Tracking the Legacy of COVID-19 in Corporate Sector: A Topic Modeling Approach*

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Abstract

This paper quantifies the topical and sentimental information contained in *earning call transcripts* of publicly traded companies to track the concerns of businesses in real-time, with a focus on COVID-19 pandemic. First, we explore the channels through which COVID-19 pandemic affects businesses using a machine learning approach. A formally estimated topic model for earning call transcripts quantifies the distribution of topic attention during COVID-19 discussions, and shows that the concerns of the corporate sector showed significant variation over time and across sectors during the pandemic. Next, we construct historical uncertainty series using earning call transcripts between 2007Q1 and 2021Q2. The topic attention, sentiment, and uncertainty series show strong correlation with global economic activity, highlighting the potential of earning calls as a leading indicator.

Keywords: Uncertainty, Sentiment, Machine learning, Topic modeling, COVID-19, Earning calls.
JEL Codes: C1; E4; G1.

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1 Introduction

Real-time tracking of economic activity and the pandemic's impact on businesses is key for timely and effective policy interventions. We offer a textual approach to monitoring concerns of businesses and the state of global economic activity by quantifying the topical and sentimental information inherent in the *earning call transcripts* using machine learning and computational linguistic methods. The granular nature of our data set allows for a detailed sector-level analysis as well as macro trends. High frequency data such as industrial production, retail sales, and purchasing managers' index can also be used to assess the nature and size of disruptions from the COVID-19 shock, however these are usually provided with significant lags, and presented at mostly aggregate level.

Earning conference calls provide insights on companies' outlook as well as broader financial and economic developments, and they serve as an important communication channel between market participants and management of publicly traded companies. Given the significant link between the stock market movements and economic activity, these conversations could contain potentially crucial and timely information on broader economic activity beyond idiosyncratic corporate performance.[1] Yet, limited research has been done utilizing the information content of earning calls. This paper provides a detailed textual analysis of roughly 170,000 earning call transcripts between 2007-January and 2021-May, using natural language processing (NLP), a set of recently adopted tools in economics and finance from machine learning literature.[2]

[1]There is a wealth of evidence on the strong link between stock market and real economic activity. Fama (1990), Demirgüç-Kunt and Levine (1996), Beck and Levine (2004), Bekaert, Harvey and Lundblad (2005), and Jermann and Quadrini (2012) are only a few examples.

[2]NLP methods have been proven as a reliable tool for studying the narrative of economic activity. For instance, Bybee, Kelly, Manela and Xiu (2020) and Cong, Liang and Zhang (2019) estimate the structure of economic news using topic models such as Latent Dirichlet Allocation (LDA) of Blei, Ng and Jordan (2003) and Word2Vec of Mikolov, Chen, Corrado and Dean (2013). Hansen, McMahon and Prat (2018) use transcripts of Federal Open Market Committee (FOMC) minutes and an LDA model to document the effects of transparency on the behavior of board members.

Another group of papers study uncertainty and broader sentiment measurements, using a variety of metrics based on the keyword frequency in text. For instance, Baker, Bloom and Davis (2016) use the frequency of uncertainty keywords in news articles to construct a number of uncertainty measures and examine their link with economic activity. Hassan, Hollander, Van Lent and Tahoun (2019) measure political risk at the

We first estimate a *topic model* for earning calls, summarizing the textual content as a distribution of topics that allows for intuitive interpretation. Topic models are primarily used as a dimension reduction method, based on two assumptions about the structure of textual material, which is a collection of documents by construction. First, each document (an earning call in our context) is assumed to be a distribution of topics. Second, each topic is assumed to be a distribution of words. The ultimate goal of this technique is to approximate these distributions, more specifically the distribution of topics within each document, and the distribution of words in each topic. As a result, it condenses a very large dimensional representation of text corpus into a lower dimensional collection of topics, allowing for an intuitive interpretation.

Our first set of results document the distribution of topics during the COVID-19 discussions in earning calls. We show that global supply chains were the most highlighted topic in the earlier stages of the pandemic and its significance dropped in the subsequent quarters, followed by a another wave of increased topic attention, with supply shortages. Sales and recovery discussions intensified over the course of the pandemic, and ranked at the top after the positive immunization developments. Employee health concerns elevated during the first peak of the COVID-19 cases, and diminished significantly afterwards. Throughout the pandemic, digital technologies showed no discernible downward trend, with at least twice as much attention in professional&business services sector as other key sectors. Employee health, on the other hand was not a major concern in this sector, owing to the possibilities of alternative work arrangements and weaker requirements for face-to-face encounters as documented by Dingel and Neiman (2020). Moreover, topic attention on COVID-19 moves in lockstep with major indicators of global economic activity, emphasizing its role as a real-time tracker during the pandemic.

Next, we compute sentiment scores in earning calls based on the tone of language in the textual data. The findings from our sentimental analysis reveal further important trends in

firm-level using earning call transcripts and study its implications for corporate activity.

the evolution of the pandemic and significant heterogeneity across sectors. For example, COVID-19 was highlighted by less than 20 percent of companies in their earning calls in the first quarter of 2020, but this quickly increased to 100 percent in the second quarter and remained so subsequently. However, the average intensity of COVID-19 discussion–measured as the share of terms related to the pandemic on a given earning call–dropped rapidly after June 2020, reflecting positive developments since then. Average sentiment score of COVID-19 discussions declined sharply and bottomed in the second quarter of 2020, and has returned gradually to its initial and more neutral levels by the first quarter of 2021. The level of uncertainty around pandemic discussions displayed a mirror image of the sentiment scores, however it has not yet converged to its initial lower levels as of 2021-Q1. It arguably reflects the uncertainties related to global vaccination rates, developments in virus variants, and business challenges in the post-COVID-19 era.

The empirical results show that the tone of the language in earning calls measured by sentiment and uncertainty indices, display a strong contemporaneous correlation with global industrial production growth. To study this link quantitatively, we estimate a structural vector autoregression model (SVAR), in line with earlier benchmark models of Baker, Bloom and Davis (2016) and Bybee, Kelly, Manela and Xiu (2020). We show that a one standard deviation shock to sentiment score in earning calls associates with a 1.1 percent decline in global industrial production within two months, which is consistent with the range of previous estimates using uncertainty indicators. Furthermore, when our constructed series are included in forecast models for global economic activity, the predictive power of the models improves, pointing to potential benefits of using textual data for macroeconomic forecasting.

Prior research

Our research contributes to the rapidly growing COVID-19 literature as well as the textual studies in economics and finance. More specifically, we contribute to the body of research that uses computer linguistics methods on digital text in economics and finance to quantify sentiment, uncertainty, and the topical structure of text (Buckman et al., 2020; Bybee, Kelly, Manela and Xiu, 2020).[3] For instance, Hassan, Hollander, Van Lent and Tahoun (2019) use earning call transcripts to construct a measure of firm-level political risk, and study its link with corporate decisions. Baker, Bloom and Davis (2016) develop an index of economic policy uncertainty for the United States and find that it spikes during events that have a direct impact on fiscal policy. More recently, Ahir, Bloom and Furceri (2022) and Baker et al. (2020) document the unprecedented rise in uncertainty during the COVID-19 pandemic, applying a similar approach to textual content in country surveillance material and major newspapers, respectively. Manela and Moreira (2017) documents the link between news-based uncertainty and economic disasters using the textual information on front-pages of The Wall Street Journal between 1890 and 2007. Engle et al. (2020) build on the *narrative economics* approach by Shiller (2015), and emphasize the possible role of information included in news articles for hedging portfolios against climate change risk.[4] Our research differs from the previous papers by highlighting the significance of textual analysis in quantifying various channels of disruptions faced by the corporate sector during a global economic shock, such as the one caused by COVID-19 pandemic. We quantify the topical structure in earning calls, and use it together with sentiment measures to examine the relationship between those metrics and economic activity.

The present paper is closely related to Hassan et al. (2020), which examine the earning calls to document sentimental movements in earning calls during the current and earlier pandemics. The paper also reports a significant correlation between COVID-19 sentiment and stock price changes at the firm-level. We differ in several dimensions. First, we systematically document the channels through which the pandemic affects the corporate sector using topic modeling, a machine learning technique for text analysis. Second, rather than

[3]See Gentzkow, Kelly and Taddy (2019) for a recent survey of research related to the use of text as data.

[4]For further evidence on the link between media coverage and stock market performance, see Engelberg and Parsons (2011) and Dougal et al. (2012).

a broad assessment of multiple epidemic diseases, we focus only on the COVID-19 pandemic and provide a detailed investigation of the global economic collapse and recovery stages, offering an insight on the path forward that could possibly help with recovery from the economic losses during the pandemic. Third, we provide an in-depth sector-wise investigation of the pandemic using all available earning call transcripts between 2019-Q1 and 2021-Q2 by highlighting differences across sectors during the pandemic. Finally, we study the link between our empirical findings and global macroeconomic dynamics, and highlight the potential role of earning call transcripts as a real-time tracker of economic activity.

Recent studies provided high-frequency indicators of economic activity during the pandemic using various data such as mobility, lockdown measures, consumption of electricity, trends in point-of-sale transactions, and so forth (e.g., see Chen et al., 2020 and Diebold, 2020 for United States; Delle-Monache, Emiliozzi and Nobili, 2020 for Italy; Maloney and Taskin, 2020 for a wide range of countries). Instead, we provide a real-time tracker of global economic activity using the measures derived from a large volume of textual material covering a wide range of developing and developed economies.

One of the key aspects of the present pandemic is the sectoral and demographic variation in COVID-19 impacts. A number of studies have found substantial differences of COVID-19 impact on workers and economic activity across occupations and demographics as well as the nature of layoffs (Alon, Doepke, Olmstead-Rumsey and Tertilt, 2020; Mongey, Pilossoph and Weinberg, 2020; Dingel and Neiman, 2020; Sanchez et al., 2021; Koren and Pető, 2020; Avdiu and Nayyar, 2020; Kouchekinia, Kudlyak, Ochse and Wolcott, 2020). We bring evidence on these patterns at global scale by showing sectoral heterogeneity in the topics extracted (employee health concerns, for example) from earning calls, and their evolution over time.

Another body of work focused on heterogeneity as well as linkages across sectors and firms. For instance, Barrot, Grassi and Sauvagnat (2021) study the sectoral effects of labor supply shocks for the United States and highlight the nonlinearities in the production network across sectors in accounting for the fall in aggregate output. Gourinchas, Kalemli-Özcan, Penciakova and Sander (2020) estimate the impact of the pandemic on small and medium enterprises—measured by business failures and non-performing loans—using firm-level data across a wide range of countries. Osotimehin et al. (2020) document how the risk of infection and collapse in economic activity vary across sectors in the United States. Bennedsen, Larsen, Schmutte and Scur (2020) report on the effectiveness of government policies across sectors in Denmark using a large firm-level survey conducted during the COVID-19. Markussen, Natvik and Wulfsberg (2020) use real time compensation data in Norway to assess the impact of employment incentives during COVID-19. Alstadsæter, Bjørkheim, Kopczuk and Økland (2020) analyze business support programs in the United States and Norway, and show that measures that assist payroll and fixed costs had a similar impact on reducing firms' economic suffering in both countries. Apedo-Amah et al. (2020) conduct firm-level phone-call surveys and provide a comprehensive assessment of the short-term impact of the COVID-19 pandemic on businesses across the world.

A number of recent macroeconomic models, augmented with epidemiological dynamics, highlighted the role of sectoral and demographic heterogeneity in optimal policy design. Glover, Heathcote, Krueger and Ríos-Rull (2020), Baqaee and Farhi (2020), and Guerrieri, Lorenzoni, Straub and Werning (2020), for instance, study the effects of the pandemic and optimal policy design in models with sectoral heterogeneity. Çakmaklı et al. (2020) study the inter-sectoral and international linkages as well as optimal policy design during the pandemic, using a small open economy model calibrated to an emerging market economy. Our empirical findings contribute to these policy debates by providing a near-real-time tracker of sectoral effects from earning calls that can be utilized as a starting point for designing targeted interventions.

Acemoglu, Chernozhukov, Werning and Whinston (2020b), Atkeson (2020) and Checo, Grigoli and Mota (2021) study the effects of targeted and aggregate shutdown policies on infection rates and economic activity. Buera et al. (2021) build a macroeconomic model featuring financial and labor market frictions as well as firm dynamics to study the effects of labor and financial policy interventions. Fang, Nie and Xie (2020), on the other hand, extend a search and matching model with epidemiological dynamics to study the impact of unemployment benefit extensions on infection rates and unemployment in the United States. Hall, Jones and Klenow (2020) study the welfare implications of COVID-19 within a heterogeneous-agent model, based on the trade-off between mortality rates and the drop in economic activity. Acemoglu, Makhdoumi, Malekian and Ozdaglar (2020a) present a theoretical framework with endogenous social distancing behavior. They illustrate a non-monotonic relationship between testing and infection rates, implying an optimal testing policy that takes into account the adverse effects on social distancing.

The remainder of the paper is organized as follows: next section presents our data, section 3 discusses topic modeling methodology and results, section 4 describes sentimental measurement techniques and presents results, section 5 relates our findings to the state of the global economy, and finally section 6 discusses policy implications and concludes.

2 Data

Our empirical analysis is based on earning calls of companies that are publicly listed in the United States stock market. An earning call is a press conference between the management of a publicly traded company, market participants, and media to discuss the company's outlook as well as recent financial and economic developments.

The vast majority of publicly traded corporations hold quarterly earning calls to disclose their financial performance and discuss broader economic and financial developments.[5] Therefore, these calls may contain potentially critical and timely information re-

[5]Companies hold earning call conferences at different times during the quarter, which allows for pooling at higher frequencies (month, in our case) with significant numbers of observations most of the time. However, this could lead to a composition (sector and/or country) bias in monthly pooled series. Therefore, as a robustness alternative to simple pooling strategy, we controlled sector and country fixed effects to help

garding the status of the economy as well as the performance of the company.

Transcripts of the earning calls are obtained from Factiva's Fair Wire Disclosure.[6] We collect the complete set of 169,191 earning call transcripts between 2007-Q1 and 2021-Q2, of 9,718 companies (listed at some point within the covered period) headquartered in 54 different countries, including both developing and developed economies.[7] We use the entire data set for the sentimental analysis, however restrict to the period between 2020-Q1 and 2021-Q2 when we estimate topic models to assess the significance of topics discussed around COVID-19 pandemic. This period covers 23,801 earning calls, conducted by 5,328 companies headquartered in 52 different countries.[8]

We clean the textual data using standard NLP techniques to make it suitable for a quantitative analysis.[9] The standard pre-processing steps to prepare the text for analysis include removing stop words, tokenization, and stemming (Gentzkow, Kelly and Taddy, 2019). *Tokenization* splits sentences into individual words (tokens) based on text delimiters such as spaces and commas. It is an important step in preparing data to be input into models because it converts text into a machine-readable format. The next step is to *lemmatize* the words, which reduces the inflected words into their base form. For example, "talking" will be reduced to "talk". This process is important to not only reduce the total number of unique terms in each document but to also arriving at the accurate count for words within each document. This tokenized and lemmatized text was further cleaned by

alleviate this when we used monthly series. More specifically, we estimated coefficients of monthly time fixed effects controlling for country, sector fixed effects, and their interaction. Then, plotted the coefficients of monthly time fixed effects. The time trends in monthly series remained broadly similar when we applied this robustness check.

[6] Appendix A reports sample excerpts from a number of earning calls to illustrate examples regarding the content of these calls.

[7] The headquarter information is missing for some companies, therefore the actual country coverage could be larger than the number stated. It's worth noting that the number of companies in our data collection exceeds the current total number of publicly traded companies. This is due to the fact that several companies that were listed in the sample's earlier years have since delisted.

[8] We actually analyze another subset of earning calls between 2019-Q1 and 2021-Q2 to compare evolution of broader topics before and during the pandemic. This subset covers 39,923 calls, conducted by 5,849 companies headquartered in 54 different countries. See section 3.2 for further details.

[9] NLP is a field in machine learning with a focus on textual data. The methods developed in this field aims to improve the ability of computers to understand and analyze textual data.

removing stop words and names. Lastly, the words containing less than three letters were removed from the text. The cleaned textual data is then used to create necessary inputs (a set of mathematical objects representing the allocation of words in the entire text) for the computation of the topic model presented in next section.

3 Topics in earning calls

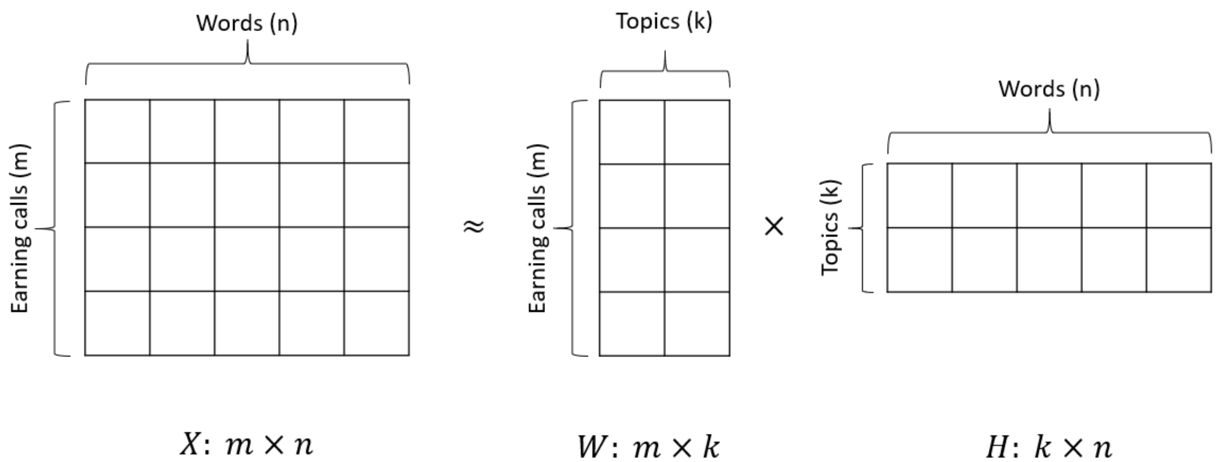
In this section, we describe our approach to exploring topics discussed in earning calls. First, we examine the complete transcripts of earning calls to determine the relevance of COVID-19 (identified as a standalone topic) in comparison to other issues discussed on the calls. Second, once we identify where COVID-19 discussions arise during the calls, and estimate the topic model using the text surrounding these conversations to discover the topic attention around COVID-19.

We use the complete set of 39,923 earning call transcripts between 2019-Q1 and 2021-Q2 to identify topics in the entire calls. This helps us to identify topics beyond COVID-19 and the evolution of attention allocated to those topics during the pandemic as well as the period leading up to the COVID-19 era. Since COVID-19 is almost absent in earning calls before 2020, we restrict to 23,801 earning calls between 2020-Q1 and 2021-Q2 when we focus on extracting topics discussed around COVID-19.[10] With such a large set of earning call transcripts in our textual database, locating a topic by reading is extremely challenging, pointing us to machine learning algorithms for topic modeling.

The topic modeling methodology makes two assumptions on the structure of textual content, which is a collection of documents. First, each document (an earning call in our context) is assumed to be a distribution of topics. Second, each topic is assumed to be a distribution of words. The ultimate goal of this technique, as well as other topic models, is to approximate these distributions, more specifically the distribution of topics within

[10]COVID-19's absence—as an estimated topic—prior to 2020 is reflected in its estimated topic weights near zero. See Figure 2 in section 3.2.

Figure 1: **An illustration of the NMF model**



Note: The document/word (X) matrix can be approximated by the multiplication of two smaller matrices, i.e. document/topic (W) and topic/word (H).

each document, and the distribution of words in each topic.

This method enables a systematic and quantitative analysis of topic attention in earning calls by providing an enormous reduction in the dimension of the material to be studied. For instance, one can look at the distribution of topics in an earning call and have an idea of what is highlighted without reading the entire document. Similarly, making aggregations of topic attention over time and sector makes it possible to view trends without reading the entire set of earning call transcripts.

3.1 A topic model for earning calls: Non-Negative Matrix Factorization

Our approach to identify the topics discussed in earning calls follows Non-negative Matrix Factorization (NMF) model, a dimension reduction method based on Lee and Seung (2001). More specifically, it decomposes a given non-negative matrix $\boldsymbol{X}$ into two lower rank matrices $\boldsymbol{W}$ and $\boldsymbol{H}$ with non-negative elements and a desired lower dimension k, such that:

$$\boldsymbol{X} \approx \boldsymbol{W} \times \boldsymbol{H}. \tag{1}$$

In the topic modeling context, the document/word matrix $\boldsymbol{X}$ represents the entire corpus, which is composed of m rows (each row denoting an earning call transcript), and n columns (words). $\boldsymbol{W}$ denotes document/topic matrix, and $\boldsymbol{H}$ represents topic/term matrix (Figure 3.1).[11] The goal of NMF is to find non-negative matrices $\boldsymbol{W}$ and $\boldsymbol{H}$ such that $k < \min\{m, n\}$, and product of document/topic and topic/word matrices, $\boldsymbol{W} \times \boldsymbol{H}$, approximates document/word matrix, $\boldsymbol{X}$.

Each row x_i in $\boldsymbol{X}$ refers to a document created from earning call i, and each element x_{ij} denotes the weight of word j in document i. Each row w_i in $\boldsymbol{W}$ refers to a document and each element w_{ij} refers to the weight of topic j in document i. Similarly, each row h_i in $\boldsymbol{H}$ refers to a topic and each element h_{ij} denotes the weight of word j in topic i.[12] Accordingly, each column of $\boldsymbol{X}$ is the sum of each column of $\boldsymbol{W}$ weighted by the corresponding row of $\boldsymbol{H}$ as follows:

$$x_i = \boldsymbol{W} \times h_i. \tag{2}$$

The model is computed twice. First, we construct the set of documents ($\boldsymbol{X}$) based on the entire earning call transcript and computed the distributions of approximated topics within entire earning calls. Second, we focus on the topics around COVID-19 discussions. In this case, we first identify the location of COVID-19 mentions, then we create x_i from each call i using the language around these discussions. More specifically, we merge the terms that are +/- 20 words around COVID-19 mentions to focus on topics around the pandemic talks. The results for these two cases are presented in separate subsections below.

[11] We use “word” and “term”, and “document” and “earning call transcript” interchangeably throughout the paper.

[12] The weights are calculated using *term frequency–inverse document frequency* (*TF-IDF*) method. See Appendix B for a detailed description of the model, and the computational algorithm.

For the sake of clarity, we present our results using two alternative metrics created from the estimated raw weights in the NMF model. First, the weights are converted to relative terms and presented in percentages. In an earning call conference, for example, 10 percent weight for a topic means that it receives 10 percent of all attention during the call. Or, a 30 percent weight for a topic in a sector s at time t, means 30 percent of attention was allocated to that topic in the earning calls of sector s at time t. As a second metric, we rank topics based on their weights in earning calls: the topic with the highest weight is ranked first, and so forth. Some of the charts reflect the attention allocated to a given topic in terms of the percentage of documents in which that particular topic was ranked first.

3.2 Topic distribution

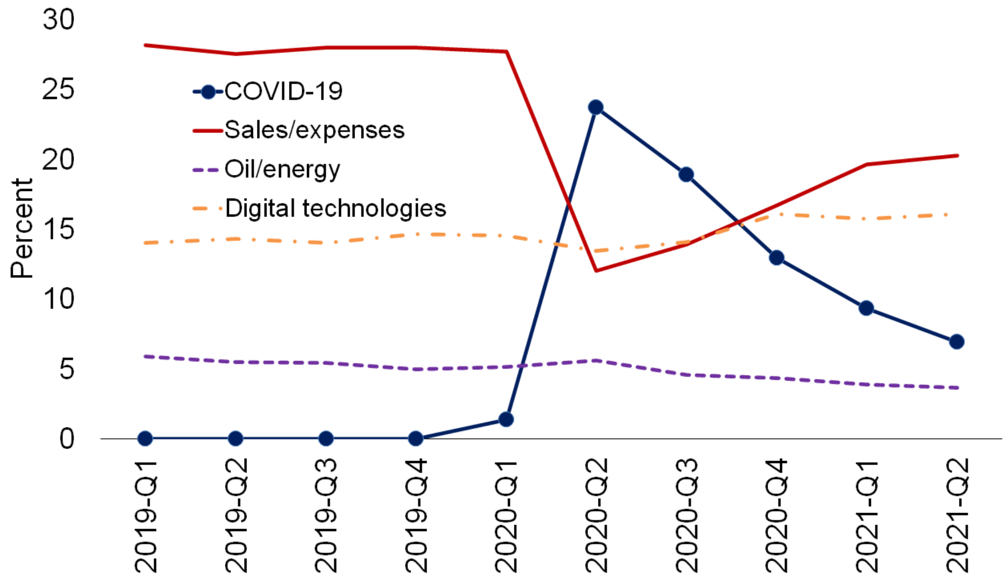
This section presents the results based on the the computed NMF model with entire earning call transcripts, as described in Section 3.1. It identifies 20 latent topics in earning calls using the text available in complete transcripts, and quantifies their distribution in each call between 2019-Q1 and 2021-Q2.[13]

For the sake of brevity, a selected list of major topics and their evolution over the past nine quarters plotted in Figure 2. The extracted topics and the terms in each topic show that the model does a fairly good job in capturing the related terms in a meaningful context. The topic that is labeled "COVID-19", obviously captures the pandemic, characterized by terms such as covid, employee, and vaccine. More importantly, it is one of the intensely discussed topics, especially since the first quarter of 2020 (right panel). The red line with label "Sales/expenses", merges two topics: one with featuring the terms revenue, service, and expense, and the other with featuring the terms sale, segment, and customer.

Among other major topics, "Oil/energy" is characterized with terms such as oil, en-

[13] Note that NMF model takes the number of topics as given. Our selection of 20 topics is based on standard coherence score calculations. More specifically, we estimated the model using a number of topics ranging from 5 to 50, and the estimated topics' average coherence score was maximum at the neighbourhood of 20 topics, which was chosen as the benchmark case.

Figure 2: **Topic attention in the complete earning calls**



Source: Authors' calculations.
Note: The figure plots selected major topics extracted from complete earning call transripts using the NMF model described in section 3.1. At any given time, the attention metric for each topic is calculated as the percentage of earning calls in which the topic was ranked first. See text for further details.

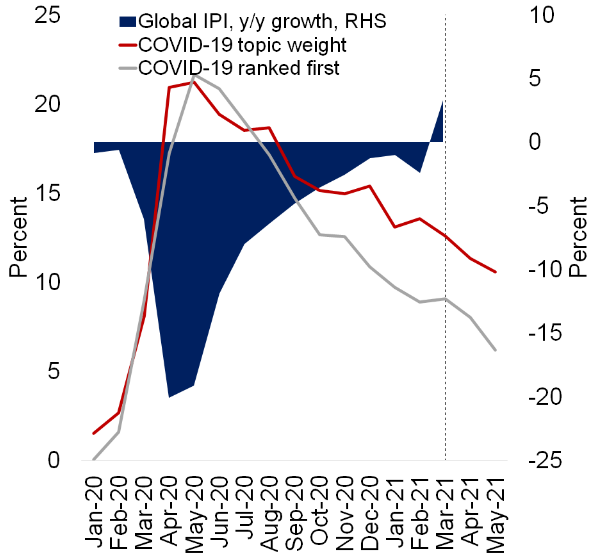
ergy, and production. The topic labeled with "Digital technologies" merges two topics: one reflecting terms digital, platform, client, and the other characterized with terms cloud, enterprise, and subscription.

As expected, COVID-19, as an identified topic in the earning calls, was nearly non-existent until the first quarter of 2020. Its topic attention peaked in the second quarter of 2020, as assessed by the percent of calls in which it has the highest weight, and then decreased, but remained significant as of 2021-Q1.

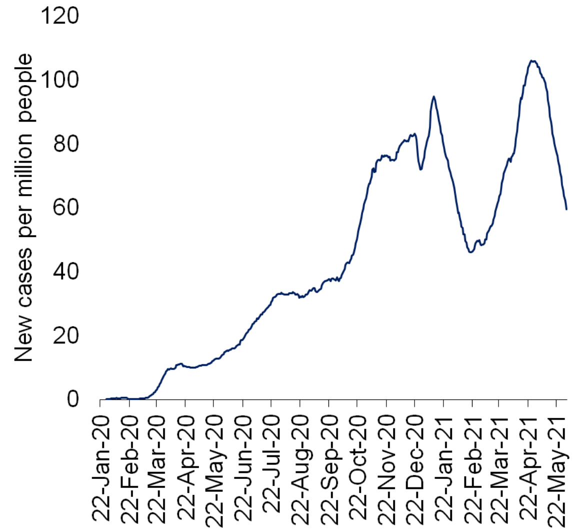
The attention allocated to oil/energy and digital technologies remained broadly stable over the course of the pandemic, close to their pre-pandemic levels. However, obviously, some of the attention allocated to "Sales/expenses" topic shifted toward COVID-19 since the second quarter of 2020.

Figure 3: **COVID-19 topic attention, global economic activity, and cases**

A. Earning calls and global economic activity



B. Global cases per million people



Source: Authors' calculations, Haver Analytics, Our World in Data.
Note: Global IPI is measured excluding China. COVID-19 topic weights are calculated using the NMF model presented in section 3.1. The daily series of new cases are smoothed for visual purposes.

COVID-19 topic attention and global economic activity

Figure 3 illustrates the strong co-movement between the attention allocated to COVID-19 and the state of the global economic activity, measured as the growth rate of global industrial production index (IPI). The correlation coefficient between global IPI growth and the share of earning calls in which COVID-19 was ranked first turns out to be -0.76, highlighting the relationship between economic activity and the concerns related to the pandemic. The left panel shows the global new cases per million people, and illustrates that the number of new cases have been less relevant to tracking economic activity, especially recently. In this sub-section, we remain with this descriptive evidence since we have a very short time series. We purse a rather formal econometric exercise in section 5 in which we are able to compute a relatively longer time series using the earning calls available since 2007.[14]

3.3 Topics around COVID-19 discussions

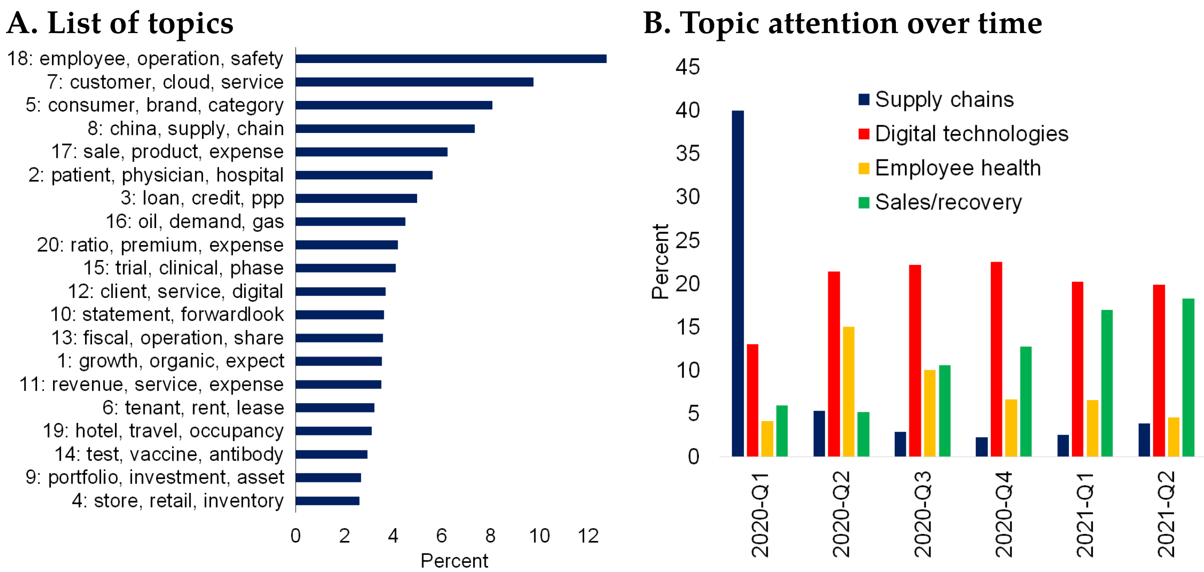
Next we turn to the COVID-19 conversations and compute the NMF model around them.[15] In the earning calls, the COVID-19 mentions are identified using a list of keywords related to COVID-19. For each earning call, we first merge text in $+/-$ 20 words around each COVID-19 mention. Then we convert this corpus into a document/word matrix as described in section 3.1, and compute the NMF for this new matrix. The model detects 20 latent topics around COVID-19 discussions, and quantifies their weights in each call between 2019-Q4 and 2021-Q1.

The left panel of Figure 4 reports the list of 20 topics extracted from the calls–labeled by

[14]Note that we are naturally constrained with a period of one to two years when we examine COVID-19. However, a broader examination of earning calls is possible for a longer time frame, which we conduct in section 4.

[15]The location of COVID-19 discussions were detected based on the following set of keywords related to COVID-19: {coronavirus, covid, virus, pandemic, epidemic, epicenter, precovid, postcovid, prepandemic, postpandemic, infection, outbreak, quarantine}. Because the keyword search is applied to the cleaned textual data, this set also captures phrases such as COVID-19, corona-virus, covid19, outbreaks, and so on. Selection of keywords is based on World Health Organization description as well as our judgement.

Figure 4: **COVID-19 topics**



Source: Authors' calculations using earning call transcripts.
Note: Topic weights are calculated using the NMF model presented in section 3.1. Panel A reports topic weights in percentage terms. In panel B, at any given time, the attention metric for each topic is calculated as the percentage of earning calls in which the topic was ranked first. See text for further details.

the top three term in each topic–and their weights during the entire sample period from 2020-Q1 to 20221-Q1. The extracted topics and the terms in each topic show that the model does a fairly good job in capturing the related terms in a meaningful context.

Topic 8, for instance, obviously captures supply chain issues, characterized by terms such as China, supply, chain, factory, and production. More importantly, it is one of the intensely discussed topics, especially during the first quarter of 2020 (right panel). Among the most discussed, topics 7 and 12 capture digital technologies, featured by terms such as cloud, service, digital, and technology. Topic 5 reflects online shopping with terms including consumer, online, channel, and e–commerce. Topic 16 obviously highlights oil and broader energy issues, articulated with terms such as oil, gas, vessel, and crude.

The aggregate figures mask important trends over the course of the pandemic. The panel on the right (Figure 4) shows how the rank of the topics evolved over the course of the pandemic. In the first quarter of 2020, for instance, supply chain was the most highlighted topic, with the highest weight in more than 35 percent of all earning calls. Its relative significance has waned over the course of the pandemic, as other topics such as sales/recovery, and employment safety took over the attention in the calls. Sales/recovery has been an essential topic since 2020-Q3, with positive developments in vaccination and testing. Digital technologies remained significant throughout the pandemic, both in the collapse and recovery periods.

Next, we turn to sector-level topic trends to shed light on how the impact of COVID-19 changes depending on the nature of businesses.

3.4 Heterogeneity in topic attention across sectors

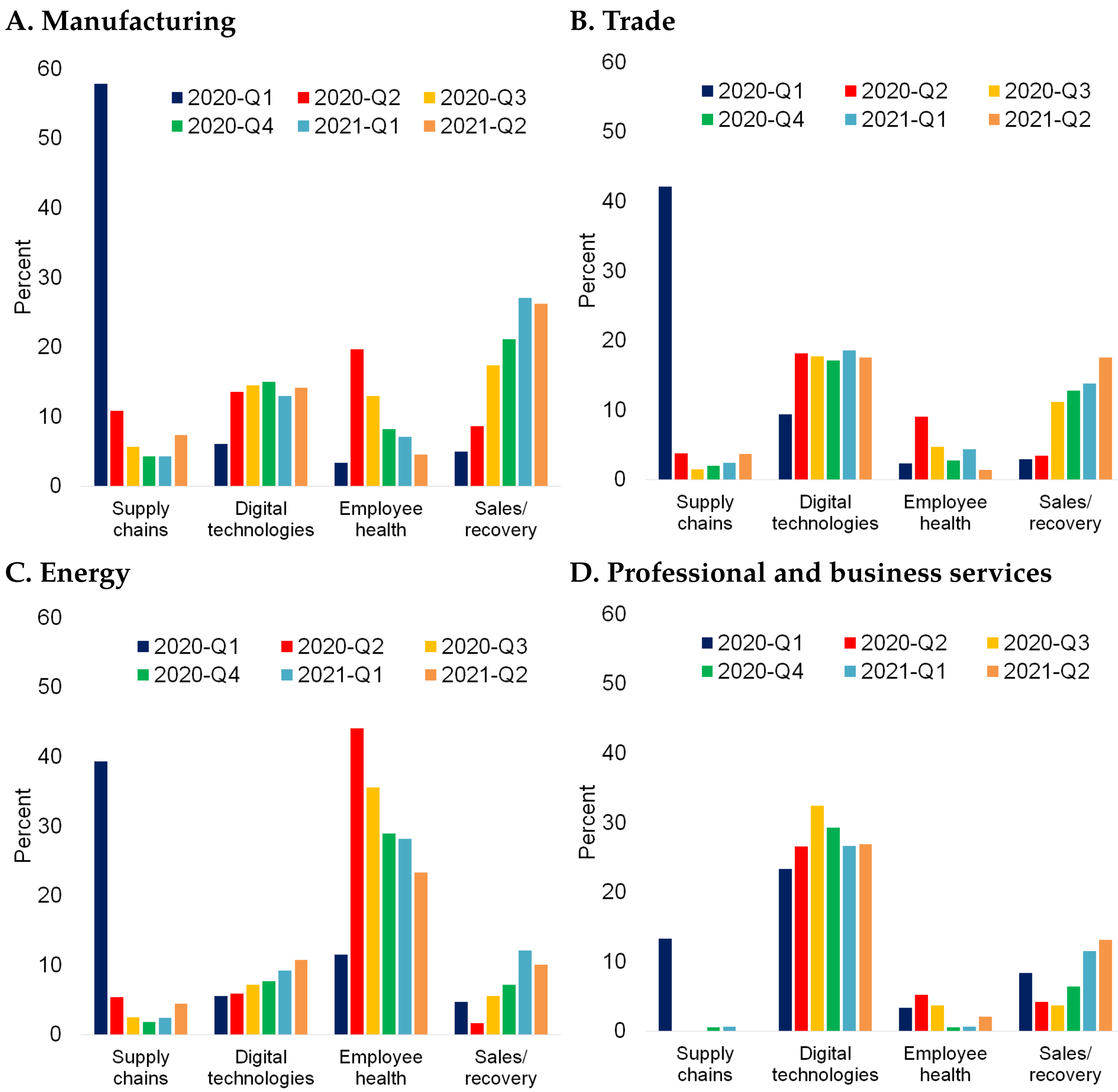
In this section, we present trends in selected topics in major sectors. Topic attention displays significant heterogeneity as well as certain common trends across sectors (Figure 5). In the early phases of the pandemic, supply chain was the most important issue by far, in all major sectors except professional&business services. In manufacturing sector, for instance, it was the highest-ranked topic in more than half of the earning calls during 2020-Q1. Another common trend belongs to the sales/recovery topic, which was among the least significant topics in 2020-Q1 and ranked at top in all major sectors as of 2021-Q1.

Employee health topic peaked in the second quarter of 2020 across all major sectors, then broadly declined, receiving far more attention within the energy sector. Throughout the pandemic, digital technologies showed no discernible downward trend, with at least twice as much attention professional&business services as other key sectors.

The limited attention in employee safety topic in the professional&business services is noteworthy since it highlights the pandemic's little impact on the supply conditions of the sector. This is in line with well-known facts concerning the industry's limited face-to-face interaction needs and the potential of alternate working arrangements.[16]

[16] See, for instance, Dingel and Neiman (2020) and Sanchez et al. (2021).

Figure 5: **Topic attention around COVID-19 discussions, major sectors**



Source: Authors' calculations using earning call transcripts.
Note: Topic weights are calculated using the NMF model presented in section 3.1. In a given sector, at a given time, the attention metric for each topic is calculated as the percentage of earning calls in which the topic was ranked first. See text for further details.

4 COVID-19 sentiment in earning calls

Having identified the evolution of topic attention in the earning call transcripts during the past two years, now we turn to the sentiment of language on the calls, and study its link with real economic activity.

Given the lower computational cost of calculating sentimental scores compared to the estimation of topic models, we work with a longer sample in this section, covering the period between 2007-Q1 and 2021-Q2. It allows for a formal econometric study for testing the link between the sentimental series produced from earning calls and real economic activity.

We calculate sentimental scores for both entire earning call transcripts and for the discussions surrounding the pandemic, as described in the following subsections.

4.1 Measurement

We follow the methodology proposed by Hassan et al. (2020) to measure sentimental scores in the earning call transcripts. Mentions of COVID-19 on each call is calculated by a simple word-counting process, defined as the frequency of COVID-related words divided by the total number of words in a given call:

$$Mention_{it} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \mathbf{1}^{\boldsymbol{COV}}(b), \tag{3}$$

where B_{it} denotes the entire list of words in the call of firm i at time t, and $\mathbf{1}^{\boldsymbol{COV}}(\cdot)$ is an indicator function which takes value 1 if the input word is in the COVID-19 word list, and 0 otherwise.[17]

COVID-19 sentiment on a given call is obtained by aggregation of sentiment score around each COVID-19 mention. The score around each COVID-19 discussion is com-

[17]See footnote 15 for the complete list of keywords related to COVID-19, which is based on World Health Organization description and our judgement.

puted by the frequency of positive tone words minus negative tone words within r words around of COVID-19 mention, divided by the total number of words on a given call. More specifically, the score is calculated as follows:

$$Sentiment_{it} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \left\{ \mathbf{1}^{\boldsymbol{COV}}(b) \times \left(\sum_{c \in C^r(b)} S(c) \right) \right\}, \tag{4}$$

in which, $C^r(b)$ denotes the list of words in the r words around of b, and the function $S(c)$ is defined as follows:

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

where S^+ and S^- denote sets of positive and negative tone words. Finally, COVID-19 uncertainty on a given call is measured by aggregating uncertainty scores around each COVID-19 discussion. The score around each COVID-19 discussion is computed by the frequency of uncertainty-related words within r words around of COVID-19 mention, divided by the total number of words on a given call. More specifically, the uncertainty score of a given call is calculated as follows:

$$Uncertainty_{it} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \left\{ \mathbf{1}^{\boldsymbol{COV}}(b) \times \left(\sum_{c \in C^r(b)} \mathbf{1}^{\boldsymbol{UNC}}(c) \right) \right\}, \tag{5}$$

where, $\mathbf{1}^{\boldsymbol{UNC}}(\cdot)$ denotes an indicator function which takes value 1 if the input word is in the words related to uncertainty, 0 otherwise.

The positive, negative, and uncertainty words are identified using the sentimental word lists within the context of economics and finance, provided by Loughran and McDonald (2016). This approach allows us to accurately identify the most relevant sentimental words in the earning calls.

4.2 Evolution of COVID-19 sentiment over time

This section presents the evolution of COVID-19 sentiment and uncertainty as described in section 4.1. The time series cover the period between 2020-Q1 and 2021-Q1. Figure 6 shows that COVID-19 has been a significantly important topic in the earning calls. In January 2020, just 20 percent of corporations cited COVID-19 in their earning calls; by April 2020, simply all earning calls included COVID-19, and this is still the case (as of March 2021). However, by March 2021, the average intensity of COVID-19 discussions, measured as the share of COVID-19 related words in earning calls, has roughly halved since it peaked around May and June 2020.

The tone of conversations around COVID-19 has evolved notably between early-2020 and 2021. The average COVID-19 sentiment score was broadly neutral in January 2020, which dropped sharply and bottomed in the second quarter of 2020, and has returned gradually to its initial and more neutral levels by the first quarter of 2021, owing to progress in immunization efforts and economic recovery. To put it in context, the average sentiment score in March 2021 was nearly three standard deviations above its trough level in April 2020.

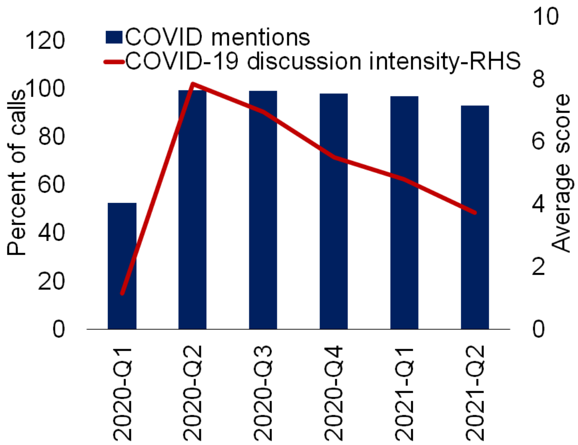
The average COVID-19 uncertainty score displayed a mirror image of the sentiment scores, however has not yet converged to its initial lower levels, arguably reflecting the uncertainties related to global vaccination rates, performance of existing vaccines against virus variants, and business challenges in post-COVID-19 era. The average uncertainty score is still roughly 1.7 standard deviation higher than its level in January 2020.

4.3 Heterogeneity in COVID-19 sentiment across sectors

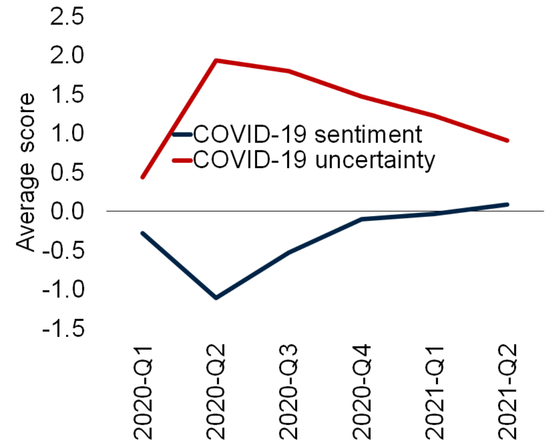
The trends in COVID-19 exposure in earning calls were broad-based, however with significant variance across sectors, especially when the virus-related concerns peaked in the second quarter of 2020. The sentiment score around COVID-19 conversations ranged from -0.76 (ITC) to -1.65 (finance) in 2020-Q2. Companies in the ITC sector, which require less

Figure 6: **COVID-19 mentions, sentiment, and uncertainty**

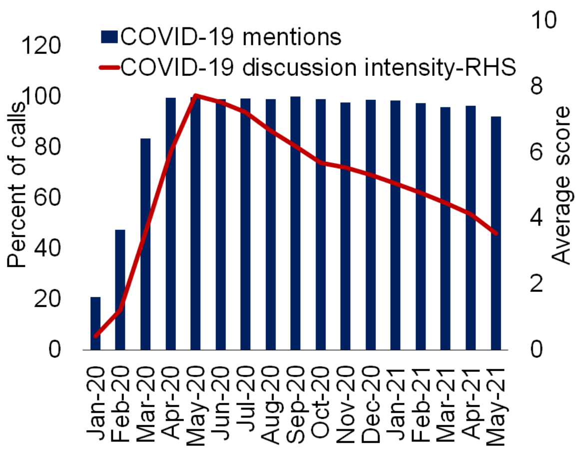
A. Mentions, quarterly



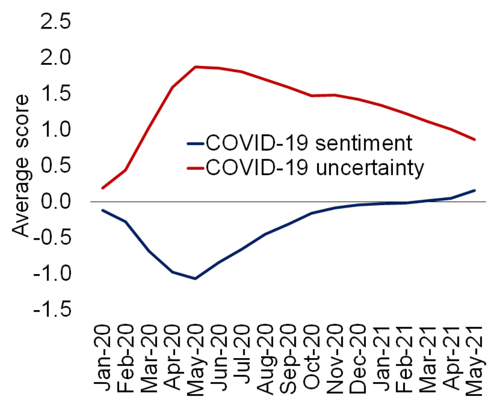
B. Sentiment and uncertainty, quarterly



C. Mentions, monthly

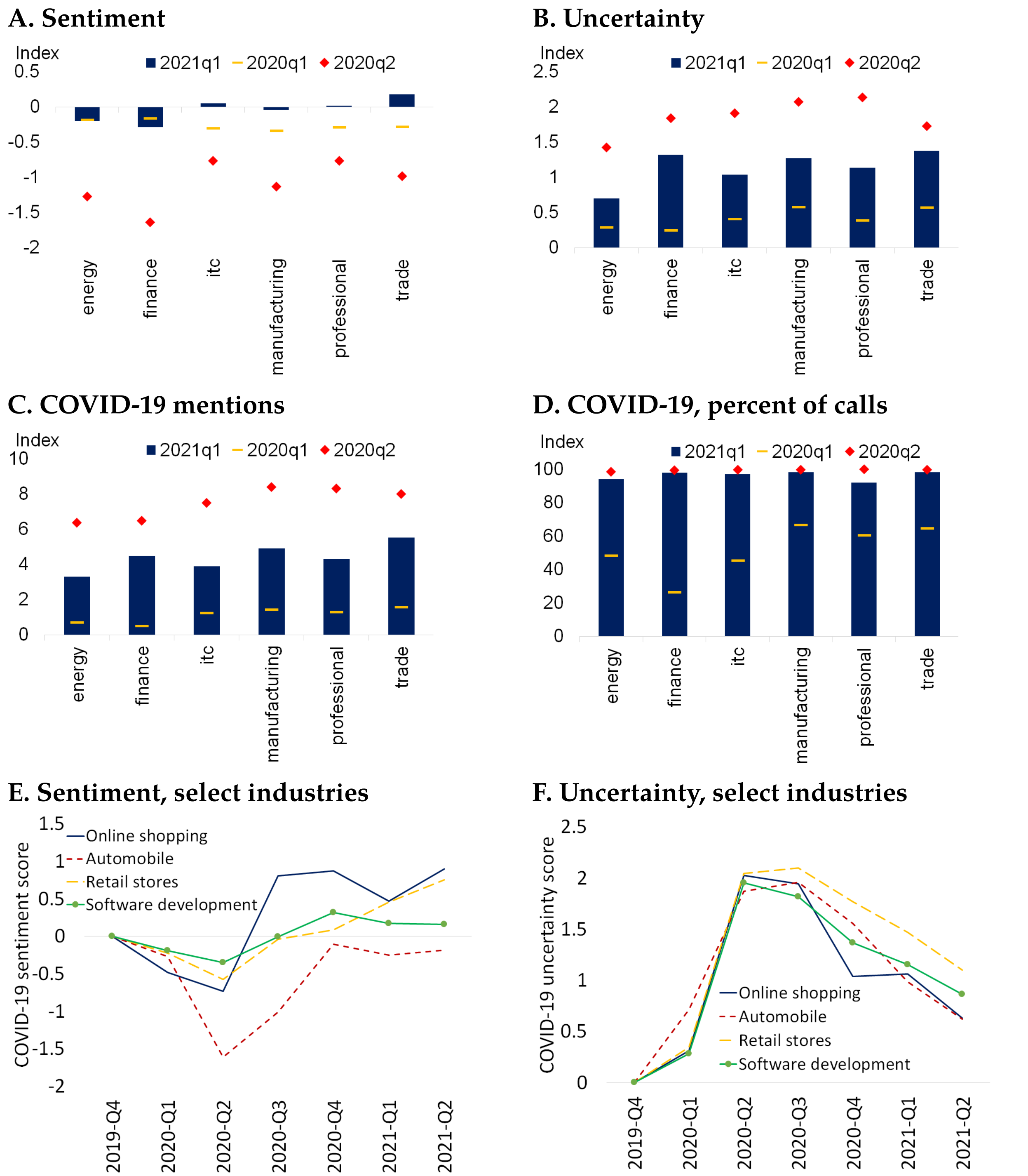


D. Sentiment and uncertainty, monthly



Source: Authors' calculations using earning call transcripts.
Note: Sentiment, uncertainty, and mention series are calculated as described in section 4.1. The quarterly series of discussion intensity, sentiment, and uncertainty reflect raw scores, re-scaled for visual purposes. As an alternative, we calculated z-scores using firm-level observations since 2020-Q1, and time patterns in the aggregate series remained broadly similar. For detailed information on the construction of monthly series, see footnote 5.

Figure 7: **COVID-19 mentions, sentiment, and uncertainty: major sectors and select industries**



Source: Authors' calculations using earning call transcripts.
Note: Sentiment, uncertainty, and mention series are calculated as described in section 4. See text for further details.

face-to-face interaction to provide their services, fared better during the pandemic (Dingel and Neiman, 2020). On the other hand, concerns about the fall in overall economic activity, which could harm the finance sector's customer portfolio, could explain the low sentiment score in this sector.[18]

COVID-19 uncertainty has been broadly similar across sectors since the second quarter of 2020. During the early phases of the pandemic, however, it was higher in manufacturing and trade than in other sectors, arguably owing to supply chain disruptions. Due to favorable advancements in vaccination, the intensity of COVID-19 debates decreased over time across the board. Nonetheless, as of 2020-Q1, COVID-19 continued to be cited in practically every earning call (Figure 7).

A close examination of selected sub-sectors reveals important patterns. The sentiment around COVID-19 discussion in the online shopping and software development industries has been significantly milder than other sectors, and it rebounded fast, especially in online shopping. The automobile industry, on the other hand, experienced a sharper decline in sentiment followed by a slower rebound, reflecting the supply shortages in certain raw materials.

The swings in sentiment surrounding COVID-19 conversations in earning calls warrant a closer examination of its link to economic activity, which we conduct in the next section.

5 Earning calls and global economic activity

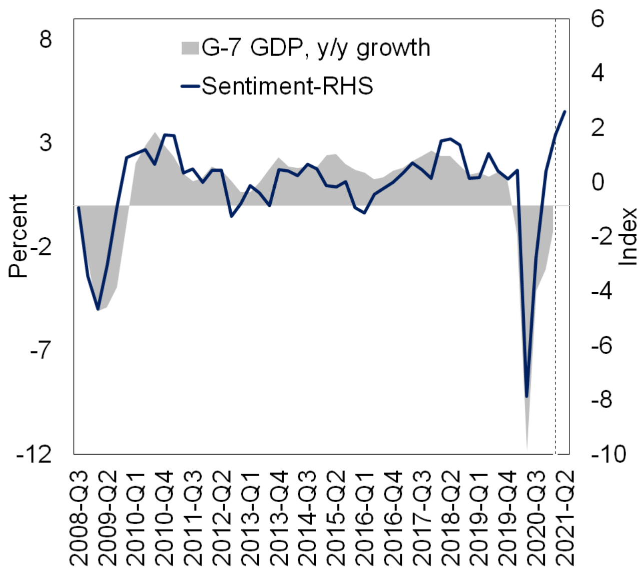
In this section we look into the link between our empirical results and the state of the global economic activity, following the method proposed by Bybee et al. (2020) who examine the relationship between economic news and standard economic variables. We use monthly global IPI (excluding China), as a high frequency measure of global economic activity.

In order to investigate the value added by the earning call transcripts to the predic-

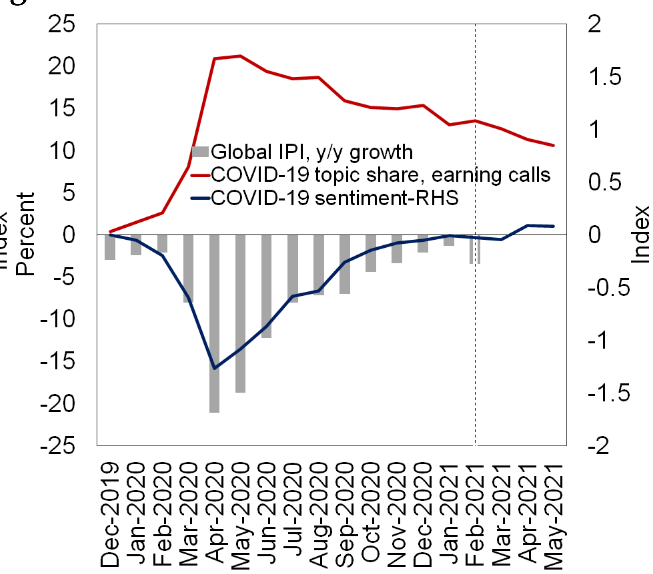
[18] For a detailed examination of how banks were affected by the pandemic, see Demirgüç-Kunt et al. (2020) and Beck and Keil (2021).

Figure 8: **Earning calls and global activity**

A. Earning calls' sentiment and global GDP



B. COVID-19 topic weight, sentiment, and global IPI

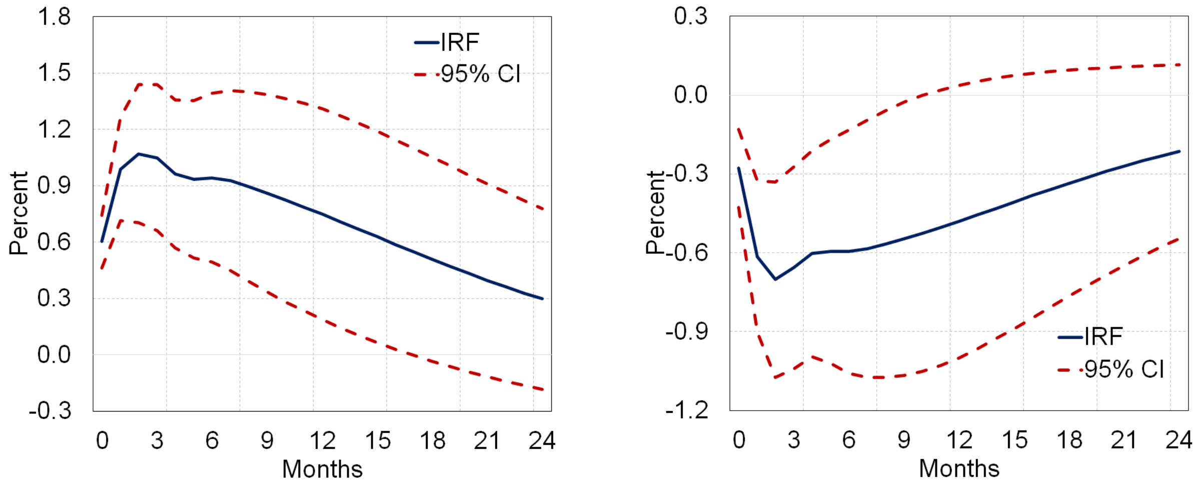


Source: Authors' calculations using earning call transcripts, Haver Analytics.
Note: Global IPI is measured as weighted average of countries excluding China. Uncertainty score is calculated using the methodology presented in section 4, seasonally adjusted and HP filtered. COVID-19 topic weight is calculated using the NMF model presented in section 3.1. See text for further details.

Figure 9: **Global IPI and earning calls, SVAR**

A. IRF of global IPI: one-standard deviation shock to sentiment

B. IRF of global IPI: one-standard deviation shock to uncertainty



Source: Authors' calculations using earning calls, Haver Analytics.
Note: Impulse response functions (IRF) from a 3-variable SVAR with sentiment score, federal funds rate, and log global IPI (in order). See text for further details on identification assumptions and model selection which is based on earlier studies in similar context (Baker, Bloom and Davis, 2016; Bybee, Kelly, Manela and Xiu, 2020).
A. IRF of a one standard deviation shock to sentiment score on log level of global IPI.
B. IRF of a one standard deviation shock to uncertainty score on log level of global IPI, from the estimated 3-variable SVAR model in which sentiment was replaced with uncertainty.

tive power of standard time series models, we regress the year-on-year growth of global IPI against our sentiment and uncertainty measures. The model returns an R^2 equal to 47 percent. Panel A of Figure 8 plots the global IPI against uncertainty index. Panel B illustrates the strong correlation between the COVID-19 topic weight–from the computed NMF model in Section 3– and the global economic activity. Given the short sample of data for which the NMF topic model was estimated, we stick with the visual illustration for this co-movement and refrain from a formal econometric estimation.

Next, we estimate the impact of orthogonalized shocks to the sentiment and uncertainty indexes on global economic activity. We use a 3-variable structural vector autoregressive model (SVAR) with an identification strategy based on Cholesky decomposition. The set of variables includes (in order) sentiment index (seasonally adjusted), effective federal funds rate, and log level of global IPI (seasonally adjusted) similar to the models estimated by Baker, Bloom and Davis (2016) and Bybee, Kelly, Manela and Xiu (2020).[19] The model includes three lags of each endogenous variable. Formally, the model is specified as follows:

$$Y_t = BX_t + M_t, \tag{6}$$

where Y_t is an $N \times 1$ vector of endogenous variables, X_t is an $N \times p+1$ vector of lagged dependent variables and an intercept term and where p is the lag length, B is an matrix of coefficients, and M is a $N \times 1$ vector of residuals.

Impulse response functions from the estimated SVAR model plotted in Figure 9. A one standard deviation shock to sentiment index associates with roughly a 0.6 percent decline in global IPI on impact, and 1 percent within a month. As a robustness check, we estimated the same model with uncertainty index as well as alternative orderings for the sentiment index, all resulting in comparable output. Given a roughly 8 standard deviation drop in sentimental score during the peak of pandemic, the estimated SVAR implies a roughly 8 percent decline in global IPI from its long-term trend within a month. Accordingly, the sharp rise in the most recent observations of sentimental scores point to a strong progress in global economic activity as of 2021-Q2 (Figure 8, panel A). This is further confirmed with the drop in topic attention paid to COVID-19 and improving sentiment scores around pandemic discussions (Figures 8, panel B).

[19] The benchmark SVAR in Baker, Bloom and Davis (2016) is estimated for United States and includes employment as well as industrial production. We repeated the same exercise for United States with our sentimental measures and obtained comparable findings.

6 Conclusions and policy implications

The COVID-19 pandemic has triggered a global collapse in economic activity.[20] Governments across the world have taken unprecedented national and sectoral measures to mitigate the impact of COVID-19 as well as to facilitate a safe and swift recovery. Fiscal measures have provided some breath to households as well as businesses by providing unemployment benefits and covering wage bills of small businesses. Central banks have expanded ongoing asset purchase programs to soften the impact of the financial uncertainty caused by the pandemic. However, the optimal design and effectiveness of these measures depend on how COVID-19 affects economic activity, which is a topic that is currently understudied. By providing a quantitative analysis of corporate earning calls, the present paper contributes to closing this gap.

Several patterns emerge from our examination of earning call transcripts, which employs computational linguistic methods to uncover sentimental swings and extract latent topics in these calls. First, the COVID-19 has been an increasingly dominant topic in earning calls over the course of the pandemic, peaking in mid-2020 and diminishing since then. Second, the average sentiment score of COVID-19 discussions declined sharply and bottomed in the second quarter of 2020, and has returned gradually to its initial and more neutral levels by the first quarter of 2021. The uncertainty scores around pandemic discussions, however, has not yet converged to its initial lower levels as of 2021-Q1, arguably reflecting the uncertainties related to global vaccination rates, developments in virus variants, and business challenges in the post-COVID-19 era.

The distribution of topics during the COVID-19 discussions in earning calls varied substantially over the course of the pandemic and across sectors. Global supply chains were the most highlighted topic in the earlier stages of the pandemic and its significance dropped sharply in the subsequent quarters. On the other hand, sales and recovery dis-

[20]See, for example, World Bank (2021), Yilmazkuday (2020), and Guenette and Yamazaki (2021) for a detailed description of how global economic activity evolved during the pandemic.

cussions intensified over time, and ranked at the top since 2020-Q3. Employee health concerns peaked in 2020-Q2 and diminished significantly since 2020-Q3 with the progress in immunization efforts. Throughout the pandemic, digital technologies showed no discernible downward trend, with at least twice as much attention in professional&business services as other key sectors. Employee health, however, was not a major topic of discussion in this sector, owing to the possibilities of alternative work arrangements and weaker requirements for face-to-face encounters.

The results presented in this paper offer a parsimonious tool for real-time tracking of economic activity during the pandemic which is paramount to effective design of policy measures. Substantial sectoral heterogeneity in COVID-19 impact is noteworthy for policy interventions, which requires enabling a productive reallocation of existing resources while limiting the adverse consequences of the pandemic.[21]

[21] See OECD (2020) and UN (2020) for sectoral policy discussions and country examples.

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Appendix

A Sample excerpts

BOEING, 29-Apr-20
To balance the supply and demand given the **COVID**-19 shock and to preserve our long-term potential and competitiveness, we have decided to reduce the production rates of several of our commercial airplane programs. These rate decisions are based on our current assessment of the demand environment, taking into account a host of **risks** and **opportunities**. We will closely monitor the key factors that affect our skyline including the wide-body replacement cycle and the cargo market.
But the sharp reduction in demand for our airplanes that we see out over the next several years won't support the size of the workforce we have today... the **COVID**-19 pandemic has significantly impacted aircraft demand, we're taking actions as a result of these new realities by adjusting production rates and our infrastructure, which will position us for the future and help us bridge to **recovery**. These rate decisions are based on current assessment of our demand environment and we will continue to closely monitor these factors that affect our skyline and make rate adjustments as appropriate in the future.
We're also doing everything we can to support our global supply chain health. A number of our **suppliers** have suspended or reduced their operations resulting in some **supply shortages** for our own operations. In some cases, this contributed to our site suspension decisions. We've taken mitigating actions where we can, but **supply disruption** remains a key watch item for us.
On the services side, we are seeing a direct impact on our commercial supply chain business as fewer flights result in a **decreased demand** for our parts and logistics offerings. Air Force to develop and integrate our new Remote Vision System, while the remaining costs reflect productivity inefficiencies and **COVID**-19 related factory disruption.
A number of other programs, including the VC-25B, were also impacted by **COVID**-19 further reducing margin in the quarter. There are provisions of **the Care Act** in our contracts that may provide an opportunity to **recover** some of these costs related to **COVID**-19 over time, and we'll continue to evaluate them. During the quarter, BDS won key contracts worth \$6 billion and our backlog now stands at \$64 billion with 28% from outside the United States.

APPLE, 30-Apr-20
During a quarter where circumstances evolve by the hour, we have been gratified by the resilience and adaptability of our **global supply chain**. While we felt some **temporary supply constraints** in February, our operations team, **suppliers** and manufacturing partners have been safely returning to work and production was back at typical levels toward the end of March.
In the next five weeks of the quarter, as **COVID**-19 started impacting China, iPhone supply was temporarily affected, as well as demand for our products within China. This caused us to withdraw our revenue guidance in February. At that point, demand for our products outside of China was still strong and in line with our expectations. During the last three weeks of the quarter, as the **virus** spread globally and **social distancing measures** were put in place worldwide...
On the supply side, we suffered from some **temporary supply shortages** during February, but we've been extremely pleased with the resilience and adaptability of our **global supply chain**, as well as its ability to get people back to work safely when circumstances allow. Our operations team and manufacturing partners put forth an extraordinary effort to restore production quickly, and we exited the quarter in a good supply position for most of our product lines.
And if you look up underneath the full quarter, we saw a strong January, and then a significantly **reduced demand** in February as the shelter-in-place orders and the **lockdowns** went into effect in China and the stores closed. And then, in March, as stores reopened, the recovery began. And then, we've seen further **recovery** in April. Where that goes, we will see. But that's kind of what we've seen so far there.
During the last three weeks of the quarter, as the **virus** spread globally and **social distancing measures** were put in place worldwide, including the closure of all our retail stores outside of Greater China on March 13th, and many channel partner points of sales around the world, we saw **downward pressure on demand**, particularly for iPhone and Wearables.
iPhone **revenue** of $29 billion, declined 7% year-over-year as both iPhone supply and demand were affected by the impact of **COVID**-19 at some point during the quarter.
We have shown the consistent ability to meet and manage **temporary supply challenges** like those caused by **COVID**-19.

B Non-Negative Matrix Factorization

B.1 Model

Given a non-negative matrix $\boldsymbol{X} \in \mathbb{R}_+^{m \times n}$, and a desired lower dimension k, NMF decomposes $\boldsymbol{X}$ into two lower rank matrices $\boldsymbol{W} \in \mathbb{R}_+^{m \times k}$ and $\boldsymbol{H} \in \mathbb{R}_+^{k \times n}$ with non-negative elements such that:

$$\boldsymbol{X} \approx \boldsymbol{W} \times \boldsymbol{H}. \tag{7}$$

In the topic modeling context, the document/word matrix $\boldsymbol{X}$ represents the entire corpus, which is composed of m rows (earning calls), and n columns (words). $\boldsymbol{W}$ with m rows and k columns represents document/topic matrix, and $\boldsymbol{H}$ with k rows and n columns represents topic/term matrix.

Specifically, each row x_i in $\boldsymbol{X}$ refers to an earning call, and each column x_j refers to a word in the corpus. Each row w_i in $\boldsymbol{W}$ refers to a call and each column w_j refers to a topic. Similarly, each row h_i in $\boldsymbol{H}$ refers to a topic and each column h_j in $\boldsymbol{H}$ refers to a word. The entries in matrices represent the weights of corresponding topics in calls and terms in topics. Accordingly, each column of $\boldsymbol{X}$ is the sum of each column of $\boldsymbol{W}$ weighted by the corresponding row of $\boldsymbol{H}$ as follows:

$$x_i = \boldsymbol{W} \times h_i. \tag{8}$$

The goal of NMF is to find non-negative matrices $\boldsymbol{W}^{m \times k}$ and $\boldsymbol{H}^{k \times n}$ such that $k < \min\{m, n\}$, and product of document/topic and topic/word matrices, $\boldsymbol{W} \times \boldsymbol{H}$, approximates document/word matrix, $\boldsymbol{X}$.

First, we apply a standard data cleaning process to the text and construct the document/word matrix, $\boldsymbol{X}$. Each entry x_{ij} of matrix $\boldsymbol{X}$ represents word j's frequency in document i. Instead of absolute frequency numbers, we use the Term Frequency Inverse Document Frequency (TF-IDF) approach, which is a measure of how important the word is in a document, taking into account the frequency of the word in the entire corpus. TF-IDF ranks words that occur many times across different documents lower than words that occur less frequently. The term is calculated by multiplying the term frequency which is the simple raw count by the inverse of the document frequency which calculated by taking the log of the total number of documents in the corpus divided by the number of documents that contain the word. TF-IDF scores create word vectors which are then fed into our models.

Given the constructed document/word matrix $\boldsymbol{X}$, document/topic ($\boldsymbol{W}$) and topic/word

($\boldsymbol{H}$) matrices are approximated by minimizing the distance between $\boldsymbol{X}$ and $\boldsymbol{W} \times \boldsymbol{H}$. This paper uses a commonly-used formula, Frobenius-norm, as a distance measure between two matrices, and approximates the document/topic and topic/word matrices as follows:

$$[\boldsymbol{W}, \boldsymbol{H}] = \underset{\boldsymbol{W} \geq 0, \boldsymbol{H} \geq 0}{\arg\min} \, ||\boldsymbol{X} - \boldsymbol{W} \times \boldsymbol{H}||_F, \tag{9}$$

where, the constraint in equation (9) indicates the non-negativity of all the entries of $\boldsymbol{W}$ and $\boldsymbol{H}$.

B.2 Computational algorithm

Infer topics through non-negative matrix factorization

Input: document/word matrix, $\boldsymbol{X} \in \mathbb{R}_+^{m \times n}$
Output: document/topic matrix $\boldsymbol{W} \in \mathbb{R}_+^{m \times k}$, and topic/word matrix $\boldsymbol{H} \in \mathbb{R}_+^{k \times n}$

Initiate non-negative $\boldsymbol{W}$ and $\boldsymbol{H}$ matrices.
for $i = 1$ to $max\_iteration$ **do**
  update $\boldsymbol{W}$ to minimize the objective function described in equation (9), iterate once over all coordinates.
  update $\boldsymbol{H}$ to minimize the objective function described in equation (9), iterate once over all coordinates.
  if convergence criterion has reached **then**
    break
  end if
end for