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

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We organize this appendix as follows. In Appendix A, we discuss how our (supervised) approach compares to a frequently used unsupervised topic identification approach: LDA. In Appendix B, we provide several additional figures and tables that we refer to in the main text of the paper.

Appendix A. Identifying topics: details and discussion

This appendix contains a brief comparison of our topic discovery step with a popular unsupervised method for topic discovery: Latent Dirichlet Allocation (LDA). Specifically, we compare the five categories from our topic discovery step with LDA. Recall that we leverage our team members' economic judgment to find a set of categories that does justice to our goal of tracing the channels of a particular macro-level shock—the outbreak of COVID-19—to a firm. Thus, the categories should strike a reasonable balance between representing multifaceted coronavirus-related discussions and being economically meaningful for subsequent analyses. It is worth noting that this balance is difficult to strike even for a human reader. We report the results from several LDA runs in the form of word clouds in Appendix Figure 3. It is not always easy to make sense of word clouds. Nevertheless, the word clouds suggest that none of the topics align with what economists would view as supply or demand-related impacts, let alone represent useful categories that allow us to trace the channels of the coronavirus outbreak to firms.

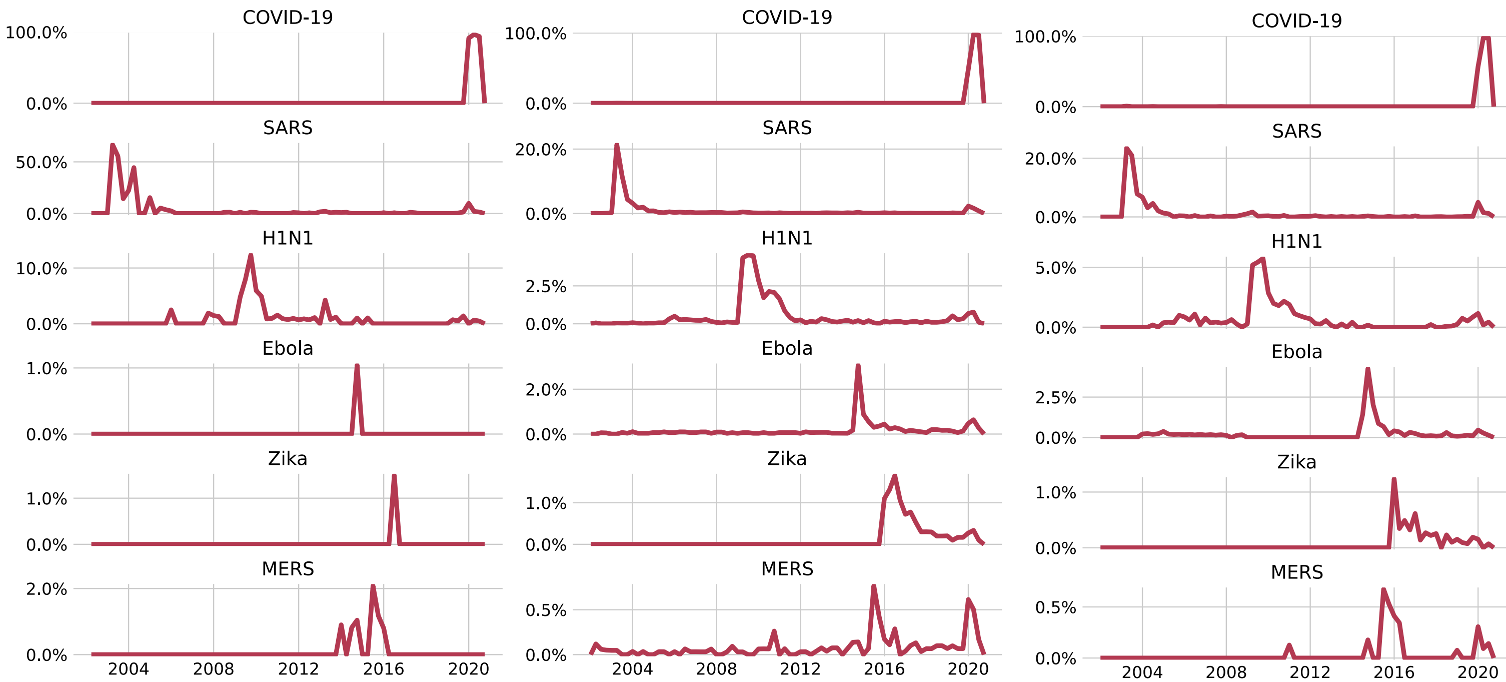
We believe that it is not accidental but results from a key logical issue that limits the applicability of automated topic detection in this context. Conversations in earnings calls are multi-dimensional by nature and 'off-the-shelf' LDA algorithms cannot tell in which of these dimensions we are interested. For example, a typical discussion of a supply-side impact might read, "On the top line, organic sales in the first quarter declined by 1.3%, including the negative impact of our facilities in China being closed for a full month due to the COVID-19 pandemic." This discussion touches on multiple logical planes: the firm's total profits, closed facilities, supply-side impacts, and the firm's activities in China. LDA attempts to cluster topics discussed and, instead of identifying the relation between this firm's closed facilities and another firm's difficulties in sourcing parts, might find that this discussion is closest to other discussions of the firms' foreign activities, profits, or closed facilities. All of these inferences are, of course, correct. Deciding on which of these dimensions we are interested in is thus inherently a task that requires judgment, which we exert by defining topics in our training sample.

In addition, it is worth pointing out that researchers have significant discretion when using LDA to identify a text's topics, as the algorithm requires the choice of several parameters that can meaningfully change the resulting topics. With LDA's non-deterministic nature (multiple runs on the same data and using the same parameters may generate different topics), this suggests that it is not trivial to credibly tie the researcher's hands and generate a reproducible result with LDA. Taken together, we believe that for our context the usage of our economic judgment, as opposed to unsupervised methods such as LDA, is appropriate.

Appendix B. Additional figures and tables

Appendix Figure 1: Percentage of earnings calls discussing epidemic diseases across regions

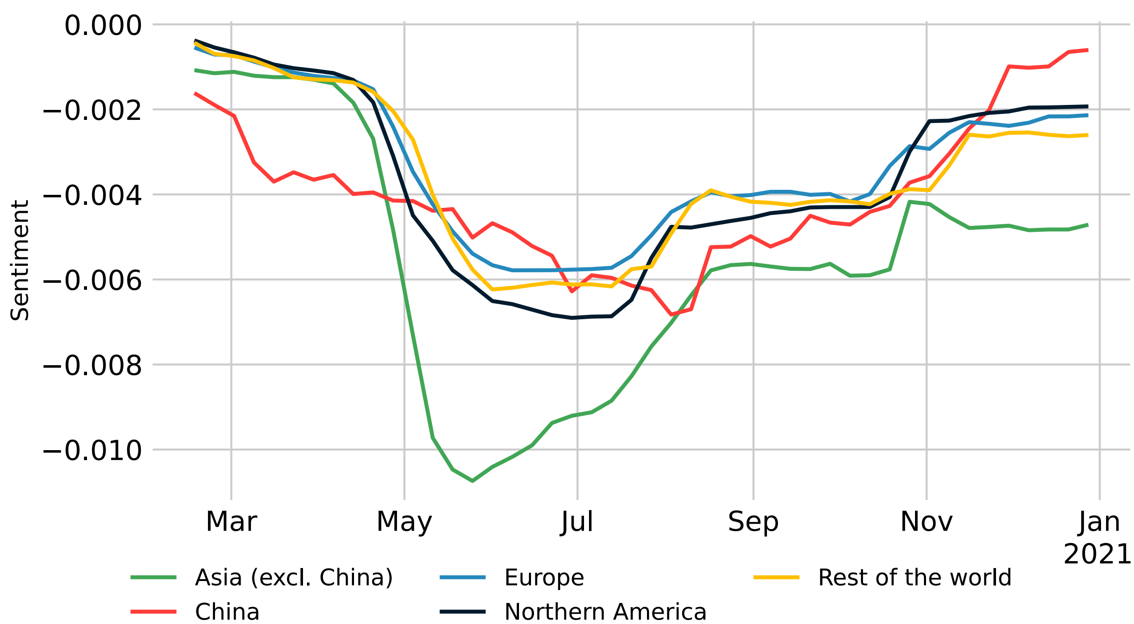
(a) China (b) United States (c) Europe



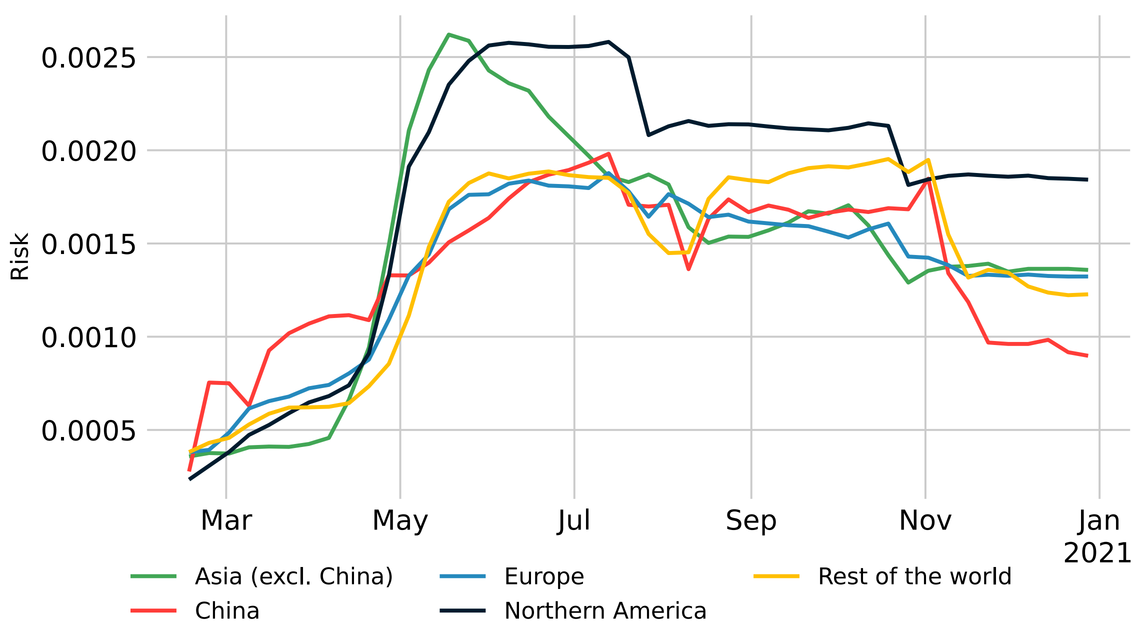
Notes: This figure plots the percentage of earnings calls discussing epidemic diseases (COVID-19, SARS, H1N1, Ebola, Zika, and MERS) by quarter from January 2002 through December 2020, separately for firms headquartered in China (Panel a), the United States (Panel b), and Europe (Panel c).

Appendix Figure 2: Time-series of average *COVID-19 sentiment*$_{i,t}$, and *risk*$_{i,t}$ by region

(a) Regional average of *COVID-19 sentiment*$_{i,t}$ over time

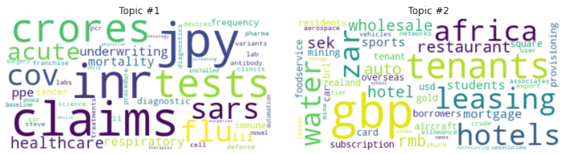


(b) Regional average of *COVID-19 risk*$_{i,t}$ over time



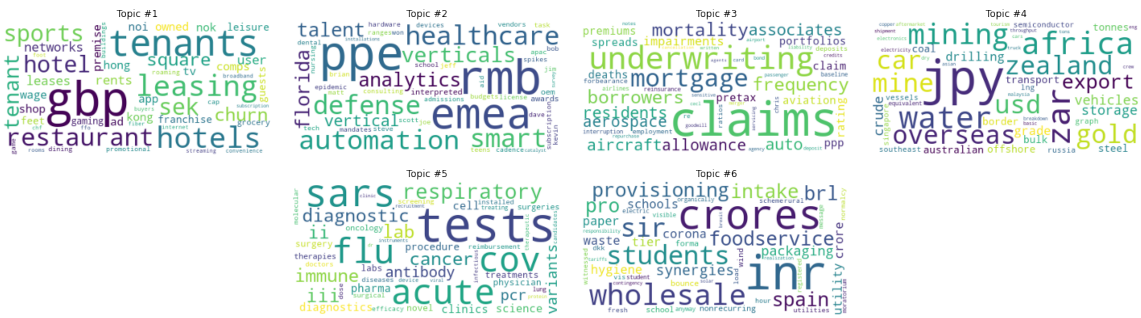
Notes: This figure plots the weekly average of *COVID-19 sentiment*$_{i,t}$, and *COVID-19 risk*$_{i,t}$ by region—i.e., Asia (excl. China), China, Europe, Northern America, Rest of the world—using all earnings conference calls held in the indicated time period by firms headquartered in the indicated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

Appendix Figure 3: Topic word clouds based on LDA

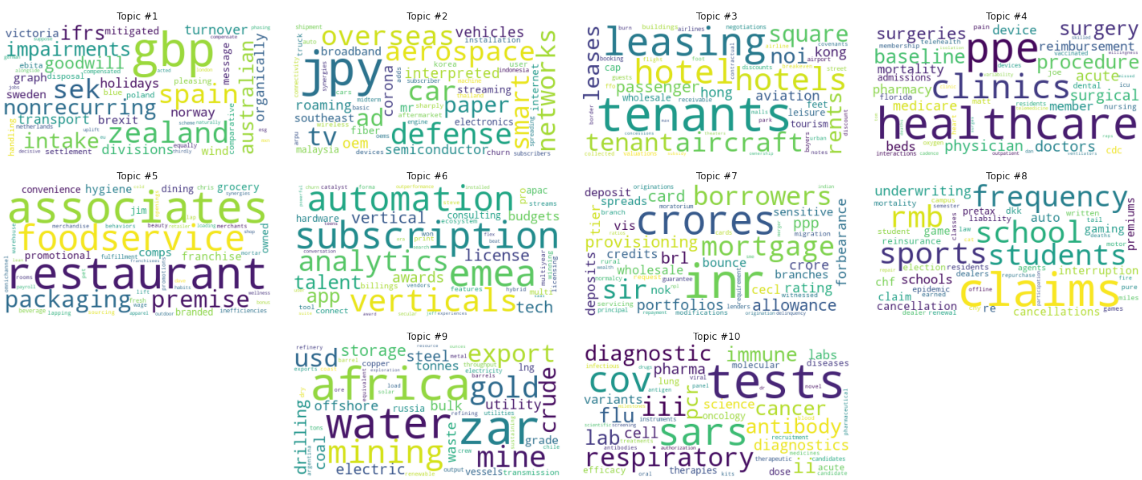


(a) Word clouds for $n = 2$

(b) Word clouds for $n = 4$



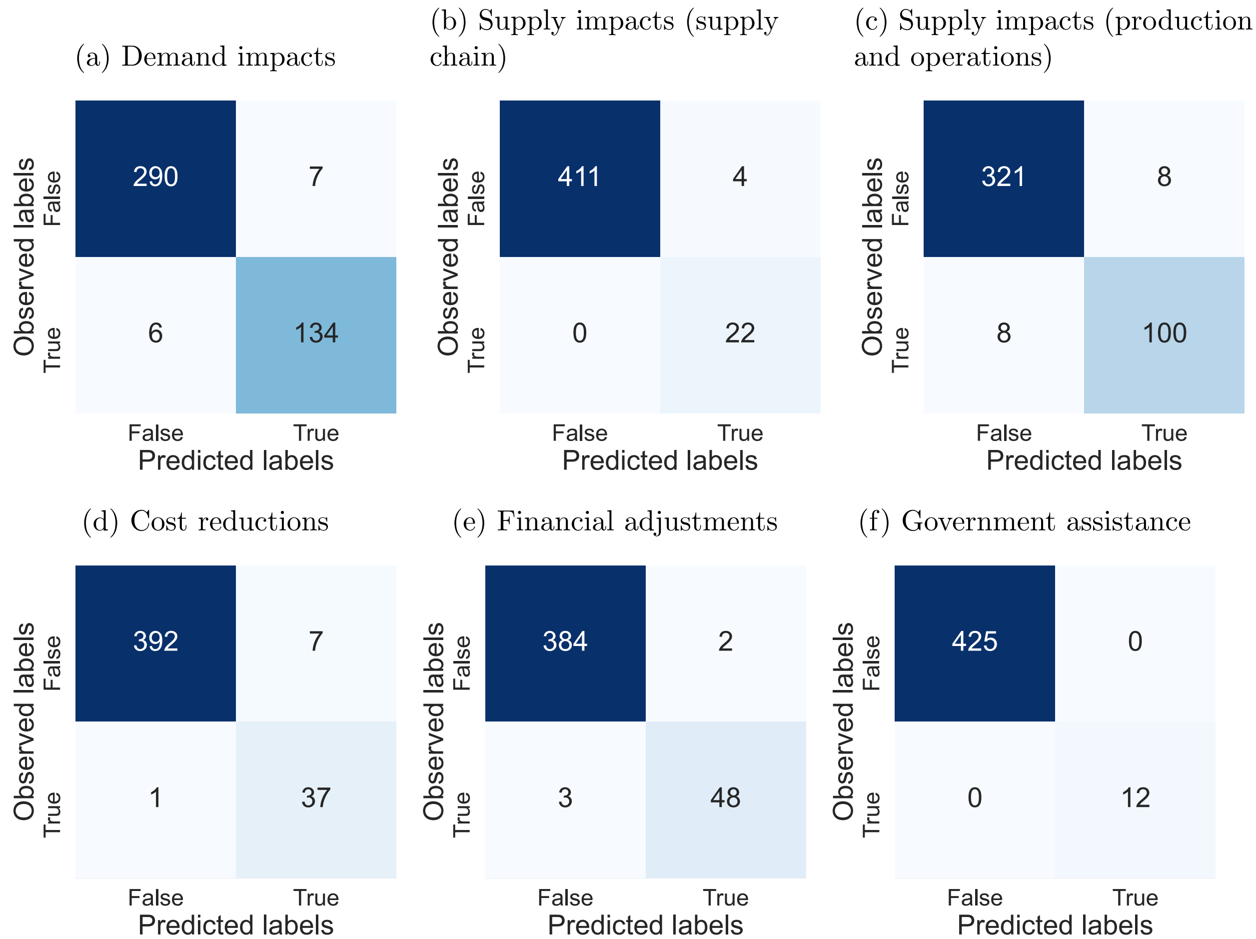
(c) Word clouds for $n = 6$



(d) Word clouds for $n = 10$

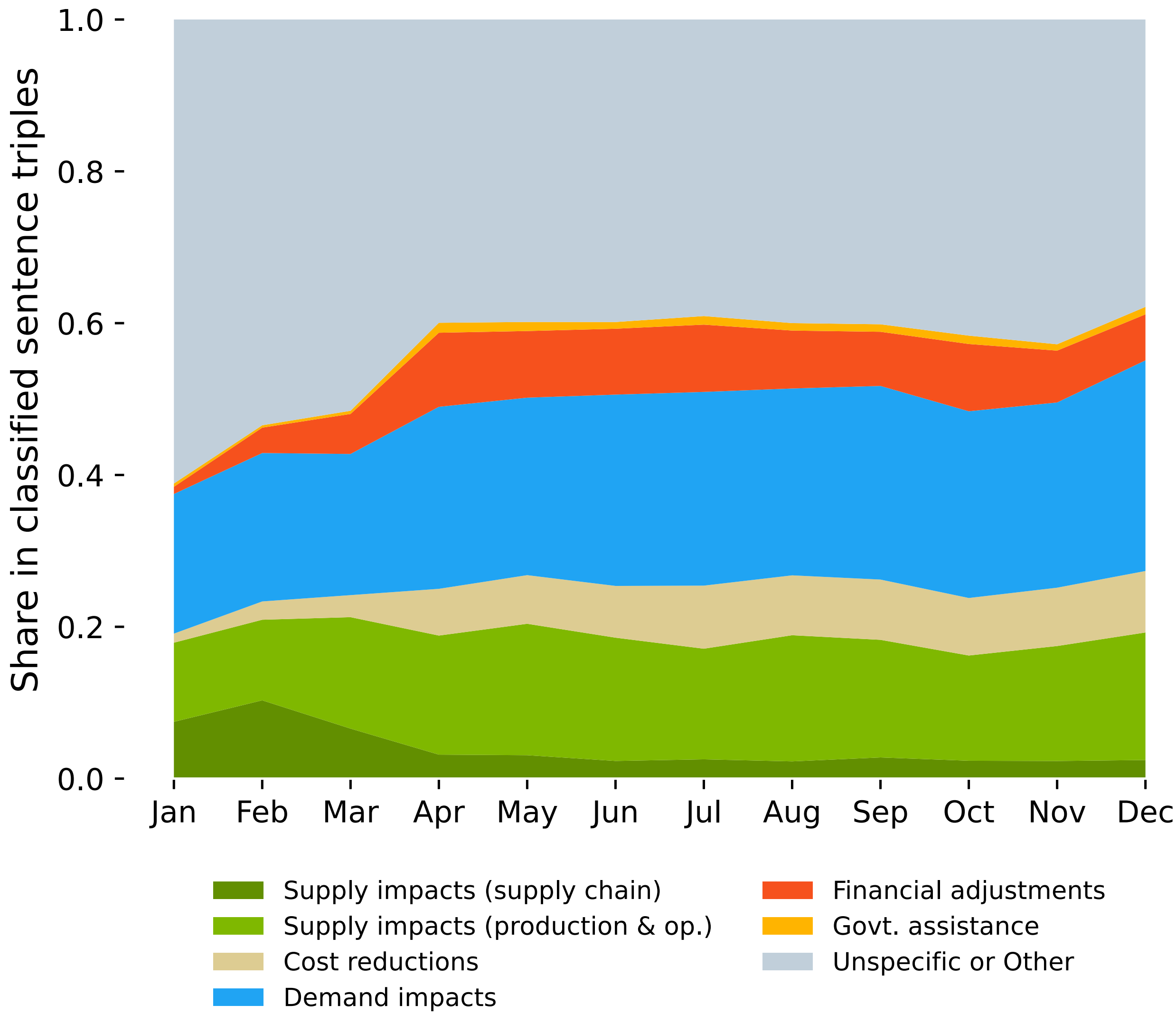
Notes: This figure shows word clouds corresponding to Latent Dirichlet Allocation (LDA) topic models with $n \in \{2, 4, 6, 10\}$ topics. The underlying data are all sentence triples; i.e., text fragments consisting of three consecutive sentences by the same speaker, with the middle sentence containing a keyword related to COVID-19 as specified in Appendix Table B.2. We split the sentence triples into words, remove stopwords, and stem the remaining tokens. We concatenate all tokens from sentence triples belonging to the same earnings call into one vector, and keep the 10,000 highest-ranking tokens when sorted on tf×idf. The unit of analysis for the LDA model consists of the remaining tokens from all sentence triples belonging to the same earnings call. We implement LDA using the collapsed Gibbs sampling algorithm (using the priors recommended by Griffiths and Steyvers (2004)) and use the Python module developed by Hansen et al. (2018) and available on https://github.com/alan-turing-institute/topic-modelling-tools.

Appendix Figure 4: Confusion matrices for disease-related topics on training data



Notes: This figure shows confusion matrices, with two dimensions ("predicted" and "observed"), summarizing the performance of our pattern-based classifier for each individual topic (Panel (a) 'demand impacts,' (b) 'supply impacts (supply chain),' (c) 'supply impacts (production and operations),' (d) 'cost reductions,' (e) 'financial adjustments,' (f) 'government assistance') on the training dataset of manually-classified sentence triples about the topic, showing the number of true positives, false positives, true negatives, and false negatives.

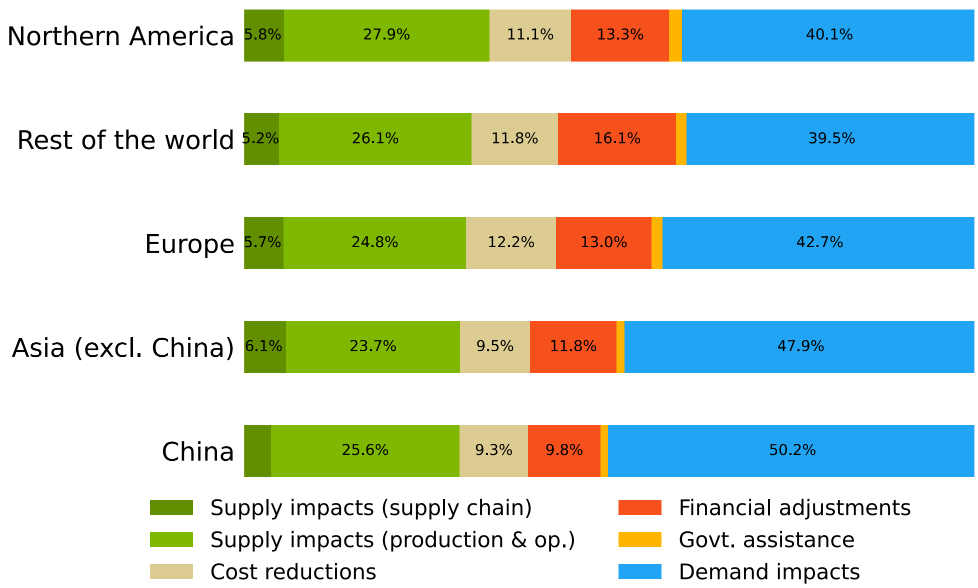
Appendix Figure 5: COVID-19-speech topic decomposition, including *Unspecific or Other*



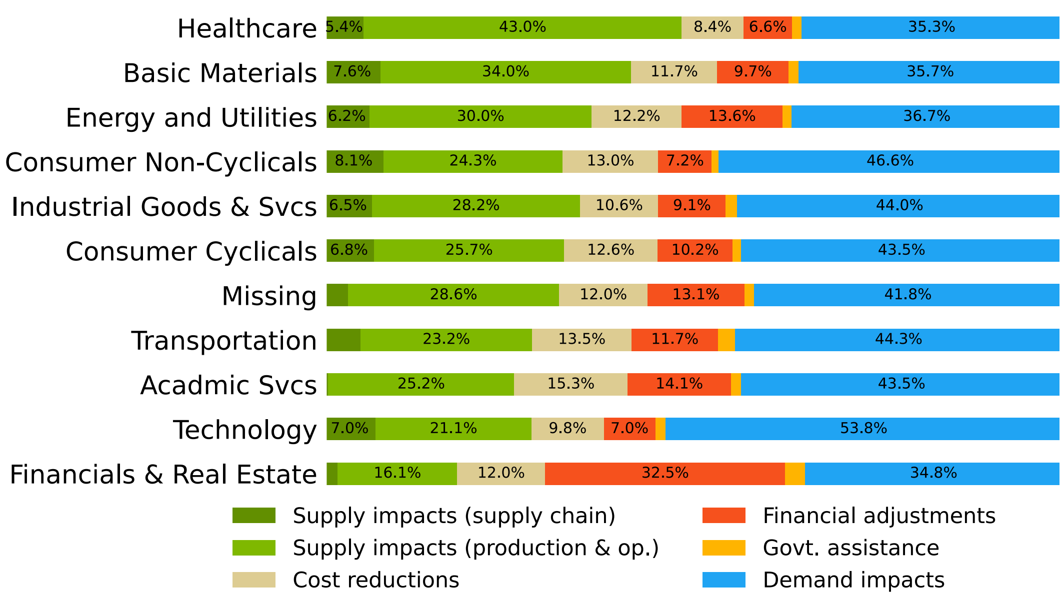
Notes: This figure is similar to Figure 5 but now also includes the share of sentence triples mentioning COVID-19 that cannot be classified to one of the following topic categories: 'supply impacts' (i.e., 'supply chain' and 'production and operations'), 'cost reductions,' 'demand impacts,' 'financial adjustments,' 'government assistance'. We label this remaining category *Unspecific or Other*. 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 assigned to more than one topic are duplicated for the purpose of determining the denominator; by doing so, shares add up to one. Sentence triples are obtained from transcripts of all earnings conference calls held from January through December 2020.

Appendix Figure 6: Regional and sectoral decomposition of COVID-19-related topic shares

(a) By region

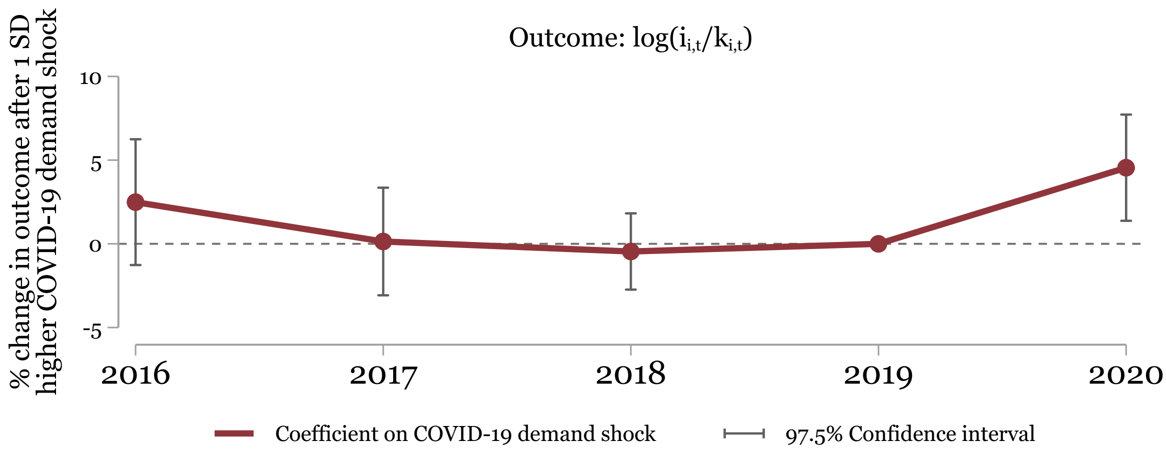


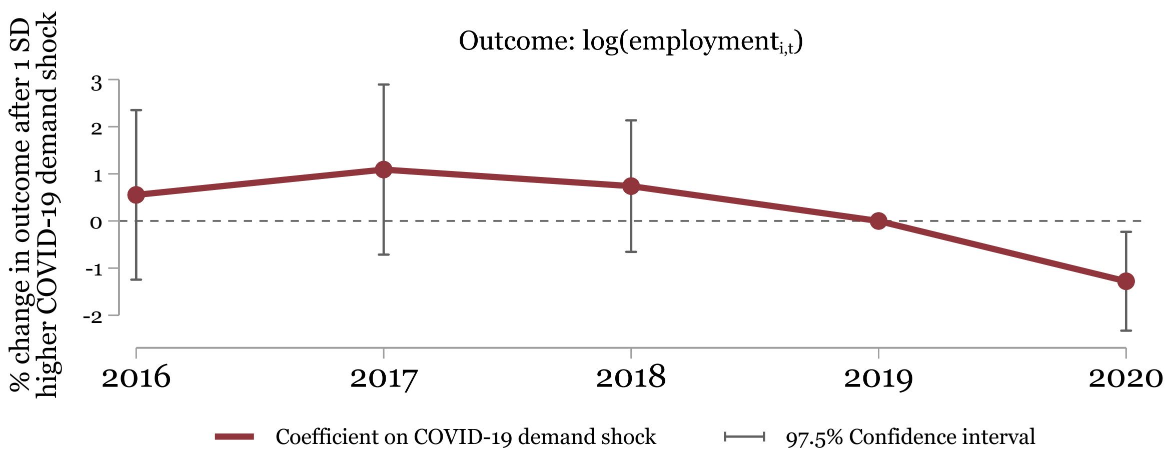
(b) By sector



Notes: This figure plots the regional (Panel a) and sectoral (Panel b) average share of sentence triples mentioning COVID-19 on the following five topics: 'supply issues' (i.e., 'supply impacts (supply chain)' and 'supply impacts (production and operations)'), 'cost reductions,' 'demand impacts,' 'financial adjustments,' 'government assistance.' 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 assigned to more than one topic are duplicated for the purpose of determining the denominator; by doing so, shares add up to one. Sentence triples are obtained from transcripts of all earnings conference calls held from January through December 2020. The sector classification corresponds to the "Economic Sector" as obtained from the Refinitiv Eikon database.

Appendix Figure 7: Parallel trend assumption test





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

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

where $y_{i,t}$ is $\log(i_{i,t}/k_{i,t})$ in the top panel and $\log(\mathit{employment}_{i,t})$ in the bottom panel; δ_i and γ_t are firm and quarter fixed effects, respectively; *COVID-19 net demand shock* and *COVID-19 negative supply shock* are measured as defined in Section 3; and $\mathbf{x}_{it}$ contains the log of firm i's total assets in 2019 interacted with a *post* dummy variable. All other variables are as defined in Table 1. The sample of firms is restricted to large US firms (more than 500 employees) as in column 3 of Table 9. The sample period is restricted to $t = \{2016, \ldots, 2020\}$. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent significance, respectively.

Appendix Table 1: Distribution of sample earnings conference calls by country

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

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

Appendix Table 2: Disease-related keywords

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

Notes: This table lists for each of the six diseases considered in the paper (i.e., SARS, MERS, Ebola, H1N1, Zika, and COVID-19), as described in Section 2.1, the list of keywords used to identify a disease. In pre-processing, we remove all non-letters and, in addition, set all text to lower case (hence, for example, "H1N1" becomes "hn" and "COVID-19" becomes "covid").

Appendix Table 3: Frequency risk or uncertainty synonyms in disease-related discussions

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

Notes: This table shows the frequency across all transcripts of earnings conference calls held between Q1-2020 and Q4-2020 of all single-word synonyms of "risk," "risky," "uncertain," and "uncertainty" as given in the Oxford Dictionary (excluding "question" and "questions") that appear within 10 words of a disease-related keyword for each of the six diseases considered in the paper: SARS, MERS, H1N1, Zika, Ebola, and COVID-19.

Appendix Table 4: Frequently used tone words in disease-related discussions

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

Notes: This table shows the frequency across all transcripts of earnings conference calls held between Q1-2020 and Q4-2020 of the top 100 positive and negative tone words from Loughran and McDonald (2011) (note: their list contains 354 positive and 2,352 negative tone words) that appear within 10 words of a disease-related keyword for each of the six diseases considered in the paper: SARS, MERS, H1N1, Zika, Ebola, and COVID-19.

Appendix Table 5: Does epidemic data predict firm-level COVID-19 measures?

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

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

Appendix Table 6: Timing of *COVID-19-sentiment* and *-risk* discussions

Panel A: *COVID-19 sentiment*	
Ongoing or ex-post in nature: 81%	**Future or ex-ante in nature: 19%**
Example: "Yes, there's been no change in Europe with Roche. Other than just the COVID impact on their clinic access with patients and providers. We are seeing that rebound as well." (Senseonics Holdings Inc; June 9, 2020)	Example: "We might also continue to experience production constraints, and we're entering Q3 and the high season at a lower inventory level than normal as our production rate in Q2 was impacted by the pandemic." (Electrolux AB; July 17, 2020)
Panel B: *COVID-19 risk*	
Ongoing or ex-post in nature: 24%	**Future or ex-ante in nature: 76%**
Example: "We recognized early the potential severity of the worldwide COVID-19 pandemic, and we moved quickly to adjust our operating budget to reflect that uncertainty, including a voluntary 10% salary cut for our executive team; a freeze on raises during 2020; and a cut in our regulatory budget, among other serious cuts." (Marrone Bio Innovations Inc; May 11, 2020)	Example: "And while COVID shutdowns and related economic slowdown will likely create uncertainty in the quarters and perhaps even year to come, we're at the doorstep of a new era." (Logitech International SA; July 21, 2020)

Notes: This table shows the results from a human audit on the timing (i.e., ongoing or ex-post vis-a-vis future or ex-ante in nature) of COVID-19 sentiment and risk discussions, in Panel A and B, respectively, based on a randomly-drawn sample of 100 sentence triples. 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. For each, in the first row, we report in the left (right) column the tabulated proportion of sentence triples—out of 100—that are ongoing or ex-post (future or ex-ante) in nature, as well as an example excerpt from a sentence triple.

Appendix Table 7: Correlation of COVID-19 measures with realized volatility

Panel A	*Realized volatility*$_{i,t}$			
	(1)	(2)	(3)	(4)
COVID-19 exposure$_{i,t}$ *(std.)*	1.179***			
	(0.205)			
COVID-19 sentiment$_{i,t}$ *(std.)*		–0.656***		–0.602***
		(0.187)		(0.190)
COVID-19 risk$_{i,t}$ *(std.)*			0.521***	0.449***
			(0.165)	(0.168)
R^2	0.338	0.337	0.336	0.337
N	18,506	18,506	18,506	18,506
Panel B	*Realized volatility*$_{i,t}$			
	(1)	(2)	(3)	(4)
COVID-19 net demand shock$_{i,t}$ *(std.)*	–0.527***		–0.392**	–0.381*
	(0.189)		(0.196)	(0.197)
COVID-19 negative supply shock$_{i,t}$ *(std.)*		0.656***	0.560***	0.486***
		(0.178)	(0.184)	(0.184)
COVID-19 risk$_{i,t}$ *(std.)*				0.390**
				(0.169)
R^2	0.336	0.337	0.337	0.337
N	18,506	18,506	18,506	18,506
Quarter FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes

Notes: This table reports regression estimates at the firm-quarter level. *Realized volatility* is the standard deviation of firm i's daily stock return, measured during the quarter, adjusted for dividends and stock splits. *COVID-19 net demand shock* and *COVID-19 negative supply shock* are measured as defined in Section 3. All regressions control for the log of firm i's total assets in 2019 and its market beta in 2018. Sector fixed effects are defined using Refinitiv Eikon's `Business sector`, which has 30 sectors in our sample. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 8: False positive rate in final pattern matching iteration

Topic	No. false positives
Demand impacts	6/30
Supply impacts (supply chain)	3/30
Supply impacts (production and operations)	8/30
Cost reductions	5/30
Financial adjustments	3/30
Government assistance	1/30

Notes: This table reports the false positive rate obtained in the final iteration of our pattern matching. Specifically, for each individual topic (i.e., 'demand impacts,' 'supply chain,' 'production and operations,' 'cost reductions,' 'financial adjustments,' and 'government assistance') we randomly drew 30 sentence triples and compare the prediction of the topic-specific pattern with a manual assessment of the triple's topic. Each row lists the number of false positives out of these thirty randomly-drawn sentence triples. 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.

Appendix Table 9: Additional channel-specific restrictions on word patterns

Channel:	Additional restrictions:
Supply impacts (supply chain)	*Words not allowed to be between word combinations:* "million"
Supply impacts (production and operations)	*Words not allowed to between word combinations:* "loss," "fund," "demand," "revenue," "expenditure," "interest rate," "customer[s]," "thank," "consumer," "sale," "payment," "cost," "highlight," "result," "global economy"
	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"
Demand impacts	*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"
	Word-specific restrictions: "customer," "consumer," and "client" may not be preceded by "support"
Cost reductions	*Words not allowed to be between word combinations:* "safe," "support," "help," "inventory," "shipment," "customer," "last quarter," "last year," "guidance," "operational," "material," "out-of-pocket"
Financial adjustments	*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"
	Word-specific restrictions: "debt" may not be preceded by "sovereign" and "cash" may not be followed by "purchase"
Government assistance	*Words not allowed to be between word combinations:* "mandate," "order," "shutdown," "guideline"
	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 channel-specific restrictions on word patterns.

Appendix Table 10: Example of predicted COVID-19-related sentence triple by channel

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

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

Appendix Table 11: Hyperparameter space for grid search

Naive Bayes	Laplace smoothing parameter:	[0.0001, 0.001, 0.01, 0.1, 1]
Logistic Regression	L2 Regularization strength:	[0.0001, 0.001, 0.01, 0.1, 1]
Feedforward Neural Network	Hidden layer sizes:	[(64,), (128, 64,), (256, 128, 64,)]
	Activation function:	[`relu`, `tanh`]
	Solver:	[`adam`]
	L2 penalty:	[0.0001, 0.001, 0.01]
	Learning rate:	[0.001, 0.0001]
	Maximum iterations:	[300]

Notes: This table reports the parameters that we consider for the grid search of the three alternative classifiers: Naive Bayes, Logistic Regression, and Feedforward Neural Network. We use scikit-learn for both the classification algorithms and the grid search; for more information about each parameter's meaning, please consult the documentation of scikit-learn and the references therein (https://scikit-learn.org/stable/index.html).