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

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Abstract

Using tools described in our earlier work (Hassan et al., 2019, 2020), we develop text-based measures of the costs, benefits, and risks listed firms in the US and over 80 other countries associate with the spread of Covid-19 and other epidemic diseases. We identify which firms expect to gain or lose from an epidemic disease and which are most affected by the associated uncertainty as a disease spreads in a region or around the world. As Covid-19 spreads globally in the first quarter of 2020, we find that firms' primary concerns relate to the collapse of demand, increased uncertainty, and disruption in supply chains. Other important concerns relate to capacity reductions, closures, and employee welfare. By contrast, financing concerns are mentioned relatively rarely. We also identify some firms that foresee opportunities in new or disrupted markets due to the spread of the disease. Finally, we find some evidence that firms that have experience with SARS or H1N1 have more positive expectations about their ability to deal with the coronavirus outbreak.

Keywords: Epidemic diseases, pandemic, exposure, virus, firms, uncertainty, sentiment, machine learning

JEL code: I15, I18, D22, G15

The data set described in this paper is publicly available on www.firmlevelrisk.com.

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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 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, and to support a suddenly wobbling economy, providing emergency relief measures and funding, it became quickly clear that the shock would leave few untouched.

While the Covid-19 pandemic provides an extreme case, outbreaks of epidemic diseases are not without precedent in recent times and much can be learned about the resilience of the corporate sector from previous examples. However, given the extraordinary nature of the current crisis, these earlier experiences need to be carefully calibrated against the unique features of today's challenge: existing models and policy remedies might no longer apply (Adda, 2016; Barro et al., 2020). In an effort to aid evidence-based policy responses, in this paper, we construct a time-varying, firm-level measure of exposure to epidemic diseases.

The measure we introduce is based on a general text-classification method and identifies the exposure of firms to an outbreak of an epidemic disease by counting the number of times the disease is mentioned in the quarterly earnings conference call that public 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

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

to shocks such as the Fukushima nuclear disaster.

Intuitively, the idea of constructing a measure of firm-level exposure to a particular shock from earnings call transcripts rests on the observation that these calls are a venue in which senior management has to respond *directly* to questions from market participants about the firm's prospects. Not only are these disclosures therefore *timely*, but as they 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, earnings conference calls are held quarterly, which allows us to track changes in firm-level disease exposure over time. Indeed, we plan to continuously update our measures to reflect the impact of concurrent (Covid-19 related) events as they unfold. At the same time, we begin by using our approach to consider a given firm's exposure to earlier significant epidemic diseases, namely SARS, MERS, H1N1, Ebola, and Zika.

In addition to this exposure measure, we also construct—following Hassan et al. (2019, 2020)—measures of epidemic disease *sentiment* and *risk*. These latter two 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. While it might sound callous to talk about firms benefiting from a life-threatening disease as "winners," we use these labels nevertheless for ease of exposition. 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.

Having constructed these new firm-level epidemic disease exposure measures, we document a set of empirical findings for the impact of outbreaks on firms in 71 countries. We present findings that are not just of interest in their own right, but which also help to allay any potential concerns about the validity of our measures. For example, we show that the time-series pattern of exposure to certain diseases follows the infection rates in the population of these diseases, consistent with the idea that investors are most concerned about the firm's exposure when an outbreak is most virulent. We not only document over-time patterns, but also show, by aggregating exposure scores geographically, how countries differ in the average impact of an outbreak. What is more, we show how sensitive different sectors in the economy are to epidemic diseases.

Moving beyond validating the measure, we then examine the resilience of the corporate world to the rise and spread of Covid-19. An emerging literature on the macroeconomic impact of pandemics emphasizes that the spread of the disease itself, and the policy responses attempting to mitigate it, may result in large shocks to supply, demand, and financing (Eichenbaum, Rebelo, and Trabandt, 2020; Gourinchas, 2020). At the firm level, these shocks may manifest in a variety of different ways. For example, the firm's supply chain may be disrupted, it may suffer labor shortages, shutdowns of production facilities, a sudden drop in demand, or difficulty in accessing credit lines.[2,3]

We produce evidence on which of these potential concerns are current for firms around the globe during the coronavirus outbreak. Based on a detailed reading of the conversations in the transcripts, we document that concerns as of the first quarter in 2020 concentrate on (1) decreasing demand, (2) disruption of the supply chain and closure of production facilities, and (3) increased uncertainty. By contrast, as of the first quarter in 2020, relatively few firms appear concerned with their financing position. For a smaller subset of firms we find that they see opportunities arising from the disruption of competition in their markets. For this group of firms, the shock to demand can even be positive rather than negative, for example because they sell medical supplies or believe that the competitor's brand is tainted

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

[3] Some prior work even points to effects on labor supply several generations in the future (Almond, 2006), and that disease shocks can divert savings away from investment in all types of capital into treatment of the sick and that the loss of lifetime family income can further reduce savings, ultimately producing a fall in the level of physical capital (Bell and Lewis, 2004).

by association with regions stricken by the virus. We also document the extent to which firms (especially early on in the pandemic) argue that their business is not affected by the disease. Having a deeper understanding of the various ways in which epidemics affect firms, is a sound starting point for developing effective government and/or corporate intervention policies. Clearly, supply-side disruptions should be met with a substantially different toolkit than is appropriate for demand-related shocks.

We also show that firms which previously experienced an epidemic disease generally have higher (more positive) sentiment; i.e., their expectations about how the disease will affect their future cash flows are more positive than firms without such experience. These more optimistic expectations are also reflected in subsequent stock market tests. In these analyses, we show that short-window earnings-call returns, capturing the information released during the earnings call, as well as first-quarter cumulative returns, are generally lower for firms with higher measured exposure, negative sentiment, and risk related to the Covid-19 outbreak.

In sum, we provide novel data and first evidence on the extent to which epidemic diseases (and in particular the Covid-19 outbreak) affects 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. It also highlights the variety of issues firms and markets worry about amid the coronavirus outbreak; while uncertainty about the consequences of the outbreak is prevalent, it is foremost the firms' expectations about reductions in future cash flows that catch the limelight in earnings calls and explain the stock market's response.

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 326,247 English-language transcripts from January 2001 to March 2020 for 11,943 firms headquartered in 84 countries.[4] 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 in the world. 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 total assets, which are taken from Standard and Poor's Compustat North America (US) and Compustat Global (non-US) files. Stock return information is from Center for Research in Securities Prices and Refinitiv Datastream. Data on firms' headquarters country are also from Refinitiv Datastream.[5]

2. Measuring Firm-Level Exposure to Epidemic Diseases

We base our approach on a combination of the methods described in Hassan et al. (2019) and Hassan et al. (2020). The computational linguistic algorithms described in these 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 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. Nevertheless, parts of that study are devoted to showing how researchers can construct a list of identifying words when the shock or event of interest is less well-circumscribed, such as in the case of the Fukushima disaster.

[4]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.

[5]Note that this 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.

Herein, we follow an approach close to the recommendations of Hassan et al. (2020) for the latter case. Specifically, 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.[6] 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 words in the transcript to account for differences in transcript length:

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

where $b = 0, 1, ...B_{it}$ represents the words contained in the transcript of firm i in quarter t.

To construct a measure of epidemic disease *risk*, denoted $DiseaseRisk^d$, we augment this

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

procedure by conditioning on the proximity to synonyms for risk or uncertainty:

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

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.[7]

A major challenge for any text-based measure of risk is that innovations to the variance of shocks 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. Thus, 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:[8]

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

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

[8] 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 $DiseaseSentiment^{d}$.

where S assigns sentiment to each c:

$$S(c) = \begin{cases} +1 \text{ if } c \in \mathbb{S}^+ \\ -1 \text{ if } c \in \mathbb{S}^- \\ 0 \text{ otherwise.} \end{cases}$$

Positive words include 'good,' 'strong,' 'great,' while negative include 'loss,' 'decline,' and 'difficult.'[9,10] Appendix Tables 4 and 5 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.

3. Exposure to Epidemic Diseases

3.1. Descriptive evidence

In this section, 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 corona 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

[9] 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.

[10] 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 exceedingly rare in our sample, so we chose not to complicate the construction of our measures by explicitly allowing for it.

MERS, respectively (moving from the top panel to the bottom).[11] 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 coronavirus disease, starts to become a subject in earnings calls again in the first quarter of 2020, when it becomes clear that Covid-19 shares much in common with the former outbreak.

Nonetheless, even at this early point in the development of the epidemic, Covid-19 is exceptional. Forty percent of transcripts discuss the outbreak: a much larger proportion than all previous outbreaks (with SARS as the closest "competitor" at just over 20 percent). In Appendix Figure 1, 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 (even more so than Covid-19 so far), whereas the Ebola-virus did not feature at all in earnings calls of firms headquartered in China. Also, the time span over which diseases are discussed in earnings calls held by China-based companies is much tighter than for firms in Europe and in the US.

We further compare the time series of Covid-19, SARS, and H1N1 in more detail in Figure 5. For each of these three diseases, we zoom in on the period in which the epidemic was ongoing, and plot the weekly average frequency in which a given disease is mentioned in earnings-call transcripts. We do so separately for different regions/countries in the world. One immediate takeaway that follows from comparing the plots is that Covid-19 is unique. The "peak"—i.e., the maximum value of frequency—is much higher than for any of the previous outbreaks. Further, the discussion frequency of diseases during their epidemic episode is much less synchronised for SARS and H1N1 than for Covid-19. In the latter case, we also observe that Chinese companies appear to have reached their peak late February, and

[11] Our sample currently ends with calls held on March 7, 2020, so that the first quarter of 2020 is cut short by 24 days.

the frequency of its discussion in earnings calls thereafter is trending downward—consistent with the hot spot of Covid-19 infections moving from China to Iran and Italy at the same time.

Figure 2 shows the percentage of transcripts by country in which Covid-19 is mentioned (provided that more than 25 transcripts are available for a given country). The figure excludes transcripts from firms in the healthcare industry and pharmaceuticals in an effort to highlight the country-level exposure in sectors other than health. Not surprisingly, China has the highest exposure (to date), with over 80 percent of the transcripts mentioning Covid-19; followed by Singapore and Germany. Perhaps more remarkable is the relatively low ranking of heavy-hit areas such as South Korea and Italy. About 40 percent of firms headquartered in the United States discuss the coronavirus in their earnings calls (again, this includes all earnings calls held through March 7, 2020).

The frequency of Covid-19 discussion in transcripts varies not only by country, but also by sector, as shown in Figure 3. One noteworthy finding, which is likely due to our sample period ending in the first week of March (i.e., before the extreme stock market volatility started), is that the Finance, Insurance and Real Estate sector has little discussion of the outbreak, whereas transcripts of earnings calls held by firms in the Manufacturing and the Wholesales and Retail trade sectors discuss Covid-19 in about half of the cases.

A similar pattern is apparent in Table 1, Panel A, which provides a list of the top ten firms that discuss the coronavirus most extensively in their earnings calls. These calls take place mostly at the end of February and early March, 2020. Fashion retail firms such as Abercrombie & Fitch and Crocs Inc. feature prominently, as do firms active in healthcare and pharmaceuticals, including PPD Inc. and Agilent Technologies Inc. Panel B of Table 1 adds further color to this description by listing the firms with the earliest earnings calls featuring discussion of the coronavirus. Not completely unexpected, airline firms such as American Airlines Group and United Airlines Holdings vie for a top position with Covid-19 discussions in their earnings calls already happening at the end of January 2020.[12] Although one might expect Chinese companies to feature high on the list of early discussions, an institutional factor might prevent this from happening: by law, firms reporting under Chinese accounting rules have a fiscal year end in December, making it likely that their first opportunity to discuss the pandemic is in an earnings call held in the first quarter of 2020, when their annual financial statements for 2019 are released.

3.2. Content Analysis of Earnings Calls

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 much deeper into the underlying concerns of firms and financial analysts about *how* a disease impacts corporate policies and performance.

Focusing on the case of the coronavirus, we identify all 2,175 transcripts that mention a Covid-19 synonym and single out all text fragments within a given transcript that include these synonyms. These "snippets" contain ten words on each side of the synonym. In total, we find 8,600 snippets. Then, we randomly sample 200 transcripts, spread equally over the months January, February, and March 2020, read all the snippets in each transcript within this random sample, and identify which issue associated with the coronavirus is discussed therein.

We identify six key issues: (1) supply chain disruption, (2) a fall in demand, (3) employee welfare and labor market, (4) production capacity reduction and/or retail store closures, (5) increased uncertainty, and (6) financial market/financing concerns. In addition, some managers indicate that the coronavirus crisis (1) has had no impact (yet) or (2) creates market opportunities for the firm. In 18.5 percent of the transcripts, the coronavirus is

[12] Much earlier, however, is the appearance of talk about the coronavirus in the November 11, 2019 earnings call of Immucell Corp, an animal health company which develops disease prevention products against the coronavirus for cattle.

mentioned in a snippet but we are not able to specify the concern. Typically, in these instances, management would say something non-specific similar to "all of us around the world follow the dynamic situation regarding the outbreak of the coronavirus in China ... [and we are] monitoring any impact it may have on our business."[13]

Table 2 tabulates the findings from our human reading of the sample of coronavirus transcripts. (Note that each transcript can mention more than one corona-related concern, and thus the percentages do not add up to 100; instead the reported percentages are the proportion of total transcripts that mention a given concern.) The most commonly voiced concern when the discussion turns to the possible impact of the pandemic on the firm is the sudden drop in demand that happened as more and more countries in the world adopted stringent "social distancing" measures. Indeed, 43.5 percent of transcripts mention a *"softening of demand,"* sometimes as witnessed in our showcased snippet, in particular markets (often China), but sometimes referring to a global shock in the demand for the firm's products.

Financial analysts also question management about disruptions to the *supply chain* (27 percent) and the closure of a given firm's own *production facilities* and/or stores (18 percent). These discussions are frequently couched in terms of increased (generic) *uncertainties* (27.5 percent). In some cases, firms explicitly mention that they have taken precautionary measures to diversify the supply lines based on their prior experience with an epidemic disease (most often SARS). As mentioned above, in 18.5 percent of the transcripts the coronavirus is mentioned, but without offering any further context. Very few transcripts mention *financing* issues, which at this point in the crisis, appears not to be the most prominent worry.

In addition to these concerns, some transcripts highlight (13.5 percent) that the firm is currently not experiencing *any impact* on their operations. A handful of firms (7.5 percent), in particular those that have business lines in antiviral medication, testing equipment, and specialist pulmonary equipment, describe that the corona outbreak provides *market opportunities*. Some see chances in the market disruption associated with the crisis, others see

[13]This quote is taken from the February 2, 2020 earnings call of Fluence Corp. Ltd.

branding opportunities, such as the spokesperson of Shiseido Co. in the snippet reported in Table 2: "First is the Chinese people as a result of this kind of coronavirus, they may actually heighten or elevate the trust to reliability to Japan or Japanese products. So including that ..." (*sic*).

Table 3 presents the changes in frequency in which each of these aforementioned categories are discussed in earnings calls over the three months of the first quarter of 2020. Perhaps the most noteworthy finding is that, as the quarter progresses, more and more firms express concerns about the welfare of their employees and describe the measures they have implemented (including travel restrictions and the ability to work from home). Similarly, over the course of three months, concerns related to firms' supply chain almost triple from 12.12 percent to 32.84 percent of snippets mentioning the virus.

Together, these findings showcase the richness of earnings call transcripts as a source of detailed data on the operations of firms and how these are affected by shocks like the coronavirus outbreak. Combining this source material with simple but powerful computational linguistic algorithms offers deep insights in a large and important part of the global economy. We exploit these possibilities more in the case studies described next.

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 4, Panel A depicts the case of United Airlines, 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.

The second case study, shown in Panel B of Figure 4, 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.

4. 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.[14] In particular, based in part on our reading of earnings-call transcripts, we consider whether a firm's prior exposure to the next-most virulent diseases, SARS and the swine flu 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

[14] In the appendix, we report fully on our findings for $Covid19Exposure_i$ and $Covid19Risk_i$.

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:

$$(2)\ Covid19NegativeSentiment_i = \delta_c + \delta_s + \beta PriorEpid_i + \theta itCovid19Exposure_i + Z_i^{'}\nu + \epsilon_i$$

where *PriorEpid* is the scaled (by the length of the transcript) count of the SARS and H1N1 synonyms (measured at the peak of their outbreaks in 2003 and 2009, respectively). $Covid19NegativeSentiment_i$ (scaled by the length of the transcript) counts the use of negative-tone words used in conjunction with discussions of Covid-19. This variable, as well as $Covid19Exposure_i$, is indexed by i as we only have at most one earnings call transcript per firm that discusses the coronavirus at this time.

The vector Z contains the natural logarithm of the firm's (one year) lagged 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). We include both headquarters country (δ_c) and two-digit SIC industry (δ_s) fixed effects. We drop firms in the healthcare industry and pharmaceuticals as their circumstances during a public health crisis are plausibly different in manifold ways from all other companies. In these essentially cross-sectional estimations, standard errors are robust.

Summary statistics for all these variables are reported in Table 4. For ease of interpretation, we multiply all firm-level exposure, sentiment, and risk variables by 1,000, so that, for example, the mean of *Covid19Exposure* of 0.246 means that, on average 0.0246 percent of words used in earnings call transcripts in the first quarter of 2020 are synonyms for coronavirus. Further, we winsorize the control variables at the one percent level.

Table 5 presents our estimation results. Discussions surrounding the coronavirus are overwhelmingly negative. Accordingly, in column 1, the estimated coefficient on $Covid19Exposure$ shows that on average, each mention of the coronavirus is accompanied by 0.280 (s.e.=0.0154) 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 $PriorEpid$), 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.

In Appendix Table 7, we supplement these analyses by considering $Covid19Exposure$ and $Covid19Risk$ as the dependent variables. While we find that prior experience with SARS or H1N1 is associated with higher *exposure* to the current coronavirus outbreak, there is no significant correlation between prior experience with SARS and H1N1 and coronavirus-related discussions of risk. Taken together, these results suggest that while a firm's dealings with past epidemic diseases is likely associated with their current corona pandemic exposure, this historical experience improves the sentiment, but does not change the firm's epidemic disease risk.

Having documented that the discussions about the coronavirus in earnings calls of firms with prior disease experience is somewhat more positive than for firms without such history, we next ask whether this sentiment explains the variation in stock price changes in a short window centered on the earnings call date or in a longer window covering the first quarter of 2020 (ending on 15 March). 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.

We test these predictions using the following regression:

$$Ret_i = \alpha_0 + \delta_j + \delta_c + \beta Covid19X_i + Z_i^{'}\nu + \epsilon_i, \tag{3}$$

where *Ret* is either the cumulative return over a three-day (-1,1) window around the date of the earnings call or the "quarter to date" cumulative return starting on January 1 and ending on March 15, 2020; $Covid19X$, is either our coronavirus *Exposure*, *Sentiment*, or *Risk* score; and the vector Z includes our standard set of control variables. Return variables are winsorized at the one percent level. As before, we include sector and country fixed effects and report robust standard errors.

Table 6 presents our estimation results using the short-window returns as the dependent variable, which we detail for the full sample (columns 1-4) and separately for the US (columns 5-8). We document a significantly negative association between a firm's coronavirus *Exposure* score and its stock return (in columns 1 and 5). 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. For example, in column 1, a one standard deviation increase in $Covid19Exposure$ (0.455) is associated with a 1.16 percentage point lower return in this narrow window around the conference call. Next we consider whether this return response derives from investors revising their expectations of future cash flows, as measured by $Covid19Sentiment$, or their expectations of the firm's required rate of return, captured by $Covid19Risk$ (Gorbatikov et al., 2019).

When regressing each of these variables onto the cumulative returns separately, results show that both explain variation therein (columns 2-3 and 6-7). Note, however, that the association between $Covid19Sentiment$ and returns appears to be due to *negative* Covid-19 sentiment. Indeed, *positive* Covid-19 sentiment, measured by conditioning the presence of coronavirus-related synonyms on nearby positive-tone words only, is not significantly associated with the short-window return. However, when we include both *Sentiment* and *Risk* at the same time (in columns 4 and 8), it becomes evident that the market responds most strongly to the extent of negative sentiment related to the coronavirus, consistent with revised cash flow expectations, rather than changes in beliefs about risk, driving these findings.

We repeat this analysis in Table 7, using a long-window return accumulated over the period January 1-March 15, 2020.[15] For the full sample, the patterns using these quarter returns are very similar to what we have documented using short-window returns: higher $Covid19Exposure$ is associated with lower returns, though now the association is quantitatively larger. A one standard deviation increase in coronavirus exposure is now associated with a 2.48 percentage point decrease in the firm's stock return (8% of the average decline in stock prices during this period reflected in the large constant term of -29.87%). Bifurcating this exposure effect into its components, we find again that $Covid19NegativeSentiment$ explains most of the return variation. However, over this long-window, belief revision is not limited to expected future cash flows. In column 4, we find significant negative coefficients on both $Covid19NegativeSentiment$ and on $Covid19Risk$, suggesting that investors also (re)consider the firm's discount rates. Indeed, turning to the US sample specifically, we find that the association between $Covid19Exposure$ and quarter returns is mostly due to changes in $Covid19Risk$ rather than $Covid19Sentiment$.

5. Conclusions

At the time of the writing of this paper, we are still in the early stages of the Covid-19 outbreak. Despite this, we are witnessing events unimaginable since the Spanish flu outbreak a century earlier. Severely overcrowded hospitals, doctors and nurses succumbing to infections contracted while treating critically ill patients, far-reaching limits on personal

[15]We also report tests using a long-window return measured over (-90,0), with the earnings call date as t = 0, in Appendix Table 6.

freedoms, and governments stretched to the limits to provide an adequate response to this public health emergency. Uniquely, these events are not confined to a small region or set of countries, but affect the entire world. Also unprecedented is the effect on the global economy. Stock markets have plummeted, more than 3 million American lost their jobs in a single week in March (Bui and Wolfers, 2020), and governments committed trillion dollar relief packages in an effort to support the economy.

Having data on how the Covid-19 pandemic is affecting corporations, employees, consumers, and markets is paramount if one hopes to formulate an effective policy answer to the challenges posed by the crisis. Just as data appears to have guided the first effective health policy responses to the virus, so is data likely going to be helpful in improving the efficiency of government interventions. Media reports about abuses of government aid packages have already emerged (Lipton and Fandos, 2020; Alemany, 2020) and the scramble by professional lobbyists to get a foot in the door when the various governments draw up their rescue plans has been called a *gold rush* (Vogel et al., 2020).

We provide measures of the exposure of individual firms to epidemic diseases, including the firm's exposure, sentiment, and risk related to the corona pandemic. We do so for a global sample of firms, based on their quarterly earnings conference calls with market participants to discuss the release of their earnings numbers. Using these earnings-call transcripts, we can not just measure each firm's exposure to the disease, but can also extract information about the nature of the concern. This additional detail, together with the timely measurement of the firm's exposure (as firms host these calls every quarter), renders the data potentially well-suited for policy purposes as well as for longer-haul fundamental work which 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.

Alemany, J. (2020, Mar 23). Power up: Trump won't rule out possibility his private business could benefit from coronavirus stimulus. *The Washington Post*.

Almond, D. (2006). Is the 1918 Influenza Pandemic Over? Long-Term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population. *Journal of Political Economy 114*(4), 672–712.

Atkeson, A. (2020, March). What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios. Working Paper 26867, National Bureau of Economic Research.

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*.

Barro, R. J., J. F. Ursúa, and J. Weng (2020, March). The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. Working Paper 26866, National Bureau of Economic Research.

Bell, C. and M. Lewis (2004). The economic implications of epidemics old and new. *World Economics 5*(4), 137–174.

Bui, Q. and J. Wolfers (2020, Mar 26). More than 3 million Americans lost their jobs last week. See your state. *The New York Times*.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020, March). The macroeconomics of epidemics. Working Paper 26882, National Bureau of Economic Research.

Gorbatikov, E., L. van Lent, N. Naik, V. Sharma, and A. Tahoun (2019). Is firm-specific political exposure priced? *Working paper, London Business School*.

Gourinchas, P.-O. (2020). Flattening the pandemic and recession curves. *mimeo UC Berkeley*.

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. Working Paper 26609 (NBER) and 106 (INET), National Bureau of Economic Research and Institute for New Economic Thinking.

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.

Lipton, E. and N. Fandos (2020, Mar 19). Senator Richard Burr sold a fortune in stocks as G.O.P. played down coronavirus threat. *The New York Times*.

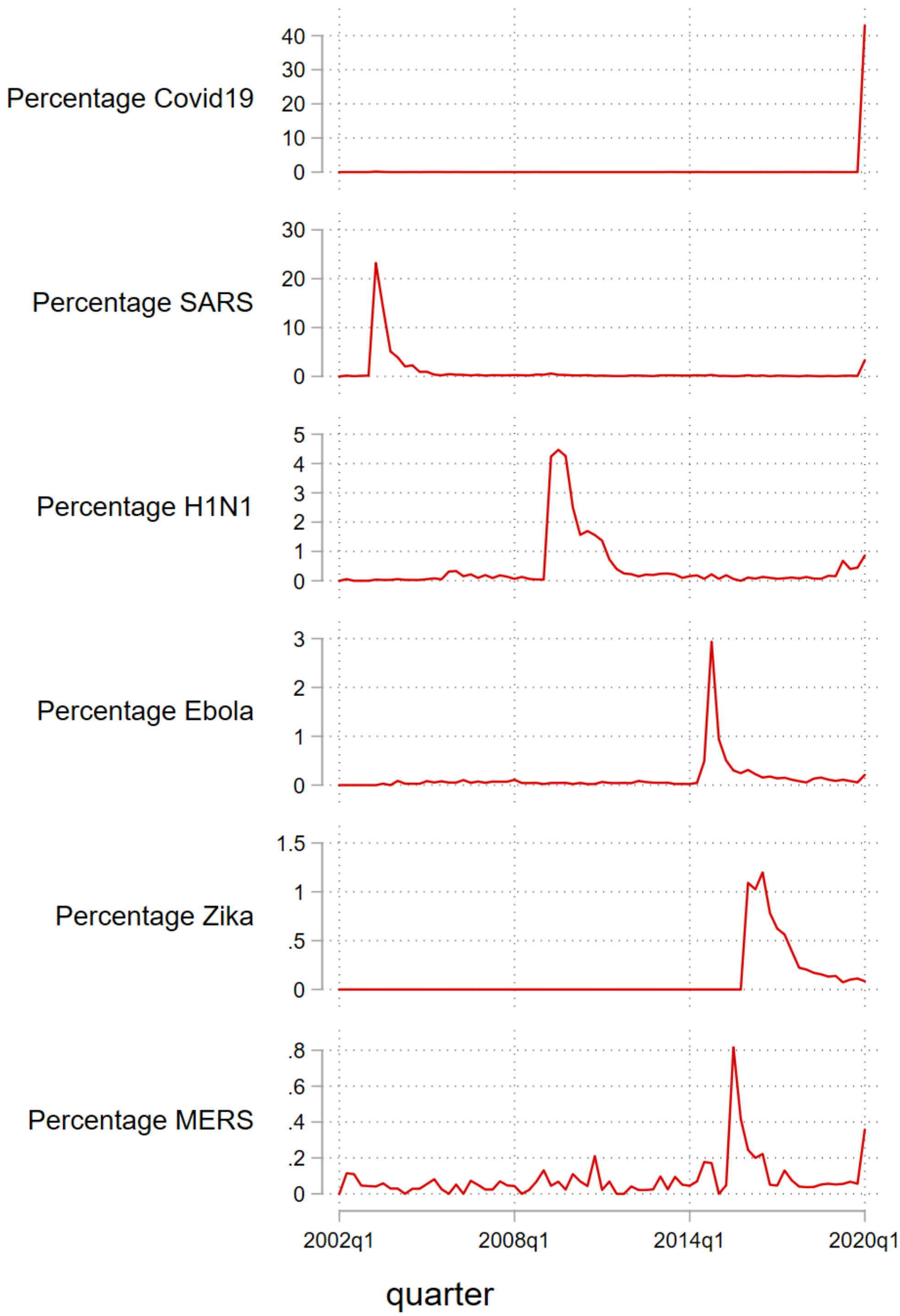
Loughran, T. and B. McDonald (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance 66*(1), 35–65.

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

Ramelli, S. and A. Wagner (2020, Mar 9). Feverish stock price reactions to covid-19. *Swiss Finance Institute Research Paper, No. 20-12*.

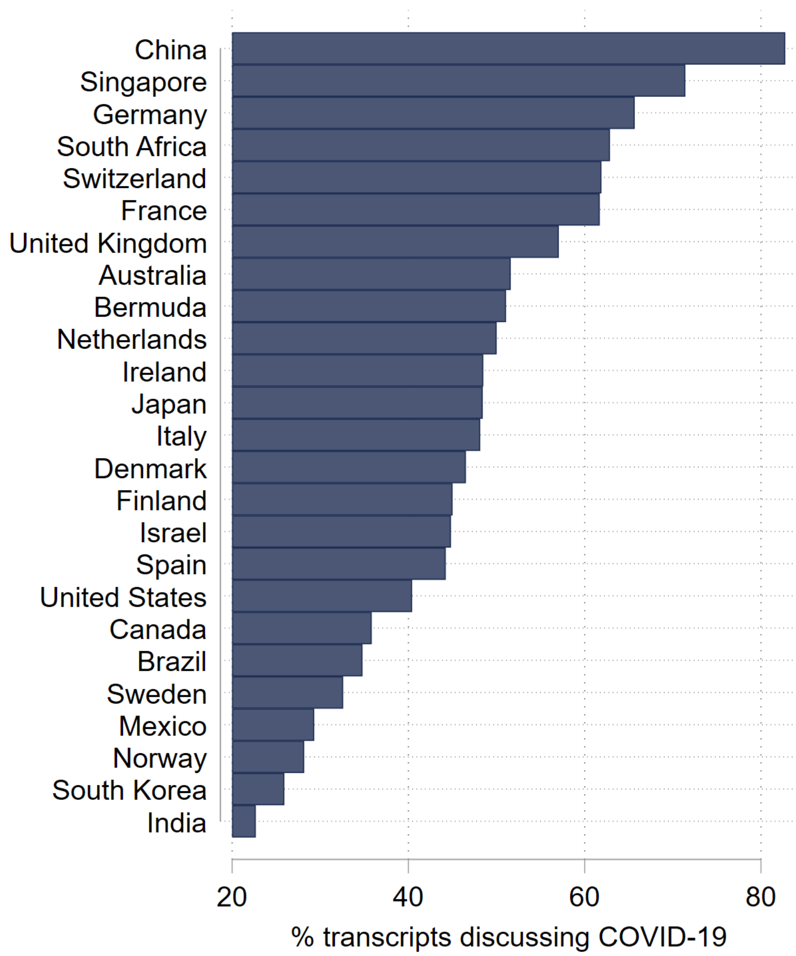
Vogel, K., C. Edmondson, and J. Drucker (2020, Mar 20). Coronavirus stimulus package spurs a lobbying gold rush. *The New York Times*.

Figure 1: Percentage of Earnings Calls Discussing Epidemic Diseases



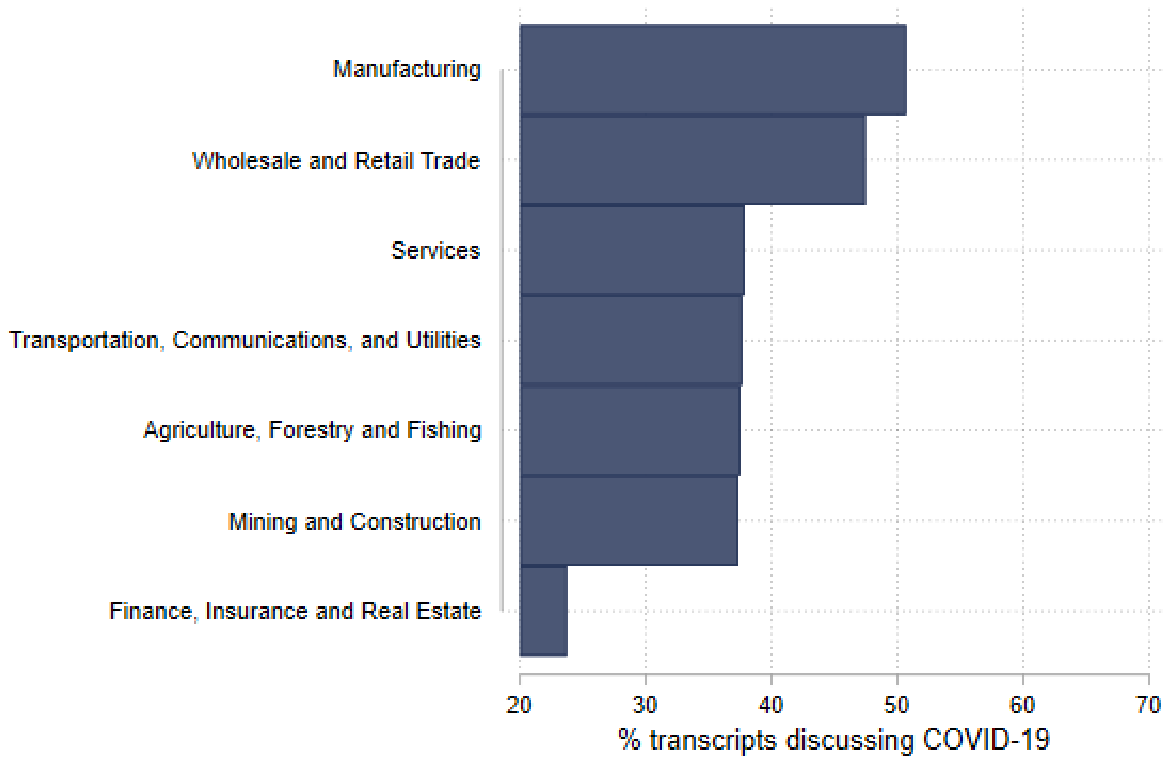
Notes: This figure plots the percentage of earnings calls discussing epidemic diseases (COVID-19, SARS, H1N1, Ebola, Zika, and MERS) by quarter, from Q1-2002 to Q1-2020. We exclude pharmaceuticals (SIC = 2834) and healthcare firms (2-digit SIC = 80).

Figure 2: Percentage of Earnings Calls Discussing Covid-19 by Country



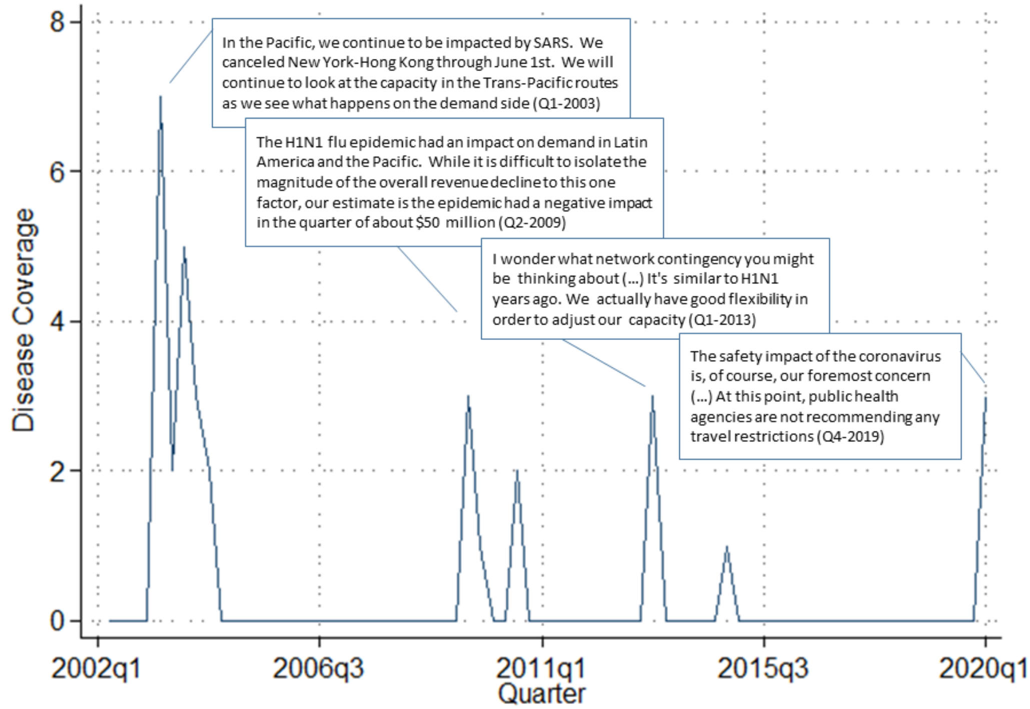
Notes: This figure shows the percentage of earnings calls discussing covid-19 by country in the first quarter of 2020. We only include countries for which the total number of earnings call transcripts held in 2020 (till March 7, 2020) per country ≥ 25. Pharmaceuticals (SIC = 2834) and healthcare firms (2-digit SIC = 80) are excluded.

Figure 3: Percentage Earnings Calls Discussing COVID-19 by Industry

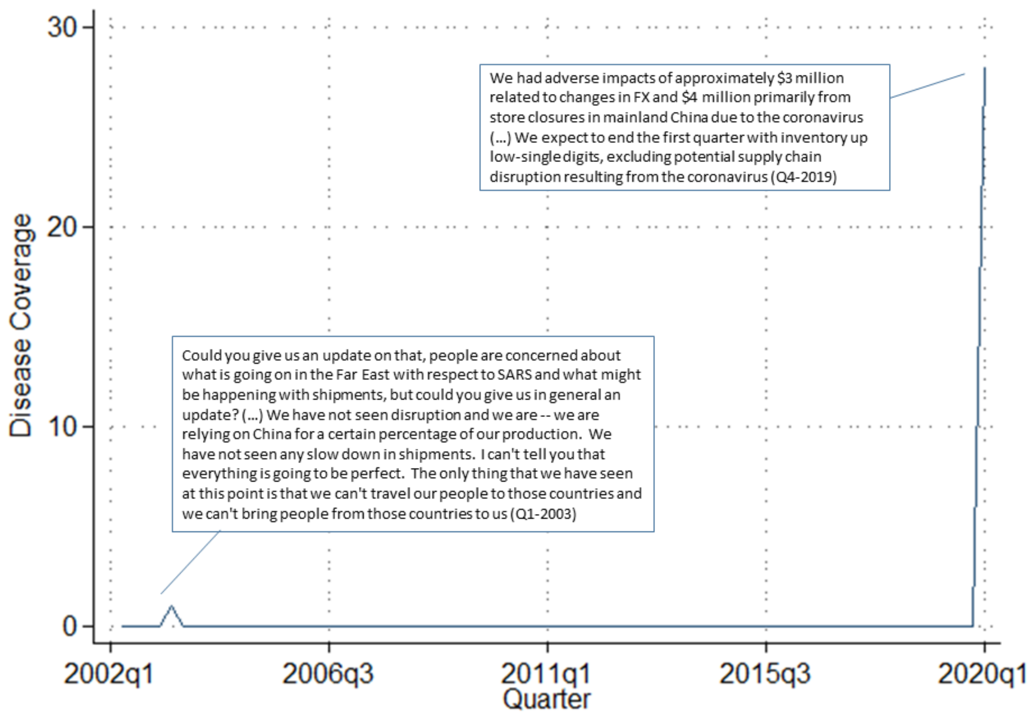


Notes: This figure shows the percentage of earnings calls held in the first quarter of 2020 (through March 7) discussing COVID-19 by industry (one-digit SIC). Pharmaceuticals (SIC = 2834), healthcare firms (2-digit SIC = 80), and SIC $\geq$ 9900 ("Nonclassifiable") are excluded.

Figure 4: Two Case Studies



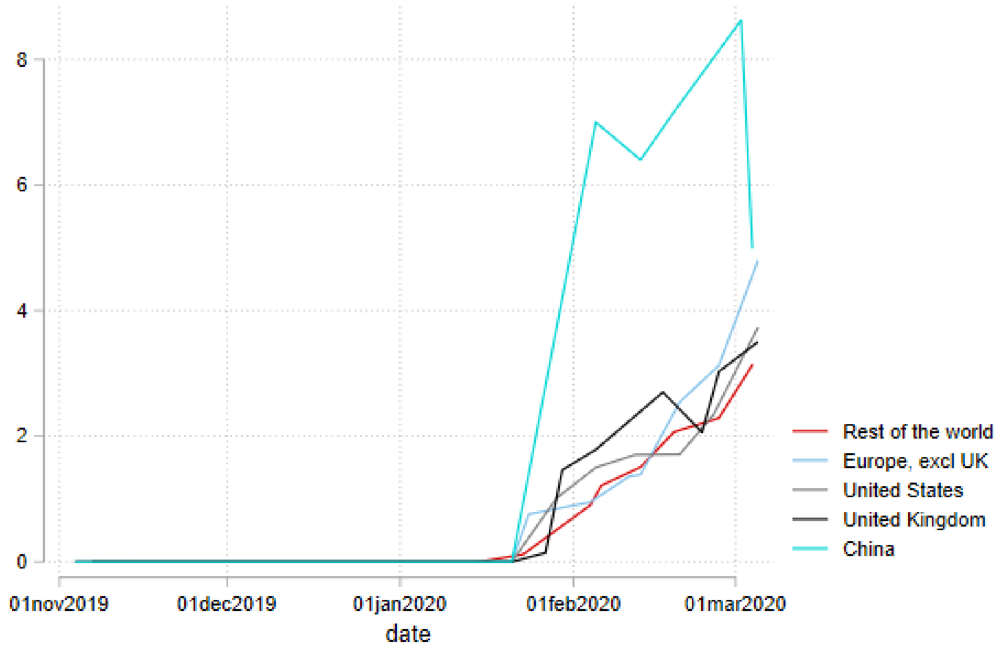
(a) United Airlines



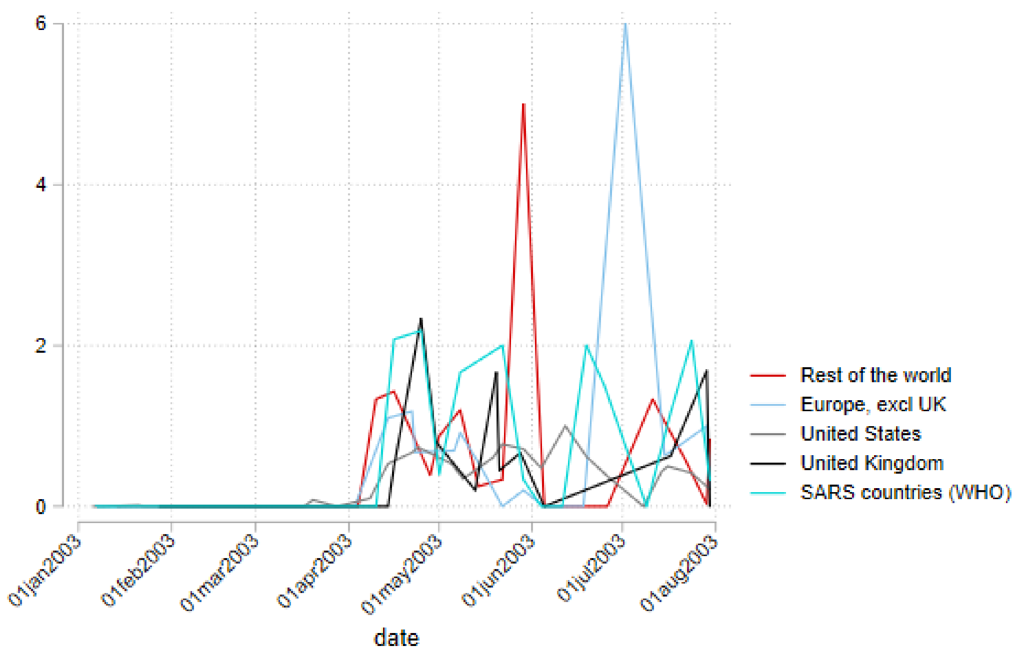
(b) Abercrombie & Fitch

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

Figure 5: Discussion COVID-19, SARS, H1N1 by Region

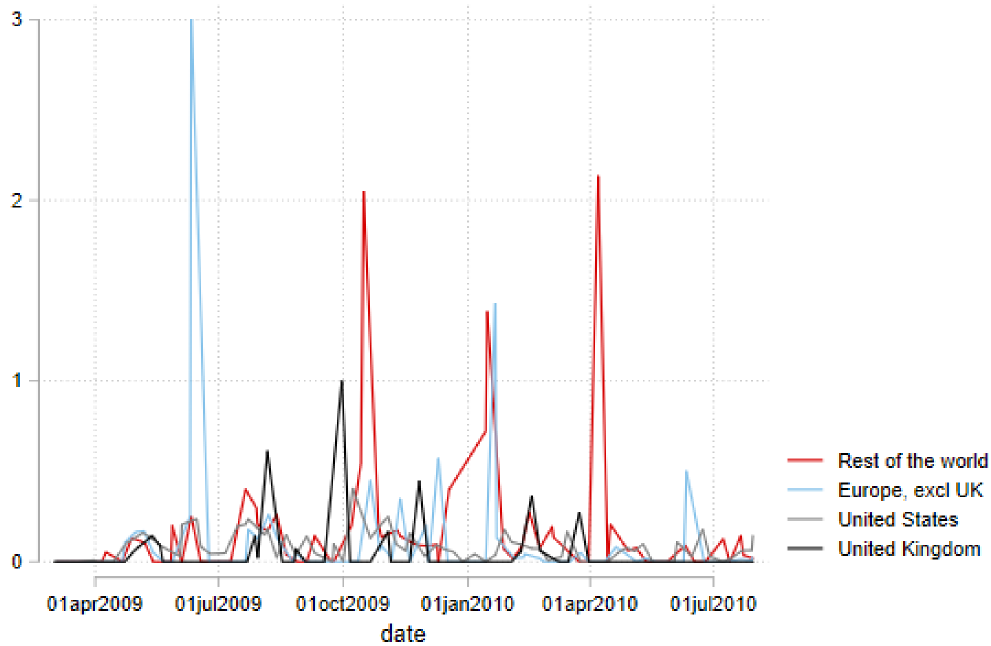


(a) COVID-19: November 1, 2019 to March 10, 2020



(b) SARS: January 1-July 31, 2003

Figure 5: Discussion COVID-19, SARS, H1N1 by Region (C'd)



(c) H1N1: March 1, 2009 to July 31, 2010

Notes: This figure plots the mean number of times an epidemic disease (Panel A: Covid-19, Panel B: SARS, Panel C: H1N1) is mentioned in earnings call transcripts by week per region. SARS affected countries include China, Hong Kong, Singapore, Vietnam, and Canada (https://www.who.int/ith/diseases/sars/en/).

Table 1: Firms with Extensive or Early Discussion of Covid-19

Company name	Call date	*Covid19 Exposure*	Country
Panel A: Top-10 firms with highest $Covid19Exposure$			
Abercrombie & Fitch	04-Mar-2020	0.31	United States
Biomerieux SA	26-Feb-2020	0.30	France
Crocs Inc	27-Feb-2020	0.29	United States
Advanced Energy Industries Inc	18-Feb-2020	0.28	United States
PPD Inc	05-Mar-2020	0.27	United States
Wolverine World Wide Inc	25-Feb-2020	0.27	United States
Descartes Systems Group Inc	04-Mar-2020	0.26	Canada
Agilent Technologies Inc	18-Feb-2020	0.25	United States
Watts Water Technologies Inc	11-Feb-2020	0.25	United States
Matson Inc	25-Feb-2020	0.24	United States
Panel B: Top-10 firms with highest $Covid19Exposure$ in January			
United Airlines Holdings Inc	22-Jan-2020	0.03	United States
Vinda Intl Hldgs Ltd	22-Jan-2020	0.01	Hong Kong
Keppel Corporation Ltd	23-Jan-2020	0.01	Singapore
Avnet Inc	23-Jan-2020	0.01	United States
American Airlines Group Inc	23-Jan-2020	0.01	United States
SThree	27-Jan-2020	0.01	United States
Dr Reddy's Laboratories Ltd	27-Jan-2020	0.01	India
Sanmina Corp	27-Jan-2020	0.02	United States
Perkinelmer Inc	27-Jan-2020	0.05	United States
Whirlpool Corp	28-Jan-2020	0.02	United States

Notes: Panel A lists firms with the highest $Covid19Exposure$ ($\times 1000$). Only observations for which length > the sample mean are included. Panel B lists the first ten firms discussing covid-19 in earnings calls held in 2020.

Table 2: Covid-19-related Concerns and Opportunities expressed by Management

Category	Perc.	Transcript excerpt
Negative demand shock	43.5	the waterborne coatings tied especially to container shipping containers is still off because of the trade war now because the **coronavirus** is exacerbating that situation so demand is relatively soft in china epichlorohydrin specifically i dont know george if you have (Q4-2019 Hexion Inc, March 3, 2020)
Increased uncertainties	27.5	not a crystal ball to predict to what duration and to what extent important markets will be affected by the **coronavirus** we have to deal with the fact that our business has been already affected significantly in china to a lesser (Q4-2019 Hugo Boss AG, March 5, 2020)
Supply chain disruption	27.0	been getting these questions im sure others have as well anything we should be concerned or thinking about around the **coronavirus** impact on potentially supplies of strips cuffs or devices no we have a varied supply chain across the world and (Q4-2019 Livongo Health Inc, March 2, 2020)
Production capacity reduction/retail store closures	18.0	i turn it over to john i want to take a minute to talk about the recent outbreak of the **coronavirus** in china similar to other companies that operate in the region we are keeping our factory shut down week longer (Q4-2019 Knowles Corp, February 4, 2020)
Concerns about employee welfare and labor market	17.5	the economy was trending in a positive direction and seemed to be better until the most recent macro event the **coronavirus** briefly dxp was developing programs to help keep our employees safe as possible therefore keeping our customers exposure to a (Q4-2019 DXP Enterprises Inc, March 6, 2020)
Financial market/financing concerns	2.5	lower it is important to reiterate that the thirdparty price used is not necessarily our expectation with respect to the **coronavirus** that its having a significant global impact on everything from travel to supply chain to the financial market we are (Q4-2019 IDH Finance PLC, March 5, 2020)
No impact	13.0	a very little amount thats happening in asia in january we didnt see an impact to our business because of **coronavirus** we did see slight softness in hong kong and australia but youre talking about since asia is a relatively small (Q4-2019 WEX Inc, February 13, 2020)
Market opportunities	7.5	i think theres ways to look at this first is the chinese people as a result of this kind of **coronavirus** they might actually heighten or elevate the trust to reliability to japan or the japanese products so including that that (Q4-2019 Shiseido Co Ltd, February 6, 2020)

Notes: We manually classified a total of 200 randomly selected covid-19-related excerpts (+/- 10 words around the synonym for coronavirus or covid-19) into predefined categories. This table reports a breakdown per category. Numbers in the column 'Perc.' denote percentages out of classified transcripts. We do not tabulate a separate category of "unspecified" which includes the 18.5 percent of transcripts which have snippets that while mentioning the coronavirus do not state an explicit related concern.

Table 3: Covid-19-related Concerns and Opportunities expressed by Management by Month

	2020			
	Jan	Feb	Mar	Overall
Negative demand shock	42.42	37.31	50.75	43.50
Increased uncertainties	18.18	29.85	34.33	27.50
Supply chain disruption	12.12	35.82	32.84	27.00
Production capacity reductions/retail store closure	12.12	22.39	19.40	18.00
Concerns about employee welfare and labor market	15.15	10.45	26.87	17.50
No impact	6.06	14.93	17.91	13.00
Market opportunities	7.58	10.45	4.48	7.50

Notes: We manually classified a total of 200 randomly selected covid-19-related excerpts (+/- 10 words around the synonym for coronavirus or covid-19) into predefined categories. This table reports a breakdown per category by month separately for January, February and March 2020, respectively. The numbers given denote percentages out of classified transcripts in the respective month. We do not tabulate a separate category of "unspecified" which includes the 18.5 percent of transcripts which have snippets that while mentioning the coronavirus do not state an explicit related concern.

Table 4: Summary Statistics

	All firms			US firms		Non-US firms		Total
	Mean	Median	SD	Mean	SD	Mean	SD	N
Panel A: Covid19 variables								
Covid19NegativeSentiment	0.069	0.000	0.187	0.068	0.195	0.070	0.175	3,392
Covid19NetSentiment	-0.040	0.000	0.164	-0.040	0.168	-0.042	0.158	3,392
Covid19Exposure	0.246	0.000	0.455	0.240	0.461	0.256	0.446	3,392
Covid19Risk	0.022	0.000	0.084	0.020	0.081	0.025	0.088	3,392
PriorEpid	0.865	0.000	4.044	1.129	4.746	0.487	2.697	3,392
Panel B: Other epidemic variables								
Sars03Exposure	0.046	0.000	0.199	0.040	0.172	0.074	0.288	11,550
H1N1Exposure	0.017	0.000	0.153	0.015	0.142	0.019	0.173	17,687
Panel C: Firm specific variables								
Total assets, log	8.418	8.297	2.126	8.031	1.874	8.990	2.337	3,351
Market beta	0.661	0.636	0.428	0.870	0.365	0.361	0.321	3,046

Notes: This table shows the mean, median, standard deviation, and the number of firms for the variables used in the subsequent analysis. Columns 1 to 3 refer to the sample of all firms, Columns 4 and 5 to the sample of US firms, and Columns 6 and 7 to the sample of non-US firms. Covid19NegativeSentiment, Covid19NetSentiment, Covid19Exposure, and Covid19Risk are calculated, as defined in Section 2 and multiplied by 1,000. All Covid19 variables are calculated using firms' transcripts from the first quarter in 2020. PriorEpid is the sum of SARSExposure (measured for calls held in 2003) and H1N1Exposure (measured for calls held in 2009) by firm, multiplied by 1,000. Total assets per 2019 year-end are obtained from Compustat. Market beta is calculated by regressing daily returns in 2018 for firm i on the SP500 index.

Table 5: Prior Exposure to Epidemic Diseases and Covid19 Negative Sentiment

	(1)	(2)	(3)
Sample	Full	Full	US
		$Covid19NegativeSentiment$	
PriorEpid		-0.00162**	-0.00204**
		(0.000769)	(0.000874)
Covid19Exposure	0.280***	0.281***	0.273***
	(0.0154)	(0.0156)	(0.0212)
Total assets, log	-0.00141	-0.000699	-0.00112
	(0.00142)	(0.00145)	(0.00204)
Market beta	-0.0212**	-0.0216**	-0.0286**
	(0.0102)	(0.0102)	(0.0133)
Constant	0.0254**	0.0208*	0.0374**
	(0.0121)	(0.0122)	(0.0150)
Observations	3,000	3,000	1,786
R-squared	0.517	0.518	0.512
Country FE	YES	YES	NO
Industry FE	YES	YES	YES

Notes: This table reports estimates from a regression of $Covid19NegativeSentiment$ on an index for prior experience with H1N1 or Ebola ($PriorEpid$), with robust standard errors. $PriorEpid$ is the sum of the number of times SARS (H1N1) is mentioned in firm i's earnings calls held in 2003 (2009), scaled by the number of words in the transcript. Columns 1 and 2 use the full sample; column 3 includes only US firms. All specifications include sector fixed effects (two-digit SIC) and, where appropriate, country fixed effects. ***, **, * represent statistical significance at the 1, 10, and 5 percent level, respectively.

Table 6: Covid-19 Exposure and Earnings-Call Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Full	Full	Full	Full	US	US	US	US
					Returns[-1,+1]			
$Covid19Exposure$	-2.543***				-2.789***			
	(0.598)				(0.846)			
$Covid19NegativeSentiment$		-4.553***		-4.282***		-4.864**		-4.652*
		(1.615)		(1.618)		(2.399)		(2.404)
$Covid19PositiveStatement$		-1.606		-1.120		-3.100		-2.631
		(3.591)		(3.671)		(4.680)		(4.877)
$Covid19Risk$			-5.842**	-2.700			-6.405**	-2.051
			(2.273)	(2.449)			(2.923)	(3.345)
Market beta	-0.398	-0.611	-0.608	-0.612	-1.206	-1.473	-1.347	-1.463
	(0.896)	(0.897)	(0.901)	(0.898)	(1.126)	(1.122)	(1.128)	(1.125)
Total assets, log	0.217*	0.203	0.193	0.199	0.364**	0.354**	0.342**	0.350**
	(0.132)	(0.132)	(0.132)	(0.132)	(0.173)	(0.173)	(0.172)	(0.174)
Constant	-1.799	-1.798	-1.958	-1.731	-2.795*	-2.717*	-3.027*	-2.675*
	(1.245)	(1.248)	(1.245)	(1.251)	(1.553)	(1.567)	(1.554)	(1.571)
Observations	1,654	1,654	1,654	1,654	1,031	1,031	1,031	1,031
R-squared	0.097	0.093	0.086	0.094	0.107	0.106	0.097	0.106
Country FE	YES	YES	YES	YES	NO	NO	NO	NO
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports estimates from a regression using cumulative stock returns (-1,+1) around earnings call date as the dependent variable, with robust standard errors. Columns 1-4 use the full sample; columns 5-8 includes only US firms. All specifications include sector fixed effects (two-digit SIC) and, where appropriate, country fixed effects. ***, **, * represent statistical significance at the 1, 10, and 5 percent level, respectively.

Table 7: Covid-19 Exposure and Cumulative Stock Returns (Jan 1–Mar 15, 2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Full	Full	Full	Full	US	US	US	US
				Returns in 2020Q1				
$Covid19Exposure$	-5.445***				-4.365**			
	(1.446)				(2.121)			
$Covid19NegativeSentiment$		-12.29***		-10.80***		-7.608		-5.895
		(4.002)		(4.078)		(5.694)		(5.903)
$Covid19PositiveSentiment$		-0.178		1.936		-3.333		-0.713
		(7.224)		(7.309)		(9.777)		(9.858)
$Covid19Risk$			-20.62***	-14.12**			-20.08**	-15.35*
			(5.886)	(6.257)			(7.885)	(8.635)
Market beta	-8.352***	-8.826***	-8.735***	-8.839***	-10.14***	-10.50***	-10.20***	-10.41***
	(2.929)	(2.975)	(2.942)	(2.973)	(3.885)	(4.002)	(3.908)	(4.010)
Total assets, log	0.852**	0.819**	0.826**	0.817**	1.346***	1.331***	1.303***	1.307***
	(0.369)	(0.370)	(0.370)	(0.370)	(0.500)	(0.500)	(0.501)	(0.501)
Constant	-29.87***	-29.75***	-30.28***	-29.57***	-31.39***	-31.38***	-31.63***	-31.14***
	(4.092)	(4.101)	(4.067)	(4.103)	(5.862)	(5.888)	(5.799)	(5.890)
Observations	2,230	2,230	2,230	2,230	1,331	1,331	1,331	1,331
R-squared	0.211	0.211	0.209	0.212	0.204	0.203	0.203	0.204
Country FE	YES	YES	YES	YES	NO	NO	NO	NO
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports estimates from a regression using cumulative stock returns (Jan 1–Mar 15, 2020) as the dependent variable, with robust standard errors. Columns 1-4 use the full sample; columns 5-8 includes only US firms. All specifications include sector fixed effects (two-digit SIC) and, where appropriate, country fixed effects. ***, **, * represent statistical significance at the 1, 10, and 5 percent level, respectively.

Appendix

to

"Firm-level Epidemic Exposure: Covid-19 and other Viruses"

by

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Appendix Table 1: Distribution of Earnings Conference Calls by Country

Country	Freq.	Perc.	Cum.	Firms
Argentina	475	0.15	0.15	21
Australia	3586	1.1	1.24	414
Austria	859	0.26	1.51	35
Bahamas	55	0.02	1.52	3
Bahrain	18	0.01	1.53	3
Belgium	988	0.3	1.83	42
Bermuda	2853	0.87	2.71	89
Brazil	4283	1.31	4.02	170
British Virgin Islands	28	0.01	4.03	4
Canada	20090	6.16	10.19	886
Cayman Islands	426	0.13	10.32	18
Chile	783	0.24	10.56	31
China	4619	1.42	11.97	328
Colombia	319	0.1	12.07	17
Costa Rica	6	0	12.07	1
Croatia	5	0	12.07	1
Cyprus	269	0.08	12.16	21
Czech Republic	207	0.06	12.22	6
Denmark	1751	0.54	12.76	60
Egypt	149	0.05	12.8	8
Estonia	1	0	12.8	1
Faroe Islands	11	0	12.81	1
Finland	1984	0.61	13.41	62
France	3834	1.18	14.59	160
Germany	5679	1.74	16.33	216
Gibraltar	60	0.02	16.35	2
Greece	987	0.3	16.65	41
Guernsey	110	0.03	16.69	15
Hong Kong	1348	0.41	17.1	114
Hungary	198	0.06	17.16	4
Iceland	58	0.02	17.18	5
India	4161	1.28	18.45	304
Indonesia	294	0.09	18.54	18
Ireland	2352	0.72	19.26	74
Isle of Man	45	0.01	19.28	5
Israel	2630	0.81	20.08	109
Italy	2654	0.81	20.9	105
Japan	7398	2.27	23.16	283
Jersey	207	0.06	23.23	15
Kazakhstan	85	0.03	23.25	6
Kenya	19	0.01	23.26	2
Kuwait	18	0.01	23.27	3
Luxembourg	1033	0.32	23.58	50
Macao	9	0	23.58	1
Malaysia	260	0.08	23.66	21

Appendix Table 1: Distribution of Earnings Conference Calls by Country (C'd)

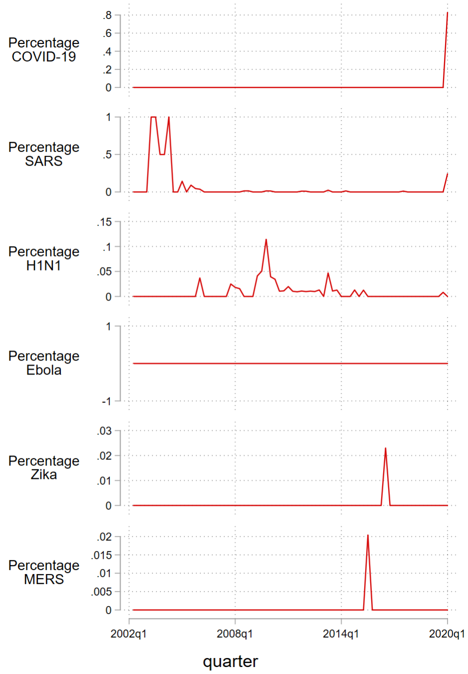
Country	Freq.	Perc.	Cum.	Firms
Malta	31	0.01	23.67	4
Marshall Islands	32	0.01	23.68	1
Mauritius	10	0	23.69	3
Mexico	2198	0.67	24.36	97
Monaco	263	0.08	24.44	11
Morocco	15	0	24.45	1
Netherlands	2869	0.88	25.32	105
New Zealand	416	0.13	25.45	52
Nigeria	104	0.03	25.48	15
Norway	1960	0.6	26.09	90
Oman	57	0.02	26.1	3
Pakistan	14	0	26.11	3
Panama	116	0.04	26.14	3
Papua New Guinea	30	0.01	26.15	2
Peru	173	0.05	26.2	10
Philippines	222	0.07	26.27	19
Poland	589	0.18	26.45	30
Portugal	525	0.16	26.61	14
Puerto Rico	219	0.07	26.68	8
Qatar	46	0.01	26.7	3
Romania	32	0.01	26.71	3
Russia	1145	0.35	27.06	54
Saudi Arabia	28	0.01	27.06	2
Singapore	1056	0.32	27.39	55
South Africa	1344	0.41	27.8	95
South Korea	1231	0.38	28.18	45
Spain	2167	0.66	28.84	74
Sweden	3850	1.18	30.02	180
Switzerland	3175	0.97	31	122
Taiwan	1298	0.4	31.39	49
Thailand	335	0.1	31.5	23
Turkey	559	0.17	31.67	27
U.S. Virgin Islands	27	0.01	31.68	2
Ukraine	36	0.01	31.69	3
United Arab Emirates	236	0.07	31.76	21
United Kingdom	9804	3.01	34.76	528
United States	212780	65.22	99.98	6467
Uruguay	32	0.01	99.99	1
Venezuela	19	0.01	100	2

Appendix Table 2: Disease Synonyms

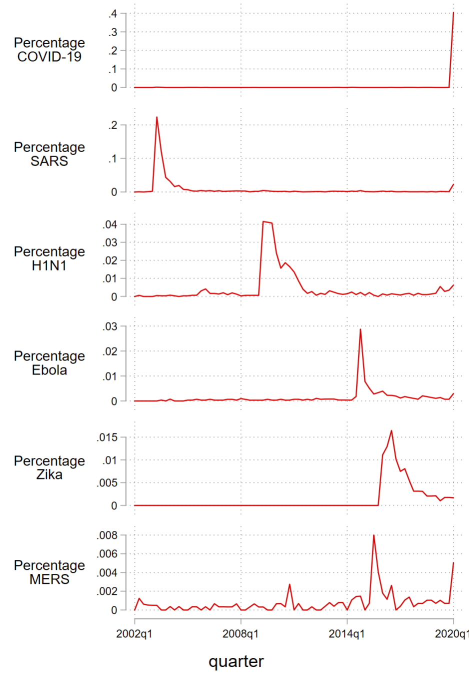
SARS	MERS	Ebola
‘sars’ ‘severe acute respiratory syndrome’	‘merscov’ ‘middle east respiratory syndrome’ ‘mers’	‘ebola’
H1N1	**Zika**	**COVID**
‘hn’* ‘swine flu’ ‘ahn’	‘zika’	‘sarscov’ ‘coronavirus’ ‘corona virus’ ‘ncov’ ‘covid’

*) In pre-processing the transcripts, we removed (among others) all numerical characteristics.

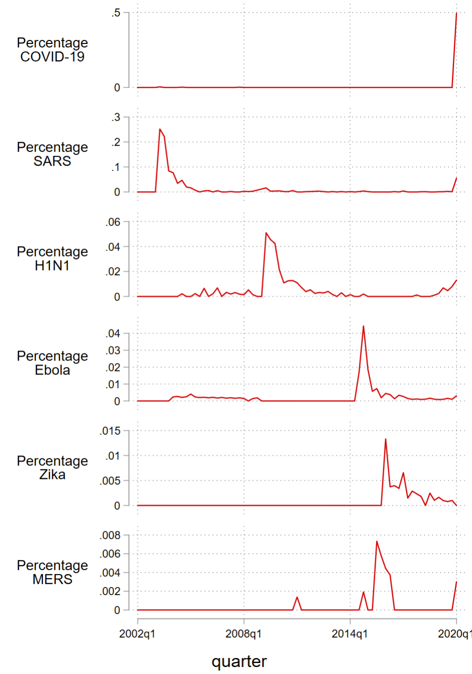
Appendix Figure 1: Percentage Earnings Calls Discussing Epidemic Diseases



(a) China



(b) United States



(c) Europe

Appendix Table 3: Most Frequent Synonyms for Risk or Uncertainty

Word	Frequency	Word	Frequency
uncertainty	344	unsure	2
risk	199	debatable	1
threat	96	hesitant	1
uncertainties	84	unstable	1
risks	84	hazardous	1
unknown	67	unsafe	1
uncertain	61	danger	1
fear	50	hesitancy	1
exposed	30	halting	1
unclear	24	vague	1
possibility	20	hairy	1
doubt	19	jeopardize	1
unpredictable	14	unforeseeable	1
variable	12		
chance	11		
pending	10		
variability	7		
instability	6		
prospect	6		
dangerous	6		
likelihood	5		
queries	4		
varying	4		
probability	4		
tricky	3		
unpredictability	3		
fluctuating	2		
reservation	2		
speculative	2		
dilemma	2		
unsure	2		

Notes: This table shows the frequency across all 326,247 earnings call transcripts between 2001 and 2020 of all single-word synonyms of "risk," "risky," "uncertain," and "uncertainty" as given in the Oxford Dictionary (excluding "question" and "questions") that appear within 10 words of $Disease^d$.

Appendix Table 4: Most Frequent Positive Tone Words

Word	Frequency	Word	Frequency
good	329	easy	24
strong	285	success	24
despite	197	tremendous	22
positive	175	favorable	22
great	162	boost	21
able	146	encouraging	21
better	108	achieved	21
benefit	91	gain	21
opportunity	82	easier	20
progress	76	perfect	19
opportunities	61	positively	18
best	59	happy	17
improvement	49	advantage	16
improved	48	excited	16
pleased	47	improvements	15
benefited	47	encouraged	15
stronger	42	achieve	15
successful	42	successfully	15
improve	41	progressing	14
greater	41	excellent	14
confident	41	proactive	13
effective	39	stabilize	13
optimistic	36	exceptional	13
leading	35	gains	12
strength	33	advancing	11
rebound	31	rebounded	11
profitability	28	exclusive	11
collaboration	27	highest	11
improving	26	greatly	11
stable	25	exciting	11
easy	24	profitable	10

Notes: This table shows the frequency across all 326,247 earnings call transcripts between 2001 and 2020 of all positive tone words from Loughran and McDonald (2011) (their list contains 354 positive tone words) appearing within 10 words of $Disease^d$.

Appendix Table 5: Most Frequent Negative Tone Words

Word	Frequency	Word	Frequency
against	322	unfortunately	51
concerns	312	fear	50
crisis	265	cancellations	50
negative	253	delay	49
difficult	238	unfortunate	44
strain	221	problems	43
concern	159	conflict	43
disruption	145	delayed	43
strains	136	adverse	42
challenges	133	slowed	41
decline	120	declined	38
problem	110	bad	37
concerned	102	prevention	35
threat	94	worse	34
negatively	89	absence	33
disruptions	85	difficulty	33
weak	77	unexpected	33
challenge	77	claims	31
slowdown	75	lack	31
fears	70	downturn	30
late	69	threats	30
volatility	69	closed	29
challenging	67	lingering	29
weakness	65	closing	28
loss	64	severely	27
slow	62	recession	27
recall	62	weaker	27
serious	58	unrest	27
delays	54	exposed	27
severe	51	impossible	26
unfortunately	51	incidence	26

Notes: This table shows the frequency across all 326,247 earnings call transcripts between 2001 and 2020 of all negative tone words (with the exception of "question," "questions," and "ill") from Loughran and McDonald (2011) (their list contains 2,352 negative tone words) appearing within 10 words of $Disease^d$.

Appendix Table 6: Cumulative Stock Returns (-90,0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Full	Full	Full	Full	US	US	US	US
$Covid19Exposure$	-5.873***				-5.173***			
	(0.914)				(1.217)			
$Covid19NegativeSentiment$		-8.858***		-8.322***		-6.930**		-6.011*
		(2.398)		(2.430)		(3.076)		(3.158)
$Covid19PositiveSentiment$		-8.183		-7.424		-11.72		-10.32
		(5.441)		(5.506)		(7.583)		(7.676)
$Covid19Risk$			-12.68***	-5.071			-16.50***	-8.232
			(3.750)	(4.083)			(5.305)	(6.066)
Market beta	-0.937	-1.255	-1.367	-1.259	-2.091	-2.341	-2.204	-2.291
	(1.517)	(1.530)	(1.524)	(1.529)	(1.857)	(1.870)	(1.864)	(1.870)
Total assets, log	0.279	0.251	0.252	0.251	0.672**	0.660**	0.633**	0.647**
	(0.212)	(0.214)	(0.215)	(0.214)	(0.286)	(0.288)	(0.291)	(0.289)
Constant	2.525	2.379	1.858	2.446	-0.0714	-0.170	-0.575	-0.0413
	(2.086)	(2.100)	(2.109)	(2.101)	(2.762)	(2.766)	(2.773)	(2.769)
Observations	2,230	2,230	2,230	2,230	1,331	1,331	1,331	1,331
R-squared	0.165	0.159	0.149	0.160	0.137	0.136	0.129	0.137
Country FE	YES	YES	YES	YES	NO	NO	NO	NO
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

This table reports estimates from a regression using cumulative stock returns (-90,0) as the dependent variable, with robust standard errors. Columns 1-4 use the full sample; columns 5-8 includes only US firms. All specifications include sector fixed effects (two-digit SIC) and, where appropriate, country fixed effects. ***, **, * represent statistical significance at the 1, 10, and 5 percent level, respectively.

Appendix Table 7: Prior Exposure to Epidemic Diseases, Covid19 Exposure, Covid19 Risk

	(1)	(2)	(3)	(4)
VARIABLES	Full	US	Full	US
PriorEpid	0.00729**	0.00692*	0.000311	0.000216
	(0.00309)	(0.00364)	(0.000363)	(0.000392)
Total assets, log	0.00383	0.00259	0.000225	-0.000939
	(0.00465)	(0.00603)	(0.000928)	(0.00106)
Market beta	0.0528*	0.0130	0.000904	-0.00132
	(0.0284)	(0.0369)	(0.00585)	(0.00730)
Constant	0.172***	0.199***	0.0195**	0.0291***
	(0.0399)	(0.0482)	(0.00804)	(0.00945)
Observations	3,000	1,786	3,000	1,786
R-squared	0.224	0.230	0.099	0.124
Country FE	YES	NO	YES	NO
Industry FE	YES	YES	YES	YES

This table reports estimates from a regression of $Covid19Exposure$ (Columns 1-2) and $Covid19Risk$ (Columns 3-4) as the dependent variable, with robust standard errors. $PriorEpid$ is the sum of the number of times SARS (H1N1) is mentioned in firm i's earnings calls held in 2003 (2009), scaled by the number of words in the transcript. Columns 1 and 3 use the full sample; columns 2 and 4 include only US firms. All specifications include sector fixed effects (two-digit SIC) and, where appropriate, country fixed effects. ***, **, * represent statistical significance at the 1, 10, and 5 percent level, respectively.