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FIRM-LEVEL EXPOSURE TO EPIDEMIC DISEASES: COVID-19, SARS, AND H1N1

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Firm-Level Exposure to Epidemic Diseases: Covid-19, SARS, and H1N1*

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November 15, 2020

Abstract

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"[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. At that point, 118,319 infections with the virus had been confirmed, and 4,292 people had died from the disease. 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. After an Oval Office address by then US President Trump failed to calm markets on March 11, major stock indices fell another 10 percent on the following day.[1] Even though governments rushed in equal measure to stem the further spread of the virus, locking down entire regions and restricting (international) travel as well as to support a suddenly wobbling economy, providing emergency relief measures and funding, 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 respond to large aggregate, unexpected "shocks." Those wishing to avail themselves of this opportunity, however, face two formidable challenges. First, how to quantify the differences across firms in their exposure to a macro shock. Second, how to disentangle whether the shock relates to demand contractions, supply disruption, or credit tightening. To understand the dynamics in macro-variables during and after a shock, such an understanding of determinants is essential.[2]

Addressing these challenges, we have two objectives in this paper: (1) to construct a time-varying, firm-level measure of exposure to epidemic diseases, as one example of such a macro shock, and (2) to identify whether the firm-level exposure to the shock relates to

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

[2] Consider, e.g., 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).

demand, supply, financing, or other concerns. We believe these efforts to be timely given the concern in the literature that the extraordinary nature of the current 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 identifies the exposure of firms to the outbreak of Covid-19 by counting the number of times the disease is mentioned in the quarterly earnings conference call that publicly-listed firms host with financial analysts. 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.

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 consists 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. To illustrate the flexibility of our approach, we also construct measures of a given firm's exposure to earlier significant epidemic diseases, namely SARS, MERS, H1N1, Ebola, and Zika. In this way, we can examine whether firms learn from previous experiences with a given type of shock, such as with earlier infectious disease outbreaks.

In addition to this exposure measure, we also construct—per the method described in Hassan et al. (2019, 2020)—measures of epidemic disease *sentiment* and *risk*. These measures intend to capture the first and second moment, respectively, of a given firm's exposure to an epidemic disease outbreak. Doing so is important, not only because first and second moments tend to be correlated and estimating the impact of uncertainty on firm outcomes requires one to control for the effect of the outbreak on the mean of the firm's expected future cash flows, but also because it allows us to separate those firms which expect to gain from these events from those that expect to lose. Once we identify these winners and losers, we can then turn to the details of the conversation in their transcripts to systematically catalogue the reasons why they believe they can benefit from or are harmed by the outbreak.

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 which of these potential concerns are current for firms around the globe during the coronavirus outbreak. Guided by the results of a pilot study, we label Covid-19 related discussions into six topics: (1) demand, (2) supply chain, (3) production and operations, (4) costs, (5) finance, and (6) government. Based on an automated reading of all text fragments from transcripts that mention Covid-19, we document the frequency in which each concern is voiced between January and September 2020, paying especial attention to over-time changes in patterns.

Based on the new firm-level epidemic disease exposure measures, we document a set of empirical facts for the impact of outbreaks on firms in 84 countries, the most important of which are as follows: First, the Covid-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. 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 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 somewhat in the third quarter of 2020, lead by a slight uptick in optimism among Asian firms.

Third, underlying these overwhelmingly negative aggregate trends, significant heterogeneity across firms and sectors exists. For example, firms are most pessimistic (have negative sentiment) in the Transportation sector, consistent with that industry being hit hard by cancelled air routes and closed borders. 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.

We also find that short-window earnings-call stock returns, capturing the information released during the earnings call, as well as first-quarter cumulative stock returns, are generally lower for firms with more negative sentiment and higher risk related to the Covid-19 outbreak. These firm-level exposures to the disease account for significant variation in the cross-section of US and international stock returns.

Fourth, digging 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 concerns roughly balanced between these two categories. In the early days of the pandemic, many firms highlighted concerns relating to their supply chains. Later calls (in the second and third quarter of 2020) instead emphasize concerns relating to production, operations, and financing with relatively higher frequency. In regions of the world where the outbreak is more virulent, financing and supply problems tend to be relatively more significant (perhaps due to stricter lockdown measures or other public health restrictions). As a result, concerns among Chinese firms relate relatively more to demand than supply, while their peers in North America emphasize supply-related concerns relatively more frequently.

Finally, comparing the specific concerns firms associate with Covid-19 with those they associated with Ebola and other epidemic diseases, we find that Covid-19 stands out due to its relatively large supply and financing-related impact. More broadly, the pattern emerging suggests that those outbreaks affecting relatively fewer firms, such as Mers and Zika, have relatively lower supply-side impact than outbreaks that affect many firms at once.

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 fragments in conference calls and other firm disclosures.

Related literature. The paper contributes to two fast-growing literatures in economics and finance on Covid-19.[3] One literature asks whether the Covid-19 recession is caused by a demand shock, a supply shock, or a financial shock. Guerrieri et al. (2020) present a theory of Keynesian supply shocks: they argue that deterioration of demand associated to the Covid-19 pandemic will have larger economic effects than the supply shock that caused it. The optimal policy, then, to face the pandemic in their model, combines loosening of monetary policy and abundant social insurance. In a related study, Baqaee and Farhi (2020) focus on complementarity, as opposed to substitutability (Guerrieri et al., 2020), between sectors' goods. In a stylized quantitative model of the U.S., they find supply and demand shocks each explain about half the reduction in real GDP. Exploiting non-Gaussian features of macroeconomic forecast revisions, Bekaert et al. (2020) attribute two thirds of the decline in first- (second-) quarter 2020 GDP to a negative shock to aggregate demand (supply). Other studies include Fornaro and Wolf (2020) (considering the pandemic as a

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

negative shock to the growth rate in productivity) and Faria-e Castro (2020) (modeling the pandemic as a large negative shock to the utility of consumption).[4] 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. For policymakers, then, it is essential to know what caused the Covid-19 recession to develop effective policy responses. This requires granular data, not just of which firms are mostly affected by exposure to the pandemic, but also on what precisely describes the main challenge(s) they face. Our paper complements this literature by identifying for each firm the extent to which their Covid-19 exposure relates to demand, supply, or financing shocks, as well as the extent to which policy interventions are on the mind of executives and capital market participants.

Beyond the Covid-19 crisis, 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)). We believe that our work, and the empirical methods we develop here may also be useful in this broader debate.

This paper also contributes to the literature 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-related stock returns, Ding et al. (2020) use data on Covid-19 cases from the John Hopkins University Cornonavirus Covid-19 Global Cases database, to measure

[4] Atkeson (2020) and Eichenbaum et al. (2020) argue for integrating SIR models of the spread of a disease with conventional macroeconomic models to study the effect of policy interventions in this context. 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).

changes in the economy's exposure to the pandemic. Davis et al. (2020), on the other hand, rely on risk factor discussions in firms' pre-pandemic financial disclosures (Form 10-K filings) to characterize firm-level risk exposures, and find that pandemic-induced return reactions covary with firms' prior risk exposures. 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.

Beyond this, as a methodological contribution, we introduce a novel approach to topic identification: a new word pattern-based method, which enables us to automatically classify firms' primary concerns related to the Covid-19 pandemic. Other topic classification methods, in particular Latent Dirichlet Allocation (LDA), are viewed with suspicion by linguistics—e.g., for involving considerable subjectivity and for being non-deterministic (i.e., repeating the same procedure multiple times may generate different topic word lists).

In sum, we provide new data and first 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, however, we show how our text-based approach allows researchers, more generally, to investigate how corporations respond to 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 September 30, 2020 for 12,765 firms headquartered in 82 countries.[5] 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 and to 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, including data on firms' total assets and the location of the firm's headquarters from Refinitiv Eikon.[6] Stock return data are from the Center for Research in Securities Prices (CRSP) and Refinitiv Eikon.

2. Measuring Firm-Level Exposure to Epidemic Diseases

We measure and characterize firm-level exposure to epidemic diseases by combining methods described in our earlier work (Hassan et al., 2019, 2020) with a novel pattern-based approach designed to isolate firms' specific concerns relating to each disease.

2.1. Isolating discussions of epidemic diseases

The computational linguistic algorithms described in our two prior studies ultimately rest on a simple count of word combinations in earnings call transcripts to measure a given firm's political uncertainty or exposure to Brexit in a given quarter, respectively. In Hassan et al. (2019), a fundamental step is to determine which word combinations denote discussions about political topics. These political "bigrams" follow from comparing training libraries of

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

[6]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.

political text with those containing non-political text. In contrast, in Hassan et al. (2020), the word needed to identify discussions about "Brexit" is self-evident.

To identify keywords informative about the discussion of epidemic diseases, we begin by taking the list of pandemic and epidemic diseases maintained on the website of the World Health Organization and focus on those outbreaks that occur within our sample period, which starts in 2002.[7] 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 such outbreaks as the 2019 Chikungunya events in Congo and the 2018 Monkeypox in Nigeria.

For the remaining list of outbreaks, we identify the most common synonyms of 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 transcripts to verify that we are using the disease word (combinations) that were in use during each of these outbreaks. Finally, we verify that word combinations intended to capture diseases 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 word (combination) list, our time-varying measure of a given firm's *exposure* to an epidemic disease d, denoted $DiseaseExposure^d$, is constructed by parsing the available earnings call transcripts and 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 sentences in the transcript to account for differences in transcript length:

$$DiseaseExposure_{it}^{d} = \frac{1}{S_{it}} \sum_{b=1}^{B_{it}} 1[b = Disease_d], \tag{1}$$

where $b = 0, 1, ...B_{it}$ represents the words contained in the transcript of firm i in quarter t and S is the total number of sentences in the transcript.

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

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

To construct a measure of epidemic disease *risk*, denoted $DiseaseRisk^d$, we augment this procedure by conditioning on the proximity to synonyms for risk or uncertainty:

$$DiseaseRisk_{it}^d = \frac{1}{S_{it}} \sum_{b=1}^{B_{it}} \{1[b = Disease_d] \times 1[|b - r| < 10]\},$$

where r is the position of the nearest synonym of risk or uncertainty. Following the example of Hassan et al. (2019, 2020), we condition on a neighborhood of 10 words before and after the mention of an epidemic disease and obtain a list of synonyms for "risk" and "uncertainty" from the Oxford English Dictionary.[8]

We also require a measure of shocks to the firm's prospects, to gauge whether a disease outbreak is considered good or bad news to the firm.[9] 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, we condition on positive- or negative-tone words to capture the first moment. These positive- and negative-tone words are identified using the Loughran and McDonald (2011) sentiment dictionary:[10]

$$DiseaseSentiment_{it}^d = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} \left\{ \{1[b = Disease_d] \times \left(\sum_{c=b-10}^{b+10} S(c) \right) \right\},$$

where S assigns $+1$ if $c \in \mathbb{S}^+$, -1 if $c \in \mathbb{S}^-$, and zero otherwise. Positive words include 'good,'

[8] See Appendix Table 3 for a list of these synonyms.

[9] 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.

[10] Thirteen of the synonyms of 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. Empirically, when we include both $DiseaseRisk^d$ and $DiseaseSentiment^d$ in a regression, any variation that is common to both of these variables (as a result of overlapping words) is not used to estimate parameters of interest. For this reason, overlap does not, in principle, interfere with our ability to disentangle $DiseaseRisk^d$ from $DiseaseSentiment^d$.

'strong,' 'great,' while negative include 'loss,' 'decline,' and 'difficult.'[11,12] Appendix Table 4 show 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.

2.3. Measuring specific concerns relating to each epidemic disease

While our algorithm to measure firm-level exposure to epidemic diseases centers on counting synonyms of each disease in earnings-call transcripts, having the full conversation between management and market participants available, allows us to probe deeper into the underlying concerns of firms and financial analysts to understand *how* a disease impacts on 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] Rather than relying on a human reading of these snippets, we develop a word pattern based algorithm that automatically classifies sentence triples with minimal human judgement. Indeed, human judgement is limited to just two instances in the process.

[11] 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.

[12] 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.

[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 slightly more context than the interval of 10 words before and after the mentioning of the disease used in our definitions of $DiseaseRisk$ and $DiseaseSentiment$.

In a 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 below. Following this procedure, we identify six key topics: (1) demand, (2) supply chain, (3) production and operations, (4) costs, (5) financing, and (6) government support, where we sometimes collectively refer to categories 2-4 as supply-related.

In the second step, we automatically classify all sentence triples into these six key topics and a residual category that collects all other mentions of a disease, in particular those that are unspecific as to the impact on the firm.[14] 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 mention supply chains explicitly, they might instead mention that the SARS-crisis impacts their ability to source components. The challenge of this second step, therefore, is to do justice to such subtle variations when classifying sentence triples.[15] 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 six specific topics.

A *word pattern* consists 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 being actively discussed. For example, for a sentence triple to be assigned to the "supply chain" category, we require it to either include a directly-related phrase such as "supply

[14]For example: "There is no doubt that COVID-19 is impacting our business."

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

chain" or, for example, the combination of the words "component" and "impact." In addition, we allow a word pattern to specify topic-specific constraints that need to be satisfied 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. Or, to give another example, the word combination consisting of the words "cost" and "increased" may be not valid if the phrase "last year" appears in between these words.

To obtain such word patterns for each of the six topics we read and hand-label 600 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 six topics. This is our training data set. 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 data sets 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 set and that are economically closely linked to the topic (e.g., "stimulus" for the "government" category). We then check the fit of the pattern in our training data. 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.[16] We continue this process until the pattern predicts the labels in our training data with no more than 10 false positives and negatives. Once this threshold is met, we audit the pattern with a validation data set: We randomly draw 30 sentence triples that comply with the new pattern from the population of sentence triples mentioning Covid-19 in our earnings conference call data. 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

[16] 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.

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 data and, if needed, iterating and auditing again with another validation data set. Once we have arrived at a pattern that meets both criteria the iteration ceases.

Table 1 shows our final word pattern for each of the six topics. 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, which are somewhat more tedious to read and summarized in Appendix Table 5.

Looking across Table 1 shows that the word patterns are largely intuitive, where for example the "Production and Operations" topic features any discussions of [government] permits, productivity, throughput, closures, and shutdowns in conjunction with a mention of 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 six topics after the final iteration. 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. Finally 290 sentence triples relating to one of the other five topics are correctly identified as not relating to demand. Appendix Table 6 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.*

Finally, given our pattern-based classification of all sentence 174,582 triples mentioning Covid-19, we define each firm-quarter's exposure to a given Covid-19-related topic as

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

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

3. Exposure to Epidemic Diseases

3.1. Descriptive evidence

Next, we use our newly developed measures of firm-level exposure to epidemic diseases to document some salient empirical patterns present in the data. The emphasis in the discussion is on the firm-level exposure to the 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).[17] 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. SARS, which is also a disease 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. 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

[17] Our sample currently ends with calls held on September 30, 2020.

in China. Also, the time span during which diseases are discussed in earnings calls of China-based companies is much tighter than for firms in Europe and in the US.

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: in the Summer of 2020, more than three percent of all sentences in our transcripts contain 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 pattern 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 the summer months, albeit that sentiment remains negative overall. 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. Nevertheless, despite some recovery in the firm's assessment of the impact of the pandemic on their future cash flows, their risk assessment continue to be unabated high throughout the first three quarters of 2020. In this sense, for the average firm, Covid-19 is not only bad news but also confronts management with a major increase in uncertainty.

These aggregate patterns are important but mask interesting variation at the sector level as shown in panel A of Figure 4 (again using data for the first three quarters of 2020, up to September 30). High Covid-19 Risk is found in sectors such as Education and Healthcare, but also in Technology, whereas perceived risk associated with Covid-19 is noticeably lower for Energy and Utilities and Consumer Cyclicals. Importantly, the average sentiment is negative across sectors, but at the same time, outlooks are much less negative in Technology and Consumer Non-Cyclicals than in Transportation and Energy and Utilities. 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, the education and healthcare sectors face tremendous changes and volatility as Covid 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, still hide substantial heterogeneity between firms *within* a given sector. We illustrate this point in Figure 5 in which we plot Covid-19 Sentiment scores for firms in the S&P500 within the Transportation (Panel A) and Technology (Panel B) sectors, respectively. Reflecting the average sector scores in Figure 4, most of the Transportation-related firms have negative sentiment scores, whereas a substantial subset of Technology firms cluster in the positive region of the scale. Airline companies, such as United, American, and Delta feature prominently in panel A. Accordingly, when connecting their Covid-19 sentiment scores with the fragments in the earnings call transcript that weigh heavily into their position on this scale, we find negatively toned discussions. For example, United Airlines Holdings mentions in its May 2020 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". Delta likewise in July 2020 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 airlines, 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, to illustrate the (relatively) more optimistic tone in the Technology sector, consider Intel's assessment about its role in the pandemic in April 2020: "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 ...". 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 exposure, risk and sentiment vary across sectors, but also, significantly, 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 executives highlight production challenges and disruptions of the supply chain; United Continental reports severe financial impacts of a dramatic drop in demand; and Apple and ServiceNow experience increased demand for their products. We exploit these possibilities more in in our topic-based analysis below. Before doing so, however, we first briefly discuss whether epidemic data (on infection and mortality rates in the population) predict firm-level Covid-19 measures.

3.2. Infection rates and Covid-19 Exposure

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. Indeed, our Covid exposure measures could be subsumed by infection rates if what truly matters to understand the effects of the pandemic on firms, is simply the aggregate incidence of infections in the economy. We explore these questions closer in Appendix Table 7. In short, we find that infection and mortality rates in a country are positively associated with $\textit{COVID-19 Negative Sentiment}_{i,t}$, 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.

3.3. Two Case Studies

We further demonstrate the working of our $DiseaseExposure^d$ measure by providing two case studies. We choose two illustrative firms, plot their exposure scores to epidemic diseases during the sample period (summing across all diseases d), and include text excerpts taken from their conference call transcripts to explain the peaks in exposure. Figure 6, Panel A depicts the case of United Airlines Holdings (and its various predecessors), which has had significant exposure to successively SARS, H1N1, and Covid-19. An interesting excerpt from the Q1-2013 earnings call refers to United's earlier experience with H1N1 and how the airline has made sure it has flexibility in its capacity to deal with demand shocks. Both SARS and H1N1 receive ample attention during their respective outbreaks as the firm discusses how demand for air travel is (regionally) affected. The coronavirus makes its appearance in the first quarter of 2020, but the firm indicates that travel has not been impacted yet by any restrictions imposed by public health agencies. Nevertheless, measured exposure to the coronavirus remains very high throughout 2020.

The second case study, shown in Panel B of Figure 6, is on the US casual wear retailer Abercrombie & Fitch. In some ways, this company provides a good illustration of how unique the coronavirus outbreak is—its plot shows very little exposure to epidemic diseases before Covid-19, yet a large peak in Q1 2020. There is some discussion of how company operations are impacted during the SARS epidemic. The excerpt provided in the plot discusses how the firm experienced little disruption in its supply chain, even though movement of employees had been restricted. In the earnings call held in the first quarter of 2020, however, the outlook is much different. Abercrombie & Fitch estimate a drop in earnings due to store closures in mainland China, possible supply chain disruption, and increases in inventory. Compared with the earlier SARS exposure, the amount of discussion of the disease in the earnings call is much more extensive. Exposure scores decline somewhat as 2020 progresses, but remains at levels far exceeding the SARS outbreak.

3.4. Stock market response to 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 in (1) a long-window accumulated over the first three quarters of 2020, (2) the first quarter only, or (3) over a short window centered on the earnings call date (using earnings calls for all three quarters of 2020). Intuitively, standard asset pricing models suggest that a change in stock price occurs when investors, on 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 prices, 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:

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

where $Ret_{i,t}$ is either the cumulative quarterly return or the cumulative return a 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. Return variables are winsorized at the one percent level.

The vector Z contains the natural logarithm of the firm's assets as a control for size and the stock return beta, calculated by regressing daily returns in 2018 for firm i on the S&P500 index (to measure the firm's exposure to the US capital market). Where possible, we include both quarter (δ_t) and two-digit SIC sector (δ_s) fixed effects, as well as headquarter country fixed effects (δ_c) when we do not focus specifically on the sample of US firms. In all of these regressions, standard errors are robust.

Summary statistics for all variables are reported in Table 2. For ease of interpretation, we multiply all firm-level exposure, sentiment, and risk variables by 100, so that, for example, the mean of *COVID-19* $Exposure_{i,t}$ of 2.221 means that during the first three quarters of 2020, there are on average 2.221 Covid-19-related words per 100 sentences in an earnings call.

Table 3, panel A presents our estimation results using the quarterly returns over the first three quarters 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 deviation increase in *COVID-19 Exposure*$_{i,t}$ (0.023) is associated with a 1.92 percentage point lower 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 required rate of return, captured by *COVID-19 Risk*$_{i,t}$.

When regressing each of these variables onto the cumulative 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 in both the full and US samples (though the magnitude of the coefficients tends to remain stable across specifications). For example, in column 2, a one standard deviation increase in negative covid sentiment (1.225) is associated with a 1.9 percentage point decrease in stock returns.

We repeat this analysis in Table 3, panel B. In this panel, our attention is on the first quarter stock price response only. In this period, especially in January and February 2020, arguably, much of the impact of Covid-19 on the corporate world *in the US* was still unclear, whereas elsewhere in the world, most notably of course in China, the pandemic's consequences were already manifest. Accordingly, we observe some more pronounced differences between columns 1-3, reporting on the full sample, and columns 4-6, for the US only.

COVID-19 Exposure$_{i,t}$ is significantly negatively associated with first quarter returns in the full sample (column 1), but not in the US (column 3). Although the coefficient estimate for the US sample is sizeable, standard errors are about 35 percent higher than in the full sample. In the full sample, when we consider *COVID-19 Sentiment*$_{i,t}$ and *COVID-19 Risk*$_{i,t}$ separately, both are significantly associated with first quarter cumulative returns, with the predicted signs (column 2). Moreover, consistent with a much larger swing in aggregate stock prices in the first quarter, all estimated coefficients are about three times larger than those in Panel A.

In panel C, finally, we examine the short window returns surrounding the earnings call in which Covid-19 is discussed. We use earnings calls from all three quarters of 2020. Both in the full and US samples, we document a significant negative association between *COVID-19 Exposure*$_{i,t}$ and three-day returns (columns 1 and 4), consistent with the view that conference calls reveal some incremental information about firms' covid exposure. In column 1, the estimated coefficient implies that a one standard deviation increase in *COVID-19 Exposure*$_{i,t}$ (0.023) is associated with a 0.54 percentage point lower return in this narrow window around he 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 required rate of return, captured by *COVID-19 Risk*$_{i,t}$. We find, both in the full and US samples, 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.

Across all the panels of Table 3, the conclusion emerges that our measures of covid risk and sentiment indeed contain information relevant to firms' fortunes during the coronavirus pandemic, and that some of this information may in fact be originally transmitted to markets through conference calls (Panel C). The association between stock returns and our measures is strongest in the first quarter, when markets world-wide first crashed in response to the outbreak, but remains significant throughout all three quarters. That is, the fall and subsequent recovery in aggregate stock prices in the winter and summer of 2020 mask significant covid-induced heterogeneity in the cross-section of firms. We aim to systematically exploit the discussions of how a firm is affected by the pandemic in the earnings call transcripts in the next section, in which we identify the content of covid-related concerns and use this to shed light on how the speed of recovery and the type of concern are related.

4. The Supply, Demand, and Financing Impacts of Epidemic Diseases

Table 4 presents the findings from our automated reading of the full sample of coronavirus sentence triples. We assess the frequency with which a topic category is mentioned in the conference call by computing the percentage of Covid-19 related triples with a given topic label among all Covid-19 related sentence triples in our corpus. As shown, the most commonly voiced concern when the discussion turns to the possible impact of the pandemic on the firm is the sudden change in demand. Indeed, 30.91 percent of all sentence triples mention *demand*, as witnessed in our showcased sentence triple in Table 4, which explicitly links a negative impact on revenues to Covid-19 .

Financial analysts also question management about disruptions to the *supply chain* (4.14 percent) and operations or the closure of a given firm's own *production* facilities and stores (20.00 percent). A typical example is management noting that "traditional and convenience stores are closing or suffering from a significant in-store traffic decline" and "several of our factories and warehouses are closed to comply with local government regulations." Higher costs, and cost-saving measures, due to Covid-19 represent a further "supply side" concern, that is discussed in 9.44 percent of the sentence triples. In some cases, firms explicitly mention that they have taken precautionary measures to diversify their supply lines based on their prior experience with an epidemic disease (most often SARS).

Turning to *financing* frictions, a concern that becomes more prominent for many firms in the second quarter of 2020, as we will document below, we classify 10.08 percent of triples in this category. A relatively small percentage of triples (viz., 1.41 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. Figure 7 provides a visualization of the changes in frequency in which each of these aforementioned categories are discussed in earnings calls over the period between January and September 2020. At least three takeaways are noteworthy. First, throughout the sample period, demand-side and supply-side issues (i.e., the combination of supply chain, costs, and production and operations concerns) are discussed the foremost, with the remaining topics trailing considerably in the attention garnered in calls. Second, supply-side and demand-side concerns 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 unspecific covid discussions that can *not* be specifically attributed to one of our six categories. One takeaway from this figure is that in the first quarter, relatively more mentions of Covid-19 did not touch on specific concerns but rather voiced a generic uncertainty about what would happen next. As the impact of the pandemic unfolds over the following quarters, this "unspecific" category shrinks as more and more mentions are tied directly to one of our six topics. By the end of our sample, we can allocate about 60 percent of 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 8, we examine the relative importance of (1) demand versus supply exposure (in panel A) and (2) financing versus non-financing exposure (in panel B) by geography and by sector, respectively.[18] Values larger than unity on the scale denote demand exposure exceeds supply exposure in the first panel. Financing exposure is always lower than exposure to the other five non-financing topics.

In Asia and in China (which we separate from Asia in the Figure), and to a lesser extent in Europe, Covid-19 Exposure is relatively more demand-related. In contrast, in North America and other regions of the world, supply and demand exposure carry almost equal

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

weight. While this broad geographic pattern could be accounted for by a number of different factors, it is notable that regions in which the outbreak is relatively more controlled in the second and third quarter (particularly China and many other Asian countries) skew more towards demand-related concerns.

At the sector level, in Basic Materials, Health Care, and Energy and Utilities, supply exposure clearly dominates, whereas for Technology demand exposure is 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 China. Interestingly, whereas Healthcare and Energy and Utilities have similar relative supply exposure, they are on opposite ends with regard to their exposure to financing. In Healthcare, transcripts of few firms feature concerns about access to credit or liquidity constraints, whereas the conversation turns to these issues much more for Energy and Utilities, Academic services, and Transportation.

Returning to our sample of S&P 500 firms, Figure 9 plots the variation of relative demand and supply exposure (in panel A) and relative finance and non-finance exposure (in panel B). 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 relative exposure scores, provides further details. For example, Kinder Morgan executives, in April 2020, answer the following to a question of a financial analyst on the earnings call: "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 the January Coca Cola 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. Deer & Co in February 2020 discuss 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 9 hones in on the relative finance exposure of S&P500 companies. Discussions in the conference call 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 April 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." As a final example, 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."

It is instructive to compare the relative demand, supply and financing exposure due to Covid-19 with other outbreaks. Figure 10 offers such a comparison between Covid-19 and Ebola, SARS, H1N1, Zika, and MERS. 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 skew much 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 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.

The comparison with earlier diseases is important for another reason revealed by our systematic analysis of snippets: these earlier outbreaks are frequently invoked when discussing the impact of Covid-19. For example, the January 2020 Coca Cola call described above continues 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 the call in January 2020 with the assessment that "Historically, 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 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.

5. Firm-level Resilience to Epidemic Diseases

In this section, we ask whether firms' expectations regarding their first moment exposures to epidemic diseases vary predictably in the cross-section. In particular, based in part on our analysis of earnings-call transcripts, we consider whether a firm's prior exposure to the next-most virulent diseases, SARS and H1N1, allows firms to learn from the experience and shapes their expectations for the corona-epidemic. As noted earlier, management, with some frequency, mention their prior experience with SARS (or H1N1) in the first quarter 2020 calls when the discussion turns to the possible impact of the coronavirus.

While firms might learn from their prior experience, ultimately, the SARS and H1N1 epidemics were of a much smaller magnitude and with less severe macroeconomic consequences than the Covid-19 outbreak. Thus, firms might very well *overestimate* their preparedness based on their SARS experience. *Prior* exposure, in other words, might at the outset help as well as harm firms in dealing with Covid-19. Both possibilities, however, would suggest that prior epidemic experience is associated with less negative sentiment related to Covid-19.

We provide some first evidence on this question by estimating Ordinary Least Squares regressions specified as follows:

$$\begin{aligned} \textit{COVID-19 Negative Sentiment}_{i,t} &= \delta_t + \delta_c + \delta_s + \beta \times \textit{Prior Epidemic Exposure}_i \\ &\quad + \theta \times \textit{COVID-19 Exposure}_{i,t} + Z'_{i,t}\nu + \epsilon_{i,t} \end{aligned}$$

where *Prior Epidemic Exposure*$_i$ is the scaled (by the number of sentences) count of the SARS and H1N1 synonyms (measured at the peak of their outbreaks in 2003 and 2009, respectively). *COVID-19 Negative Sentiment*$_{i,t}$ (scaled by the number of sentences) counts the use of negative-tone words used in conjunction with discussions of Covid-19. As before, we include sector fixed effects and time and country fixed effects, where appropriate, and report robust standard errors.

Table 5 presents our estimation results. In panel A, we use observations from the first three quarters of 2020. Discussions surrounding the coronavirus are overwhelmingly negative. Accordingly, in column 1, the estimated coefficient on *COVID-19 Exposure*$_{i,t}$ shows that on average, each mention of the coronavirus is accompanied by 0.410 (s.e.=0.008) negative tone words.

Turning next to the question of whether prior epidemic experiences are associated with more negative expectations for the future during the coronavirus period, we find some evidence consistent with the conjecture that firms that had more extensive discussions in their earnings calls of SARS or H1N1 in the past (i.e., higher *Prior Epidemic Exposure*$_{i,t}$), have significantly less negative coronavirus-related sentiment scores. For example, in column 2, a one standard deviation increase in prior epidemic exposure (4.044) is associated with a 2.3 percent decrease (relative to the mean) in the frequency of negative tone words used in conjunction with discussions of coronavirus. In terms of expectations (first moment) at least, it thus appears that firms with prior experience are somewhat more positive about the impact of the coronavirus on their business. We find very similar results when we consider a sample of US firms only. Indeed, *COVID-19 Exposure*$_{i,t}$ is associated with more negative sentiment; the coefficient estimate varies little compared to the full sample (0.403, s.e.=0.010).

We repeat the same analysis in Panel B, but we restrict the sample to the first quarter only (and accordingly drop the quarter fixed effects). Prior experience with an epidemic disease might plausibly be most helpful during the initial phases of the outbreak, with firms potentially having more counter-measures in place or a better understanding of the scenarios that might develop. We find that the estimate on Covid-19 exposure, while still indicating a significantly positive association with *COVID-19 Negative Sentiment*$_{i,t}$, drops by about 14 percent suggesting that earlier mentions of the pandemic tended to be more neutrally toned. More to the point, however, the coefficient on *Prior Epidemic Exposure*$_{i,t}$ increases in magnitude to -0.033 (-0.038 in the US sample), consistent with prior experience with SARS or H1N1 having a larger impact in the first quarter than in the two quarters thereafter.

Together, these findings provide some support for the idea that firms with prior disease exposure are, correctly or not, more optimistic about their ability to handle the fallout of Covid-19 inasmuch as the discussions about the coronavirus in earnings calls of firms with prior disease experience is somewhat more positive than for firms without such history,

6. 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 formulating 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 just 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 nature of the key issues firms face as they respond to the challenges of the pandemic.

Our main findings are as follows: First, even compared to other large-scale epidemics, Covid-19 is unique in that it is affecting 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, going below the aggregate of time-series patterns of Covid exposure, risk and sentiment throughout the first three quarters of 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 most 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 firms. Moreover, firms based in regions of the world where the pandemic is relatively less controlled experience relatively larger supply and financing-related impacts on their businesses.

We are able to pinpoint, for each firm, the relative importance of demand, supply, and financing shock 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), this renders the data potentially well-suited for policy purposes as well as for longer-haul fundamental work that is sure to emerge once the dust has settled.

References

Adda, J. (2016). Economic activity and the spread of viral diseases: Evidence from high frequency data. *The Quarterly Journal of Economics 131*(2), 891–941.

Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott (2020). Aggregate and firm-level stock returns during pandemics, in real time. *NBER Working paper no. 26950*.

Alon, T., M. Kim, D. Lagakos, and M. VanVuren (2020). How should policy responses to the COVID-19 pandemic differ in the developing world? *NBER Working paper no. 27273*.

Arnon, A., J. Ricco, and K. Smetters (2020). Epidemiological and economic effects of lockdown. *Brookings Papers on Economic Activity*.

Atkeson, A. (2020). What will be the economic impact of Covid-19 in the US? Rough estimates of disease scenarios. *NBER Working paper no. 26867*.

Au, S.-Y., M. Dong, and X. Zhou (2020). Does social interaction spread fear among institutional investors? Evidence from Covid-19. *Working paper, York University*.

Baker, S., N. Bloom, S. Davis, K. Kost, M. Sammon, and T. Viratyosin (2020, Mar 27). The unprecedented stock market reaction to COVID-19. *Working paper, Northwestern University*.

Baqaee, D. and E. Farhi (2020). Nonlinear production networks with an application to the covid-19 crisis. *NBER Working paper no. 27281*.

Barro, R. J., J. F. Ursúa, and J. Weng (2020). The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. *NBER Working paper no. 26866*.

Bekaert, G., E. Engstrom, and A. Ermolov (2020). Aggregate Demand and Aggregate Supply Effects of COVID-19: A Real-time Analysis. *Available at SSRN 3611399*.

Blanchard, O. and D. Quah (1989). The dynamic effects of aggregate demand and supply disturbances. *American Economic Review 79*(4), 655–673.

Bretscher, L., A. Hsu, P. Simasek, and A. Tamoni (2020). Covid-19 and the cross-section of equity returns: Impact and transmission. *The Review of Asset Pricing Studies, Forthcoming*.

Davis, S. J., S. Hansen, and C. Seminario-Amez (2020). Firm-level risk exposures and stock returns in the wake of COVID-19. *NBER Working paper no. 27867*.

Ding, W., R. Levine, C. Lin, and W. Xie (2020). Corporate immunity to the COVID-19 pandemic. *NBER Working paper no. 27055*.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). The macroeconomics of epidemics. *NBER Working paper no. 26882*.

Faria-e Castro, M. (2020). Fiscal policy during a pandemic. *FRB St. Louis Working paper no. 2020-006*.

Ferrando, A. (2020). Firms' expectations on access to finance at the early stages of the Covid-19 pandemic. *ECB Working paper no. 20202446*.

Fogli, A. and L. Veldkamp (2020). Germs, social networks and growth. *Review of Economic Studies, Forthcoming*.

Fornaro, L. and M. Wolf (2020). Covid-19 coronavirus and macroeconomic policy. *CEPR Discussion paper no. DP14529*.

Greenwald, D. L., J. Krainer, and P. Paul (2020). The credit line channel. *FRB of San Francisco Working paper no. 2020-26*.

Greenwood, J., P. Kircher, C. Santos, and M. Tertilt (2019). An equilibrium model of the african hiv/aids epidemic. *Econometrica 87*(4), 1081–1113.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020). Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages? *NBER Working paper no. 26918*.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics 134*(4), 2135–2202.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2020). The global impact of brexit uncertainty. *NBER Working paper no 26609; INET Working paper no. 106*.

Hollander, S., M. Pronk, and E. Roelofsen (2010). Does silence speak? An empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research 48*(3), 531–563.

Joaquim, G. and F. Netto (2020). Bank incentives and the impact of the Paycheck Protection Program. *Available at SSRN 3704518*.

Kaplan, G., K. Mitman, and G. L. Violante (2020). The housing boom and bust: Model meets evidence. *Journal of Political Economy, Forthcoming*.

Kaplan, G., B. Moll, and G. Violante (2020). The great lockdown and the big stimulus: Tracing the pandemic possibility frontier for the U.S. *Working paper, University of Chicago*.

Kargar, M., B. Lester, D. Lindsay, S. Liu, P.-O. Weill, and D. Zúñiga (2020). Corporate bond liquidity during the COVID-19 crisis. *NBER Working paper no. 27355*.

Loughran, T. and B. McDonald (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance 66*(1), 35–65.

Loughran, T. and B. McDonald (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research 54*(14), 1187–1230.

Ma, Y., K. Xiao, and Y. Zeng (2020). Mutual fund liquidity transformation and reverse flight to liquidity. *Available at SSRN 3640861*.

Mian, A., K. Rao, and A. Sufi (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics 128*(4), 1687–1726.

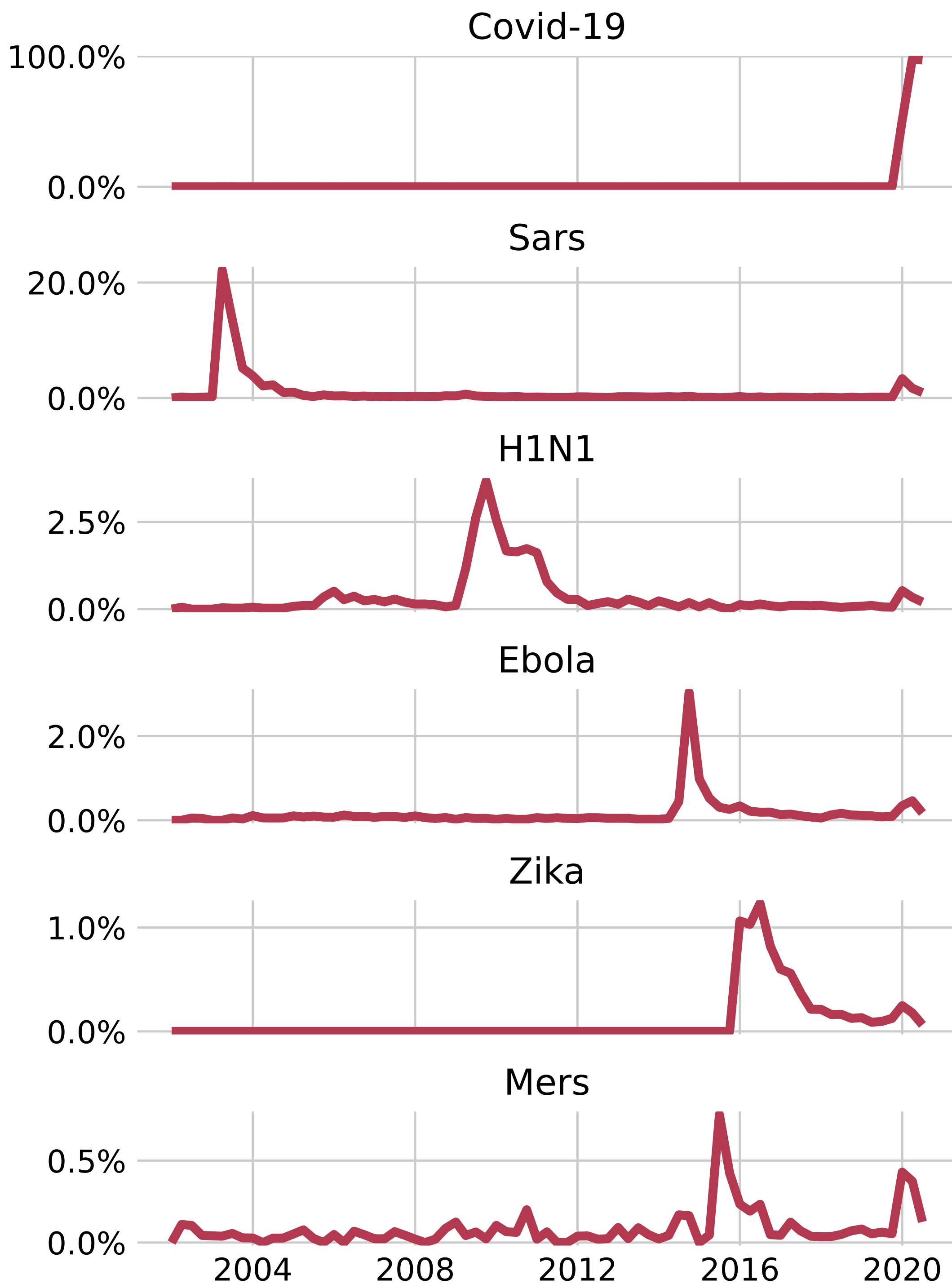
Moser, C. and P. Yared (2020). Pandemic lockdown: The role of government commitment. *NBER Working paper no. 27062*.

Ozik, G., R. Sadka, and S. Shen (2020). Flattening the illiquidity curve: Retail trading during the covid-19 lockdown. *Available at SSRN 3663970*.

Philipson, T. (1999). Economic epidemiology and infectious diseases. *NBER Working paper no. 7037*.

Ramelli, S. and A. Wagner (2020). Feverish stock price reactions to COVID-19. *Swiss Finance Institute Research Paper no. 20-12*.

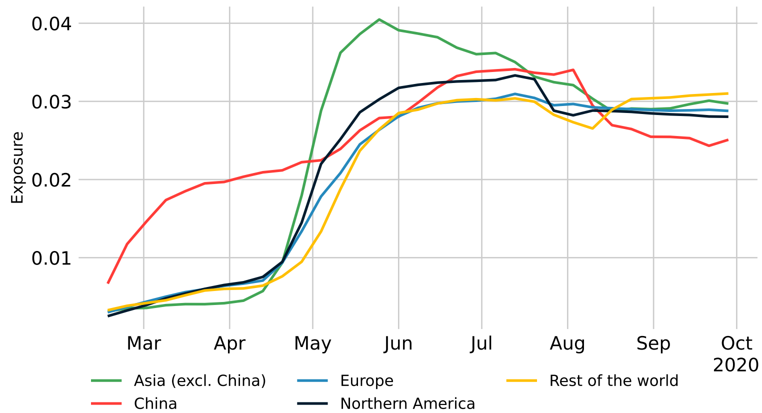
Figure 1: Percentage of earnings calls discussing epidemic diseases



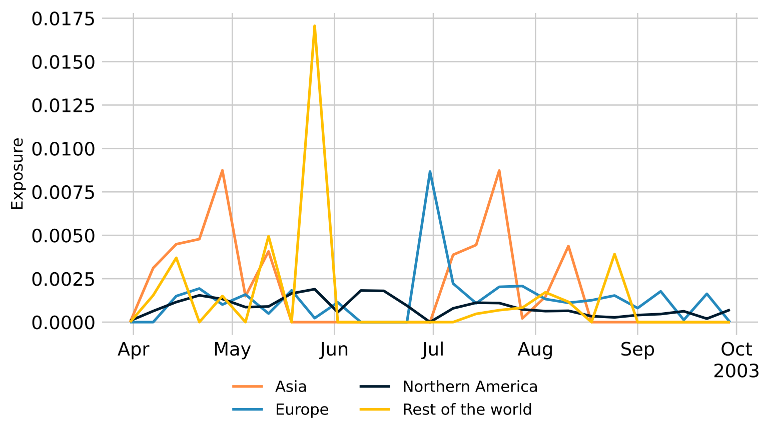
Notes: This figure plots the percentage of earnings calls discussing epidemic diseases (COVID-19, SARS, H1N1, Ebola, Zika, and MERS) by quarter from 2002q1 to 2020q3.

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

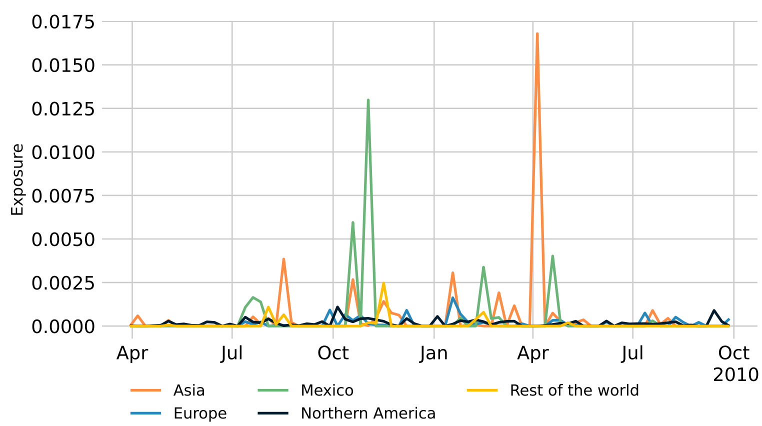
(a) Average *COVID-19 Exposure*$_{i,t}$ by region



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



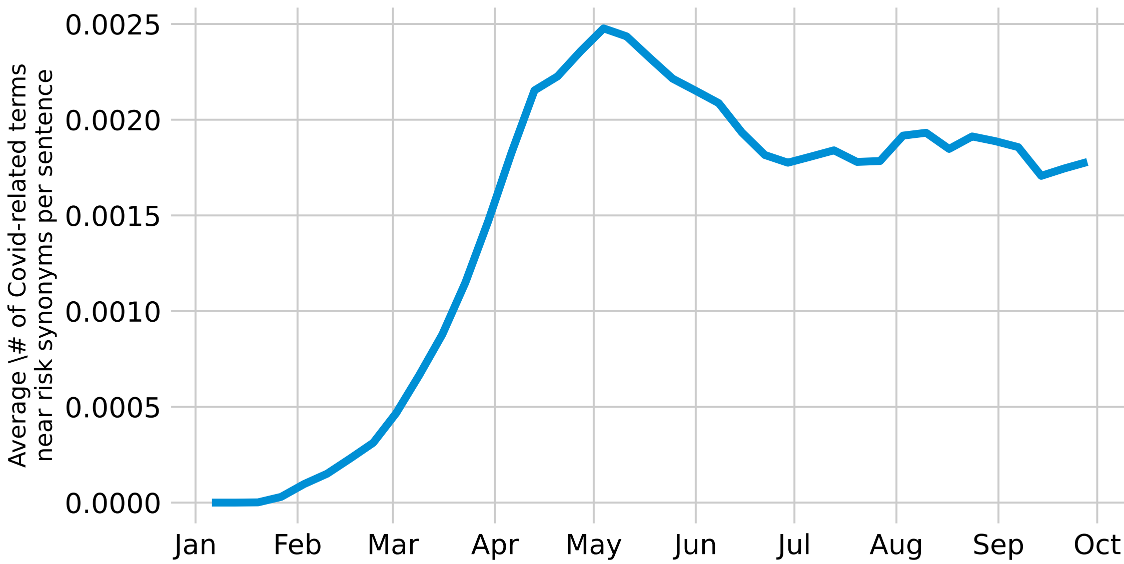
(c) Average *H1N1 Exposure*$_{i,t}$ by region



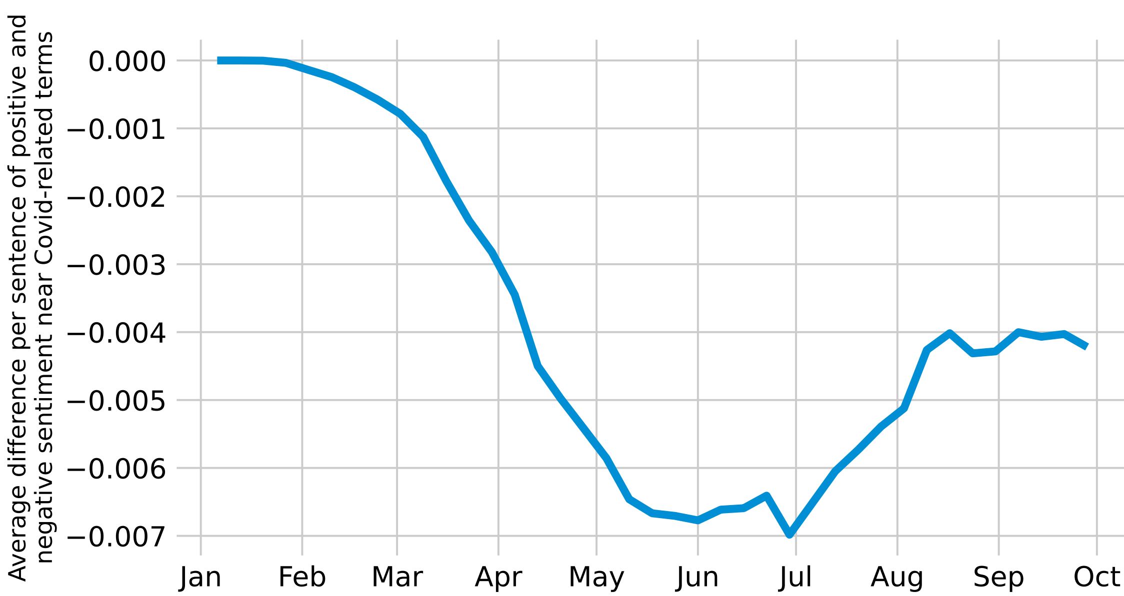
Notes: This figure plots the weekly average for firms headquartered in the indicated region of *COVID-19 Exposure*$_{i,t}$, *SARS Exposure*$_{i,t}$, and *H1N1 Exposure*$_{i,t}$ for the first 7+ months after the initial outbreak. Exposure measures are scaled by the number of sentences in the transcript. 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*



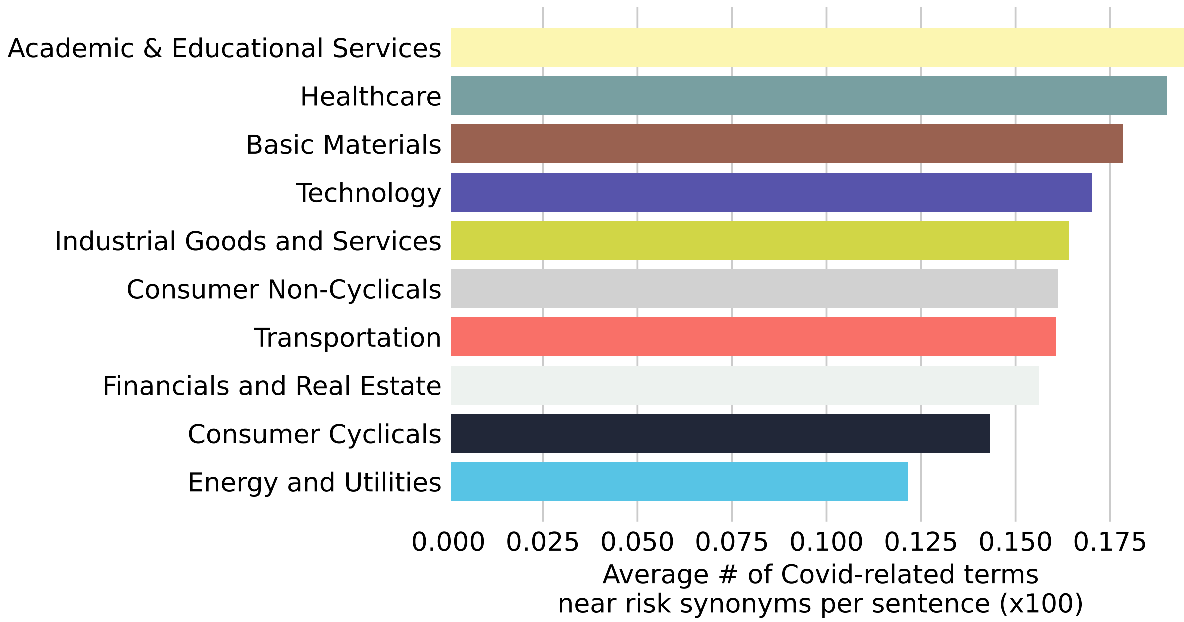
(b) Weekly average of *COVID-19 Sentiment*



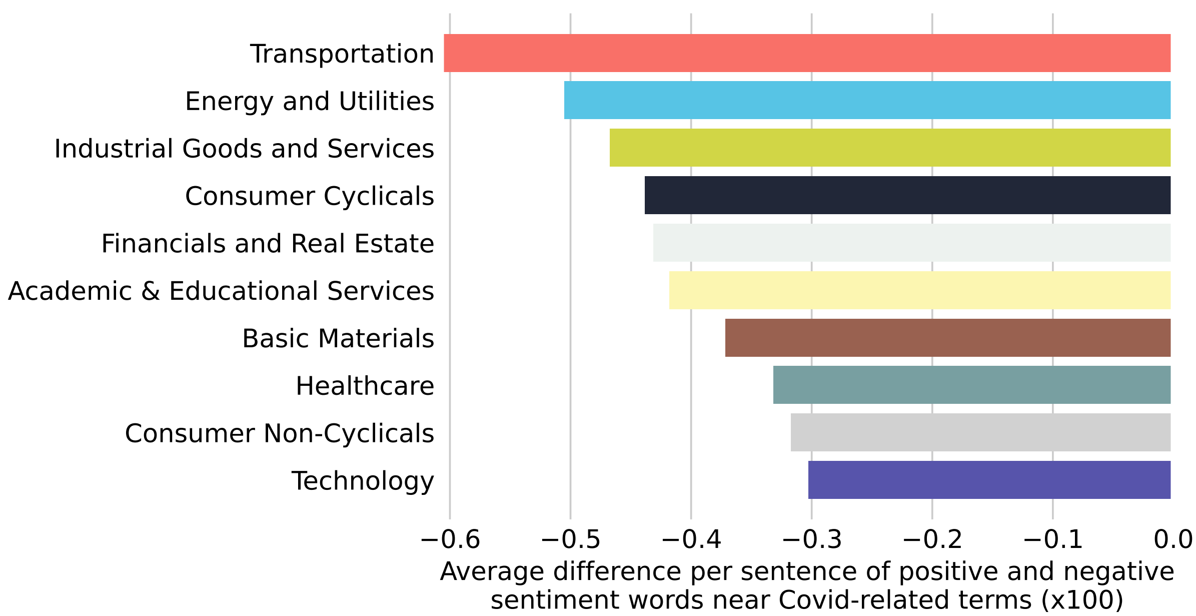
Notes: This figure plots the weekly average across all earnings calls between January 6, 2020 and September 28, 2020 of *COVID-19 Risk*$_{i,t}$ and *COVID-19 Sentiment*$_{i,t}$. The time series are smoothed with a moving-average using the last 6 weeks with equal weighting.

Figure 4: Sectoral averages of *COVID-19 Sentiment*$_{i,t}$ and *COVID-19 Risk*$_{i,t}$

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



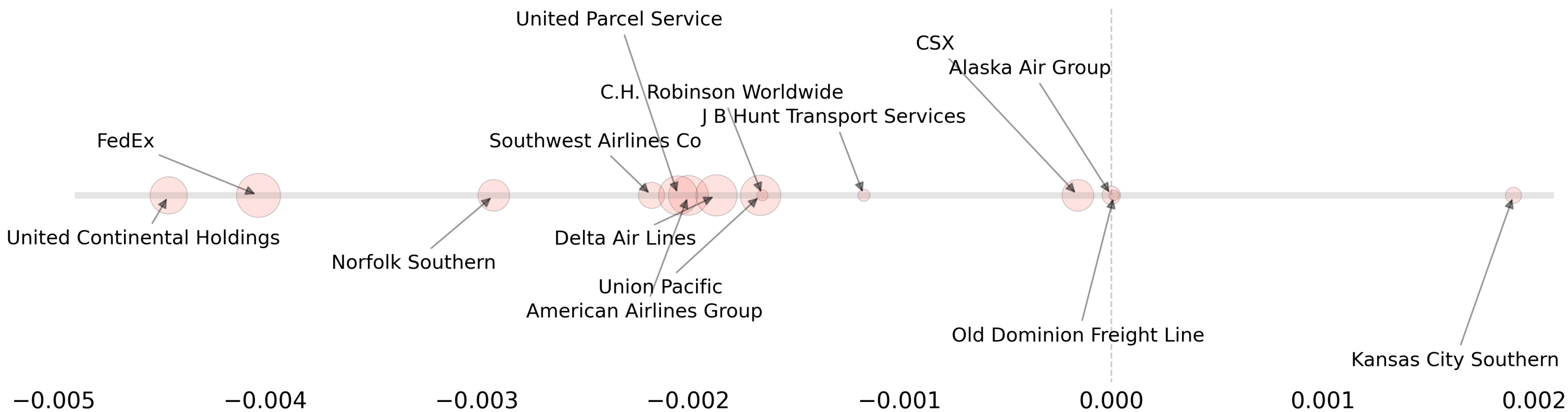
(b) Sectoral averages of *COVID-19 Sentiment*$_{i,t}$



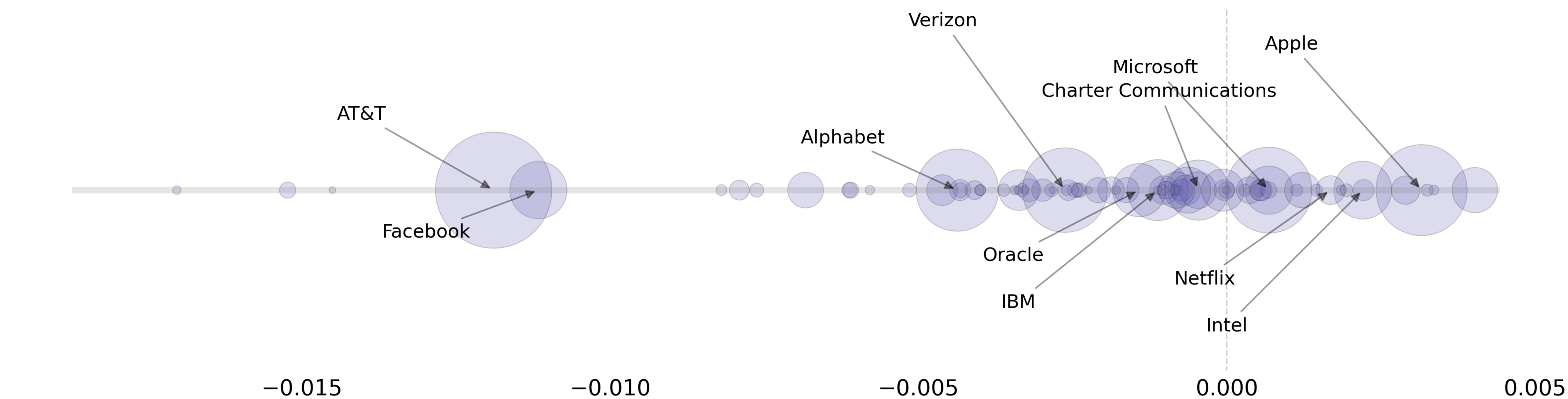
Notes: This figure plots the sectoral averages of *COVID-19 Sentiment*$_{i,t}$ and *COVID-19 Risk*$_{i,t}$ across all earnings calls by firms in the indicated sector. The averages are multiplied by 100 for easier exposition. The firm sector classification is the firm's "Economic Sector" from Thomson Eikon.

Figure 5: $COVID-19 Sentiment_i$ of S&P 500 firms: Transportation and Technology

(a) *COVID-19 Sentiment*$_i$ for sector: Transportation



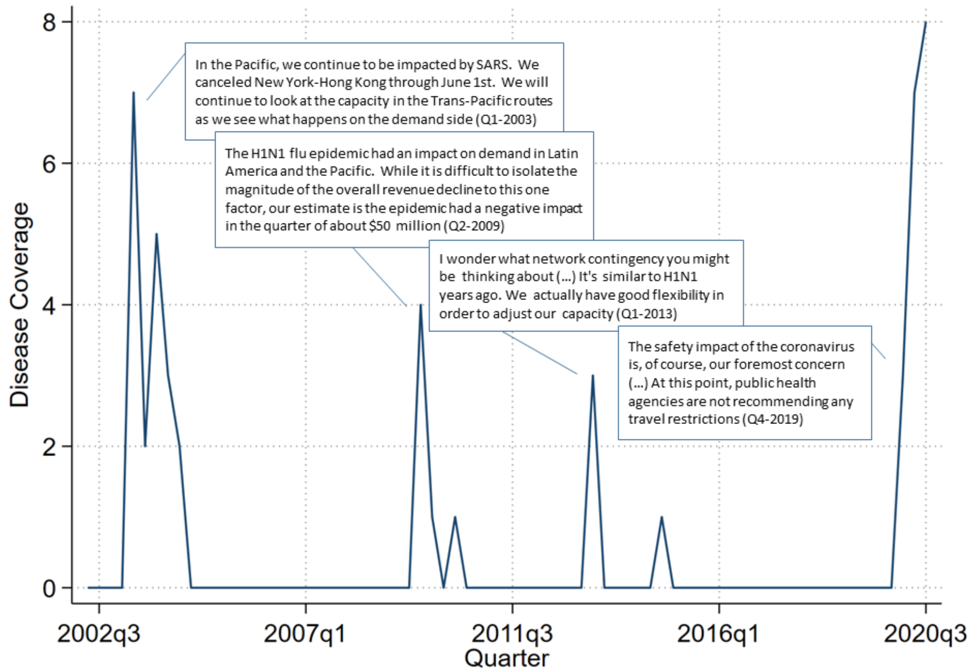
(b) *COVID-19 Sentiment*$_i$ for sector: Technology



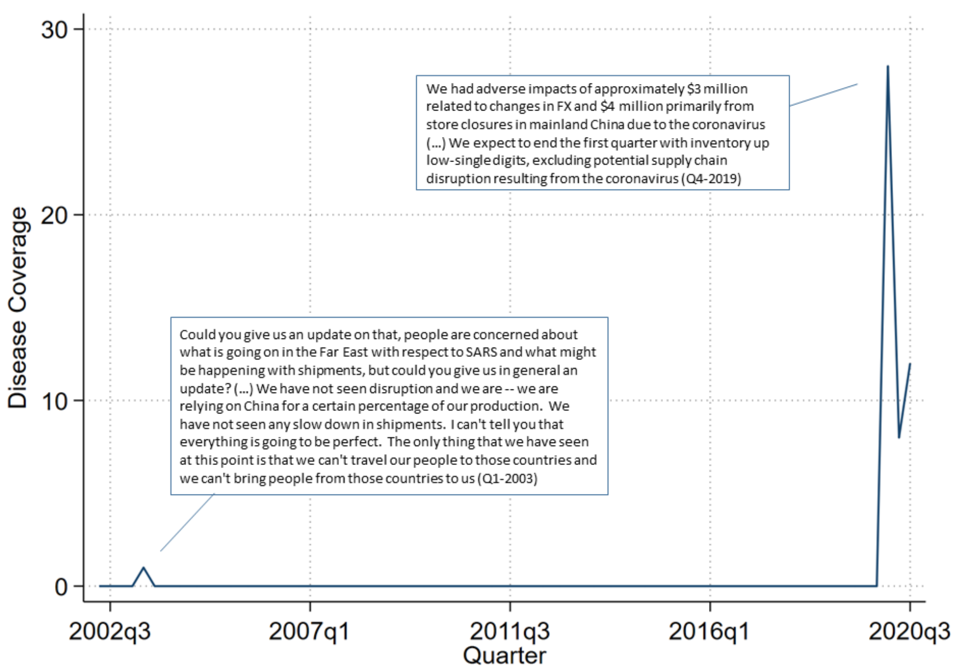
Notes: This figure plots in panels (a) and (b) the firm level average of *COVID-19 Sentiment*$_i$ of its earnings calls between January and October 2020 in the Transportation and Technology sector, respectively. Firms are restricted to be in the S&P 500. The size of the circles corresponds to the firm's latest available total assets.

Figure 6: Two case studies: United Airlines and Abercrombie & Fitch

(a) United Airlines

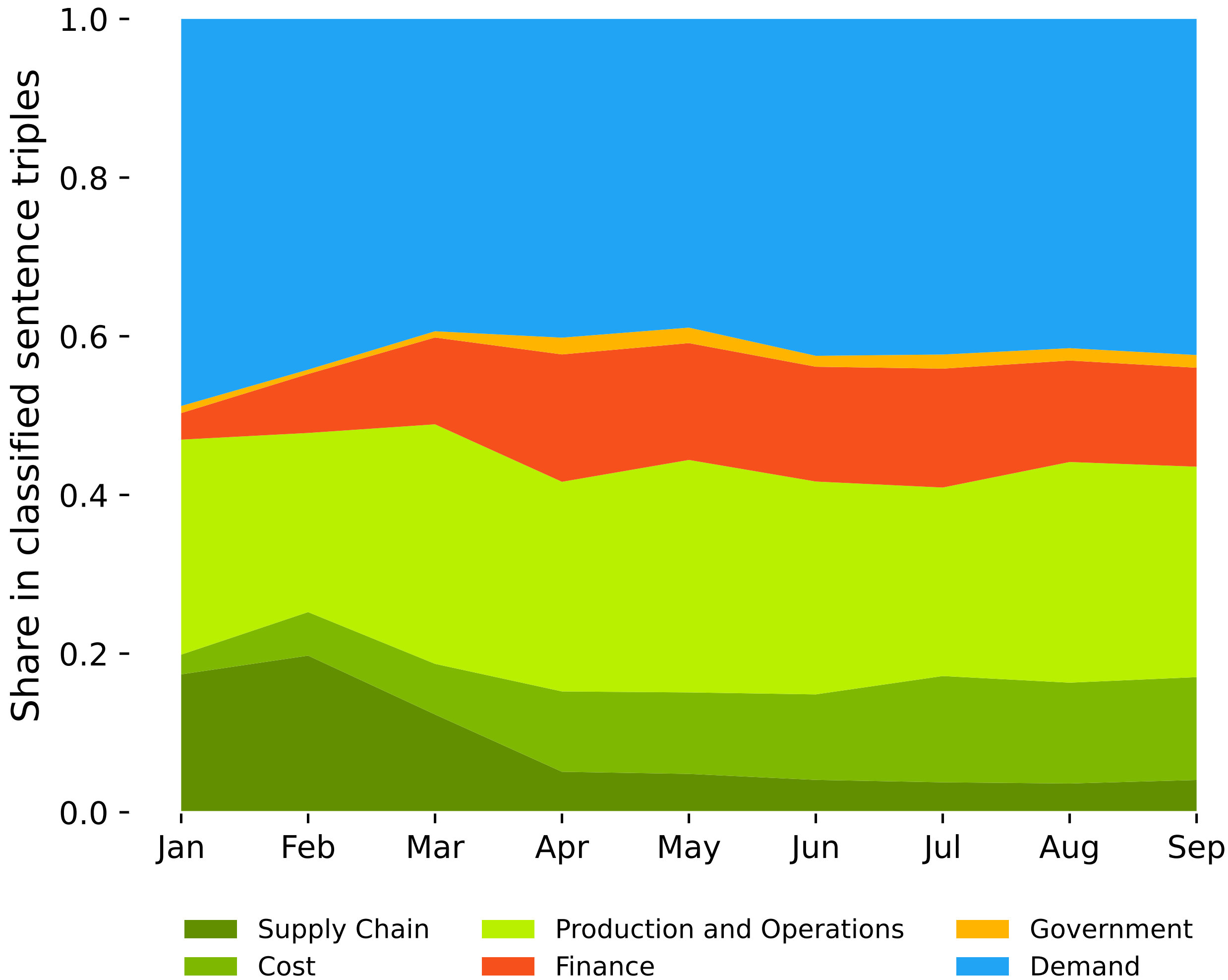


(b) Abercrombie & Fitch



Notes: This figure shows $\sum_d DiseaseExposure^d_{i,t}$ as defined in Section 2 for two illustrative firms: United Airlines (Panel a) and Abercrombie & Fitch (Panel b).

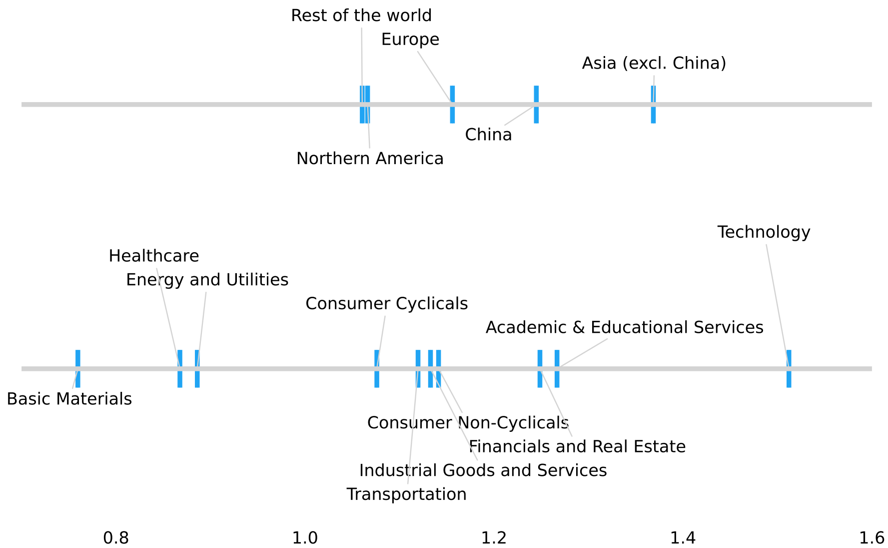
Figure 7: Classification into topics of COVID-19-related speech



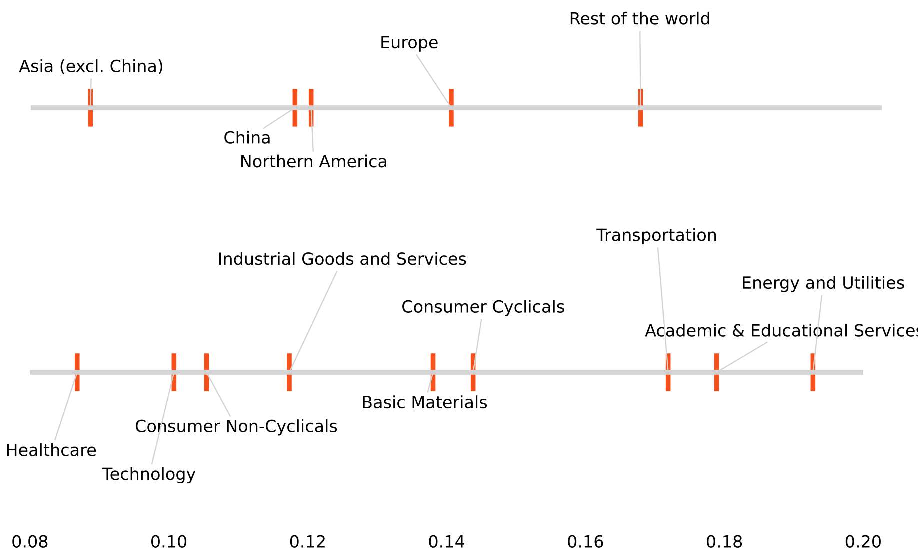
Notes: This figure plots the share of each of six topics in all classified sentence triples mentioning Covid-19 in the first three quarters of 2020. Sentences assigned to multiple topics are duplicated for the purpose of determining the denominator, so that shares add up to one. A sentence triple is 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 to (and including) September 2020.

Figure 8: Relative importance of topics in regional and sectoral averages of *COVID-19 TopicExposure*$_{i,t}$

(a) Regional and sectoral averages of *COVID-19 Demand/Supply Exposure*$_{i,t}$



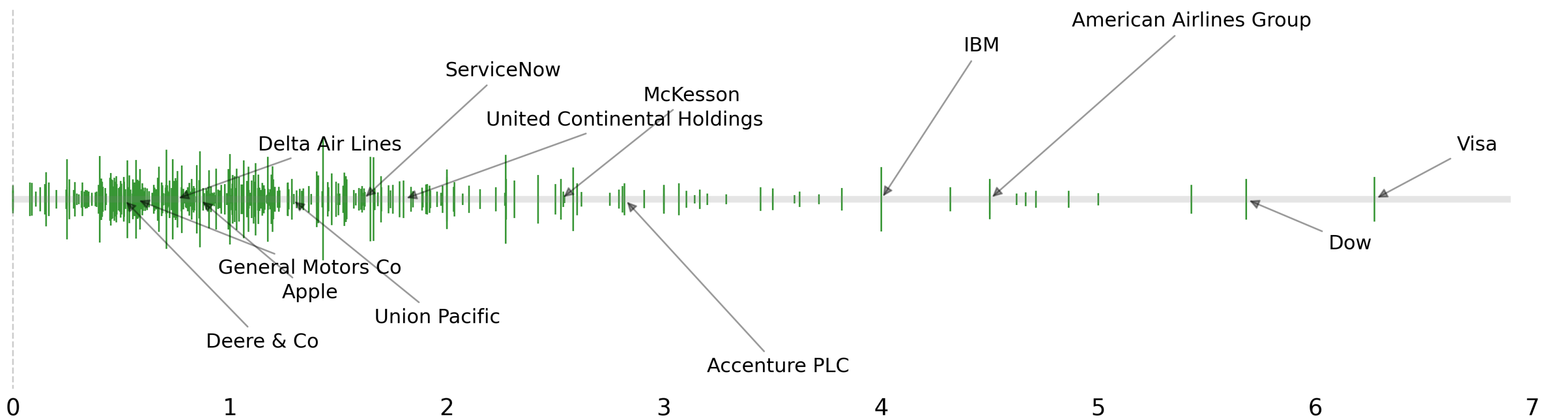
(b) Regional and sectoral averages of *COVID-19 Finance/non-Finance Exposure*$_{i,t}$



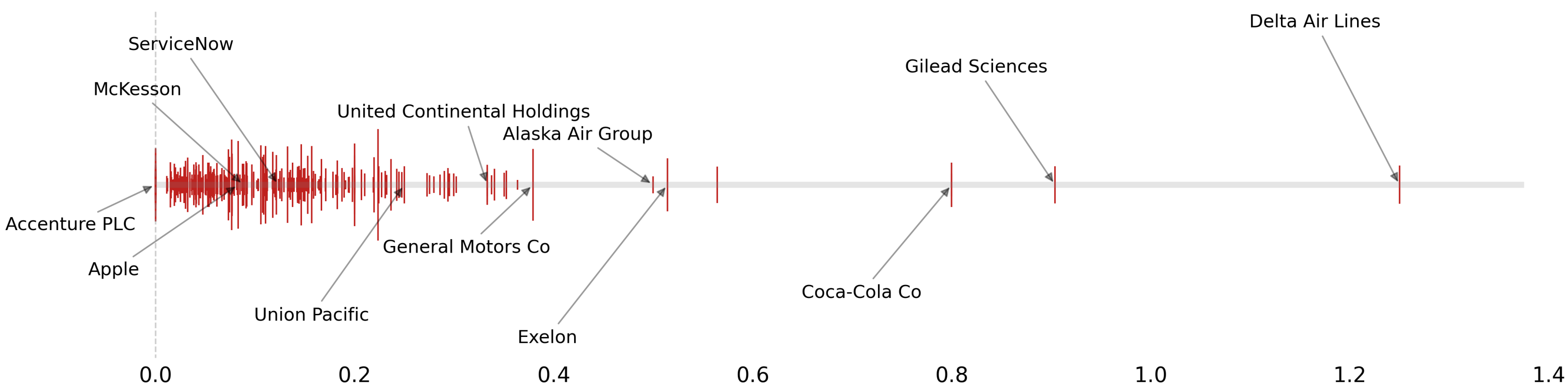
Notes: This figure plots regional and sectoral averages of *COVID-19 Demand/Supply Exposure*$_{i,t}$ (panel (a)) and *COVID-19 Finance/non-Finance Exposure*$_{i,t}$ (panel (b)). In panel (a), *COVID-19 Demand/Supply Exposure*$_{i,t}$ is defined as the ratio of *COVID-19 Demand Exposure*$_{i,t}$ to *COVID-19 Supply Exposure*$_{i,t}$, where *COVID-19 Supply Exposure*$_{i,t}$ is defined to be the sum of the COVID-19 Supply Chain, Cost, and Production and Operations exposures. In panel (b), *COVID-19 Finance/non-Finance Exposure*$_{i,t}$ is defined as the ratio of *COVID-19 Finance Exposure*$_{i,t}$ to *COVID-19 non-Finance Exposure*$_{i,t}$, where *COVID-19 non-Finance Exposure*$_{i,t}$ is defined as the sum of the COVID-19 Supply Chain, Cost, Production and Operations, Government, and Demand exposures. In panel (b) we exclude firms in the Finance and Real Estate sector.

Figure 9: Examples of non-financial S&P 500 firms for *COVID-19 Demand/Supply Exposure*$_i$ and *COVID-19 Finance/non-Finance Exposure*$_i$

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

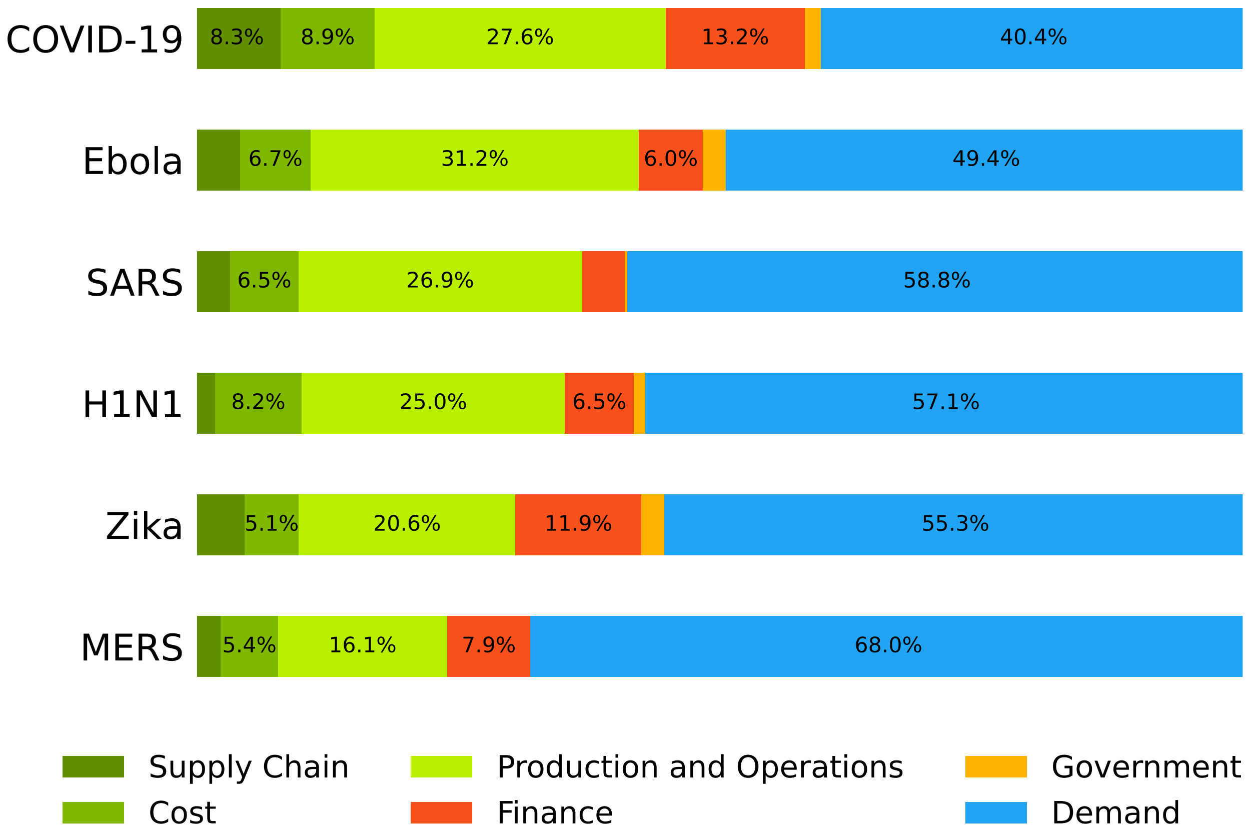


(b) *COVID-19 Finance/non-Finance Exposure*$_i$



Notes: This figure plots *COVID-19 Demand/Supply Exposure*$_i$ and *COVID-19 Finance/non-Finance Exposure*$_i$ in panels (a) and (b), respectively, of all earnings calls by non-financial S&P 500 firms that were held between January and October 2020. *COVID-19 Demand/Supply Exposure*$_i$ is defined as firm *i*s average *COVID-19 Demand*$_{i,t}$ over its average *COVID-19 Supply*$_{i,t}$. Analogously, *COVID-19 Finance/non-Finance Exposure*$_i$ is defined as firm *i*s average *COVID-19 Finance*$_{i,t}$ over its average *COVID-19 non-Finance*$_{i,t}$. Panel (a) excludes Salesforce.com Inc with *COVID-19 Demand/Supply Exposure*$_i$ of 33. The size of the marker corresponds to the firm's latest available total assets.

Figure 10: Comparison of disease-related topics in initial quarters of 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 mentions. The initial three quarters are defined as the peak quarter (see Figure 1) plus one quarter before and after. In particular, they are 2019q4-2020q2 for COVID-19, 2014q3-2015q1 for Ebola, 2003q1-2003q3 for SARS, 2009q1-2009q3 for H1N1, 2015q4-2016q2 for Zika, and 2015q2-2015q4 for MERS. A disease-related mention is defined as a sentence triple in which the middle sentence contains a disease-related term.

Table 1: Word patterns for each of six specific firm-level exposures to epidemic diseases

A sentence triple conforms to a given topic

	if it contains		**if it combines any of**		**any of**		**any of**
Supply Chain	supply chain, suppliers		supply, component		challenge, cost, supply		
Production and Operations	permit, productivity, throughput, closure, shutting down, closing down, commercial availability, mode of operation		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		start, stop, delay, launch, postpone, close, open, constrain, adjust, operate, add, build, slow, distribute, service, deliver, shut down, offset, take, commercialize, implement		
Cost	paying sick leave, cost initiative		cost, expense, spending		offset, relate		
Demand		**or**	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	**with**	inquire, spend, visit, concern, uncertainty, relate, offer, receive, add	**or with**	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
Finance			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		raise, access, keep, distribute, secure, withdraw, maintain, available, book, seet aside, consist, provide, fund		
Government	stimulus, CARES Act, Paycheck Protection Program, relief program		government, central bank, Federal Reserve bank, state		stimulus, spending, guarantee, concession, relief, liquidity, lending, intervention, response, aid, assistance, support		

Notes: This table lists the final word patterns for each of six specific topics discussed in conjunction with mentions of epidemic diseases. Verbs are stemmed prior to matching: "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 5.

Table 2: Summary Statistics

	All firms			US firms		Total
	Mean	Median	SD	Mean	SD	N
PANEL A: EPIDEMIC VARIABLES						
COVID-19 Exposure$_{i,t}$*100	2.221	1.639	2.313	2.231	2.335	17,596
COVID-19 Sentiment$_{i,t}$*100	-0.402	0.000	1.007	-0.411	0.983	17,596
COVID-19 NegativeSentiment$_{i,t}$*100	0.925	0.532	1.225	0.944	1.208	17,596
COVID-19 PositiveSentiment$_{i,t}$*100	0.523	0.230	0.775	0.532	0.775	17,596
COVID-19 Risk$_{i,t}$*100	0.160	0.000	0.320	0.177	0.330	17,596
Prior Epidemic Exposure$_i$*100	0.102	0.000	0.673	0.151	0.879	17,596
PANEL B: OTHER FIRM-SPECIFIC VARIABLES						
Stock return$_{i,t}$	0.176	1.829	33.830	2.097	36.210	16,103
Stock return [-1,1]$_{i,t}$	0.518	0.453	8.785	0.696	9.384	11,341
Log of total assets$_i$	21.519	21.537	2.147	21.216	2.135	17,596
Market beta$_i$	0.604	0.546	0.434	0.850	0.381	14,440

Notes: This table shows the mean, median, standard deviation, and the number of observations for the variables used in the regression analysis. The unit of the data is a firm-quarter pair for all firms for which we have earnings calls between 2020q1-2020q3. Columns 1 to 3 refer to the sample of all firms; and columns 4 and 5 to the sample of US firms. In Panel A, *COVID-19 Exposure*$_{i,t}$, *COVID-19 Sentiment*$_{i,t}$, *COVID-19 NegativeSentiment*$_{i,t}$, *COVID-19 PositiveSentiment*$_{i,t}$, and *COVID-19 Risk*$_{i,t}$ are defined in Section 2. *Prior Epidemic Exposure*$_i$ is the sum of (i) a firm's total *SARS Exposure*$_{i,t}$ (taken over all earnings calls in 2003) and (ii) a firm's total *H1N1 Exposure*$_{i,t}$ (taken over all earnings calls in 2009). All epidemic variables are multiplied by 100 to aid readability. In Panel B, *Stock Return*$_{i,t}$ is the cumulative winsorized daily return of firm i in quarter t; *Stock return [-1,1]*$_{i,t}$ is the cumulative winsorized daily return from one day before to one day after the earnings call of firm i in quarter t; *Log of total assets*$_i$ is the log of total assets in USD of firm i, where assets are from the latest fiscal year available and obtained from Thomson Eikon; and *Market beta*$_i$ is calculated by regressing firm i's daily stock returns in 2018 on the daily S&P 500 index.

Table 3: *COVID-19 Exposure, Sentiment*, and *Risk* correlate with stock returns

Panel A: Quarterly return; 2020q1-q3	*Stock Return$_{i,t}$*			*Stock Return (USA only)$_{i,t}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 Exposure$_{i,t}$	–83.29***			–117.72***		
	(11.68)			(17.92)		
COVID-19 Sentiment$_{i,t}$		146.42***			167.51***	
		(24.38)			(37.76)	
COVID-19 Positive Sentiment$_{i,t}$			104.80***			67.05
			(35.27)			(54.91)
COVID-19 Negative Sentiment$_{i,t}$			–154.02***			–186.22***
			(25.19)			(39.04)
COVID-19 Risk$_{i,t}$		–128.93**	–99.13		–188.16*	–115.39
		(64.79)	(66.42)		(97.50)	(100.46)
R^2	0.514	0.514	0.514	0.508	0.507	0.508
N	13,371	13,371	13,371	6,813	6,813	6,813
Panel B: Quarterly return; 2020q1	*Stock Return$_{i,t}$*			*Stock Return (USA only)$_{i,t}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 Exposure$_{i,t}$	–169.60***			–115.46		
	(58.42)			(92.02)		
COVID-19 Sentiment$_{i,t}$		404.59***			624.74***	
		(112.68)			(213.71)	
COVID-19 Positive Sentiment$_{i,t}$			385.61*			875.49**
			(215.37)			(357.00)
COVID-19 Negative Sentiment$_{i,t}$			–406.80***			–592.24***
			(114.62)			(215.32)
COVID-19 Risk$_{i,t}$		–505.09**	–495.49**		–159.35	–300.83
		(196.26)	(212.37)		(323.30)	(358.00)
R^2	0.223	0.226	0.226	0.226	0.231	0.231
N	4,719	4,719	4,719	2,330	2,330	2,330
Panel C: Before-after return; 2020q1-q3	*Stock Return [-1,+1]$_{i,t}$*			*Stock Return [-1,+1] (USA only)$_{i,t}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 Exposure$_{i,t}$	–23.61***			–29.40***		
	(5.09)			(7.11)		
COVID-19 Sentiment$_{i,t}$		55.04***			60.47***	
		(9.67)			(14.66)	
COVID-19 Positive Sentiment$_{i,t}$			45.43***			45.44*
			(16.45)			(24.43)
COVID-19 Negative Sentiment$_{i,t}$			–56.97***			–63.53***
			(9.80)			(14.88)
COVID-19 Risk$_{i,t}$		–30.53	–23.01		–54.40	–42.44
		(28.91)	(30.11)		(40.30)	(42.27)
R^2	0.069	0.071	0.071	0.080	0.082	0.082
N	9,461	9,461	9,461	5,148	5,148	5,148
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 shows regressions at the firm-quarter level. The outcome in all regressions is winsorized at the first and last percentile. All regressions in addition control for the log of firm assets and market beta of the firm. Quarter fixed effects are only included where appropriate: Panels A and B. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 4: COVID-19-related mentions of six specific topics

Topics	Perc.	Example sentence triple
Supply Chain	4.14%	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.
Production and Operations	20.00%	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	9.44%	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	30.91%	**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.
Finance	10.08%	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	1.41%	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 six topics. The topic label of the sentence triple is predicted with our pattern search as specified in the paper. The perc. column indicates the percentage of COVID-19-related sentence triples with that topic label among all COVID-19-related sentence triples. 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 all earnings call transcripts held from January to (and including) June 2020.

Table 5: Prior exposure to epidemic disease and COVID-19 Negative Sentiment

PANEL A: 2020Q1-2020Q3	COVID-19 Negative Sentiment		
	(1)	(2)	(3)
	Full sample	Full sample	US only
COVID-19 Exposure	0.410***	0.410***	0.403***
	(0.008)	(0.008)	(0.010)
Prior Epidemic Exposure		–0.024**	–0.028***
		(0.010)	(0.010)
R^2	0.635	0.635	0.646
N	14,437	14,437	7,302
PANEL B: 2020Q1	COVID-19 Negative Sentiment		
	(1)	(2)	(3)
	Full sample	Full sample	US only
COVID-19 Exposure	0.354***	0.356***	0.342***
	(0.014)	(0.015)	(0.020)
Prior Epidemic Exposure		–0.033***	–0.038***
		(0.010)	(0.009)
R^2	0.545	0.547	0.571
N	4,972	4,972	2,446
Quarter FE	yes	yes	yes
Country FE	yes	yes	n/a
Sector FE	yes	yes	yes

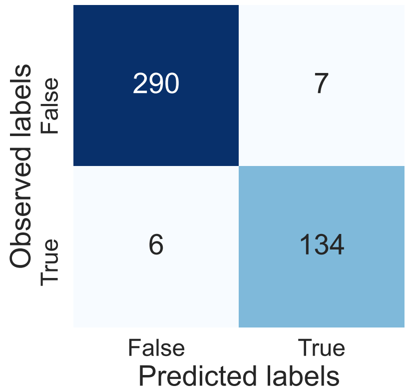
Notes: This table shows regressions at the firm-quarter level. Prior Epidemic Exposure is the scaled sum of the number of times SARS and H1N1 is mentioned in a firm's earnings call in 2003 and 2009, respectively. All regressions control for the log of firm assets and the firm's market beta in 2018. Quarter fixed effects are included only in panel A. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix

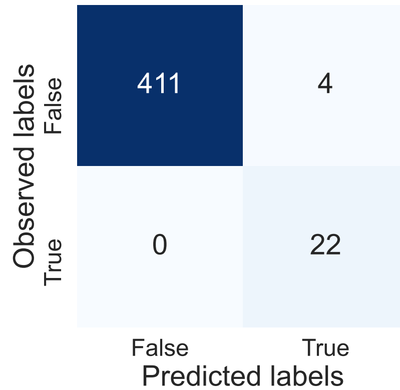
"Firm-Level Exposure to Epidemic Diseases: Covid-19, SARS, and H1N1"

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

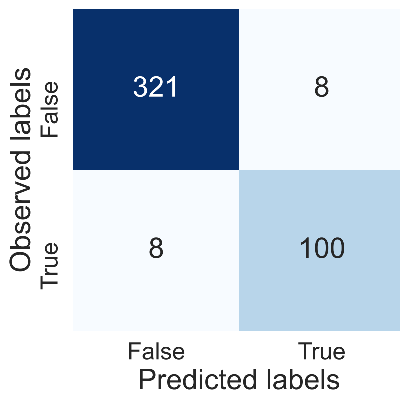
Figure 1: Confusion matrices for topics on training data



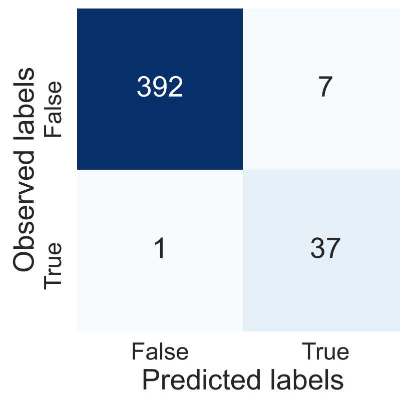
(a) Demand



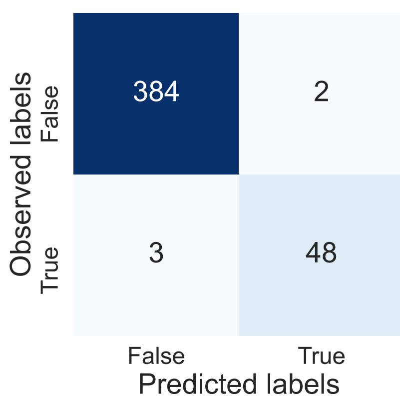
(b) Supply Chain



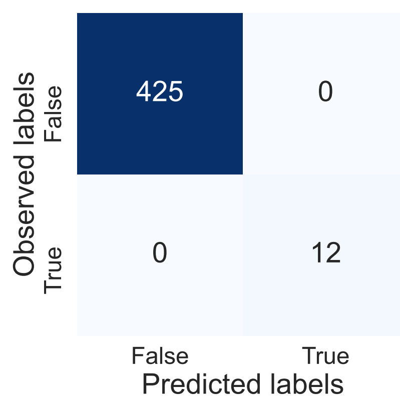
(c) Production and Operations



(d) Cost



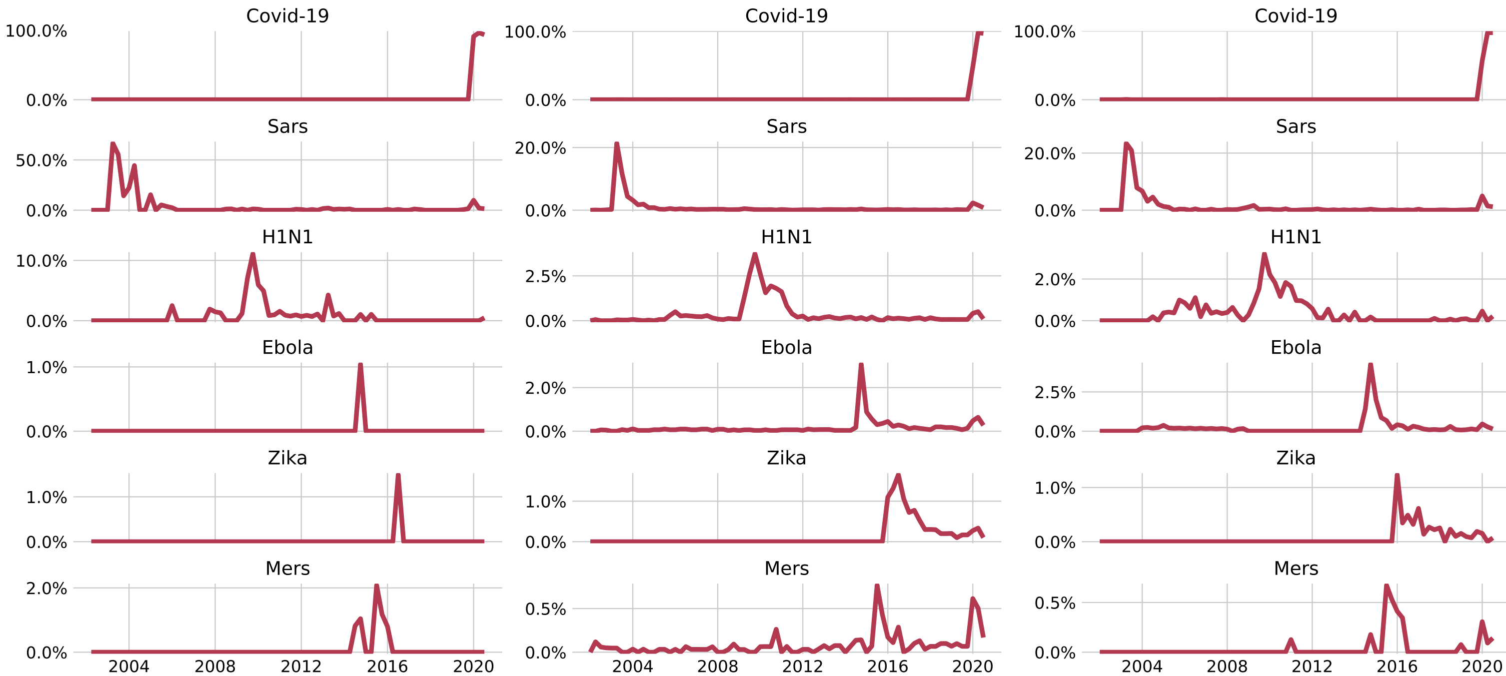
(e) Finance



(f) Government

Notes: This figure shows the performance of our final word patterns on the training data set: It shows 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.

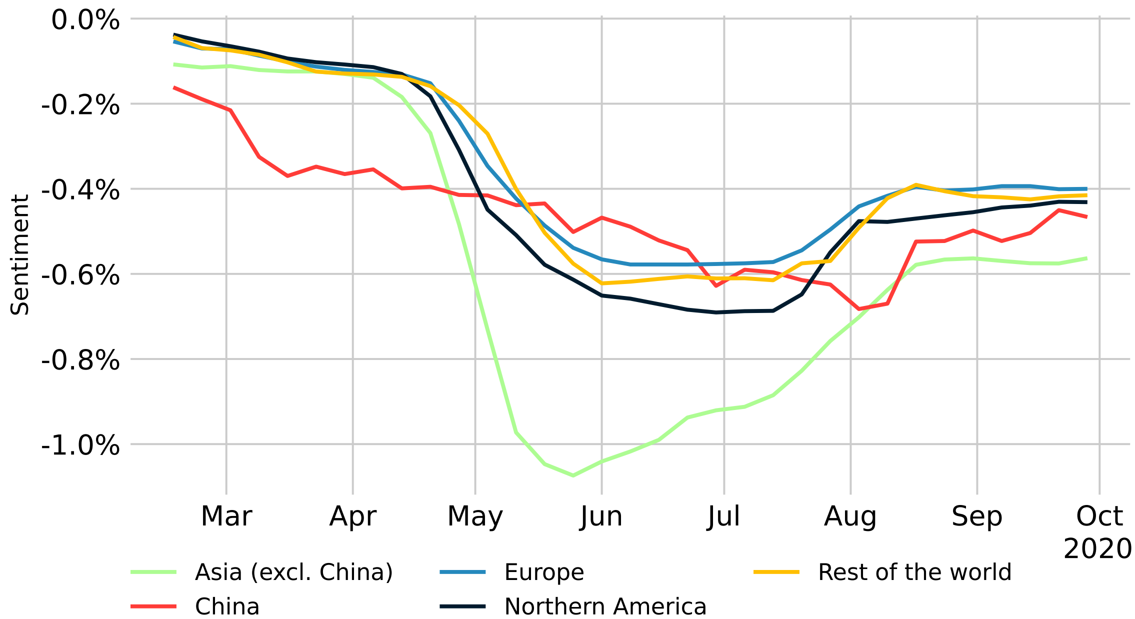
Appendix Figure 2: Percentage of earnings calls discussing epidemic diseases across regions



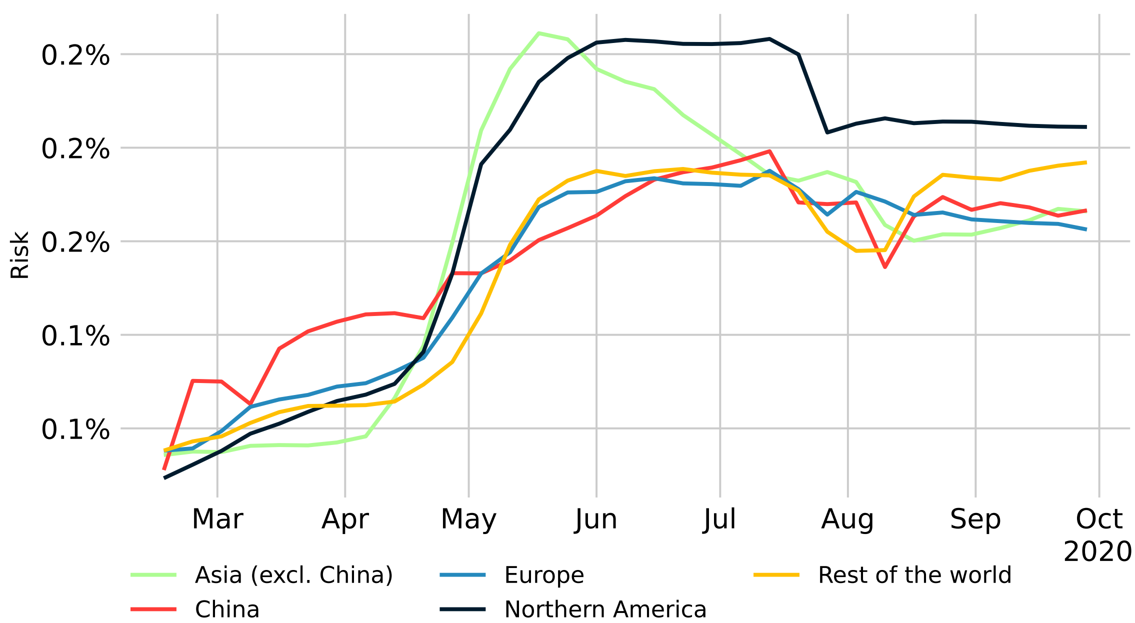
(a) China (b) United States (c) Europe

Notes: This figure plots at the quarterly frequency the percent 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: Regional evolution over time of average *COVID-19 Sentiment*$_{i,t}$, and *COVID-19 Risk*$_{i,t}$



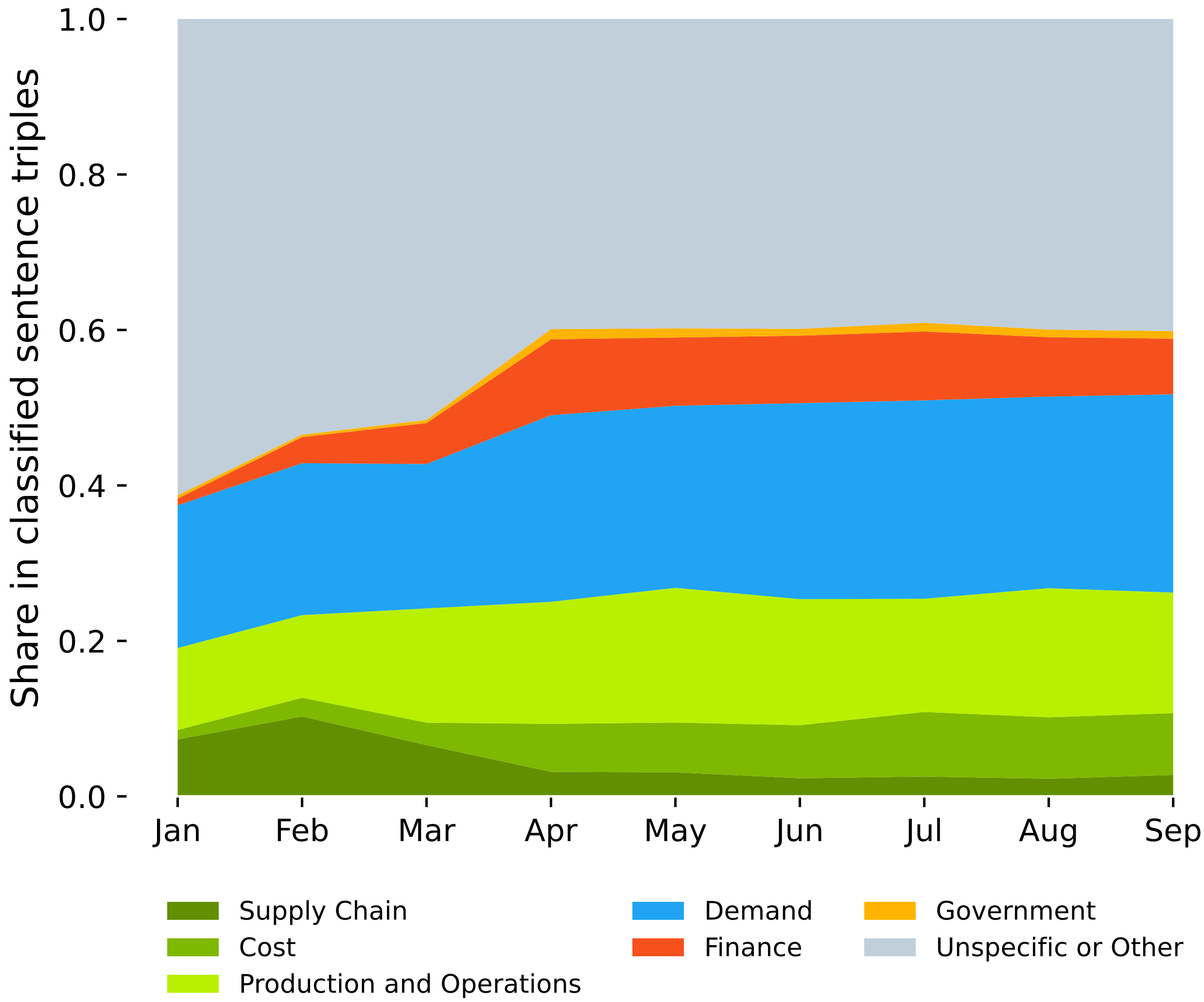
(a) Regional averages of *COVID-19 Sentiment*$_{i,t}$



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

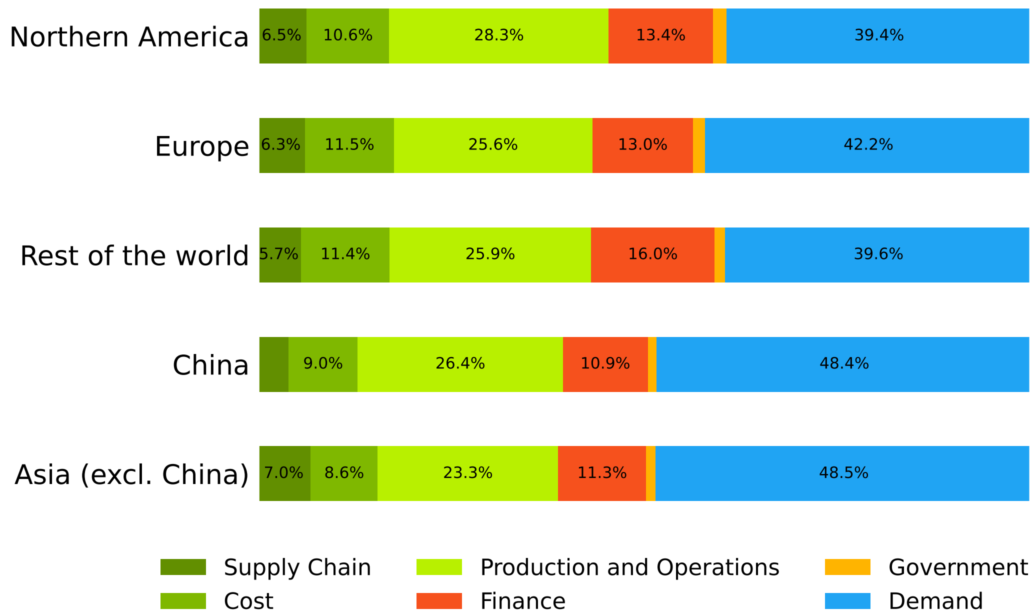
Notes: This figure plots the weekly average of *COVID-19 Sentiment*$_{i,t}$, and *COVID-19 Risk*$_{i,t}$ across all earnings calls over time by firms headquartered in the region indicated in the figure. Panel (a) plots the regional averages of *COVID-19 Sentiment*$_{i,t}$ and panel (b) of *COVID-19 Risk*$_{i,t}$. 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: Classification into topics, including *Unspecific or Other*, of Covid-19-related speech

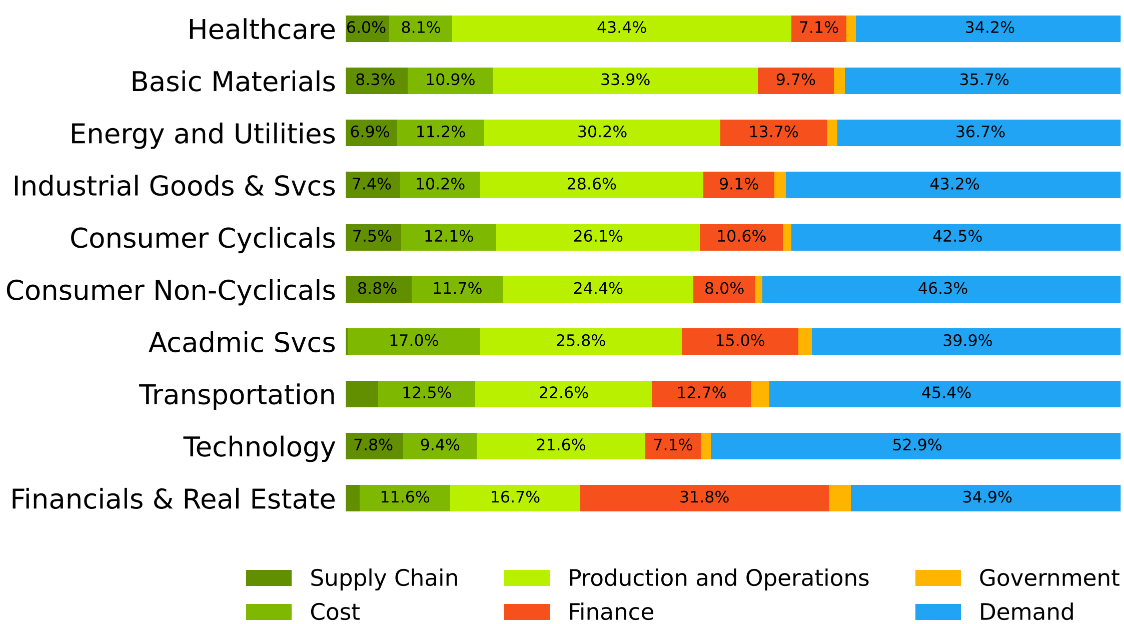


Notes: This figure plots the share in all classified sentence triples of the sentence triples classified to be about the topic. It is similar to Figure 7 but includes one additional topic: those sentence triples that are too unspecific or contain topics not encompassed by our categories. Sentences classified 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 to (and including) September 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 across all firms in 2020 of the share in all Covid-19 related topic mentions of the topic indicated in the figure. The sector classification corresponds to the "Economic Sector" obtained from Thomson Eikon.

Appendix Table 1: Distribution of earnings conference calls by country

Country	Freq.	Perc.	Cum.	Firms	Country	Freq.	Perc.	Cum.	Firms
Argentina	514	0.15%	0.15%	21	Macao	9	0.00%	24.05%	1
Australia	3889	1.17%	1.32%	447	Malaysia	283	0.08%	24.13%	24
Austria	913	0.27%	1.59%	35	Malta	39	0.01%	24.15%	4
Bahamas	57	0.02%	1.61%	3	Marshall Islands	34	0.01%	24.16%	1
Bahrain	19	0.01%	1.62%	3	Mauritius	13	0.00%	24.16%	3
Bangladesh	2	0.00%	1.62%	1	Mexico	2305	0.69%	24.85%	107
Belgium	1034	0.31%	1.93%	45	Monaco	284	0.09%	24.94%	11
Bermuda	2880	0.86%	2.79%	96	Morocco	15	0.00%	24.94%	1
Brazil	4541	1.36%	4.15%	184	Netherlands	2924	0.88%	25.82%	107
British Virgin Islands	30	0.01%	4.16%	4	New Zealand	459	0.14%	25.95%	60
Canada	20615	6.18%	10.34%	949	Nigeria	101	0.03%	25.98%	14
Cayman Islands	411	0.12%	10.46%	18	Norway	2080	0.62%	26.61%	110
Channel Islands	561	0.17%	10.63%	46	Oman	58	0.02%	26.63%	3
Chile	817	0.24%	10.88%	47	Pakistan	16	0.00%	26.63%	6
China	4991	1.50%	12.37%	352	Panama	120	0.04%	26.67%	3
Colombia	324	0.10%	12.47%	16	Papua New Guinea	31	0.01%	26.68%	2
Costa Rica	9	0.00%	12.47%	1	Peru	188	0.06%	26.73%	20
Cyprus	296	0.09%	12.56%	21	Philippines	241	0.07%	26.80%	20
Czechia	219	0.07%	12.63%	6	Poland	645	0.19%	27.00%	32
Denmark	1833	0.55%	13.17%	62	Portugal	506	0.15%	27.15%	13
Egypt	155	0.05%	13.22%	8	Puerto Rico	229	0.07%	27.22%	8
Faroe Islands	13	0.00%	13.23%	1	Qatar	54	0.02%	27.23%	4
Finland	2069	0.62%	13.85%	68	Republic of Korea	1284	0.38%	27.62%	46
France	3964	1.19%	15.03%	166	Romania	35	0.01%	27.63%	3
Germany	5712	1.71%	16.75%	231	Russian Federation	1205	0.36%	27.99%	54
Gibraltar	62	0.02%	16.76%	2	Saudi Arabia	33	0.01%	28.00%	3
Greece	1009	0.30%	17.07%	41	Singapore	1071	0.32%	28.32%	57
Hong Kong	1391	0.42%	17.48%	116	Slovenia	2	0.00%	28.32%	1
Hungary	203	0.06%	17.54%	4	South Africa	1433	0.43%	28.75%	101
Iceland	57	0.02%	17.56%	4	Spain	2194	0.66%	29.41%	76
India	4664	1.40%	18.96%	352	Sweden	4126	1.24%	30.65%	196
Indonesia	311	0.09%	19.05%	18	Switzerland	3218	0.96%	31.61%	130
Ireland	2384	0.71%	19.77%	79	Taiwan	1353	0.41%	32.02%	50
Isle of Man	45	0.01%	19.78%	4	Thailand	370	0.11%	32.13%	23
Israel	2721	0.82%	20.60%	116	Turkey	596	0.18%	32.31%	27
Italy	2719	0.81%	21.41%	108	Ukraine	23	0.01%	32.31%	2
Japan	7572	2.27%	23.68%	285	United Arab Emirates	250	0.07%	32.39%	23
Kazakhstan	92	0.03%	23.71%	7	United Kingdom	10065	3.02%	35.40%	574
Kenya	21	0.01%	23.71%	2	United States	215455	64.58%	99.98%	6819
Kuwait	20	0.01%	23.72%	3	Uruguay	35	0.01%	99.99%	1
Luxembourg	1086	0.33%	24.05%	51	Venezuela	19	0.01%	100.00%	2

Notes: This table tabulates the distribution of firms' headquarter countries in our sample of earnings calls between January 1, 2002 and September 30, 2020. The column *Freq.* indicates the number of earnings calls by firms from a particular country; the columns Perc. indicate the percentage in all (2002-2020) earnings calls of earnings calls by firms in that country; the column *Cum.* adds those percentages; and the column *Firm* indicates the number of 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**
'zika'	'sarscov'
	'coronavirus'
	'corona virus'
	'ncov'
	'covid'

Notes: This table lists for each of the six disease measures created as described in Section 2 the list of synonyms that are used to identify a disease. We remove all non-letters during pre-processing in addition to lower casing all text; hence for example "H1N1" becomes "hn".

Appendix Table 3: Frequency of synonyms for risk or uncertainty

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 333,626 earnings call transcripts between 2002q1 and 2020q3 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 from the following diseases: SARS, MERS, H1N1, Zika, Ebola, and SARS-COV-2.

Appendix Table 4: Most frequent tone words

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 333,626 earnings call transcripts between 2002q1 and 2020q3 of the top 100 positive and negative tone words from Loughran and McDonald (2011) (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 SARS-COV-2.

Appendix Table 5: Additional topic-specific restrictions on the word patterns

Topic	Additional restrictions
Supply Chain	1) 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	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"
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 6: 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 draw 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 7: Does the 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 shows regressions at the firm-quarter level. New cases per 100,000$_{C(i),t}$ is the number of confirmed Covid-19 cases per 100,000 in quarter t of the country that firm i is headquartered in; New deaths per 100,000$_{C(i),t}$ is defined similarly for the number deceased per 100,000. Both variables are obtained from Google's *COVID-19 Open Data* here: 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: Top 100 most frequent matches for topics *Demand* and *Cost*

Demand match	Frequency	*Demand match*	Frequency	*Cost* match	Frequency	*Cost* match	Frequency
revenue growth	489	increasing demand	36	related costs	317	costs down	12
sales growth	248	decline in demand	35	related expenses	247	offset by cost	12
increased demand	193	revenue recognition	32	cost reduction	199	lower spending	12
up demand	144	changes in consumer	32	cost reductions	139	managing our costs	12
lower demand	144	growth in revenue	31	costs related	136	managing expenses	12
lower sales	140	related sales	31	reduce costs	130	reduced expenses	12
revenue declined	134	reduction in demand	30	lower cost	98	increase in cost	11
revenue decreased	127	reduction in revenue	30	expenses decreased	91	manage our expenses	11
sales increased	117	volumes were down	30	cost management	88	reduced spending	11
revenue increased	112	impact on our sales	28	expenses increased	79	costs were down	11
revenue decline	108	revenue declines	28	related cost	71	expense decreased	11
revenue grew	101	impacted sales	28	expenses related	67	up costs	11
sales declined	101	reduced sales	28	cost initiatives	59	incurred additional costs	10
volume growth	94	expect demand	27	increased costs	49	reduction in operating expenses	10
sales decreased	92	sales momentum	27	reduce expenses	47	cost increase	10
lower revenue	91	sales impact	27	reduce our cost	43	reduce spending	9
revenue was down	89	related volume	26	reducing costs	34	increase in operating expenses	9
sales were down	86	volumes declined	26	cost-reduction	33	expected cost	9
lower volumes	86	demand impact	26	expense management	33	reducing expenses	9
sales decline	83	impact on our revenue	26	costs increased	31	expenses grew	9
reduced demand	82	sales declines	25	expense increased	29	reduce operating costs	9
related demand	81	impact on our customers	25	reduce cost	29	reduce our expenses	9
customer experience	80	impact on consumer	24	expense reductions	28	manage expenses	9
decline in sales	78	volume impact	24	increased cost	28	lower our cost	9
revenue impact	78	sales increase	23	lower costs	25	costs relating	9
decline in revenue	77	reduced revenue	23	expense reduction	24	manage cost	8
increase in demand	77	growing demand	22	reduced costs	23	reduced operating expenses	8
lower volume	59	revenues were up	22	manage costs	23	costs remain	8
impact on demand	58	reduced volumes	22	lower expenses	22	impact on our cost	8
revenues increased	58	decrease in sales	22	reduce operating expenses	21	cost down	8
impact on sales	56	decline in revenues	21	expenses declined	21	incurred costs	8
income increased	56	revenue was negatively impacted	21	managing costs	20	expense was down	8
revenues declined	53	income decreased	21	expenses were up	20	costs are related	7
revenues were down	52	demand disruption	21	lower operating expenses	19	increase in the cost	7
revenues decreased	51	customer growth	21	reduce our costs	18	reduced consumer spending	7
sales grew	51	changes in customer	21	cost impact	18	expect cost	7
decrease in revenue	50	lower sales volume	20	related expense	18	cost estimate	7
sales were up	49	see demand	20	cost increases	17	managed costs	7
revenue was up	47	see strong demand	20	managing our cost	17	reducing operating costs	7
lower revenues	46	revenue increase	20	expenses were down	17	decrease in operating expenses	7
impact on revenue	46	expected demand	20	costs decreased	17	impact on cost	7
related revenue	43	sales down	19	reduced cost	16	expense declined	7
increase in sales	43	see revenue	19	manage our costs	16	lower travel expenses	7
increased sales	40	impact on revenues	19	cost related	15	reduction in cost	7
increase in revenue	40	expect sales	19	manage our cost	14	lower interest expense	6
volume decline	40	impact on the demand	19	reduce the cost	14	impact on consumer spending	6
demand growth	39	additional demand	18	managing our expenses	13	reduce our overall cost	6
revenues grew	38	grow revenue	18	expense related	13	spending reductions	6
expect revenue	38	impacted revenue	18	reducing our cost	13	costs fell	6
volume declines	36	shift in consumer	18	increased expenses	12	estimated cost	6

Notes: This table lists for the topics *Demand* and *Cost* the top 100 most frequent matches that our word pattern finds in all Covid-19-related sentence triples from earnings calls held in 2020q1-2020q3.