ by sector

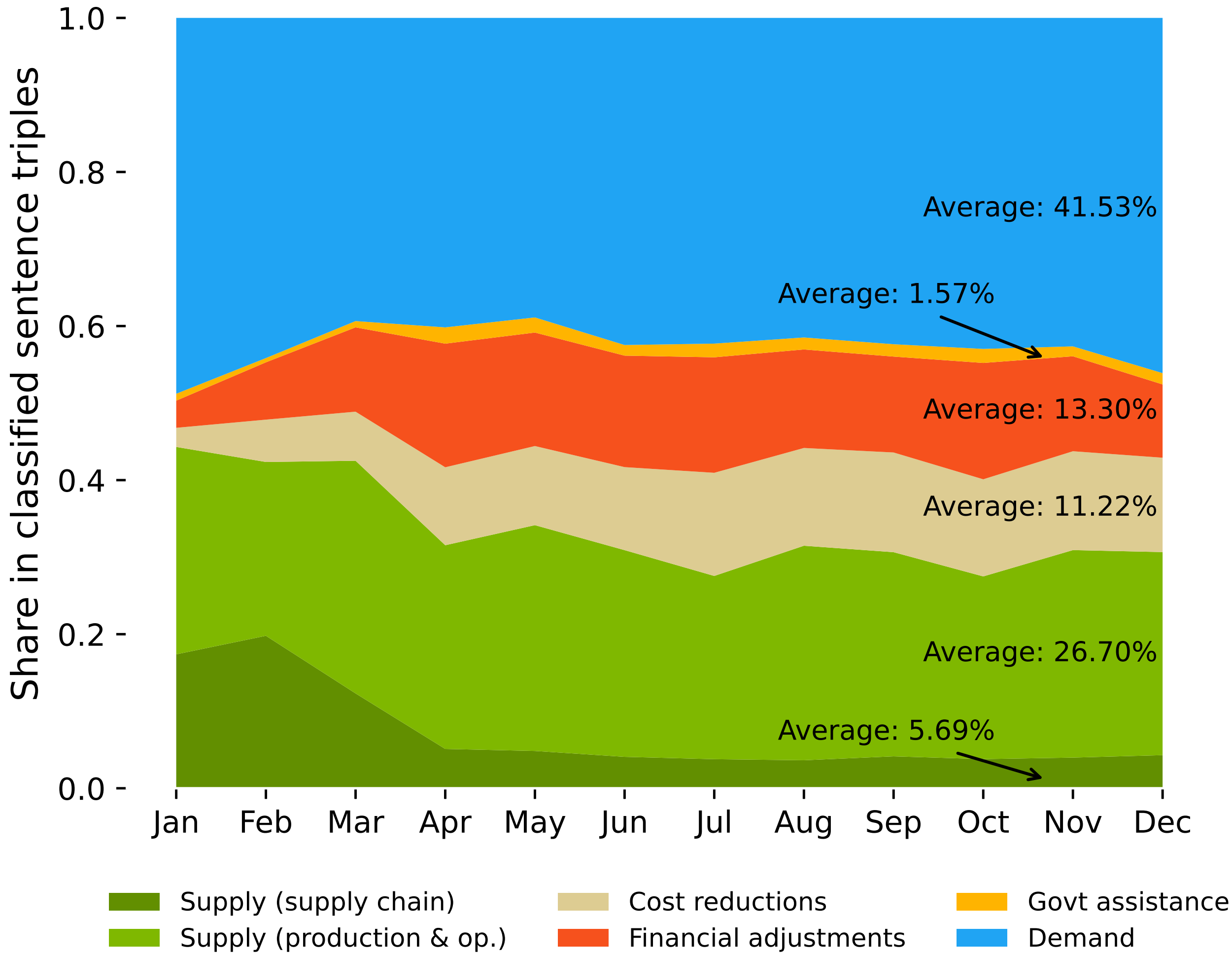


(b) Average *COVID-19 Sentiment*$_{i,t}$ by sector



Notes: This figure plots average *COVID-19 Sentiment*$_{i,t}$ and *COVID-19 Risk*$_{i,t}$ by sector across all earnings calls held by firms in the indicated sector between January and December 2020. The averages are multiplied by 100 for easier exposition. The sector classification is based on a firm's "Economic Sector" from the Refinitiv Eikon database.

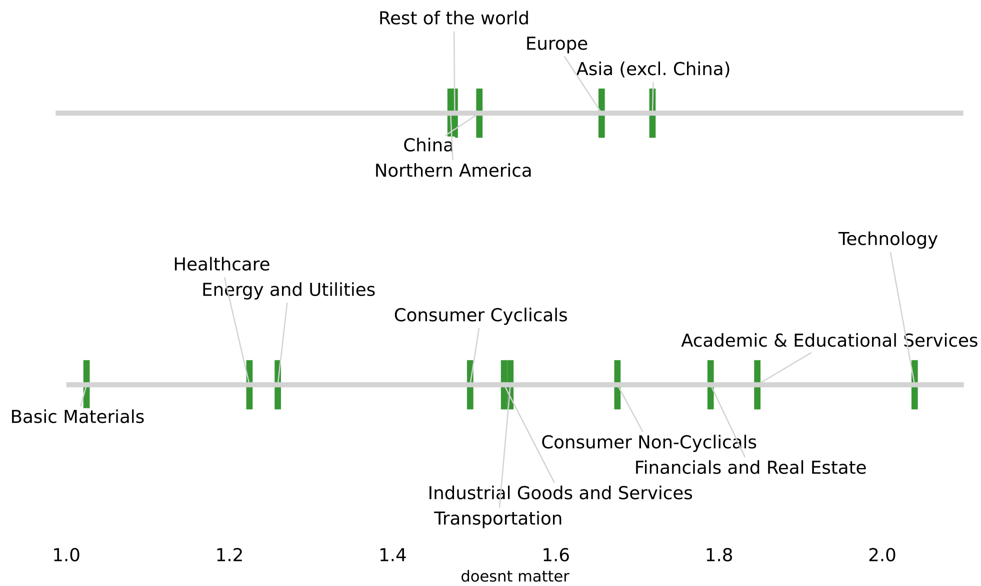
Figure 5: Topic classification of COVID-19-related speech



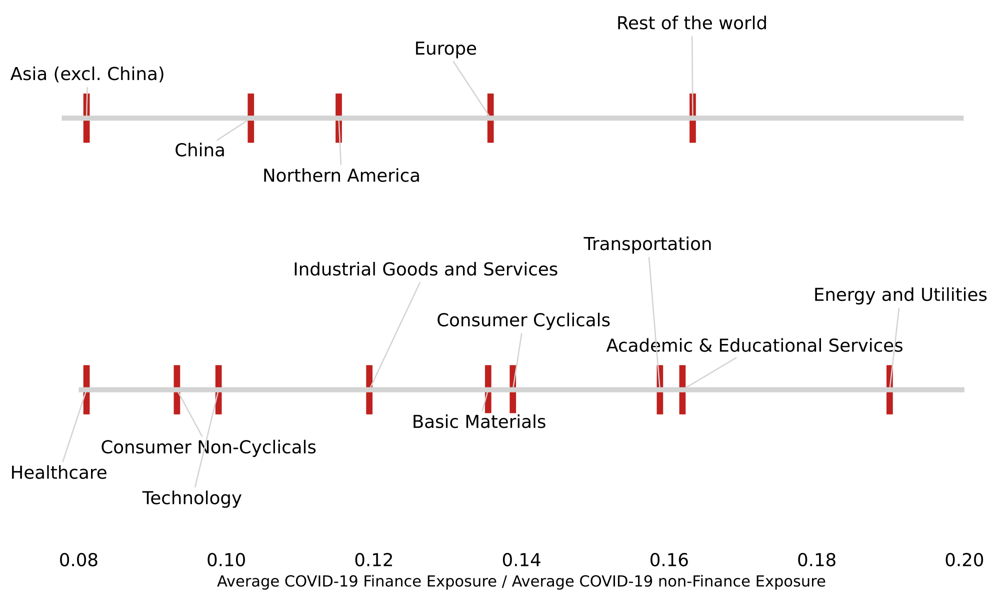
Notes: This figure plots the share of each of five topics (supply impacts (supply chain and production and operations), cost reductions, financial adjustments, government assistance, demand impacts) in classified sentence triples mentioning COVID-19 in transcripts of earnings calls held from January through December 2020. A sentence triple is defined as three consecutive sentences (if available) by the same speaker with the middle sentence containing a COVID-19-related keyword. Sentences assigned to multiple topics are duplicated for the purpose of determining the denominator—this way, shares add up to one.

Figure 6: Relative importance of COVID-19 topic exposure by region and sector

(a) Mean *COVID-19 Demand/Supply Exposure*$_{i,t}$ by region and sector



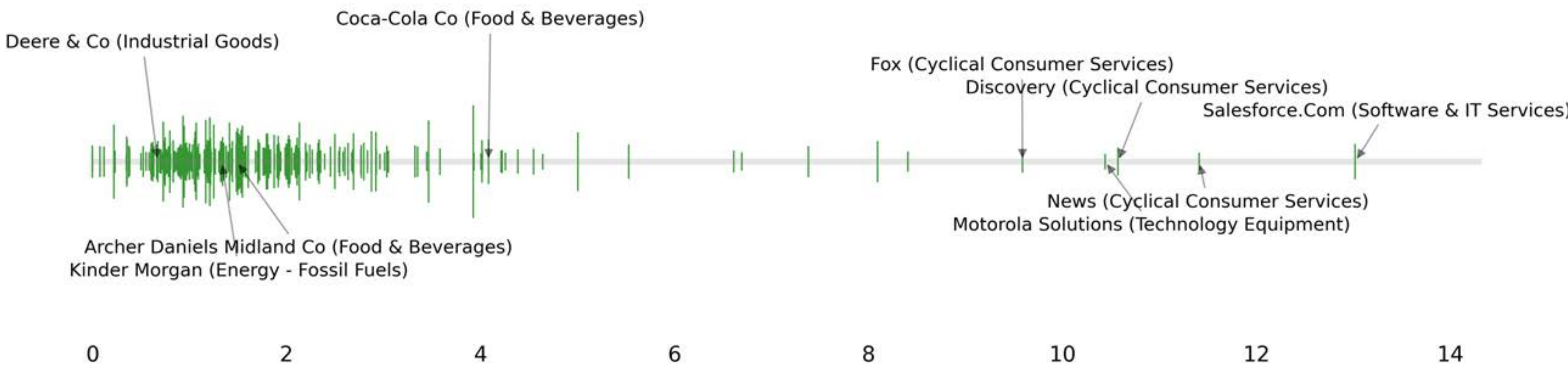
(b) Mean *COVID-19 Finance/non-Finance Exposure*$_{i,t}$ by region and sector



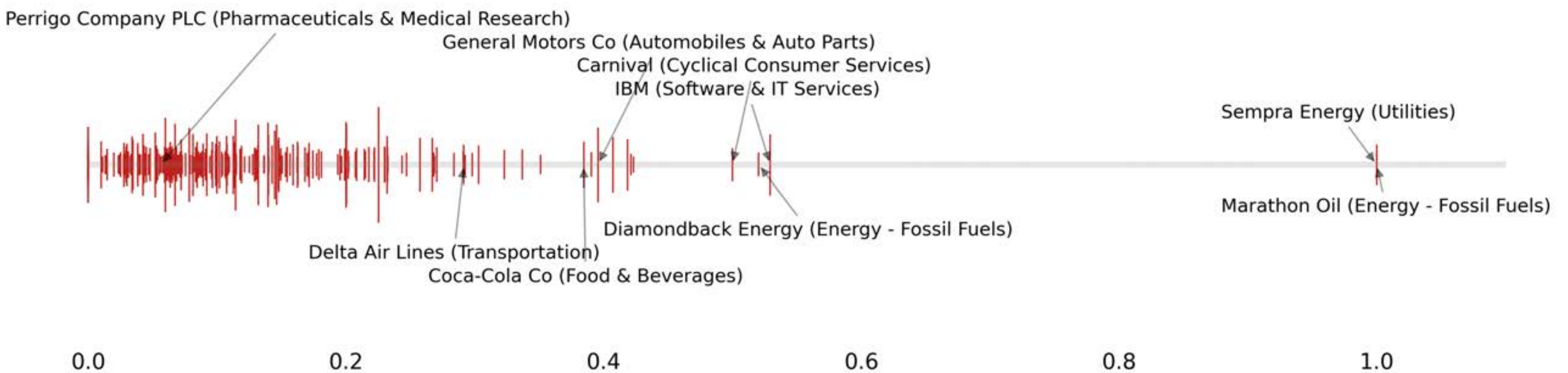
Notes: This figure plots mean *COVID-19 Demand/Supply Exposure*$_{i,t}$ (panel a) and *COVID-19 Finance/non-Finance Exposure*$_{i,t}$ (panel b). *COVID-19 Demand/Supply Exposure*$_{i,t}$ is the ratio of *COVID-19 Demand Exposure*$_{i,t}$ to *COVID-19 Supply Exposure*$_{i,t}$. *COVID-19 Finance/non-Finance Exposure*$_{i,t}$ is the ratio of *COVID-19 Finance Exposure*$_{i,t}$ to *COVID-19 non-Finance Exposure*$_{i,t}$, where *COVID-19 non-Finance Exposure*$_{i,t}$ equals the sum of the COVID-19 exposures to the four remaining topics (supply impacts, cost reductions, government assistance, and demand impacts). In panel (b), we exclude firms in the finance and real estate sector. Means are based on earnings calls held from January through December 2020.

Figure 7: Non-financial S&P 500 firms' *COVID-19 Demand/Supply Exposure*$_i$ and *COVID-19 Finance/non-Finance Exposure*$_i$

(a) *COVID-19 Demand/Supply Exposure*$_i$

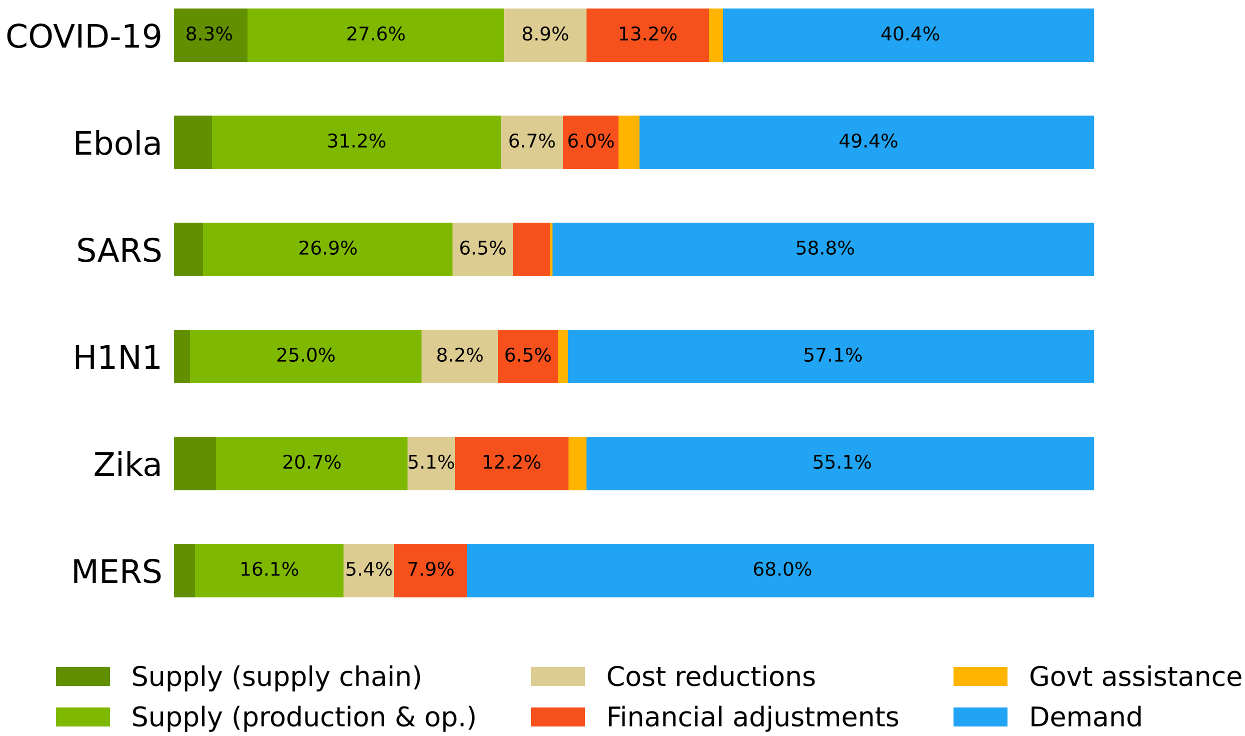


(b) *COVID-19 Finance/non-Finance Exposure*$_i$



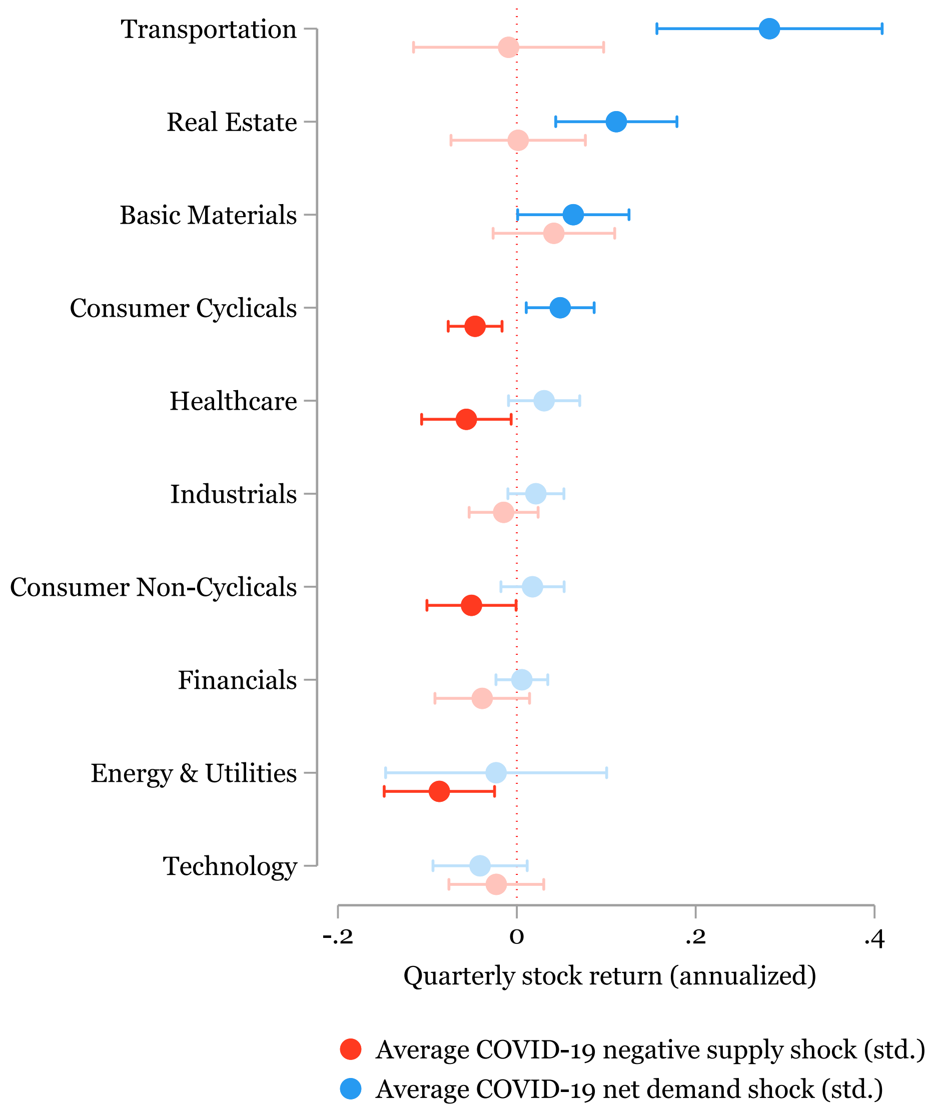
Notes: This figure plots non-financial S&P 500 firms' *COVID-19 Demand/Supply Exposure*$_i$ (panel a) and *COVID-19 Finance/non-Finance Exposure*$_i$ (panel b) based on transcripts of earnings calls held from January through September 2020. *COVID-19 Demand/Supply Exposure*$_i$ and *COVID-19 Finance/non-Finance Exposure*$_i$ is defined as in Figure 6. Panel (a) excludes Fidelity National Information Servcs Inc with *COVID-19 Demand/Supply Exposure*$_i$ of 25.3. The size of the marker reflects the firm's size, measured by the latest available total assets. We only plot firms with more than USD 10 billion assets.

Figure 8: Comparison of disease-related topics at the onset of the disease outbreak



Notes: This figure plots the average across all firms in the initial three quarters of a disease's outbreak of the share in all disease-related topic (supply impacts, cost reductions, finance adjustments, government assistance, demand impacts) mentions. The initial three quarters are defined as the peak quarter (see Figure 1) plus one quarter before and after. In particular, they are Q4-2019q through Q2-2020 for COVID-19, Q3-2014 through Q1-2015 for Ebola, Q1-2003 through Q3-2003 for SARS, Q1-2009 through Q3-2009 for H1N1, Q4-2015 through Q2-2016 for Zika, and Q2=2015 through Q4-2015 for MERS. A disease-related mention is defined as a sentence triple in which the middle sentence contains a disease-related term.

Figure 9: Industry decomposition of valuation effects from COVID-19 net demand and negative supply shock

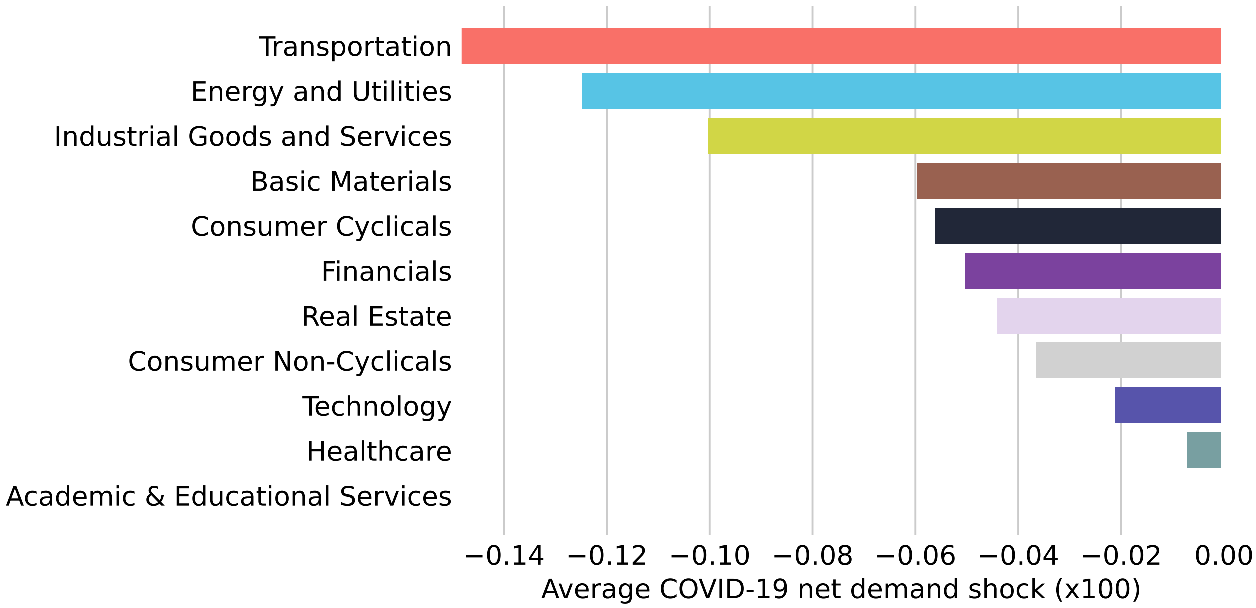


Notes: This figure plots the coefficient estimates and corresponding 95% confidence intervals for β_1 and β_2 from the following firm-quarter level regressions run separately for the industries indicated on the vertical axis:

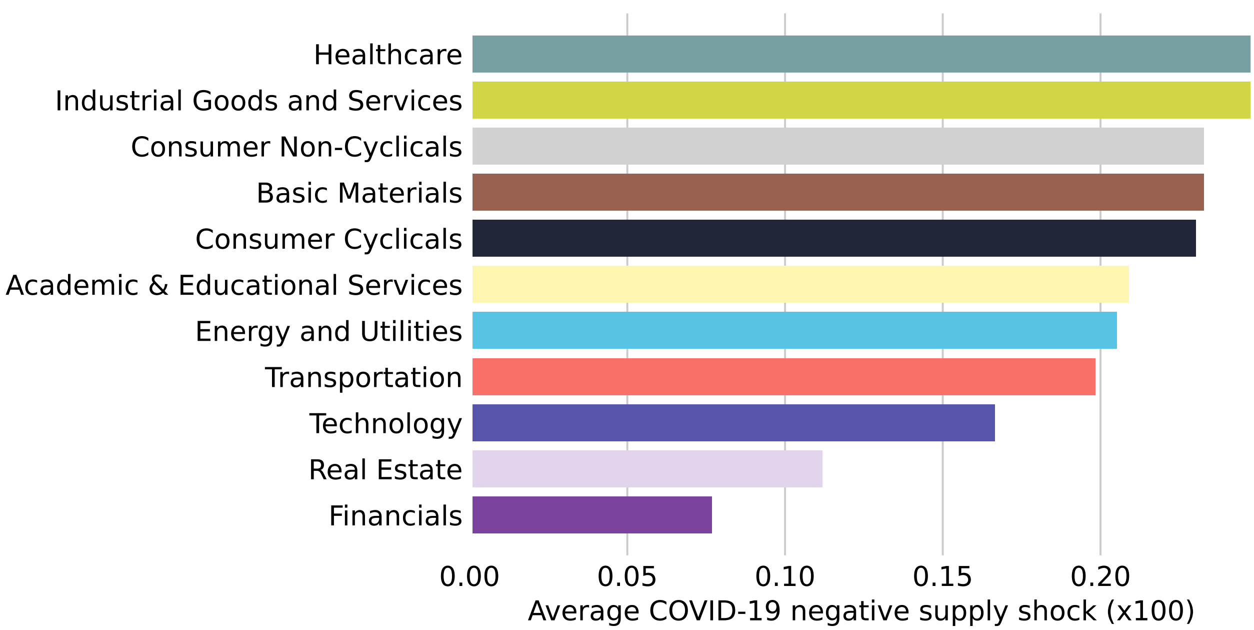
$$\begin{aligned} return_{i,t} = \delta_{s(i)} + \gamma_t + \beta_1 \textit{Average COVID-19 net demand shock (std.)}_{i,t} \\ + \beta_2 \textit{Average COVID-19 negative supply shock (std.)}_{i,t} + \mathbf{x}'_{it}\eta + \varepsilon_{i,t} \end{aligned}$$

where $Return_{i,t}$ is the annualized quarterly stock return of firm i during quarter t; $\delta_{s(i)}$ and γ_t are sector and quarter fixed effects, respectively; COVID-19 net demand and negative supply shocks are as defined in Section 3; and $\mathbf{x}_{it}$ contains the log of firm assets in 2019 and the firm's market beta in 2018, both interacted with a time dummy. All variables are as defined in Table 1. The sample of firms is restricted to US-based firms in 2020q1-2020q4. Statistically significant coefficients are highlighted in bold. Standard errors are clustered at the firm level.

Figure 10: Average *COVID-19 negative demand shock*$_{i,t}$ and *COVID-19 negative supply shock*$_{i,t}$ by sector



(a) Average of *COVID-19 net demand shock*$_{i,t}$



(b) Average of *COVID-19 negative supply shock*$_{i,t}$

Notes: This figure plots the sector averages of *COVID-19 net demand shock*$_{i,t}$ (Panel A) and *COVID-19 negative supply shock*$_{i,t}$ (Panel B) for all firms with earnings calls between January and December 2020. The averages are multiplied for easier exposition. The sector classification is based on a firm's "Economic Sector" from the Refinitiv Eikon database.

Table 1: Summary statistics

	All firms				US firms		
	Mean	Median	SD	N	Mean	SD	N
PANEL A: FIRM-QUARTER LEVEL							
COVID-19 exposure$_{i,t}$ *(std.)*	0.996	0.752	1.000	18,368	1.017	1.034	9,480
COVID-19 sentiment$_{i,t}$ *(std.)*	-0.083	0.000	1.000	18,368	-0.051	1.025	9,480
COVID-19 positive sentiment$_{i,t}$ *(std.)*	0.526	0.000	1.000	18,368	0.589	1.086	9,480
COVID-19 negative sentiment$_{i,t}$ *(std.)*	0.509	0.000	1.000	18,368	0.517	1.014	9,480
COVID-19 risk$_{i,t}$ *(std.)*	0.718	0.416	1.000	18,368	0.748	1.019	9,480
Quarterly stock return (annualized)$_{i,t}$	-0.004	0.049	0.399	18,368	0.011	0.434	9,480
Stock return [-1 day,+1 day]$_{i,t}$	-0.001	-0.000	0.098	18,151	-0.001	0.111	9,454
PANEL B: FIRM-YEAR LEVEL							
$\log(i_{i,t}/k_{i,t})$	-2.484	-2.396	0.778	8,860	-2.475	0.774	4,900
$\log(employment_{i,t})$	1.154	1.258	1.997	7,990	0.878	2.009	4,676
$\log(revenue_{i,t})$	5.564	5.705	2.077	8,454	5.365	2.161	4,551
SG&A$_{i,t}$/*assets*$_{i,t}$	0.052	0.034	0.055	7,783	0.062	0.060	4,232
PANEL C: FIRM LEVEL							
Average COVID-19 net demand shock$_i$ *(std.)*	-0.159	0.000	1.000	4,430	-0.163	0.968	2,452
Average COVID-19 negative supply shock$_i$ *(std.)*	0.566	0.126	1.000	4,430	0.618	1.041	2,452
log(*assets in 2019*$_i$)	7.567	7.613	2.012	4,430	7.371	2.060	2,452
Market beta in 2019$_i$	0.656	0.633	0.438	3,743	0.884	0.373	2,093

Notes: This table shows the mean, median, standard deviation, and the number of observations for the variables used in the regression analysis. Columns 1 to 3 refer to the full sample; and columns 4 and 5 to the sample of US firms. The unit of the data is firm-quarter, firm-year, and firm level in panels A, B, and C, respectively. All epidemic variables are calculated as defined in Section 2 and standardized by their standard deviation in the panel of the main specification. In Panel A, the quarterly sample is restricted to firms for which we have earnings calls in 2020. *Quarterly stock return (annualized)*$_{i,t}$ is the cumulative daily stock return of firm i in quarter t, multiplied by 4; and *Stock return [-1 day,1 day]*$_{i,t}$ is the cumulative daily stock return from one day before to one day after the earnings call of firm i in quarter t. In Panel B, the annual sample is restricted to firms for which we have earnings calls in 2019 and 2020. $\log(i_{i,t}/k_{i,t})$ is the annual average of the log of winsorized (at the first and last percentile) quarterly investment rate (calculated using the perpetual inventory method as in for example Stein and Stone (2013)) of firm i and year t; $\log(employment_{i,t})$ is the log of winsorized (at the first and last percentile) annual employment (`emp` in Compustat) of firm i and year t; $\log(revenue_{i,t})$ is the annual average of the log of winsorized (at the first and last percentile) quarterly revenue (`revtq` in Compustat) of firm i and year t; and *SG&A*$_{i,t}$/*assets*$_{i,t}$ is the annual average of the winsorized (at the first and last percentile) quarterly selling, general & administrative expenses (`xsgaq` in Compustat) divided by assets (`atq` in Compustat) of firm i and year t. In Panel C, log(*assets in 2019*$_i$ is the annual average of the log of quarterly assets of firm i in 2019; and *Market beta in 2019*$_i$ is firm i's market beta with the S&P 500 in 2019, obtained by regressing firm i's daily stock returns in 2018 on the contemporaneous daily S&P 500 index.

Table 2: Word patterns for each disease-related topic

<table>
<tr><th colspan="8">A sentence triple conforms to a given topic ...</th></tr>
<tr><th></th><th>if it contains:</th><th></th><th>if it combines any of:</th><th></th><th>any of:</th><th></th><th>any of:</th></tr>
<tr><td>Supply Chain</td><td>supply chain, suppliers</td><td rowspan="6">or</td><td>supply, component</td><td rowspan="6">with</td><td>challenge, cost, supply</td><td rowspan="6">or with</td><td rowspan="6">increase, accelerate, grow, gain, pickup, up, decline, decrease, cancel, reduce, fall, decelerate, lower, down, disrupt, remain, resume, experience, incur, impact, shift, affect, change, manage, see, talk, figure out, forecast, anticipate, understand, assess, raise, access, keep, recognize, observe, hear, secure, maintain, book, set aside, consist, provide, estimate, expect, withdraw</td></tr>
<tr><td>Production and Operations</td><td>productivity, throughput, closure, shutting down, closing down, commercial availability, mode of operation, permit</td><td>production, operations, operating, produce, store, shutdown, safety measures, manufacturing, innovation, R&D, factory, plant, site, facility, project, employees, workforce, laboratory, trial/study, inventory, utilization, capacity, synergy</td><td>start, stop, delay, launch, postpone, close, open, constrain, adjust, operate, add, build, slow, distribute, service, deliver, shut down, offset, take, commercialize, implement</td></tr>
<tr><td>Cost</td><td>paying sick leave, cost initiative</td><td>cost, expense, spending</td><td>offset, relate</td></tr>
<tr><td>Demand</td><td></td><td>demand, revenue, sales, customer, booking, billing, sentiment, retail, buying behavior, business activity, purchase, delivery, attendance, segment, income, consumer, client, transaction, volume, cancellation, e-commerce, subscriber</td><td>inquire, spend, visit, concern, uncertainty, relate, offer, receive, add</td></tr>
<tr><td>Finance</td><td></td><td>finance, financing, equity, debt, cash, liquidity, loan, funding, capital, write-down, past-due, delinquency, payment deferral, credit, provision, financial asset, risk rating, funds, reserve build, financial impact, business account</td><td>raise, access, keep, distribute, secure, withdraw, maintain, available, book, set aside, consist, provide, fund</td></tr>
<tr><td>Government</td><td>stimulus, CARES Act, Paycheck Protection Program, relief program</td><td>government, central bank, Federal Reserve bank, state</td><td>stimulus, spending, guarantee, concession, relief, liquidity, lending, intervention, response, aid, assistance, support</td></tr>
</table>

Notes: This table lists the word patterns used for each of the disease-related topics: supply chain, production and operations, cost, demand, finance, government. Verbs are stemmed prior to matching: e.g., "increase" becomes "increas," which allows for a match with "increase," "increasing," "increased," etc. Nouns allow for singular and plural. Word combinations are required to be close enough (100 characters). In addition, each topic may impose specific restrictions on words that occur between a word pair. These specific restrictions are listed in Appendix Table 3.

Table 3: Text snippets for finance, cost, and government

Financial Adjustments	
Thanks, El. I am pleased to present a condensed summary of the first quarter results for Cineplex Inc. and to provide additional detail on the financial impacts of COVID-19 on our operations. I would like to start with the $173.1 million impairment charge we recorded in Q1.	Cineplex Inc; 30-Jun-2020
And for foreign currency loan, except for China, most of the cities where our overseas branches and subsidiaries are located are having lockdown, which resulted in the flattish momentum of loan growth in first quarter. So we anticipate there'll be low single-digit growth for foreign currency loan because we don't know how long this COVID-19 will last.	CTBC Financial Holding Co Ltd; 11-May-2020
So turning now to cash in more detail on Slide 10. The first half had been strong, and we were well set up for the second and then COVID struck. And first, the free cash flow, which has also been impacted by COVID.	WH Smith PLC; 12-Nov-2020
Cost Reductions	
The carryover of last year's price investment and the temporary closures of our auto care centers and vision centers negatively affected the margin rate. The approximate $1.2 billion of incremental COVID-related costs as well as the restructuring costs negatively affected expense leverage by about 170 basis points. As a result, the U.S. segment deleveraged 41 basis points.	Walmart Inc; 18-Aug-2020
While most of these decisions were difficult for us to make, we made them with an eye towards not placing at risk our longer-term growth priorities and our competitive position. In late March, we made the difficult decision to resize our store and store support center payroll costs in anticipation that sales could continue to decline for some period of time from the COVID-19 pandemic and that a recovery could be slow once the economy begins to reopen.	Floor & Decor Holdings Inc; 30-April-2020
Changes have also been made to lapse in claims assumptions to allow for price increases, increased claims and reinsurance costs and potential impacts from COVID-19. To be more specific, we have allowed for COVID-19 shorter-term impacts for the next 2 years to both our best estimate assumptions and embedded value calculations for both claims and lapses.	Clearview Wealth Ltd; 25-August-2020
Government Assistance	
The bank's results in Q3 were negatively impacted by a full quarter of COVID-19, which resulted in higher loan loss provisions and lower customer activity. Lower delinquency resulted from the impact of the government stimulus and the bank payment deferral programs, while lower consumer spending also contributed to the lower revolving credit utilization rates.	Bank of Nova Scotia; 25-August-2020
When we applied for the Small Business Administration's Payroll Protection Program (sic) [Paycheck Protection Program], we were uncertain of our ability to maintain our sales growth due to the restrictions on elective procedures. We were uncertain if we could actually help with the treatment of COVID patients in a meaningful way. We were uncertain if we were able to continue to raise money from the equity markets.	CHF Solutions Inc; 12-May-2020
Pinnacle continues its approach of a well-balanced and granular portfolio. While our second quarter credit metrics likely don't yet evidence the full impact of COVID on our loan portfolio, we understand that its fiscal stimulus and PPP proceeds are expanded. Absent further stimulus, we may see these credit metrics change.	Pinnacle Financial Partners Inc; 22-July-2020

Notes: This table shows three different sentence triples about the financial adjustments, cost reductions, and government assistance topic. The sentence triples are taken from the earnings call indicated in column 2. The word pattern match that identifies the topic is highlighted in blue.

Table 4: *COVID-19 Exposure, Sentiment*, and *Risk* correlate with stock returns

	All firms			US-based firms		
Panel A: Firm-year panel 2020q1-q4	*Quarterly stock return (annualized)$_{i,t}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 exposure$_{i,t}$ (std.)	–0.089***			–0.120***		
	(0.010)			(0.017)		
COVID-19 sentiment$_{i,t}$ (std.)		0.058***			0.055***	
		(0.009)			(0.014)	
COVID-19 positive sentiment$_{i,t}$ (std.)			0.003			–0.013
			(0.011)			(0.016)
COVID-19 negative sentiment$_{i,t}$ (std.)			–0.059***			–0.076***
			(0.011)			(0.018)
COVID-19 risk$_{i,t}$ (std.)		–0.051***	–0.038***		–0.074***	–0.051***
		(0.009)	(0.011)		(0.015)	(0.017)
R^2	0.498	0.498	0.498	0.506	0.505	0.506
N	18,368	18,368	18,368	9,480	9,480	9,480
Panel C: Around earnings call	*Stock return [–1 day, +1 day]$_{i,t}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 exposure$_{i,t}$ (std.)	–0.003***			–0.005***		
	(0.001)			(0.001)		
COVID-19 sentiment$_{i,t}$ (std.)		0.005***			0.006***	
		(0.001)			(0.001)	
COVID-19 positive sentiment$_{i,t}$ (std.)			0.001			0.000
			(0.001)			(0.002)
COVID-19 negative sentiment$_{i,t}$ (std.)			–0.005***			–0.007***
			(0.001)			(0.002)
COVID-19 risk$_{i,t}$ (std.)		–0.001	–0.001		–0.001	0.001
		(0.001)	(0.001)		(0.002)	(0.002)
R^2	0.024	0.026	0.026	0.029	0.031	0.031
N	18,159	18,159	18,159	9,456	9,456	9,456
Quarter FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	n/a	n/a	n/a
Sector FE	yes	yes	yes	yes	yes	yes

Notes: This table reports regression estimates at the firm-quarter (Panel A), firm (Panel B), and firm-earnings call (Panel C) level. Quarter fixed effects are included in Panels A and C. All regressions control for the firm's log of assets in 2019 and the firm's market beta in 2018. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 5: Text snippets for negative supply, negative demand, and positive demand shock

Negative supply shock	
On the top line, organic sales in the first quarter declined by 1.3%, including the negative impact of our facilities in China being closed for a full month due to the COVID-19 pandemic.	RR Donnelley & Sons Co; 29-Apr-2020
We also experienced delayed deliveries from our suppliers due to COVID-related factory shutdowns and piece part supply chain interruptions.	Westell Technologies Inc; 18-Jun-2020
We've been facing countrywide lockdowns in Italy and Spain and voluntary production stoppages at virtually all automotive manufacturers in the region, resulting in significant reductions in production capacity at all automotive suppliers.	KEMET Corp; 14-May-2020
Installation [of the offshore loading buoy] was delayed due to COVID-19 concerns on operations earlier this year.	Tullow Oil PLC; 09-Sep-2020
Negative demand shock	
The old business outlook seems to be tough due to major decline in fuel demand because of restriction of movement due to COVID-19, and KBC suffered the biggest impact.	Yokogawa Electric Corp; 12-May-2020
Turning now to the actions we're taking in the face of COVID-19 and the resulting severe disruption to global demand for air travel.	American Airlines Group Inc; 23-Jul-2020
However, in Q2, as COVID led – COVID-19 led to schools' closures and exams being canceled, our revenues started to be impacted, largely driven by a significant downturn in order intake in our Resources business.	RM PLC; 07-Jul-2020
The decline in net revenue was primarily due to the impact of COVID-19.	DASAN Zhone Solutions Inc; 7-May-2020
Positive demand shock	
Revenue growth was driven in part by the sustained rapid increase in the number of biologics in development as well as new opportunities such as cell and gene therapies and COVID-19 therapeutics that continue to propel market growth.	Charles River Laboratories International Inc; 05-Aug-2020
As coronavirus hit the U.S. this spring, Tower saw a spike in website visits and customer service calls, creating both an opportunity and a pain point.	Yext Inc; 03-Sep-2020
Again, driven by underlying – good underlying pharmaceutical market growth and then also the COVID pandemic-related demand increase.	Oriola Oyj; 24-Apr-2020
In the first quarter, EVO delivered 4% normalized revenue growth and 12% normalized adjusted EBITDA growth, which reflects the company's strong performance in January and February, offset by the impact of COVID-19 beginning in early to mid-March.	EVO Payments Inc; 8-May-2020

Notes: This table shows annotated examples of sentences that identify demand and supply shocks. For each shock (negative supply, negative demand, and positive demand), we list four example sentences from sentence triples that contain a COVID-19 term in their middle sentence. The sentences are taken from the earnings call indicated in column 2. The word pattern match for the topic is highlighted in blue; positive and negative sentiment words in green and red, respectively.

Table 6: Stock return in response to demand and supply shock

	All firms	US firms	
		All	Large
	Quarterly stock return (annualized)$_{i,t}$		
	(1)	(2)	(3)
COVID-19 net demand shock$_{i,t}$ (std.)	0.020***	0.015*	0.023**
	(0.005)	(0.008)	(0.010)
COVID-19 negative supply shock$_{i,t}$ (std.)	–0.010**	–0.025***	–0.018**
	(0.005)	(0.007)	(0.007)
R^2	0.497	0.504	0.541
N	18,368	9,480	6,823
Quarter FE	yes	yes	yes
Sector FE	yes	yes	yes

Notes: This table shows the coefficient estimates and standard errors for β_1 and β_2 from the following firm-quarter level regression:

$$\begin{aligned} Return_{i,t} = \delta_{s(i)} + \gamma_t + \beta_1 Average\ COVID\text{-}19\ net\ demand\ shock\ (std.)_{i,t} \\ + \beta_2 Average\ COVID\text{-}19\ negative\ supply\ shock\ (std.)_{i,t} + \mathbf{x}'_{it}\eta + \varepsilon_{i,t} \end{aligned}$$

where $return_{i,t}$ is the annualized quarterly stock return of firm i during quarter t; $\delta_{s(i)}$ and γ_t are sector and quarter fixed effects, respectively; COVID-19 net demand and negative supply shocks are as defined in Section 3; and $\mathbf{x}_{it}$ contains the log of firm assets in 2019 and the firm's market beta in 2018, both interacted with a time dummy. All variables are as defined in Table 1. The sample is restricted to earnings calls between 2020q1-2020q4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent significance, respectively.

Table 7: Validation with revenue and cost

	$\log(revenue_{i,t})$	
	(1)	(2)
Average COVID-19 net demand shock$_i$ *(std.)* $\times$ *post*$_t$	0.029***	
	(0.005)	
Average COVID-19 positive demand shock$_i$ *(std.)* $\times$ *post*$_t$		0.013**
		(0.006)
Average COVID-19 negative demand shock$_i$ *(std.)* $\times$ *post*$_t$		–0.020***
		(0.005)
R^2	0.988	0.988
N	11,722	11,722
Time dummy	yes	yes
Firm FE	yes	yes

Notes: This table shows the estimated coefficients and standard errors from the differences-in-difference regression defined in equation (4). The unit of the data is a firm-year pair and are two years: 2019 and 2020. The outcome is the log of the change in average quarterly revenue (`revtq`) in 2020 as defined in Table 1. The outcome is winsorized at the first and last percentile prior to taking the log. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent significance, respectively.

Table 8: Firm outcomes after supply and demand shock

	All firms	US firms: All	US firms: Large
	$\log(i_{i,t}/k_{i,t})$		
	(1)	(2)	(3)
Average COVID-19 net demand shock$_i$ (std.) $\times$ *post$_t$*	0.037***	0.056***	0.033**
	(0.013)	(0.020)	(0.016)
Average COVID-19 negative supply shock$_i$ (std.) $\times$ *post$_t$*	–0.004	0.003	–0.021
	(0.015)	(0.022)	(0.020)
R^2	0.758	0.739	0.788
N	8,860	4,896	3,720
	$\log(employees_{i,t})$		
	(1)	(2)	(3)
Average COVID-19 net demand shock$_i$ (std.) $\times$ *post$_t$*	0.008	0.007	0.019***
	(0.008)	(0.016)	(0.006)
Average COVID-19 negative supply shock$_i$ (std.) $\times$ *post$_t$*	–0.010*	–0.012	–0.010**
	(0.005)	(0.008)	(0.005)
R^2	0.996	0.995	0.993
N	10,302	5,268	3,918
Post dummy	yes	yes	yes
Firm FE	yes	yes	yes

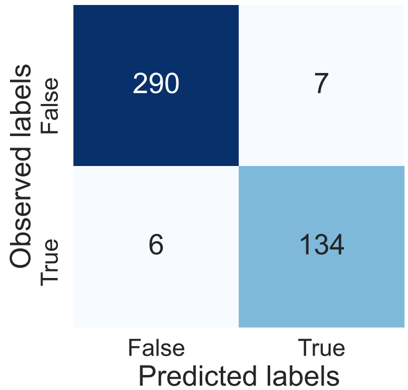
Notes: This table shows the estimated coefficients and standard errors from the differences-in-difference regression defined in equation (4). The unit of the data is a firm-year pair and are two years: 2019 and 2020. In panel A, $i_{i,t}/k_{i,t}$ is average investment rate of firm i in year t, calculated according to the perpetual inventory method detailed in Stein and Stone (2013); in panel B, $employment_i$ is the log of the number of employees in thousands (`emp` in Compustat). Both outcomes are winsorized at the first and last percentile prior to taking the log. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent significance, respectively.

Appendix

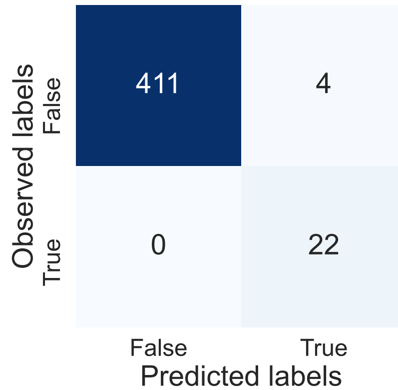
"Firm-Level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1"

Tarek A. Hassan, Stephan Hollander, Laurence van Lent,
Markus Schwedeler, and Ahmed Tahoun

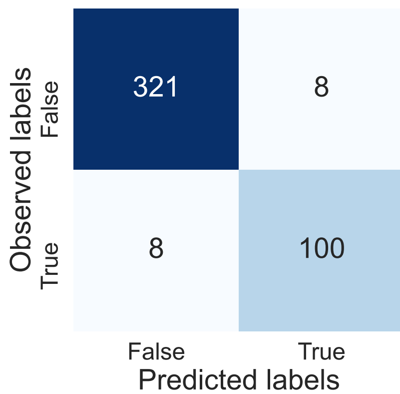
Appendix Figure 1: Confusion matrices for disease-related topics on training data



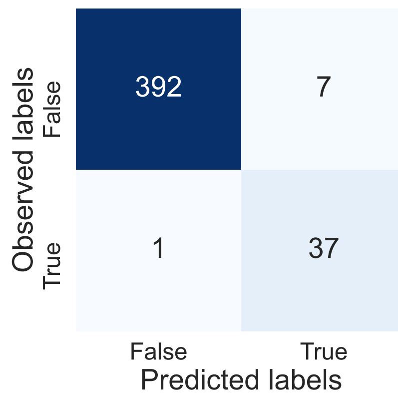
(a) Demand



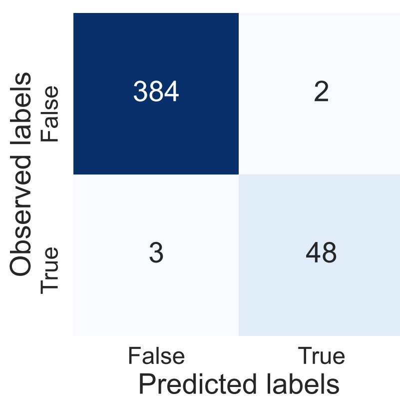
(b) Supply Chain



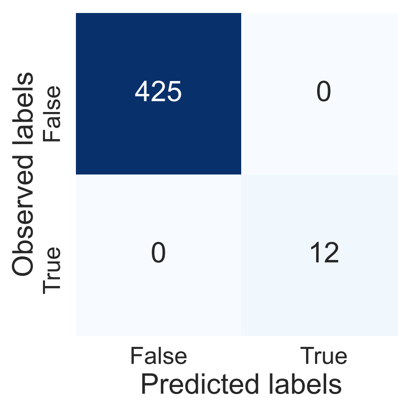
(c) Production and Operations



(d) Cost



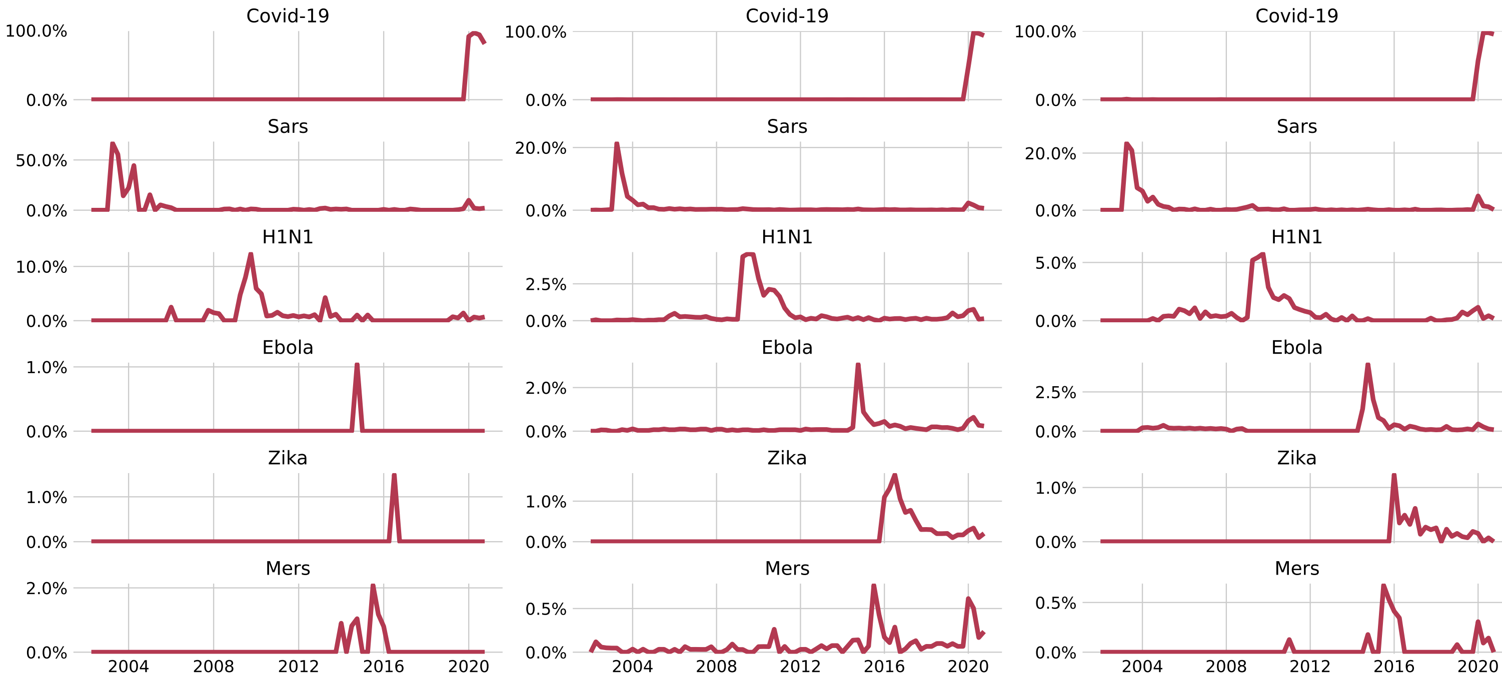
(e) Finance



(f) Government

Notes: This figure shows the performance of our word patterns for each topic (demand, supply chain, production and operations, cost, finance, government) on the training data set, showing the number of true positives, false positives, true negatives, and false negatives of the classification algorithm on the manually-labeled data. Each panel pertains to the subset of manually-classified sentence triples about the topic indicated in the panel.

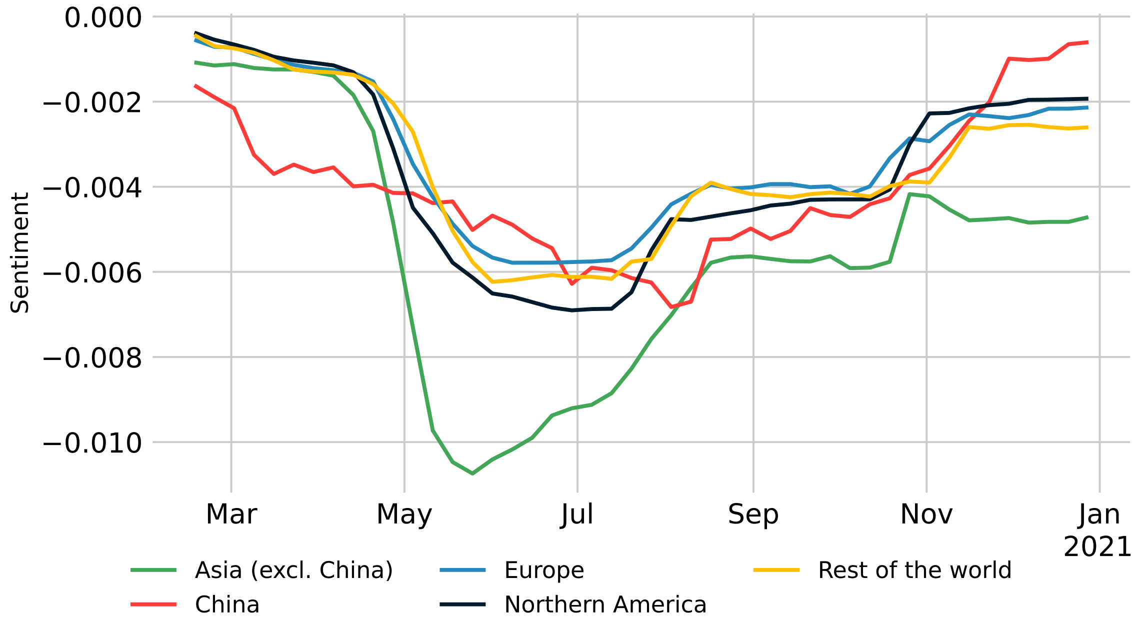
Appendix Figure 2: Percentage of earnings calls discussing epidemic diseases across regions



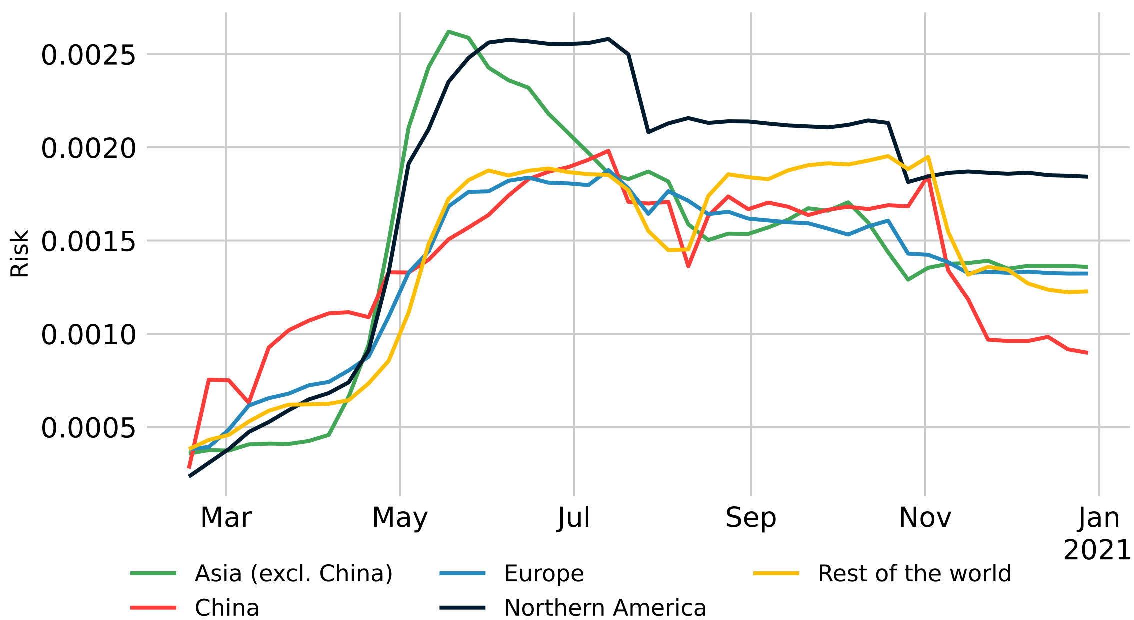
(a) China (b) United States (c) Europe

Notes: This figure plots at the quarterly frequency the percentage of earnings calls discussing the disease indicated in the figure. It does so separately for firms headquartered in China, the United States, and Europe in panels (a), (b), and (c), respectively. The diseases plotted are SARS, H1N1, Ebola, Zika, MERS, and COVID-19.

Appendix Figure 3: Time-series of average *COVID-19 Sentiment*$_{i,t}$, and *Risk*$_{i,t}$ by region



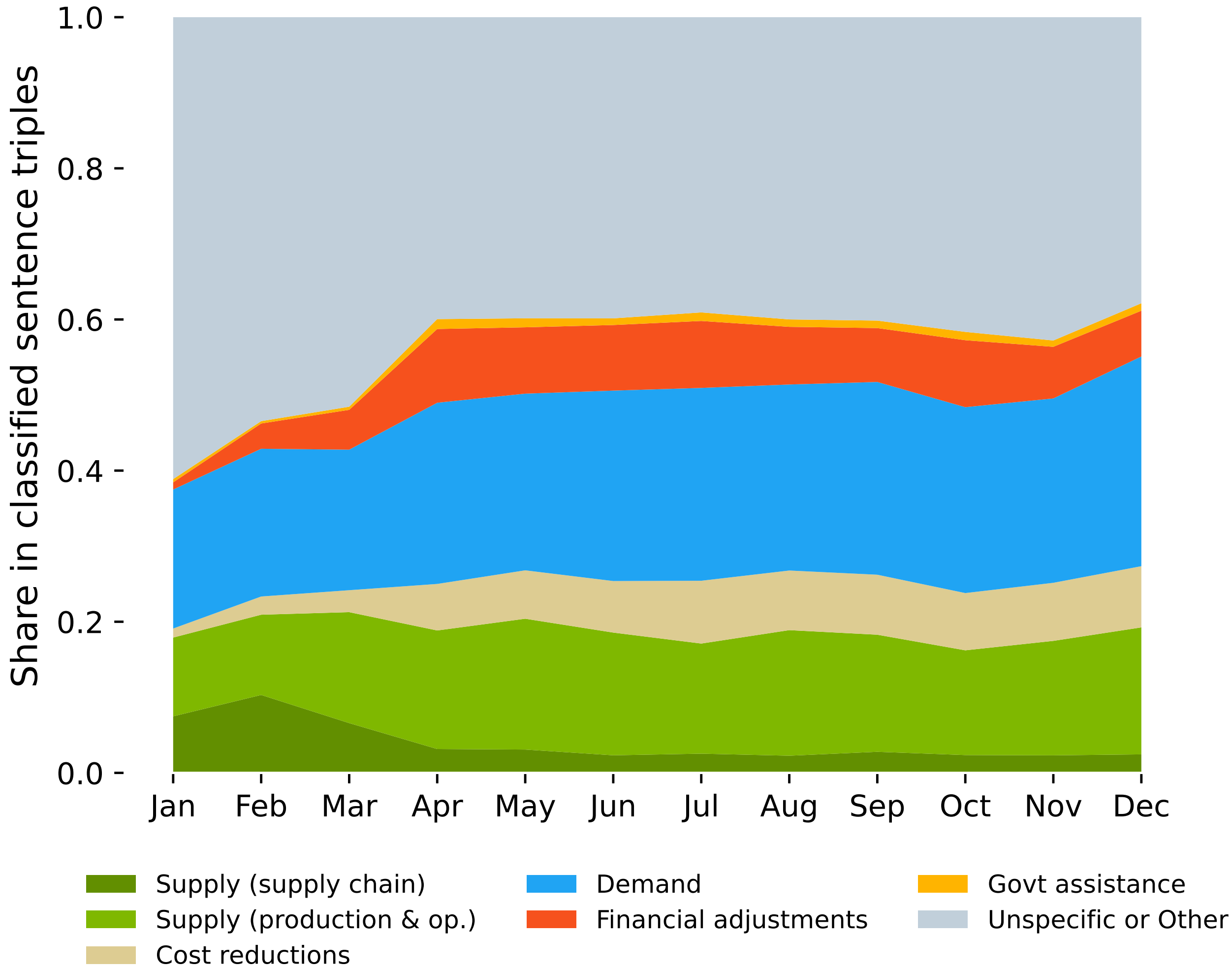
(a) Regional averages of *COVID-19 Sentiment*$_{i,t}$



(b) Regional averages of *COVID-19 Risk*$_{i,t}$

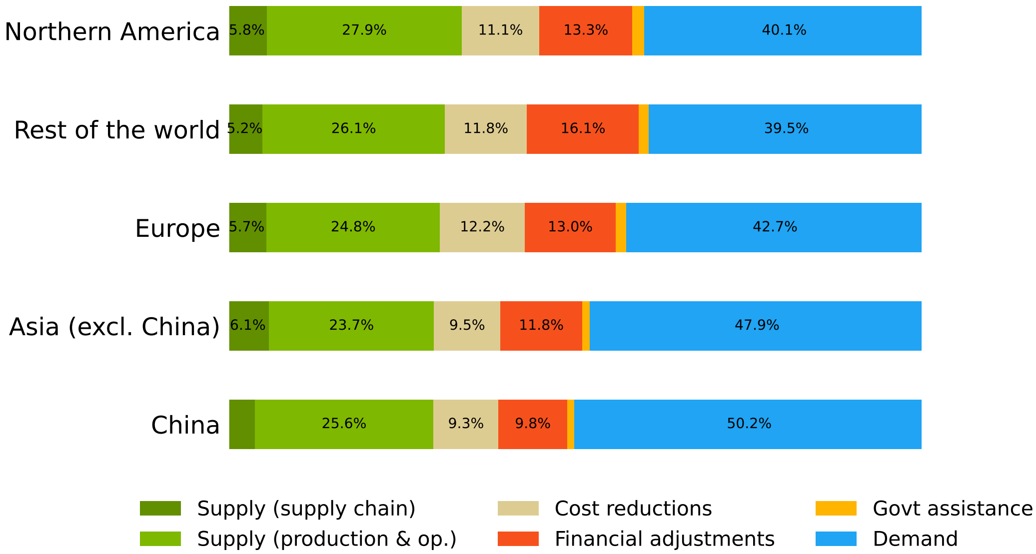
Notes: This figure plots the weekly average of *COVID-19 Sentiment*$_{i,t}$, and *COVID-19 Risk*$_{i,t}$ by region—Asia (excl. China), China, Europe, Northern America, Rest of the world—using all earnings calls held over time by firms headquartered in the region indicated in the figure. Panel (a) plots the regional averages of *COVID-19 Sentiment*$_{i,t}$ and panel (b) of *COVID-19 Risk*$_{i,t}$. The time series are smoothed using a weighted moving average using the last 12 weeks with the number of earnings calls as weights.

Appendix Figure 4: COVID-19-related topic classification, including *Unspecific* or *Other*

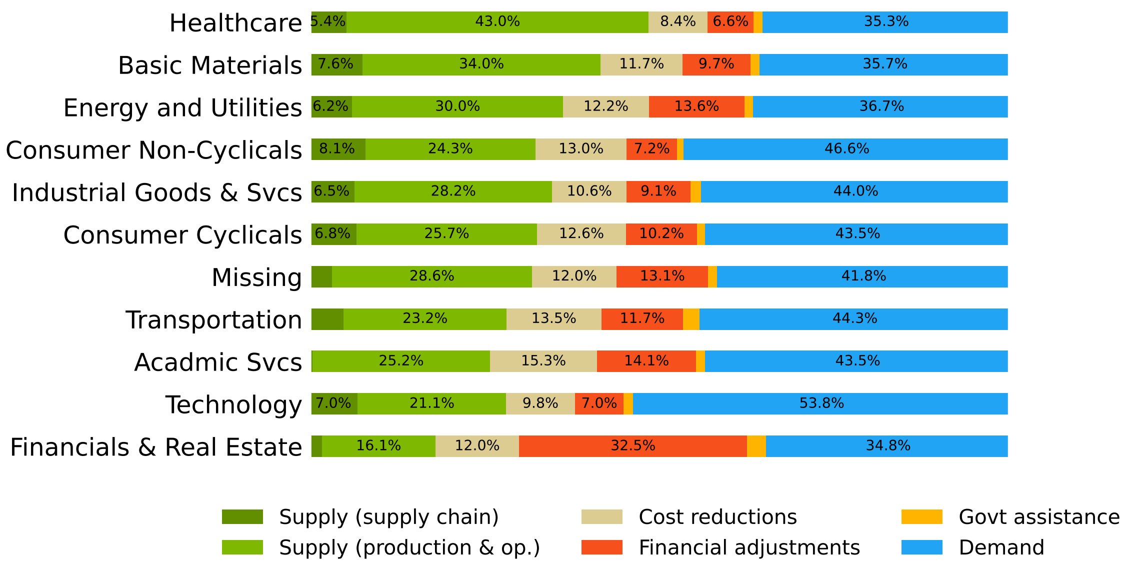


Notes: This figure is similar to Figure 5 but now also includes the share of other unspecific Covid discussions that cannot be specifically attributed to one of our five topic categories: supply issues (supply chain and production and operations), cost adjustments, demand issues, financial adjustments, government assistance. Sentences classified with multiple topics are duplicated for the purpose of determining the denominator, so that shares add up to one. A sentence triple is defined as three consecutive sentences (if available) by the same speaker with the middle sentence containing a COVID-19-related keyword. Sentence triples are obtained from all earnings call transcripts held from January through December 2020.

Appendix Figure 5: Regional and sectoral decomposition of COVID-19-related topic shares



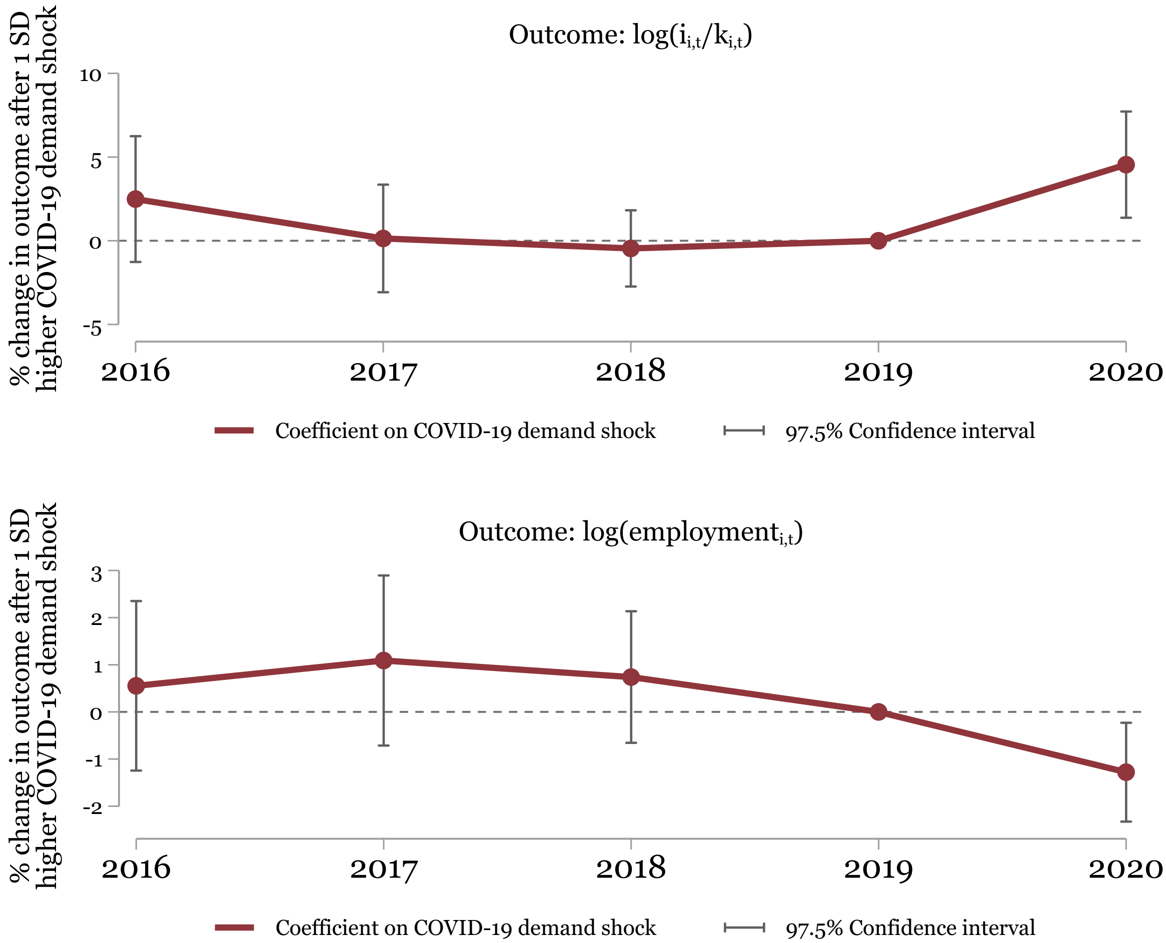
(a) By region



(b) By sector

Notes: This figure plots the regional (panel a) and sectoral (panel b) average the share in COVID-19 related topic mentions of the topic indicated in the figure, based on all earnings calls held from January through December 2020. The sector classification corresponds to the "Economic Sector" as obtained from the Refinitiv Eikon database.

Appendix Figure 6: Event study to test parallel trends



Notes: This figure plots the coefficient estimates and standard errors for β_1^t from the following firm-year level regression:

$$y_{i,t} = \delta_{s(i)} + \gamma_t + \sum_t \beta_1^t \textit{Average COVID-19 net demand shock (std.)}_{i,t} \times \textit{post}_t \\ + \sum_t \beta_2^t \textit{Average COVID-19 negative supply shock (std.)}_{i,t} \times \textit{post}_t + \mathbf{x}_{it}'\eta + \varepsilon_{i,t}$$

where $y_{i,t}$ is $\log(i_{i,t}/k_{i,t}$ in the top panel and $\log(\textit{employment})_{i,t}$ in the bottom panel; δ_i and γ_t are firm and quarter fixed effects, respectively; COVID-19 net demand and negative supply shocks are as defined in Section 3; and $\mathbf{x}_{it}$ contains the log of firm assets in 2019 interacted with a time dummy. All variables are as defined in Table 1. The sample is restricted to $t = \{2016, \ldots, 2020\}$. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent significance, respectively.

Appendix Table 1: Distribution of earnings conference calls by country

Country	Freq.	Perc.	Cum.	Firms	Country	Freq.	Perc.	Cum.	Firms
Argentina	531	0.16%	0.16%	21	Macao	9	0.00%	24.17%	1
Australia	3928	1.16%	1.31%	448	Malaysia	290	0.09%	24.26%	24
Austria	938	0.28%	1.59%	35	Malta	45	0.01%	24.27%	6
Bahamas	58	0.02%	1.61%	3	Marshall Islands	35	0.01%	24.28%	1
Bahrain	20	0.01%	1.61%	3	Mauritius	13	0.00%	24.29%	3
Bangladesh	3	0.00%	1.61%	1	Mexico	2361	0.70%	24.98%	108
Belgium	1049	0.31%	1.92%	46	Monaco	294	0.09%	25.07%	11
Bermuda	2923	0.86%	2.79%	97	Morocco	15	0.00%	25.07%	1
Brazil	4676	1.38%	4.16%	187	Netherlands	2962	0.87%	25.95%	108
British Virgin Islands	31	0.01%	4.17%	4	New Zealand	478	0.14%	26.09%	62
Canada	21044	6.20%	10.38%	970	Nigeria	104	0.03%	26.12%	15
Cayman Islands	418	0.12%	10.50%	18	Norway	2158	0.64%	26.76%	114
Channel Islands	567	0.17%	10.67%	46	Oman	58	0.02%	26.77%	3
Chile	833	0.25%	10.91%	47	Pakistan	16	0.00%	26.78%	6
China	5117	1.51%	12.42%	358	Panama	122	0.04%	26.81%	3
Colombia	338	0.10%	12.52%	16	Papua New Guinea	31	0.01%	26.82%	2
Costa Rica	10	0.00%	12.52%	1	Peru	195	0.06%	26.88%	21
Cyprus	304	0.09%	12.61%	21	Philippines	248	0.07%	26.95%	20
Czechia	223	0.07%	12.68%	6	Poland	673	0.20%	27.15%	32
Denmark	1876	0.55%	13.23%	62	Portugal	515	0.15%	27.30%	13
Egypt	157	0.05%	13.28%	8	Puerto Rico	234	0.07%	27.37%	8
Faroe Islands	14	0.00%	13.28%	1	Qatar	58	0.02%	27.39%	4
Finland	2113	0.62%	13.91%	68	Republic of Korea	1312	0.39%	27.78%	46
France	4003	1.18%	15.09%	166	Romania	37	0.01%	27.79%	4
Germany	5844	1.72%	16.81%	232	Russian Federation	1229	0.36%	28.15%	54
Gibraltar	62	0.02%	16.83%	2	Saudi Arabia	35	0.01%	28.16%	3
Greece	1028	0.30%	17.13%	41	Singapore	1086	0.32%	28.48%	58
Hong Kong	1409	0.42%	17.54%	117	Slovenia	3	0.00%	28.48%	1
Hungary	206	0.06%	17.61%	4	South Africa	1462	0.43%	28.91%	101
Iceland	59	0.02%	17.62%	4	Spain	2240	0.66%	29.57%	76
India	4942	1.46%	19.08%	367	Sweden	4286	1.26%	30.84%	208
Indonesia	319	0.09%	19.17%	18	Switzerland	3256	0.96%	31.80%	132
Ireland	2417	0.71%	19.89%	79	Taiwan	1377	0.41%	32.20%	50
Isle of Man	46	0.01%	19.90%	5	Thailand	387	0.11%	32.32%	24
Israel	2776	0.82%	20.72%	118	Turkey	616	0.18%	32.50%	27
Italy	2774	0.82%	21.54%	111	Ukraine	26	0.01%	32.50%	2
Japan	7690	2.27%	23.80%	286	United Arab Emirates	261	0.08%	32.58%	24
Kazakhstan	94	0.03%	23.83%	7	United Kingdom	10232	3.02%	35.60%	579
Kenya	23	0.01%	23.84%	2	United States	218420	64.39%	99.98%	6911
Kuwait	24	0.01%	23.84%	4	Uruguay	36	0.01%	99.99%	1
Luxembourg	1114	0.33%	24.17%	53	Venezuela	19	0.01%	100.00%	2

Notes: This table tabulates the distribution of sample earnings calls, held between January 1, 2002 and Decmeber 31, 2020, by firms' headquarters country. The column *Freq.* indicates the number of earnings calls by firms from a particular country; the column *Perc.* indicates the percentage of all 2002-2020 earnings calls held by firms from that country; the column *Cum.* cumulatively sums those percentages; and the column *Firm* indicates the number of sample firms headquartered in that country.

Appendix Table 2: Disease synonyms

SARS	MERS
'sars'	'merscov'
'severe acute respiratory syndrome'	'middle east respiratory syndrome'
	'mers'
Ebola	**H1N1**
'ebola'	'hn'
	'swine flu'
	'ahn'
Zika	**COVID-19**
'zika'	'sarscov'
	'coronavirus'
	'corona virus'
	'ncov'
	'covid'

Notes: This table lists for each of the six diseases (SARS, MERS, Ebola, H1N1, Zika, COVID-19), as described in Section 2, the list of synonyms used to identify a disease. In pre-processing, we remove all non-letters, in addition to setting all text to lower case (hence, for example, "H1N1" becomes "hn").

Appendix Table 3: Additional topic-specific restrictions on word patterns

Topic	Additional restrictions
Supply Chain	Words not allowed to be between word combinations: "million"
Production and Operations	1) Words not allowed to between word combinations: "loss," "fund," "demand," "revenue," "expenditure," "interest rate," "customers[s]," "thank," "consumer," "sale," "payment," "cost," "highlight," "result," "global economy" 2) Word-specific restrictions: "permit" may not be preceded by "condition[s]," "site" may not be followed by "deposit" or "lease," and 'facillity" may not be preceded by "credit"
Cost	Words not allowed to be between word combinations: "safe," "support," "help," "inventory," "shipment," "customer," "last quarter," "last year," "guidance," "operational," "material," "out-of-pocket"
Demand	1) Words not allowed to be between word combinations: "safe," "support," "testing," "help," "inventory," "liabilities," "accounts payable," "loss," "expense," "result," "guidance," operational," "material," "cost," "service," "payout" 2) Word-specific restrictions: "customer," "consumer," and "client" may not be preceded by "support"
Finance	1) Words not allowed to be between word combinations: "safe," "support," "help," "inventory," "shipment," "customer," "last quarter," "last year," "guidance," "operational," "material," "out-of-pocket," "companies," "cost," "spending" 2) Word-specific restrictions: "debt" may not be preceded by "sovereign" and "cash" may not be followed by "purchase"
Government	1) Words not allowed to be between word combinations: "mandate," "order," "shutdown," "guideline" 2) Word-specific restrictions: "government" may not be followed by either of "affairs," "shutdown," "mandate," "order," and "state" may not be followed by "affair"

Notes: This table lists the additional topic-specific restrictions that we require each word pattern to adhere to.

Appendix Table 4: Number of false positives from thirty randomly-drawn sentence triples

Topic	# of false positives
Demand	6/30
Supply chain	3/30
Production and operations	8/30
Cost	5/30
Finance	3/30
Government	1/30

Notes: This table shows the result of an audit of the final iteration of our pattern matching. For each topic, we randomly drew 30 sentence triples and compare the prediction of the topic-specific pattern with a manual assessment of the triple's topic. Each row lists the number of false positives out of these thirty randomly-drawn sentence triples.

Appendix Table 5: Frequency risk or uncertainty synonyms in disease-related discussions

Word	Frequency	Word	Frequency
uncertainty	4052	bet	9
risk	1812	queries	9
uncertainties	1386	unforeseeable	9
uncertain	889	risky	8
risks	816	sticky	7
unknown	309	reservation	7
threat	298	halting	7
exposed	214	suspicion	7
doubt	184	riskier	6
possibility	153	unsettled	6
fear	153	dilemma	4
unpredictable	146	apprehension	4
variable	144	tentative	3
unclear	126	undetermined	3
chance	76	jeopardize	3
pending	71	query	3
varying	70	irregular	2
variability	59	unsafe	2
likelihood	38	hazardous	2
prospect	30	hesitancy	2
instability	29	undecided	2
unpredictability	27	erratic	2
probability	24	precarious	1
tricky	22	hairy	1
dangerous	20	gamble	1
hesitant	18	unreliable	1
doubtful	18	unresolved	1
fluctuating	15	jeopardy	1
speculative	12	faltering	1
danger	11	fickleness	1
unstable	11	vague	1
insecurity	10	insecure	1
hazard	10	hesitating	1
unsure	9	debatable	1
risking	9		

Notes: This table shows the frequency across all earnings call transcripts held between Q1-2020 and Q3-2020 of all single-word synonyms of "risk," "risky," "uncertain," and "uncertainty" as given in the Oxford Dictionary (excluding "question" and "questions") that appear within 10 words of a disease synonym of the following diseases: SARS, MERS, H1N1, Zika, Ebola, and COVID-19.

Appendix Table 6: Frequently used tone words in disease-related discussions

Positive word	Frequency	Positive word	Frequency	Negative word	Frequency	Negative word	Frequency
despite	4310	gains	151	crisis	6995	stress	291
strong	3416	highest	149	challenges	3716	suspended	284
good	2644	enhanced	148	negative	2548	restructuring	284
positive	1972	positively	144	decline	1904	slower	270
able	1920	enabled	134	disruption	1821	weakness	269
better	1280	incredibly	129	against	1662	recession	261
great	1231	progressing	127	difficult	1561	closure	247
opportunities	1102	easy	124	challenging	1385	challenged	229
progress	1058	enable	124	disruptions	1087	cancellations	223
opportunity	963	strengthen	122	negatively	1020	postponed	221
pleased	727	profitable	118	loss	1005	difficulty	216
benefit	726	perfect	116	delays	994	slowing	216
best	671	efficiencies	110	delayed	945	serious	215
improved	574	greatly	110	declined	829	exposed	214
improvement	560	progressed	109	losses	789	forced	208
confident	557	attractive	108	late	762	recall	206
strength	539	incredible	108	concerns	761	lack	205
stronger	512	impressive	106	slowdown	730	weaker	203
greater	477	stability	104	challenge	693	unexpected	194
improve	451	benefiting	101	closed	676	problems	194
profitability	448	efficient	96	claims	637	prevention	193
leading	390	enhance	96	severe	613	suffered	190
stable	368	stabilize	94	shutdown	605	exacerbated	185
effective	364	stabilized	90	volatility	561	canceled	184
successfully	329	strengthened	87	delay	556	doubt	184
achieved	322	innovative	85	closures	543	strains	181
optimistic	296	boost	83	critical	540	dropped	180
successful	285	greatest	82	unfortunately	522	unfavorable	180
happy	262	exciting	81	adverse	504	deterioration	178
benefited	259	achieving	80	slowed	487	interruption	176
success	259	gained	77	shutdowns	481	worst	173
favorable	251	win	76	lost	447	stopped	173
improving	246	strengthening	76	slow	427	worse	171
advantage	244	advancing	75	concern	416	difficulties	171
proactive	236	strongest	67	declines	416	suspension	170
proactively	231	efficiently	66	bad	388	suffering	168
achieve	230	easier	64	shut	387	unemployment	166
improvements	220	achievement	64	force	380	volatile	162
tremendous	218	improves	63	downturn	365	overcome	162
rebound	198	diligently	62	concerned	362	prolonged	158
encouraged	198	enabling	62	severely	357	declining	155
exceptional	195	exceptionally	62	problem	322	fear	153
efficiency	192	gaining	59	severity	306	unable	147
excellent	185	valuable	57	adversely	305	unpredictable	146
encouraging	180	advantages	56	closing	304	caution	144
excited	180	resolve	52	impairment	304	impairments	138
leadership	178	beneficial	51	disrupted	301	destruction	131
gain	158	fantastic	47	strain	300	complications	129
innovation	155	rebounded	47	threat	298	fallout	128
collaboration	153	outperformed	46	weak	292	cut	125

Notes: This table shows the frequency across all earnings call transcripts held between Q1-2020 and Q3-2020 of the top 100 positive and negative tone words from Loughran and McDonald (2011) (note: their list contains 354 positive and 2,352 negative tone words) that appear within 10 words of the following diseases: SARS, MERS, H1N1, Zika, Ebola, and COVID-19.

Appendix Table 7: Does epidemic data predict firm-level COVID-19 measures?

	COVID-19 Negative Sentiment$_{i,t}$		*COVID-19 Exposure*$_{i,t}$	
	(1)	(2)	(3)	(4)
New cases per 100,000$_{C(i),t}$	0.006***		0.105***	
	(0.001)		(0.003)	
New deaths per 100,000$_{C(i),t}$		0.224***		4.237***
		(0.049)		(0.112)
COVID-19 Exposure$_{i,t}$	0.411***	0.410***		
	(0.007)	(0.007)		
R^2	0.614	0.614	0.064	0.088
N	16,563	16,563	16,563	16,563

Notes: This table reports regression estimates at the firm-quarter level for 2020Q1-2020Q3. New cases per 100,000$_{C(i),t}$ is the number of confirmed COVID-19 cases per 100,000 in quarter t of country C that firm i is headquartered in; New deaths per 100,000$_{C(i),t}$ is defined similarly for the number deceased COVID-19 patients per 100,000. Both variables are obtained from Google's *COVID-19 Open Data*: https://console.cloud.google.com/marketplace/product/bigquery-public-datasets/covid19-open-data. Country-quarter cells with less than 25 firms are excluded. All regressions control for the log of firm assets. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 8: Example COVID-19-related sentence triple by topic

Topics	Example sentence triple
Supply impacts (supply chain)	We have the trade tariffs, as you know, that have already led to some shifts in the global **supply chains**. And on top of that, I would say that now the coronavirus also has led to some additional shifts and rearrangement of global **supply chains**. It is not a large extent, but I would guess that some of the developments in Europe as well in North America also are the result of people trying to desperately shift **supply chains** so that might lead to a little bit of a compensation of the slowdown in China by Europe and the United States. Extracted from earnings call of Covestro AG on 19-Feb-2020.
Supply impacts (production and operations)	Moreover, most traditional and convenience **stores are closed or suffering from a significant in-store traffic decline**, notably in developing countries. Overall, we estimate the impact of the COVID-19 on our group first quarter net sales growth to be between minus 2 and minus 3 points. From a global supply chain perspective, several of our **factories and warehouses are closed** to comply with local government regulations and guidelines. (Also labeled as: Supply Chain; Demand.) Extracted from earnings call of Societe BIC SA on 23-Apr-2020.
Cost reductions	In response to the pandemic and in **recognition of mild weather entering the year, we are executing on a series of cost**-saving initiatives totaling approximately \$350 million to \$450 million or \$0.35 to \$0.45 per share. We are also **keeping our regulators informed about the specific costs** we are incurring related to COVID-19. First and foremost, our thoughts are with those who have been personally affected. Extracted from earnings call of Duke Energy Corp on 12-May-2020.
Demand impacts	**Revenue for the 3 months ended March 31, 2020 was \$63.5 million, an increase** of 31% year-over-year and 8% sequentially. Management has determined that **revenue was negatively impacted in the quarter by the COVID-19 crisis on 2 fronts: first, the company booked** additional reserves due to expectations of lost patient insurance and co-pay payments lower than historical averages. And secondly, the company has estimated that lower registrations and unit intake in the latter half of March had a material **impact on Q1 revenues**. Extracted from earnings call of iRhythm Technologies Inc on 07-May-2020.
Financial adjustments	The ratio of allowance for credit losses to NPLs held in portfolio stood 120% compared to 91% in the previous quarter. The **provision for credit losses increased by \$142 million from the prior quarter, mainly driven by the COVID-19 impact** on the macroeconomic scenarios. The provision to net charge-off ratio was 302% in the first quarter of 2020. Extracted from earnings call of Popular Inc on 30-Apr-2020.
Government assistance	On another note, as you will see in today's press release, we've returned the \$2.8 million PPP loan, which we had qualified for. When we first considered the loans, we carefully reviewed our financial condition and the economic impact and uncertainty caused by the coronavirus pandemic. At that time, we determined the funds were necessary to maintain our ongoing operations in accordance with the terms and conditions of **CARES Act**. (Also labeled as: Production And Operations; Finance.) Extracted from earnings call of inTest Corp on 08-May-2020.

Notes: This table shows one predicted COVID-19-related sentence triple for each of the five topics: supply impacts (supply chain and production and operations), cost reductions, demand impacts, financial adjustments, government assistance. The topic label of the sentence triple is predicted with our pattern search as specified in the paper. Bold text indicates the actual pattern match that results in the prediction of the topic label. If a sentence triple has multiple topic labels, we do not boldface the pattern match of those other topic labels. A sentence triple is defined as three consecutive sentences (if available) by the same speaker with the middle sentence containing a COVID-19-related keyword. Sentence triples are obtained from earnings call transcripts held from January through December 2020.