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Using the Google Places API and Google Trends Data to Develop High Frequency Indicators of Economic Activity

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ABSTRACT: As the pandemic heightened policymakers' demand for more frequent and timely indicators to assess economic activities, traditional data collection and compilation methods to produce official indicators are falling short—triggering stronger interest in real time data to provide early signals of turning points in economic activity. In this paper, we examine how data extracted from the Google Places API and Google Trends can be used to develop high frequency indicators aligned to the statistical concepts, classifications, and definitions used in producing official measures. The approach is illustrated by use of Google data-derived indicators that predict well the GDP trajectories of selected countries during the early stage of COVID-19. To this end, we developed a methodological toolkit for national compilers interested in using Google data to enhance the timeliness and frequency of economic indicators.

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I. MOTIVATION

To say the needs of users of economic statistics have changed since the start of the pandemic would be an understatement. Things are simply not what they were. We have gone from a world of short-term predictability to one where policymakers need to take a daily pulse of economic activity and adjust course often. Data consumers have become accustomed to seeing daily charts of health-related data. Case counts, moving averages and trends, cycles, peaks, and troughs are now a common part of our vocabulary and daily conversations. Users of economic data are now starting to demand a similar service from economic statisticians. Tasked with identifying the path out of the pandemic—represented by letter shapes whether that be V, W, U, K (choose your letter of choice)—data users and policy makers require more frequent, timely and granular economic statistics.

The need to modernize is clear. Traditional economic data collection and processing methods to produce indicators of economic activity do not meet the timeliness and frequency demands of policymakers during a pandemic (or any other crisis for that matter). Even among those countries with the most advanced statistical systems it often takes at least 45 to 60 days following the reference period to get a reading on what is happening. As we have seen with the pandemic, those 45 to 60 days can mean the difference between staying in business or losing your business. Just over two-thirds of the 190 IMF member countries produce quarterly estimates of gross domestic product (GDP). The rest produce annual measures of GDP and most are released 9 to 12 months following the reference period. This means that in many countries, statisticians will not have a final tally of the effect of the start of the pandemic until sometime in late 2021 and those estimates will say very little about the path of the economy since its onset.

Improving the timeliness and frequency of economic statistics while maintaining their quality is a longstanding challenge in the realm of economic measurement. Economic statisticians often refer to this as the timeliness versus quality tradeoff in which policy makers are told they need to accept lower quality data if they want improved timeliness. When constrained by traditional data sources and approaches used to compile economic indicators, this is certainly the case. Economic statisticians need to examine new data sources and develop new methods to provide users with the type of 'statistical tickers' they are becoming accustomed to. As has been widely acknowledged, "big data" and the vast amount of data collected by an increasing number of digital platforms can offer part of the solution. Statisticians need to quickly figure out how to bridge the gap between "big data" and official measures of economic activity. The challenges facing many statistical organizations are:(1) acquiring the source data; (2) processing these data; and (3) integrating these data with high quality official measures of economic activity to improve their timeliness and frequency. Data available from the Google Places and Google Trends Platforms may provide part of the answer.

Interest in the use of real time, non-traditional data sources[1] to measure economic activities is not new. Elvidge et al. (1997) identified a correlation between illuminated areas, electric power consumption, and GDP at the country level. Since then, the rapid growth of new sources of big data—enabled by internet-based technologies—has expanded the toolkit for tapping real-time information at a more scalable and granular level. Within the last decade, scanner data on purchases, credit card transaction records, and prices of various goods and services scraped from the websites of online sellers have been increasingly mainstreamed in the compilation programs of statistical agencies in advanced and emerging economies. Abraham et. al (2019) documents the progress made toward the goal—and the challenges to be overcome to realize the full potential—of using big data in the production of statistics.

Exploiting online platforms for tracking economic developments gained traction as the data observations harvested became longer, more accessible, and stable. The use of Google-sourced data to forecast private consumption was explored by Schmidt and Vosen (2011); and was followed by academic research in similar directions by Choi and Varian (2012) on predicting economic activity, and by Luca (2016) on the impact of Yelp-based consumer reviews on the restaurant industry, among others. Jun, Yoo and Choi (2016) traces the ten years of research using Google Trends since the company made this source of data available in 2006. Noting that the availability of timely data is a long standing challenge for policymaking and analysis for low-income developing countries, Narita and Yin (2018) explored the use of Google Trends data to narrow such information gaps. Many organizations have since developed timely leading indicators using Google data (Google Trends, Google Mobility data, Google APIs) that track well official measures of economic activity. More recently, the OECD Weekly Tracker of GDP growth (2020) attempts to fill the gap in real-time high-frequency indicators of activity with a large country coverage.

These research strands and experimental estimates have shaped our understanding of current (now-time) economic trends. Building on this work, over the last year, the IMF Statistics Department (STA) has been working with Google data to determine how data extracted from the Google Places and Google Trends platforms can be processed for use by data compilers in developing higher frequency and timely measures of economic activity that can be used to increase the timeliness and frequency of official measures.

This paper is organized as follows. Section II describes Google Places API and Google Trends and how they can be accessed by national statistical organizations. Section III explains how country compilers and researchers can process these data and develop high frequency indicators that align with the concepts, classifications, definitions, and methods used to produce official measures of economic activity. Section IV shows an application of these indicators to nowcast quarterly GDP of selected countries during the onset of the COVID-19 pandemic. Section V offers some concluding remarks and next steps from this

[1] Non-traditional data are characterized by high volume, velocity, and variety, often generated by social media, web-based activities, machine sensors, or financial, administrative or business operations (BIS, 2021).

work. Finally, the technical annex describes the characteristics of the Google data used in this research and the R package developed by the authors to reproduce the results.[2]

II. SOURCE DATA

A. Google Places and Google Trends

Over the last five to ten years there has been a large push within the economic statistical community to take advantage of a growing (exponentially) set of "big data" to produce official statistics. This new source of information has the potential to address a lot of the unmet needs of users of economic statistics – specifically as it pertains to their demand for more timely data, published with a higher frequency and with more granularity. While these data hold promise to significantly increase the timeliness, frequency, and granularity of official statistics there are often significant challenges that need to be addressed before they can be leveraged in the production of official statistics. These challenges are related to access / terms of use, coverage, and concepts.

The first, and generally most time-consuming challenge, is securing access to the data. Before a statistical organization can consider using a particular data source in the production of official statistics it needs to ensure it will have regular access to the data over the medium term. It also needs some assurance that the composition of the data (coverage, variables, frequency) will be stable during that period. Finally, it needs to ensure that its proposed use aligns with the terms of use as outlined by the data owner and that these terms of use will be stable over the medium term.

The second challenge that statistical organizations often face is coverage. Often big data can be very timely and granular but may only cover part of the population of interest. For example, a statistical organization may obtain scanner data from major retailers. If a significant share of purchases occurs at local markets, the scanner data, while useful, only provides partial coverage. In other cases, statistical organizations may require long-time series to establish relationships with existing official estimates. Often big data can have broad coverage, be timely and available on a daily frequency, but the data may only be available for the previous two to three years, limiting their usefulness (at least in the short term).

The third challenge that statistical organizations face is the potential conceptual misalignment between the big data source and the target statistic being produced. Statistical frameworks outline and provide definitions for concepts such as revenue, income, expenditure, exports, production, value added, etc. Statistical organizations are tasked with developing statistics that provide a numerical representation of these concepts. To do this statistical organizations often design collection instruments in which they tailor the questions

[2] The results presented in this work and the accompanying datasets are available through an R package developed by the authors. The '*imfgoogle*' package is available upon request. Please refer to Annex II for more details.

to align with the concept they are trying to measure. In the case of big data, statistical organizations have no control over the "question." It is therefore often the case that the concepts that underpin "big data" do not align with the concepts that the economic statistician is attempting to measure. In these cases, the economic statistician will need to make assumptions, build models, or make "second best measures" to align the big data with the concept being estimated.

The data that can be acquired from the Google Places and Google Trends platforms exhibit very few of these shortcomings. As shown below, data obtained from the Google Places and Google Trends platforms address the economic statisticians' needs with respect to access, coverage and conceptual alignment with official statistics.

Google Places and Google Trends - Access

Data from the Google Places platform can be obtained using the Google Places API. The Google Places API[3] is a service offered by Google that allows users to obtain information about "Places" via an HTTP request. The requests return a JSON or XML file that is easily integrated into a database. Uses of this information must comply with the Places API Policies and Google Maps Platform Terms of Service. The terms of use support research purposes and permit the results of research to be shared. There are limitations with respect to the volume of data that can be extracted, and fees may apply depending on the volume of the request and use of the information. From the perspective of compilers of official statistics, the existence of the API addresses one of the key hurdles that are often associated with the use of Big Data – access. The Google Places API provides seamless and stable access to over 20 fields of information for each *Place* on the Google Maps Platform. In addition, the Google Places API has policies which help reduce the risk of using these data in the compilation of official statistics. For example, the Google Places API has a depreciation policy which they provide users with at least one year's notice if they intend to change or discontinue a field. This provides ample lead time for statistical organizations to adjust processes and methods.

One challenge facing statistical organizations is the cost of access. For data to be useful, statistical organizations require a significant amount of data. Given the scope of their data needs, they are required to pay. During COVID-19, this limitation is being addressed by Google. Google has launched an initiative to support nonprofit organizations with COVID-19 response efforts to access its data, free of charge, provided the applications have a public good element. Since production of official statistics generally fall within the public good category, there is opportunity for statistical organizations to negotiate access free of charge.

Google Trends is a public website (trends.google.com) managed and maintained by Google that facilitates analysis of Google search queries. There is no charge to use the website or extract information from the website. The information can be downloaded into CSV files, the charts can be captured as images, shared, or directly embedded into webpages. The terms of

[3] https://developers.google.com/places/web-service/overview.

use are governed by Google's Terms of Use and Privacy Policy. While Google does not provide an API to access the Google Trends data several publicly available web-scraping scripts have been developed that facilitate the extraction of data. From the perspective of statistical organizations, the data are highly accessible and the use of these data in the compilation of official statistics falls within the Terms of Use and Privacy Policy outlined by Google. The methodology Google uses to produce the trends data are documented and available on the Google Trends website.

Google Places and Google Trends - Coverage

Both Google Places and Google Trends have wide (near census) coverage. It is safe to assume that in the countries where Google operates the Google Places platform contains a near census of *Places* - everything from businesses, to places of interest, to government offices. This is important since it implies that the estimates produced using these data will be very representative of the population of interest. In addition, given that the Google Places platform contains a near census of *Places*, scientific samples of this population can be drawn, and the characteristics and activities of the sample can be inferred on the population. Similarly, the Google Trends data contains broad country and topical coverage. In fact, given the widescale use of the Google search engine, trends can be calculated for individual businesses and products. From a coverage perspective, the data that can be obtained from the Google Places and Google Trends platforms have enough coverage to be used by most countries across most economic activities. Clearly, coverage is wide for countries where Google is used as the primary Internet search engine and there is no restriction to its use.

Google Places – Conceptual Alignment

The Google Places API allows users to extract information about *Places* from the Google Maps Platform. In total, users can extract 23 fields of information for each *Place* as identified in Table 1.

Table 1. Fields of Information that can be Extracted for Each Place using Google Places API

Basic Fields[4]
Address Component
Address
Business Status
Formatted Address
Viewport
Location
Icon
Name
Photo
Place ID
Plus Code
Type

[4] https://developers.google.com/places/web-service/place-data-fields.

URL
UTC Offset
Vicinity
Contact Fields
Phone Number
International Phone Number
Opening Hours
Website
Atmosphere Fields
Price Level
Rating
Reviews
User Ratings Total

The usefulness of these data in the production of economic indicators is determined, in part, by how well these fields align with the target concepts outlined in international statistical standards such as the System of National Accounts, Balance of Payments Statistics and *International Standard of Industrial Classification* (*ISIC*).

The statistical unit is one of the most important concepts underpinning the production of official statistics. It represents "the entity about which information is sought"[5] and ultimately for which statistics are produced. The Google Places statistical unit is the *Places ID*. The Google Places platform defines a *Place* as a "business, landmark, park, and intersection." It reflects an entity with a physical presence, where activity takes place which has a specific and identifiable location. In the field of economic statistics, there are two types of statistical units – households and legal entities. Legal units are generally classified into sectors or industries (activities). When classified to activities a statistical hierarchy is adopted. This statistical hierarchy moves from an enterprise, to an establishment, to a kind of activity unit / local unit.[6] In the statistical domain a local unit is defined as "*an enterprise or a part of an enterprise (for example, a workshop, factory, warehouse, office, mine or depot) which engages in productive activity at or from one location.*"[7] The Google Places concept of a *Place* aligns well with the statistical concept of a local unit. Given Google also identifies the "place type," the combination of the Google Places location information with the Google Places "place type" approaches the statistical concept of an establishment. The conceptual alignment between the Google Places *Place* and the statistical concept of a local unit or establishment can therefore be regarded as "High."

Table 2. Statistical Concept: Units

Target Statistical Concept	Google Field	Subjective degree of alignment with statistical concepts.
Local Unit	Places ID	High

[5] https://unstats.un.org/unsd/classifications/Econ/Download/In%20Text/ISIC_Rev_4_publication_English.pdf (p.15).

[6] https://unstats.un.org/unsd/classifications/Econ/Download/In%20Text/ISIC_Rev_4_publication_English.pdf.

[7] https://unstats.un.org/unsd/classifications/Econ/Download/In%20Text/ISIC_Rev_4_publication_English.pdf (p.17).

Establishment	Places ID / Places Type	High

The business status indicator available on the Google Places Platform also aligns well with the statistical concept of the operating status of a business. The Google Places business status indicator identifies whether a business is "operational," "temporarily closed" or "permanently closed." This status indicator aligns with the economic statistical concepts of "births" and "deaths," "entries" and "exits" or "capacity" that are employed by most statistical organizations. In addition to being conceptually well aligned the business status information available from the Google Places Platform is available in real-time and indicates when a business is temporarily closed - something that is generally not available from statistical registers.

Table 3. Statistical Concept: Operating Status

Target Statistical Concept	Google Field	Subjective degree of alignment with statistical concepts.
Business Status	Business Status Indicator	High

Most economic statistics are presented at some level of geographic detail, whether the data are presented for a country as a whole or for a specific region(s). Economic statisticians often employ the concept of a territory. A territory is generally reflective of a country's geographic boundaries with a few exceptions such as the land area associated with embassies or consulates. Given the Google Places Platform provides access to the longitude, latitude and address associated with each *Place* the Google Places data can easily be reconciled to the statistical concept of a territory.

Table 4. Statistical Concept: Territory

Target Statistical Concept	Google Field	Subjective degree of alignment with statistical concepts.
Territory	Longitude / Latitude	High
Territory	Address	High

In addition to concepts such as territory and activity most economic statisticians require information about an entity's size. In most cases countries rely on business surveys or administrative sources (such as taxation records) to obtain information about the size (e.g., revenue, number of employees) of an entity. While the Google Places Platform does not contain information related to the revenue or employment of a *Place*, it does collect and store what Google refers to as "Atmosphere Data Fields." These fields include the number of reviews associated with a given entity, its price level as well as the rating (scaled 1-5) provided by reviewers. It is fair to assume that larger / more popular / successful places will have more reviews. It is also fair to assume (but to a lesser degree) that a place with twice as many reviews as another place is roughly twice its size (or at least twice as popular). Using these assumptions, the number of reviews could therefore be used to proxy the size of a *Place*. Information about the size of an entity will assist with statistical methods such as sampling, weighting, and aggregation.

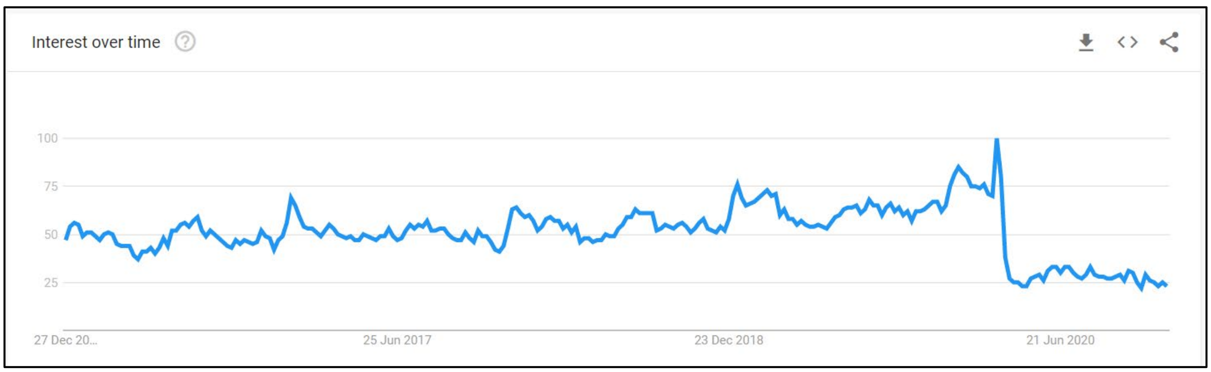
Table 5. Statistical Concept: Size

Target Statistical Concept	Google Field	Subjective degree of alignment with statistical concepts.
Size	Reviews	Medium
Size	Rating	Low
Size	Price Level	Low

Google Trends – conceptual alignment

Google Trends are a measure of interest in a topic relative to all other topics over time. A topic can be anything from a person or event to a business or specific product. To the extent that the topics relate to a business, industry, or product the trend could be indicative, at least to some extent, of economic activity. For example, consider Figure 1 which shows the Google Trend for the term "Flights" for Canada. The "interest" in flights in Canada declined significantly towards the end of the first quarter of 2020 due to the COVID-19 travel restrictions imposed by the Canadian Government. This is indicative of the decline in economic activity that occurred in the Canadian Air Transportation Industry during this period.

Figure 1. Google Trend "Flights" - Canada



Source: Google Trends – July 2020.

To illustrate how a "Google Trend" is calculated consider the following example. Assume there are 10,000 searches in week 1 in a region and that 1,000 are related to restaurants. The level of interest in restaurants is therefore 1,000/10,000=.1. Assume that each week we measure the level of interest in restaurants (e.g., week 2=.08, week 3=.09) as illustrated in Table 6. The weekly level of interest in restaurants is indexed to the week with the highest level of interest (week 4 in our example). Using search activity as a proxy for demand for restaurant services the trend would be interpreted as an indication that demand for restaurant services was increasing in the first four weeks, stable over the next three weeks and declining in the final weeks. This provides valuable information about turning points in activity.

Table 6. Construction of Google Trends Index: Example

Week	Total Searches	"Restaurant" Searches	Search Intensity	Trends Index
1	10000	1000	.1	83
2	10000	800	.08	67
3	10000	900	.09	75

Week	Total Searches	"Restaurant" Searches	Search Intensity	Trends Index
4	10000	1200	.12	100
5	15000	1200	.8	67
6	12500	1000	.8	67
7	10000	800	.8	67
8	10000	700	.7	58
9	10000	600	.6	50
10	10000	500	.5	42

The amount of information available via this platform is extensive. The platform provides users with near worldwide geographic coverage and could be considered universal coverage of social, economic, and environmental topics. This detail is an advantage and a disadvantage. Given the almost infinite number of topics, the key challenge is selecting those topics that are most indicative of a given economic activity. Therefore, it is necessary to either group topics together into meaningful categories or select a sample of topics that correspond to the activity of interest. With respect to the former, Google has developed an algorithm to aggregate search topics into 1000+ "trend" categories. Google identifies the most popular search topics related to category and aggregates the data by category. This aggregation can be done by region and for different periods of time. For example, the category "Consumer Electronics" for Australia is an aggregation of search topics in Table 7.

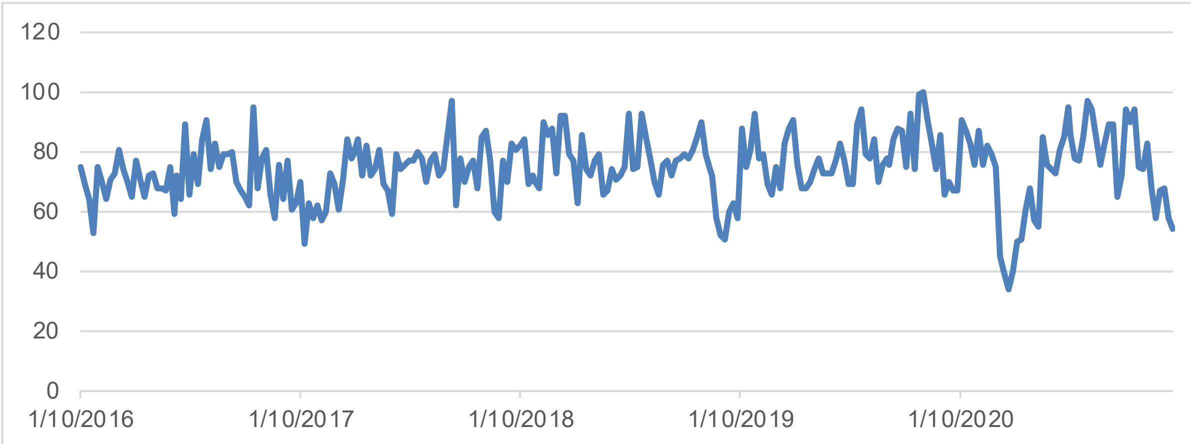
Table 7. Search Topics Related to Consumer Electronics for Australia

Related Topics		
Radar	Apple	Ultra-high-definition television
Bureau of Meteorology	Television	Kmart Pharmacy
The Good Guys	Canon	Kmart
Xbox	Canon	Rain
Xbox One	JB Hi-Fi	Meaning
Camera	Apple	Weather radar
Headphones	Battery charger	Soundbar
Australia	Sony	Bunnings Warehouse
Xbox	Price	Fitbit
PlayStation 4	Fortnite	Smart TV
Loudspeaker	PlayStation 4 Pro	JBL
Television set	Microsoft Xbox One X	Watch
Garmin Ltd.	Nintendo Switch	Nintendo
Samsung Electronics	New South Wales Education Standards Authority	Netflix
Samsung	AirPods	Garmin Forerunner 235
Samsung Group	Oppo	reddit
4K resolution	Reddit	

Source: Google Trends – July 2020.

In addition to obtaining trends by category it is also possible to extract trends for specific businesses/products. For larger firms there are enough searches made that allow trends to be calculated. For example, trends are available for *Sandals Resorts*, *Cineplex Entertainment*, *The Home Depot*, *Ikea Furniture Company, Holiday Inn Hotels*, *Oh Henry! Chocolate bar*, *Ford Escape* (see Figure 2), and *Xbox Console* in various countries. Assuming at company / product level, there is a relationship between searches and business activity, having this detail improves the potential of using Google Trends as an indicator of economic activity.

Figure 2. Google Trends: Demand for Ford Escape - Canada



Both the Google Places and Google Trends platform are a rich data source that align well with the type of data sources used to compile official statistics. Data acquired from the Google Maps platform closely aligns with the type of data used by national statistical organizations in the production of business status and dynamic type statistics. These data may be of use in helping better understand the business population and some of the entry and exit dynamics at a very granular geographic level of detail. The Google Trends data, when properly filtered, could highlight sudden turning points, and be used to improve the timeliness and frequency of official measures. The next section of this paper outlines how the Google Places and Google Trends data described above can be processed and transformed into a set of economic indicators consistent with the classifications and concepts of official measures.

III. Methods

A. Operating Status Indicators

The Google Places API permits users to extract the operating status of each place identified on the Google Places platform. Places are given the status of "Open," "Temporarily Closed" or "Permanently Closed." This information can be used to produce several useful business dynamic indicators. If we assume that the Google Places Platform has a near census coverage of all *Places* operating in a region and that the number of reviews is a good indication of the relative size of one *Place* to another – we can use this information to measure the operating status of Places in each geographic area.[8] Since there is a strong relationship between the business' operating status and its revenue and employment, these indicators could be useful

[8] This assumption is particularly valid for consumer-facing establishments, such as stores and restaurants. For businesses that do not sell directly to consumers, the number of reviews may not be a good indication of their size. Statistics agencies can use existing business register or business survey data to adjust the relative weights from reviews in a composite high-frequency indicator.

in providing an early signal of trends in the labor market or trends in aggregate economic activity for the region.

Operational Indicator

The Google Places business status field can be used to construct an operational indicator. The operational index represents the share of Places in each geographic region that are operational at a given point in time weighted by the number of reviews. Weighting by reviews is intended to capture the impact of the size of the business, in which businesses with more reviews will have a larger impact on the movement in the indicator. To illustrate, consider the following example (Table 8) in which the status of a sample of *Places* with Place Type = "restaurants" for a specific geographic region are tracked over a five-week period. Since the Google Places API does not permit users to extract a census of all *Places* in each geographic region, each week's extraction is treated as a random and representative sample of places for the region. Assume that these places are restaurants operating in the same geographic area. In week 1, we note that Place A has 1000 reviews, Place B has 500 reviews, Place C has 500 reviews, Place D has 100 reviews, Place E has 400 reviews, and it is temporarily closed.

The initial operational status of the business population of restaurants for this region is 84, which simply represents the share of reviews of *Places* in operation. To understand the dynamics of the indicator, the above example is extended such that:

- In week 2, establishment F is temporarily closed
- In week 3, establishment F re-opens
- In week 4, all establishments remain operational
- In week 5, establishment C permanently closes

Each week a business operational indicator can be calculated, as shown below.

Table 8. Construction of Operational Indicator-Example

Week 1 – Initial Status: Places A, B, C, and D operational				
Business	Reviews	Share of Reviews	Business Status	Operational Indicator
A	1000	40	Operational	
B	500	20	Operational	
C	500	20	Operational	
D	100	4	Operational	
E	400	16	Temporarily Closed	
	2500	100		84
Week 2 – Place F is temporarily closed				
Business	Reviews	Share of Reviews	Business Status	Operational Indicator
F	1000	37	Temporarily Closed	
G	700	26	Operational	
H	500	19	Operational	
I	100	4	Operational	
J	400	14	Operational	

	2700	100		63
Week 3 – All places are operational				
Business	Reviews	Share of Reviews	Business Status	Operational Indicator
F	1000	33	Operational	
K	700	24	Operational	
L	500	17	Operational	
M	400	13	Operational	
J	400	13	Operational	
	3000	100		100
Week 4 – all Places are operational				
Business	Reviews	Share of Reviews	Business Status	Operational Indicator
A	1100	30	Operational	
B	900	25	Operational	
C	600	17	Operational	
M	500	14	Operational	
L	500	14	Operational	
	3600	100		100
Week 5 – Place L permanently closes				
Business	Reviews	Share of Reviews	Business Status	Weighted Population
A	1200	31	Operational	
K	900	24	Operational	
L	600	15	Closed Permanently	
P	600	15	Operational	
Q	600	15	Operational	
	3900	100		75

The above methodology was used to construct an operational indicator for several major city centers for the period April 24, 2020 (the baseline) to August 10, 2021. The results indicate that weighting by reviews has a significant impact on the index – introducing greater variability. There is variation by city center and the operational status aligns well with the timing of the various waves of the COVID-19 pandemic experienced by each of the city centers. The variation by type of place is also consistent with the scope of the lockdown in city centers where essential businesses remained open and non-essential business were temporarily closed or altered their operations (e.g., curb-side pickup, limited capacity, limited hours of operation). The following series of charts in Figure 3 compares bars with gyms for a select set of city centers.

Figure 3. Operating Indicator (weighted by reviews) for Selected City Centers

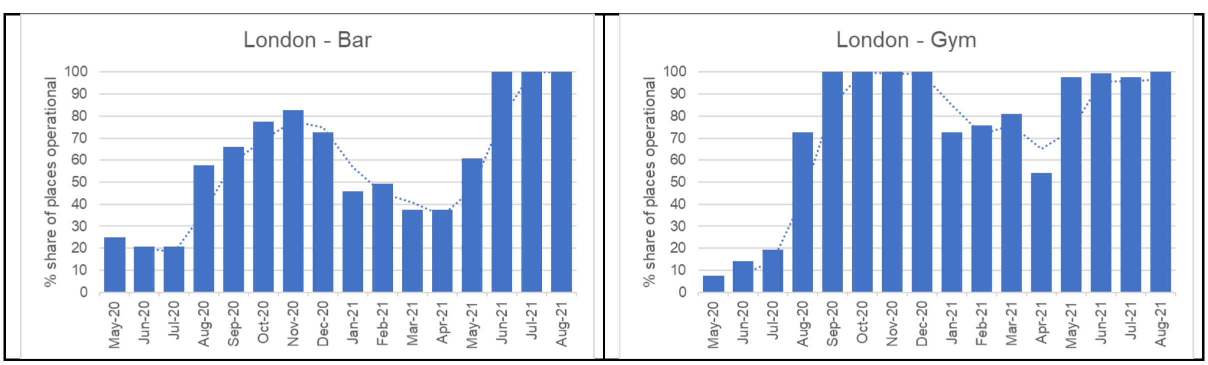
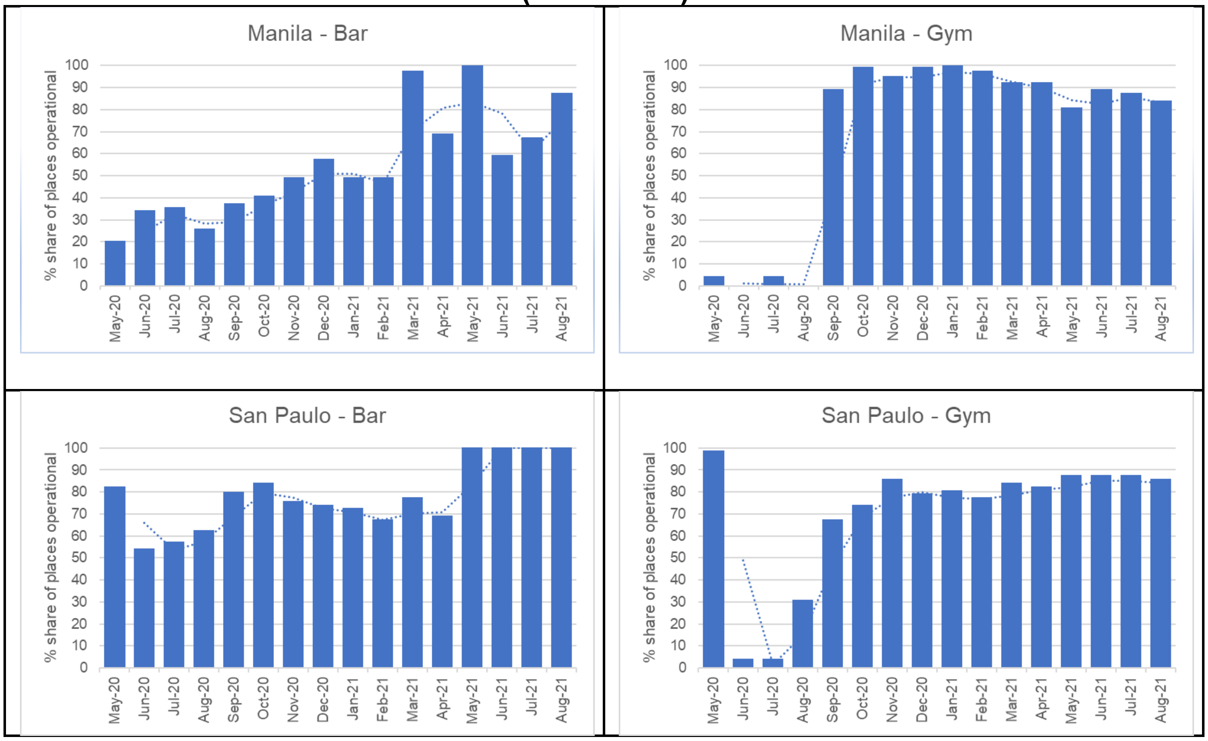


Figure 3. Operating Indicator (weighted by reviews) for Selected City Centers (continued)



Source: Google Places API – Data Extracted between April 24, 2020 and August 10, 2021.

Business Re-opening Indicator

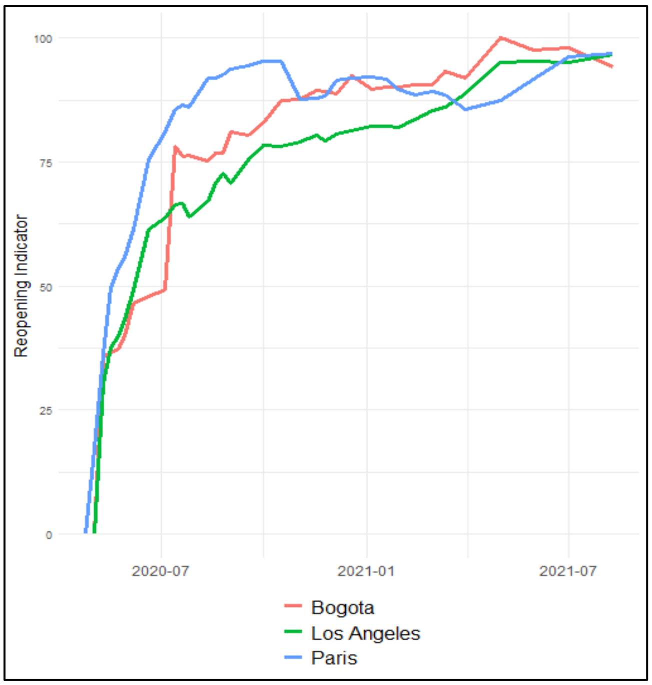
A second business status indicator that was constructed was a re-opening indicator. This indicator is used to track the path and pace at which businesses that are temporarily closed in a region re-open. This type of indicator was of particular interest during the COVID-19 pandemic where businesses were forced to shut down due to government regulations. This indicator starts with the selection of a baseline cohort of places. In this case the cohort consists of those firms that are temporarily closed. Each week (or selected time interval) the status of each of these *Places* is examined to see if they have opened of if they remain temporarily closed. The indicator reflects the share of businesses that were temporarily closed in the baseline period that are now open. To illustrate consider the case of five firms that were temporarily closed at the at time *Baseline (Period B)*. Table 9 shows their status (1=open, 2=temporality closed) in each of the following five time periods. The indicator is calculated as the number of open firms divided by the total number of firms that were temporarily closed in the baseline period.

Table 9. Reopening Indicator

Place	Period B	Period 1	Period 2	Period 3	Period 4	Period 5
A	2	2	2	2	2	2
B	2	2	2	2	2	1
C	2	2	1	2	1	1
D	2	2	1	1	1	1
E	2	1	1	1	1	1
Indicator	100	20	60	40	60	80

The above methodology was used to construct a business re-opening indicator for several major city centers for April 24, 2020 (the baseline, where 0 percent of sampled businesses had re-opened. Note below how some cities have a different baseline) to August 10, 2021. The results are consistent with what is generally understood regarding the way different governments implemented and lifted lockdown restrictions over the course of the pandemic. Some governments imposed longer lockdowns in the hope that all businesses would be able to move quickly to 100 percent operations after the lockdown. Other governments decided to impose short lockdowns and leave the business to decide if it was economically beneficial to open. Figure 4 illustrates the different path to re-opening taken in selected city centers.

Figure 4. Business Re-opening Indicator for Selected City Centers



city	sample size	baseline	24-Apr-20	24-May-20	26-Jul-20	26-Aug-20	3-Nov-20	30-Jan-21	31-Mar-21	1-May-21	1-Jul-21	10-Aug-21
Atlanta	503	2-May-20		59	82.9	96	97	96.8	97.6	98.6	98.8	99
Bogota	339	2-May-20		37.2	76.4	76.7	87.6	90	92	100	97.9	94.1
Casablanca	209	17-May-20		9.1	32.5	40.7	47.4	54.5	60.3	93.8	65.1	67.9
Istanbul	566	24-Apr-20	0	41.7	64.7	78.3	83.6	83.9	88.5	94.9	88.7	91.5
Lagos	180	24-Apr-20	0	25	38.3	38.9	53.9	58.3	62.8	98.3	76.7	76.1
London	842	24-Apr-20	0	53.4	84.8	93.1	97.1	80.8	79	89.7	97.9	98.5
Los Angeles	1,001	2-May-20		40	64	72.8	79.1	82	88.8	95	95	96.6
Madrid	1,437	24-Apr-20	0	44.6	75.9	87.3	92.3	92.9	94.7	98.3	95.8	95.9
Manila	2,750	24-Apr-20	0	41	70.1	79.6	84.6	88.1	89.8	96.6	92.1	92.8
Milan	936	24-May-20		0	59.1	77.1	84	81.9	86.3	95.8	92	90.5
Mumbai	2,939	24-Apr-20	0	45.6	66	72.8	85.7	92.8	94.2	97.2	93.4	93.9
New York	1,278	24-Apr-20	0	47.4	75.7	84.7	92.4	92.3	94.3	96.9	97.2	97
Paris	1,645	24-Apr-20	0	53.5	86	92.5	87.7	89.7	85.6	87.4	96.2	96.9
Rome	1,343	17-May-20		25.4	64.6	82.7	88.2	88.3	89.4	97.2	93.8	94.6

Sao Paulo	526	24-Apr-20	0	35.6	64.4	66.5	79.7	84.6	81.2	93	89.7	89.4
Sydney	359	2-May-20		47.4	84.7	86.9	91.6	94.4	95.8	97.2	76	74.9
Tel Aviv-Yafo	1,045	17-May-20		16.2	62.3	70.8	76.3	77.1	85.4	98.7	94.6	87.4
Tokyo	416	24-Apr-20	0	51.2	95	94.7	96.6	96.4	96.4	88	97.6	97.8
Toronto	978	24-Apr-20	0	42.1	90.8	93.4	94.7	84.6	89.9	87.1	88.9	95.9

Source: Google Places API – Data extracted from April 2020 to August 2021.

B. Business Activity Indicators

While the above indicators are intended to capture the evolution of the operation status of the *Places* population, they do not fully capture the economic activity of the Places. To do this, we require some indication of activity. As noted earlier, Google Trends capture the interest in a topic relative to all other topics at a given point in time. If we assume that there is a relationship between changes in interest in a topic(s) and changes in business activity the Google Trends could be used as a proxy for business activity (at least in the short term). Similarly, the Google Places API permits users to extract reviews from the Google Places platform. These reviews are generally posted following some form of engagement with the *Place*. If we assume that reviews reflect engagement, then this information can also be used as a proxy for business activity. In the world of official statistics, business activities are aggregated and classified in a systematic way. Most countries use the *ISIC Rev. 4* (or some variant of it) to classify business activities. It therefore seems appropriate that if we want to use the Google Trends and Google Reviews data to proxy business activity we first need to aggregate and classify these indicators by the *ISIC Rev. 4*.

Google Reviews as an Indicator of Business Activity

The Google Places API permits users to extract the number of reviews posted for a given *Place*. In addition to the review the API also allows users to extract the average rating provided for a *Place*. Ratings range from 1 (poor) to 5 (excellent). It is assumed higher change in ratings are correlated with higher economic activity. For this indicator, the rating was used to adjust the number of reviews such that a *Place* with 100 poorly rated reviews would have a lower weight than a *Place* with 100 highly rated reviews. Since the maximum score for a review is 5 the "adjusted" number of reviews was calculated as (average rate / 5) *(number of reviews). To illustrate consider the following *Places*, each with 100 reviews and various average ratings:

Table 10. Indicator of Business Activity Using Reviews

Place	Reviews	Rating	Weighted Rating	Adjusted Reviews
A	100	1	.2	20
B	100	3	.6	60
C	100	5	1	100

The review information available from the Google Places API represents the accumulated number of reviews at a point in time. In this sense they should be treated as a "stock" type variable. Since we are interested in measuring the change in activity from one period to another, the variable of interest is not the stock of reviews but the change in the stock of reviews from one period to the next. In addition to focusing on the change in reviews we also need to consider that the *Places* selected for a given period represent a sample of *Places* for the given geographic region. Ideally, we would like to track the change in reviews for the **same set** of *Places* over time to reduce any potential sampling errors in the estimate. To address this issue a month-to-month matched sample approach is taken. The match sample approach involves identifying an overlapping set of *Places* in two consecutive periods and calculating the stock of reviews for each period for this set of *Places*.[9] The stock of reviews for each period is then linked together to form a continuous time-series using the baseline stock of reviews as the initial level. To illustrate, five samples of *Beauty Salon Places in Paris were selected* for the months April, May, June, July, and August 2020. The linked stock of reviews and the change in reviews is presented in table 11.

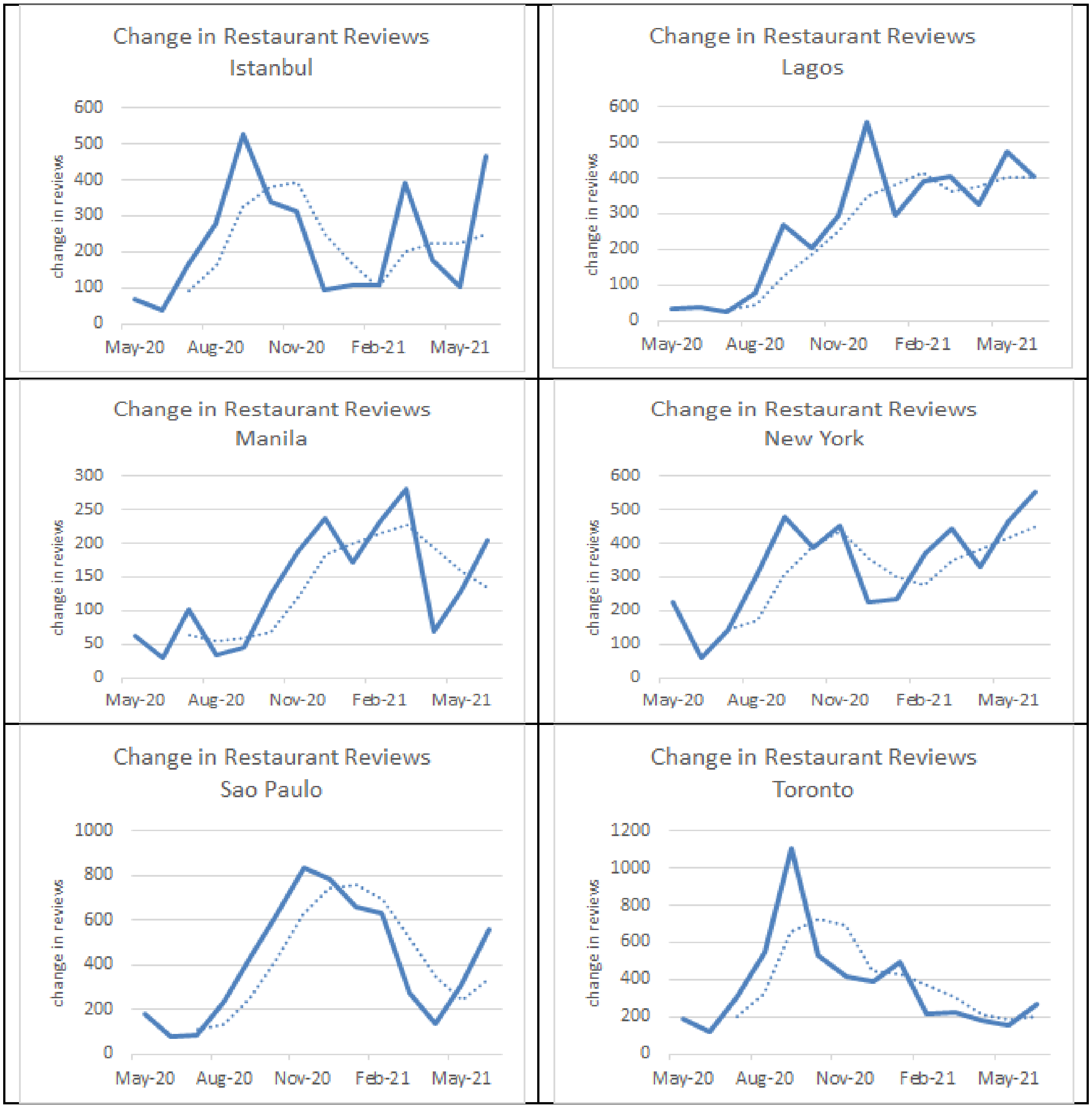
Table 11. Stock / Change in Reviews – Paris City Center Beauty Salons

Matched Sample	Apr-20	May-20	Jun-20	Jul-20	Aug-20
April-May	1,289	1,306			
May-June		1,694	1,744		
June-July			1,772	1,821	
July-August				1,664	1,727
Linked Stock of Reviews	1,289	1,306	1,344	1,381	1,433
Change in Reviews		17	38	37	52

This methodology was applied to the monthly sample of *Places* collected in this project since April 2020. The results align with the trends in activity over the last year in which activity slowed during periods of lockdown or partial lockdown. The results also indicate that the slowdown was the most pronounced during the first wave of COVID-19 and less pronounced during subsequent waves – even though the subsequent waves were more pronounced in terms of cases and severity of illness. The following series of charts in Figure 5 shows the review activity for restaurants in Toronto, London, Manila, Johannesburg, Nairobi, Seoul, and Sydney (the dotted lines in the figure are three-month moving averages).

[9] The reason the same set of Places are not used for each month is because the sample size would deteriorate and reduce the robustness of the estimate.

Figure 5. Review Activity Indicator



Source: Google Places API – Data extracted from April 2020 to June 2021.

Google Trends as an indicator of activity

While there appears to be some conceptual and statistical relationship between reviews and economic activity there are limitations associated with using reviews. First, up to this point, it is not possible to construct a long time series of reviews due to unavailability of historical Places data. Second, processes and extraction routines need to be set up at regular intervals as not to introduce any bias into the estimates. Finally, the data are essentially self-reported, and a key assumption is that the average reviews per visitor is constant over time. Given these limitations and assumptions, additional activity indicators are required. As noted in Section II, Google also provides access to information related to Google searches via the Google

Trends website. The challenge with using Google Trends data is how to best aggregate the almost infinite detail into meaningful information that can reveal current economic trends.

Google's aggregation of trends into categories provides a first step in developing meaningful aggregate indicators. While this is a good first step it is not entirely apparent how these category trends are related to the more commonplace economic indicators most analysts and policy makers use to monitor current economic trends. In the world of economic statistics, business activities are aggregated and classified in a systematic way. Most countries use the *ISIC Rev. 4* (or some variant of it) to classify business activities. It therefore seems appropriate that if we want to aggregate Google Trends to monitor current economic trends, we should aggregate them using the *ISIC Rev 4*. Classifying Google Trends according to this classification will facilitate the use of this information to improve the frequency and timeliness of economic indicators.

One approach that can be used to link the Google Trends categories to the *ISIC* classification is a textual matching process. This approach "links" the textual information underscoring a specific Google category / topic with the textual information associated with a specific *ISIC* class. There is a rich set of textual detail that underpins the Google Trends data by category. This includes the textual description of the category along with the textual description of the individual topics associated with the category. As noted earlier the category "Consumer Electronics" is comprised of topics such as "Sony," "Fortnite," "PlayStation," "Xbox," "Apple," "Canon" etc. The first approach that was used to produce *ISIC*-based Google Trends indicators was to construct a vector of Google Trend category and topic terms and match these terms with the text used to describe the activities of establishments associated with an *ISIC Rev. 4* class (see Box 1, which provides the textual description of the *ISIC* class 2640 - manufacture of consumer electronics industry).

Box 1. Textual Description of the Manufacture of Consumer Electronics Industry

2640 Manufacture of consumer electronics

This class includes the manufacture of electronic audio and video equipment for home entertainment, motor vehicle, public address systems and musical instrument amplification.

This class includes:

- manufacture of video cassette recorders and duplicating equipment
- manufacture of televisions
- manufacture of television monitors and displays
- manufacture of audio recording and duplicating systems
- manufacture of stereo equipment
- manufacture of radio receivers
- manufacture of speaker systems
- manufacture of household-type video cameras
- manufacture of jukeboxes
- manufacture of amplifiers for musical instruments and public address systems
- manufacture of microphones
- manufacture of CD and DVD players
- manufacture of karaoke machines
- manufacture of headphones (e.g. radio, stereo, computer)
- manufacture of video game consoles

Source: *International Standard Industrial Classification System of All Economic Activities Rev. 4*.

The method chosen was the natural language processing (NLP) library *word2vec* that scores the Google Trends category / topic description against the *ISIC* industry class description (at the 4-digit level). Any Google Trends category that matched to an *ISIC* industry within a given threshold is retained (See technical annex for details). The Google Trends by category are then aggregated using a simple average to the *ISIC* class. This aggregation is illustrated in Tables 12 and 13 below.

Table 12. Monthly Google Trends SVIs at *ISIC* 4-digit level for Accommodation and Food Service Activities (I) for Australia

At *ISIC* 4-digit level we take the average Google Trends SVIs of all matched categories.

***ISIC* 4-digit**	***ISIC* description**	**Trends category description**	**Trends category**	**Jan-21**	**Feb-21**	**Mar-21**	**Apr-21**	**May -21**
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Food & Drink: 71; Restaurants: 276; Fast Food: 918	918	90.0	82.0	85.0	91.0	87.0
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Business & Industrial: 12; Hospitality Industry: 955; Food Service: 957; Grocery & Food Retailers: 121	121	70.0	66.0	61.0	73.0	68.0
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Business & Industrial: 12; Hospitality Industry: 955; Food Service: 957; Restaurant Supply: 816	816*	-	-	-	-	-
5610	**Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities**	**Total 5610**	**Average SVIs**	**80.0**	**74.0**	**73.0**	**82.0**	**77.5**
5629	Accommodation and food service activities; Food and beverage service activities; Event catering and other food service activities; Other food service activities	Food & Drink: 71; Restaurants: 276; Fast Food: 918	918	90.0	82.0	85.0	91.0	87.0
5629	Accommodation and food service activities; Food and beverage service activities; Event catering and other food service activities; Other food service activities	Food & Drink: 71	71	83.0	78.0	74.0	86.0	84.0
5629	**Accommodation and food service activities; Food and beverage service activities; Event catering and other food**	**Total 5629**	**Average SVIs**	**86.5**	**80.0**	**79.5**	**88.5**	**85.5**

ISIC 4-digit	*ISIC* description	Trends category description	Trends category	Jan-21	Feb-21	Mar-21	Apr-21	May-21
	service activities; Other food service activities							
5630	Accommodation and food service activities; Food and beverage service activities; Beverage serving activities	Food & Drink: 71; Non-Alcoholic Beverages: 560; Coffee & Tea: 916	916	92.0	83.0	82.0	93.0	97.0
5630	Accommodation and food service activities; Food and beverage service activities; Beverage serving activities	Food & Drink: 71; Non-Alcoholic Beverages: 560	560	96.0	89.0	83.0	91.0	94.0
5630	Accommodation and food service activities; Food and beverage service activities; Beverage serving activities	Food & Drink: 71	71	83.0	78.0	74.0	86.0	84.0
5630	**Accommodation and food service activities; Food and beverage service activities; Beverage serving activities**	**Total 5630**	**Average SVIs**	**90.3**	**83.3**	**79.7**	**90.0**	**91.7**

* This category did not return data for Australia for this instance. Included for completeness.
Source: Author's estimates.

Table 13. Monthly Google Trends SVIs at *ISIC* Section Level for Accommodation and Food Service Activities (I) for Australia

At *ISIC* section level we take the average Google Trends SVIs of all matched categories to *ISIC* 4-digit removing duplicate categories to keep a simple average.

ISIC 4-digit	*ISIC* description	Trend's category description	Trend's category	Jan-21	Feb-21	Mar-21	Apr-21	May-21
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Food & Drink: 71; Restaurants: 276; Fast Food: 918	918	90.0	82.0	85.0	91.0	87.0
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Business & Industrial: 12; Hospitality Industry: 955; Food Service: 957; Grocery & Food Retailers: 121	121	70.0	66.0	61.0	73.0	68.0
5610	Accommodation and food service activities; Food and beverage service activities; Restaurants and mobile food service activities	Business & Industrial: 12; Hospitality Industry: 955; Food Service: 957; Restaurant Supply: 816	816	-	-	-	-	-
5629	Accommodation and food service activities; Food and beverage service activities; Event catering and other food service activities; Other food service activities	Food & Drink: 71	71	83.0	78.0	74.0	86.0	84.0
5630	Accommodation and food service activities; Food and	Food & Drink: 71; Non-Alcoholic	916	92.0	83.0	82.0	93.0	97.0

	beverage service activities; Beverage serving activities	Beverages: 560; Coffee & Tea: 916						
5630	Accommodation and food service activities; Food and beverage service activities; Beverage serving activities	Food & Drink: 71; Non-Alcoholic Beverages: 560	560	96.0	89.0	83.0	91.0	94.0
Total	**Accommodation and food service activities**	**Total**	**Average SVIs**	**86.2**	**79.6**	**77**	**86.8**	**86**

Source: Author's estimates.

The benefit of the Google Trends data is that users have access to a long and high frequency time series. These data are particularly useful in helping understand turning points and are intended to be combined with and benchmarked to official measures to improve their timeliness and frequency. Therefore, the emphasis of the series will generally be on the current period. While the emphasis is on the current period a long time series is required to establish relationships and models with existing official measures of economic activity. Since there are many factors that can influence search intensity a 5-year moving intervals is used and the weekly trends are smoothed using a five-week moving average. To derive the monthly and quarterly series the weekly series was averaged for the month or quarter. Finally, often the series exhibit lag effects and therefore for certain series – such as travel type series where vacation interest precedes the trip some consideration should be given to lagging the series. This needs to be done on a case-by-case basis. Figure 6 compares the Google Trends by *ISIC* index with real GDP for selected industries for a sample of countries. In many cases the trends exhibit similar patterns and are very good at predicting the turning points.

Figure 6. Change in Google Trends Compared to Change in Real Quarterly GDP (in percentages)

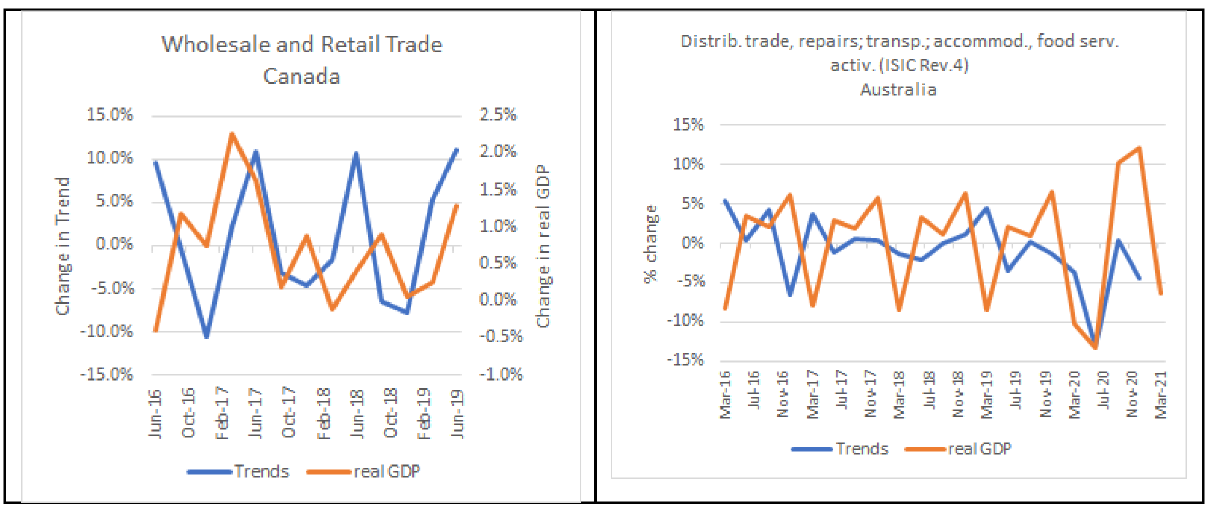
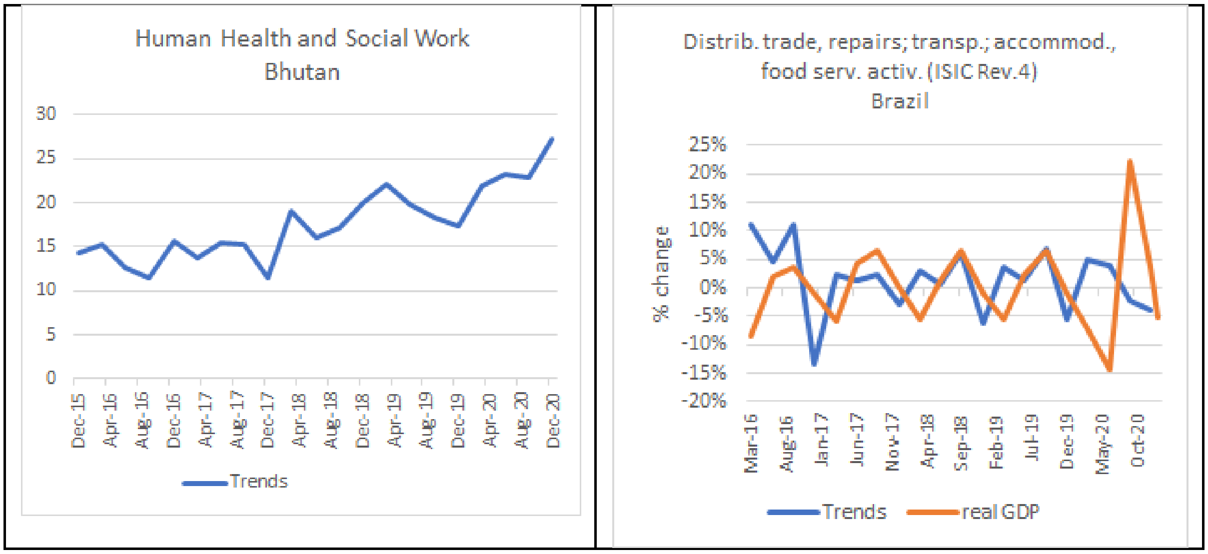


Figure 6. Change in Google Trends Compared to Change in Real Quarterly GDP (in percentages) (continued)



*Note – Bhutan does not release quarterly estimates of GDP.

IV. Using Google Data for GDP Nowcasting

In this application, we show the predictive ability of our indicators in nowcasting quarterly GDP for selected industries for a group of countries during the pandemic. Our objective is to determine if our business activity indicator, operating status indicator, reopening indicator, and Google Trends by *ISIC* correlate well with official GDP numbers and can be used to improve the timeliness and frequency of GDP preliminary estimates through simple regression techniques. Specifically, we want to show that the strength of these indicators is to closely track the fall and subsequent rebound of economic activities that were particularly hit by the effects of the pandemic in the second and third quarter of 2020.

First, we selected a sample of six countries with availability of quarterly GDP data by economic activity. The selected countries are Australia, Brazil, Canada, France, the Philippines, and South Africa. The sample is sufficiently heterogenous with respect to income level, economic structure, and geographic locations. We consider all economic activities at the one-digit level of the *ISIC* available from the official statistics agency (e.g., 19 sections in the *ISIC* rev. 4). Although longer times series were available for some of these countries, for this exercise we only considered data from 2015-Q4 to 2020-Q3 to match the five-year span available for our Trends series by *ISIC*. All data were used in seasonally adjusted form. It should be noted that we picked a sample of countries where quarterly GDP already existed, so that we could test the accuracy of nowcasting at the quarterly level using the indicators developed in this research. Nevertheless, our indicators can also be used to produce quarterly estimates of the GDP in those countries where only annual GDP is available, for example by using annual-to-quarterly benchmarking techniques.

We performed a correlation analysis at the 1-digit *ISIC* level between our Google Trends series and quarterly Gross Value Added (GVA) by economic activity in the last five years. Positive (contemporaneous) correlations were found for many *ISIC* sections in the service industry for most countries, most notably Transportation and Storage (H), Accommodation and Food Services activities (I), Professional, Scientific, and Technical activities (M), Arts, Entertainment and Recreation (R). With few exceptions, correlation for industrial activities and the primary sector was substantially lower.

Correlation for the "Transportation and Storage" activity was strikingly consistent across countries, which prompted us to focus our nowcasting exercise on this sector. Figure 7 shows the official GDP data for section H and the respective Google Trends series for the six countries in our sample. We also include in the charts the reopening indicator for the last three quarters of 2020. We found that real Transportation and Storage gross value added showed high and consistent correlation with the respective Google Trends series for all countries. Google search categories matched to Transportation were, among others, "Aviation," "Freight and Trucking," "Rail Transport," "Maritime Transport" and "Public Storage" We believe that the number of hits of search terms in these categories (e.g., "get an air ticket to New York") can track closely the movements of activities related to travel that were severely hit during the pandemic, such as air, maritime, and railroad transportation and supporting activities.

Figure 7. Transportation and Storage: Comparison between Official Data (GDP-H), Google Trends (TRE-H), and Reopening Indicator (REOP) for Selected Countries

Period: 2015-Q4-2020-Q4. Seasonal adjusted and normalized data.

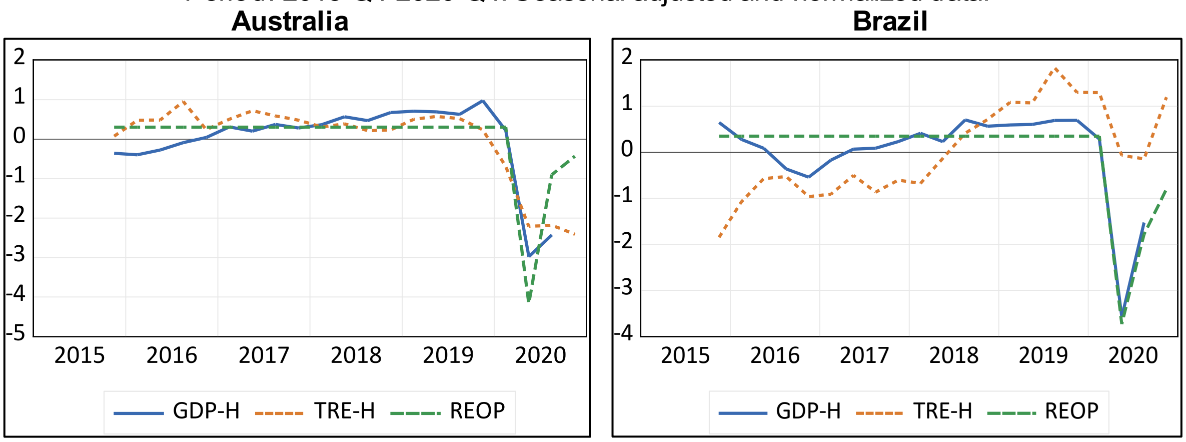


Figure 7. Transportation and Storage: Comparison between Official Data (GDP-H), Google Trends (TRE-H), and Reopening Indicator (REOP) for Selected Countries (continued)

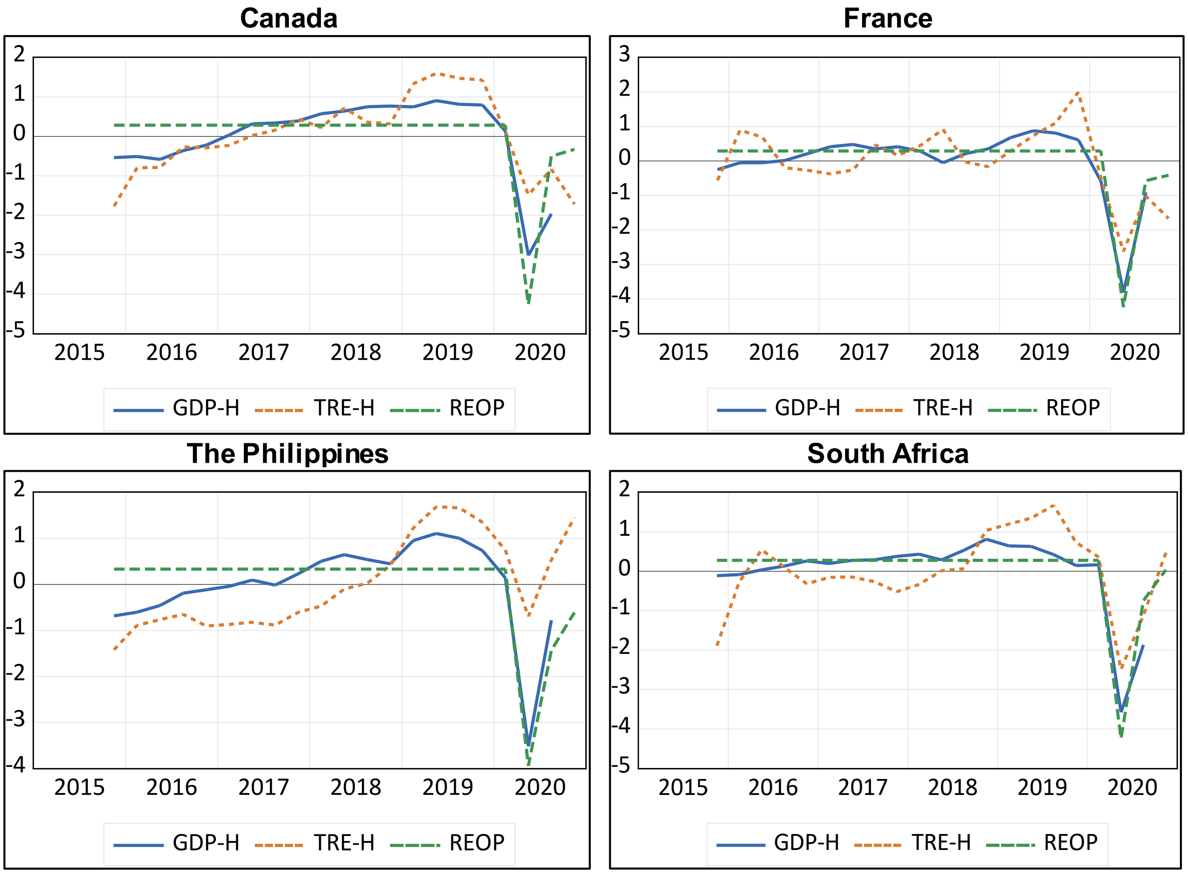


Table 14. Transportation and Storage: Regression Results

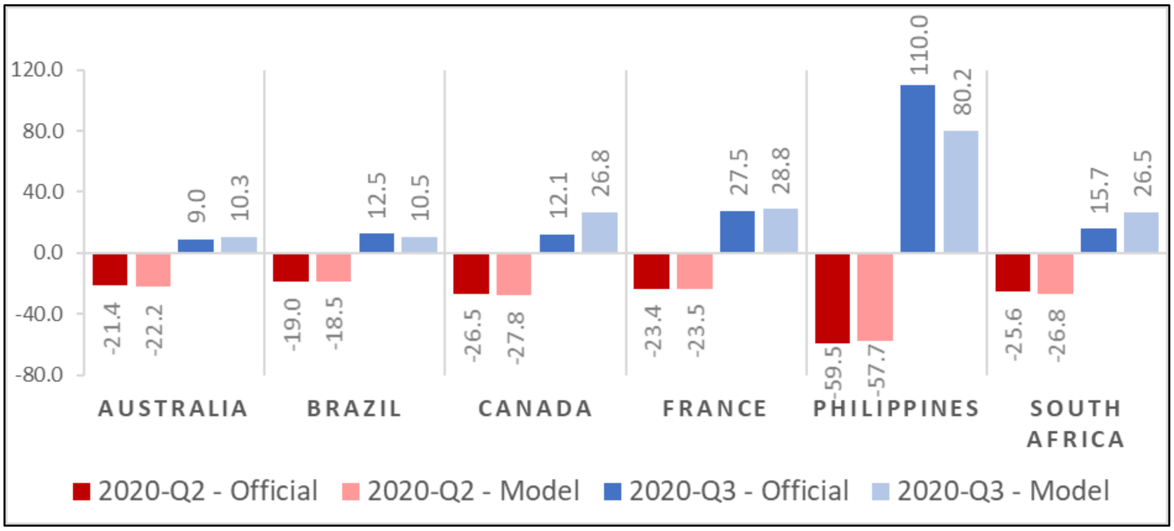
Period: 2015-Q4-2020-Q3.
Regression model in logs, no lags, plus constant. Seasonally adjusted data.

Model for GDP-H		TRE-H		REOP	
	R^2	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Australia	0.83	0.43	3.22**	0.19	2.43**
Brazil	0.91	0.10	2.21**	0.30	13.20**
Canada	0.88	0.89	5.57**	0.38	6.44**
France	0.92	0.25	2.15**	0.48	7.28**
Philippines	0.95	0.45	6.40**	1.28	15.96**
South Africa	0.92	0.25	2.47**	0.34	8.90**

Likewise, our regression results show that both indicators are good predictors of Transportation and Storage activity. Table 14 shows that the model fitting is very good for all countries, with an R^2 above 80 percent. All models are estimated in logs with a constant value. Coefficients for both indicators are positive and statistically significant. It is important to note that the reopening indicator (REOP) is a dummy variable available only for three quarters (2020-Q2, 2020-Q3, and 2020-Q4.) As shown in Figure 1, the fall and subsequent rebound of the reopening indicators almost perfectly match the effects of the pandemic noted in the official data.

Finally, we used the regression models to produce nowcasts of the second and third quarter of 2020. Figure 8 compares the official estimates produced by the national statistics agencies with our model estimates. The large drop in 2020-Q2 is accurately captured by our predictions, and those for 2020-Q3 adequately anticipate the subsequent recovery. The advantage of our nowcasts is that they could have been produced a few days after the end of each quarter, given that the Google data from Trends and Places API are available in real-time.

Figure 8. Transportation and Storage: Nowcasts for 2020-Q2 and 2020-Q3
Data expressed in quarter-to-quarter rate of change, seasonally adjusted



V. Conclusions

The pandemic highlighted the need to use nontraditional data to prepare more timely and detailed economic indicators. With the onset of the pandemic, consumption and production patterns changed dramatically. Consumers rapidly changed their preferences and behaviors, shifting from traditional brick-and-mortar stores to online shopping. As governments swiftly passed lockdown measures amid an unprecedented health crisis worldwide, businesses were forced to close or moved to remote working, when possible. As these dramatic events unfolded, real-time data on people's mobility and business-related activities made available by the private sector played a key public policy function for decision makers and the citizens.

In this work, we developed high-frequency indicators based on Google data to measure the various business dynamics and activity since the start of the pandemic. First, we used Google Places API to build indicators of "business status" for several major cities for the period April 2020 to the current period. Second, we transformed Google Trends data into "business activity" indicators that match the classifications used in the national accounts and other official business statistics. Through a simple regression experiment, we showed that the two indicators could predict very well the fall and subsequent recovery in the GDP of selected countries during the early stage of COVID-19.

Beyond assessing the impact of COVID-19, our purpose was to expand the methodological toolkit for national statistics agencies and central banks interested in increasing timeliness and frequency of economic indicators using Google data. The key advantage of Google data is that they are easily accessible in all countries. Google Trends series can be accessed at no cost from a publicly available website maintained by Google. Places API can be used to retrieve data on the operational status of businesses (and other information) for a small fee, relative to the cost of collecting the same data through surveys or interviews (when possible). Countries with significant lags in the production of quarterly national accounts may test these indicators to release early estimates of quarterly GDP. Countries producing only annual GDP data may find these indicators useful to produce sub-annual estimates on an experimental basis for selected sectors of the economy. Quality of these indicators should be tested and validated with official high-frequency indicators, such as industrial production indexes, retails sales, and value-added-tax indicators.

We encourage countries to develop experimental high frequency indicators of economic activity based on our methodology. The technical annex and the *R* package provided with this paper can be used to reproduce the step-by-step procedure for building the same indicators for any country. These indicators will need to be assessed to determine their ability to nowcast national accounts data and other official indicators available with a long delay. If these indicators show accurate and robust results vis-à-vis traditional data, countries should consider publishing experimental products to provide faster signals on the status of the economy to their users. Investing resources to develop innovative statistical products based on nontraditional sources will make these countries better equipped and prepared to tackle the next period of economic turbulence.

Annex I. Technical Aspects of Google Trends and Google Places API

This Annex outlines the data collection and processing methods IMF staff (the authors) used to transform and process the data acquired from the Google Trends Platform and Google Maps Platform (using the Google Places API).

Google Maps Platform (Google Places API)

Google Places API, part of the Google Maps Platform, provides developers access to a set of APIs and SDKs that allows them to embed Google Maps into mobile apps and web pages, or to retrieve data from Google Maps. The Places API is a service that returns information about "*Places*" using HTTP requests. Places are defined within this API as establishments, geographic locations, or prominent points of interest.

Data collection

For this study, IMF Staff selected a sample of 24 cities (initially, only 13: Bogota, Istanbul, Lagos, London, Madrid, Manila, Mumbai, New York, Paris, Sao Paulo, Sydney, Tokyo, Toronto) that were the most affected by the COVID-19 lockdowns[10] representing the world's major geographical areas. The authors drew an initial sample of n (<= 60) establishments for each Places Type[11] by distance from the center of the city.[12] For most "Places Types" the number of sample units was less than 60 (n < 60 - there will be fewer than 60 "amusement parks" in any given city). Some businesses have multiple types assigned to them by Google, (e.g.: a Place can be classified as both "restaurant" and "food delivery") so the final sample size n for certain types could be > 60 but was limited to 60 for operational reasons.

For each city, for each type, IMF staff queried the Google Places API 3 times (60 max responses concatenating 20 max responses per individual query) using *search term = type* and latitudes and longitudes of the city center as illustrated below:

```
sstring = gsub("_"," ",t),
lat = y,
lon = x,
type = t,
num_iter = round(cat_sample_size/20)
```

The frequency of the data collection has varied since the launch of the project. At the beginning of the pandemic the aim was to track the evolution of the status of businesses, so

[10] https://en.wikipedia.org/wiki/National_responses_to_the_2019%E2%80%9320_coronavirus_pandemic#Lockdowns.

[11] full list of 96 types: https://developers.google.com/places/web-service/supported_types?hl=en_US.

[12] city centers: https://simplemaps.com/data/world-cities.

IMF staff took weekly / bi-weekly samples. Since the COVID-19 lockdowns have subsided in most countries data are now being collected once per month on the last day of the month. The following variables are collected with each collection cycle:

Basic Fields
Address Component
Address
Business Status
Formatted Address
Viewport
Location
Icon
Name
Photo
Place ID
Plus Code
Type
URL
UTC Offset
Vicinity
Contact Fields
Phone Number
International Phone Number
Opening Hours
Website
Atmosphere Fields
Price Level
Rating
Reviews
User Ratings Total

A key variable collected is the business status indicator. Google does not provide an explanation of how they maintain this information but, according to Partoo,[13] they collect data from many different sources to avoid relying exclusively upon businesses action to update their businesses status.

Connecting to the Google Places API

Users of the Google Places API require a Google account, typically a Gmail account, and need to register with Google Cloud: https://cloud.google.com/gcp/getting-started. Once registered, users can create a project and select the Google APIs they are interested in using. For this study the Places API was selected.

By signing up on Google Cloud and setting up a billing account, each user receives $300 in credits, which correspond to approximately 170K queries. Depending on the scope of the

[13] https://www.partoo.co/en/blog/how-does-the-temporarily-closed-label-work-on-google-my-business/.

project this may be sufficient. For our purposes each collection cost $300 (60 establishments by 96 types by 24 cities at $.0017 per query is $235).[14] This work was generously funded by Google through the Google Maps Platform credits for crisis responders.

Data processing and exploration

IMF staff used the *googleway*[15] package in R[16] to acquire data from the Google Places API. Once the data was acquired the following variables were extracted from the HTTP request: *business status, place_id, name, icon, city, period, type, geometry.location.lat, geometry.location.lng, rating, user_ratings_total, price level*. IMF Staff then removed remove potential duplicates of (place_id, type) pairs and merged the data with the city coordinates file (see previous section, world_cities dataset) and check for outlying latitudes and longditudes, i.e., avoid places not belonging to the vicinity of the city. This was accomplished by filtering businesses such that:

lat < lat_city_center + 1 & lat > lat_city_center - 1
and
lng < lng_city_center + 1 & lng > lng_city_center – 1

where we approximate 1 degree of lat/lng to 110 km[17]

Lastly, IMF staff imputed for missing periods and assigned an *ISIC* class.

IMF staff have prepared R code that can be used to replicate the extraction of the data, the pre-processing and the generation of the indicators. This is provided in Annex II (see the documentation of the *imfgoogle* R package).

Google Trends

According to Google Trends FAQs, Google Trends provides access to a largely unfiltered sample of actual search requests made to Google. The data are anonymized (no one is personally identified), categorized (determining the topic for a search query) and aggregated

[14] Google recently (as of April 2021) updated their terms and conditions. They are now charging $.032 per call.[14]

[15] https://cran.r-project.org/web/packages/googleway/index.html.

[16] https://www.r-project.org/.

[17] Note: The reason some queries return results outside of the specified location and radius is because when Google does not find at least 20 establishments from a particular location, it will fill up the resulting data with places in the vicinity of your IP address. If, for instance, you query places API for zoos in Bogota from Washington DC, you might see the Smithsonian is part of the queried data.

(grouped together). This allows Google to display interest in a particular topic from around the globe or down to city-level geography.

Data Collection

IMF queried data at the country level using the R package *gtrendsR*[18] that wraps Google Places API calls. IMF staff queried weekly data for the past 5 years (there was a methodology change around 2016[19]) at the category level as defined by Google. To obtain "Trends" for all categories, we are limited by the number of queries for the same IP: approximately one country every 24 hours. Knowing this limitation imposed by Google, there are ways to maximize the number of countries returned each day by querying only those categories and countries of interest. We recommend users try different combinations of parameters for an optimal data collection strategy.

By default, each query to Google Trends returns 3 different datasets: Trends, Related Topics and Related Queries. The main measure is called the Search Volume Index (SVI) (for related topics and queries, this is represented in column "subject"). According to Google Trends FAQs: Google Trends normalizes search data to make comparisons between terms easier. Search results are normalized to the time and location of a query by the following process:

- Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. Otherwise, places with the most search volume would always be ranked highest.
- The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics. See methodology section for a detailed explanation

Keywords, [20] or **related queries**, are difficult to use in multi-country analysis, and may suffer from ambiguities. For example, a search for "Ibiza" could be categorized either in relation to the Island or the car (Seat Ibiza). With keywords, it is possible to capture changes in popularity at a very granular level by country and regions, but this approach is time consuming and requires heavier work on taxonomy and language.

[18] https://cran.r-project.org/web/packages/gtrendsR/index.html.

[19] For details see: https://www.oecd-ilibrary.org/economics/tracking-activity-in-real-time-with-google-trends_6b9c7518-en.

[20] The following 3 paragraphs are based on: https://www.oecd-ilibrary.org/economics/tracking-activity-in-real-time-with-google-trends_6b9c7518-en.

Individual search terms are attributed to categories encompassing words focused on a common issue. Categories[21] are structured according to a hierarchical classification developed by Google. Components of a given category are adjusted to prevent double counting. Categories are comparable across countries and grouping of searches are constructed using an algorithm that is not disclosed. Using Google Trends categories rather than keywords allows for a more comprehensive treatment of searches and makes it easier to compare results across countries. Searches are categorized across detailed groups harmonized across languages, giving a more comprehensive picture than from a single search term and allocating terms to an appropriate use. There is also a translation of terms so that searches in multiple languages are recognized.

Related topics are a collection of keywords terms which include all search terms related to a specific term. They are also constructed using an algorithm and remove some of the ambiguity associated with keywords. For some dimensions, opting for a more granular approach based on topics rather than category can prove more satisfactory to design meaningful economic indicators.

Sample results: (for a fictitious country XX)

Interest by category

date	Search Volume Index (SVI)	Geo	Time	group	category
2016-01-31 00:00:00 UTC	97	XX	today+5-y	web	3
2016-02-07 00:00:00 UTC	98	XX	today+5-y	web	3
2016-02-14 00:00:00 UTC	95	XX	today+5-y	web	3
2016-02-21 00:00:00 UTC	94	XX	today+5-y	web	3
2016-02-28 00:00:00 UTC	94	XX	today+5-y	web	3

Related topics

Subject	related_topics	value	Geo	category
100	Top	YouTube	XX	3
32	Top	Film	XX	3
19	Top	MP3	XX	3
11	Top	Gambling	XX	3
11	Top	Download	XX	3

Related queries

Subject	related_queries	Value	geo	category
100	Top	youtube	XX	3

[21] https://github.com/pat310/google-trends-api/wiki/Google-Trends-Categories.

99	Top	youtube	XX	3
24	top	mp3	XX	3
12	top	mp3 youtube	XX	3
12	top	kristal bet	XX	3

Linking Google Trends categories and *ISIC Rev. 4* products

To derive measures of economic activity from Google Trends, IMF staff developed an algorithm to map the Google-based taxonomies with the *ISIC Rev. 4*. IMF staff leveraged the hierarchical structure of Google Trends categories and *ISIC Rev 4* four-digit products to create sentences we could then use as inputs for machine-based text models. The basic steps are outlined below:

1. Build the hierarchies. For example:

ISIC hierarchy: *descriptor (code)*

Agriculture, forestry and fishing (A)
Crop and animal production, hunting and related service activities (01)
Growing of non-perennial crops (011)
Growing of sugar cane (0114)

Google Trends hierarchy: *descriptor (code)*

Business & Industrial (12)
Agriculture & Forestry (46)
Food Production (621)

2. To build the input sentences, IMF staff concatenated the elements in the hierarchy. Example:

ISIC sentence:

agriculture forestry fishing crop animal production hunting growing non perennial crops growing sugar cane

Google Trends sentence:

business industrial agriculture forestry food production

3. Transform text into vectors by using a pre-trained embeddings space based on GloVe,[22] an unsupervised learning algorithm for obtaining vector representations for words.

[22] https://nlp.stanford.edu/projects/glove/.

Each word is assigned a 50-d vector and, each sentence like the above, is assigned the average of the 50-d of its words' vectors[23]

4. Once IMF staff transformed sentences into vectors of the same 50-d space, IMF staff calculated the Euclidean distance or cosine similarity between any of these vectors, and, thus, compare the similarity of their corresponding texts. Example:

> Distance ("*agriculture forestry fishing crop animal production hunting growing non perennial crops growing sugar cane", "business industrial agriculture forestry food production"*) = 0.863

Note: the higher the Distance measure the closer the match, so this is a similarity measure, for instance:

> Distance (*"business industrial agriculture forestry food production", "business industrial agriculture forestry food production"*) = 1

5. IMF staff were able to follow this approach at any level in the hierarchy. To compensate for the differences in length and hierarchical depth of the concatenated sentences, IMF staff computed 3 different vector embeddings, and therefore 3 distances for each pair of sentences:

a) Complete hierarchy, see above example
b) Top node in the hierarchy. In our example:
   Distance ("*agriculture forestry fishing", "business industrial"*) = **0.922**
c) Bottom element in each hierarchy. In our example:
   Distance ("*growing sugar cane", "food production"*) = **0.736**

6. Finally, for each *ISIC* sentence we keep the closest 5 Google Trends categories and compute 2 custom weighted scores to further filter the best matches:

- Weighted sum of distances (0 <= sum_dist_w =< 6). Keep **sum_dist_w >= 4**
- Weighted count of the number of **distances > .85** (0 <= count_dist_w =< 6). Keep **count_dist_w >= 3**

Weights were assigned to give extra importance to higher nodes in the hierarchy:

a) Complete hierarchy, weight = 3
b) Top node, weight = 2

[23] Note: In our case, we used the 50-dimensional vector space learned from the Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased).

c) Bottom note, weight = 1

Thus, in our example:

sum_dist_w = 3*0.863 + 2*0.922 + 1*0.736 = **4.984**
count_dist_w = 3*1 + 2*1 + 1*0 = **4**

7. Because the matching is done at the 4-digit *ISIC Rev. 4*, it allowed IMF Staff to link *ISIC* sections (A, B, C, etc.) to a combination of Google Trends categories. This is explained in the paper and illustrated in tables 10, 11 and 12.

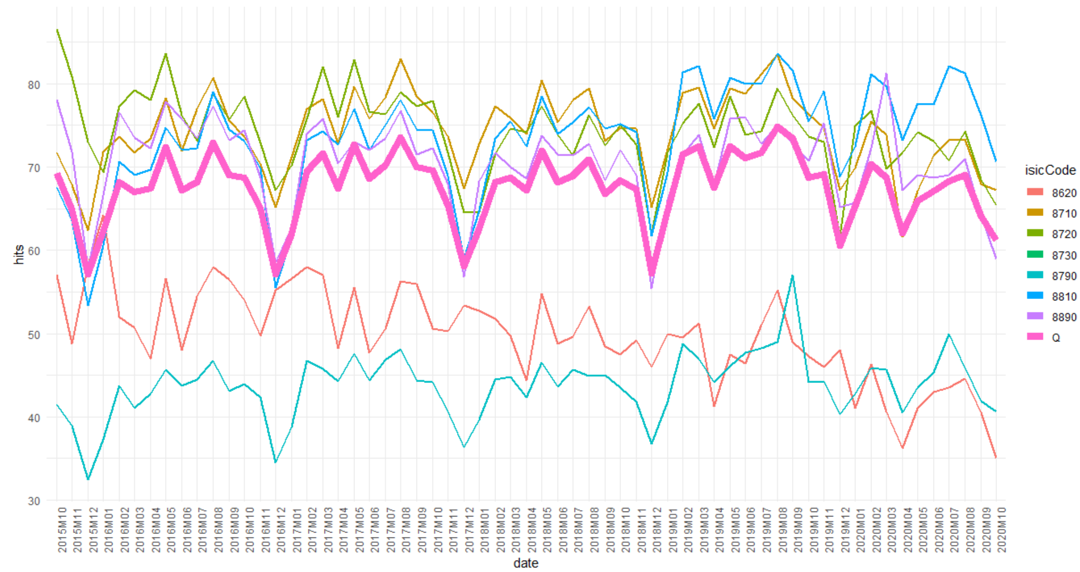
<u>From weekly to monthly Trends by *ISIC* industries</u>

Once we have a system in place to map Google categories to standard economic classifications by industry, we can construct practical indicators. As explained in the paper, if we want to find correlations with standard GDP variables, we may want to transform our weekly data into monthly or quarterly. Below we explain how to achieve this for the monthly data:

- Monthly SVIs are calculated as the average of the weekly SVIs for a given category and country
- Monthly SVIs for *ISIC* level 4 is the average of the monthly SVIs for matched categories
- Monthly SVIs for *ISIC* section is the average of the monthly SVIs for all unique categories mapped to this section.

For instance, we can plot each of the monthly SVIs by *ISIC Rev. 4* at 4-digit and at section levels:

Figure 1: Monthly SVIs (hits) at ISIC Rev 4 4-digit and section levels for section Q: Human health and social work activities, from October 2015 to October 2020



Similarly, we can compute the growth over time:

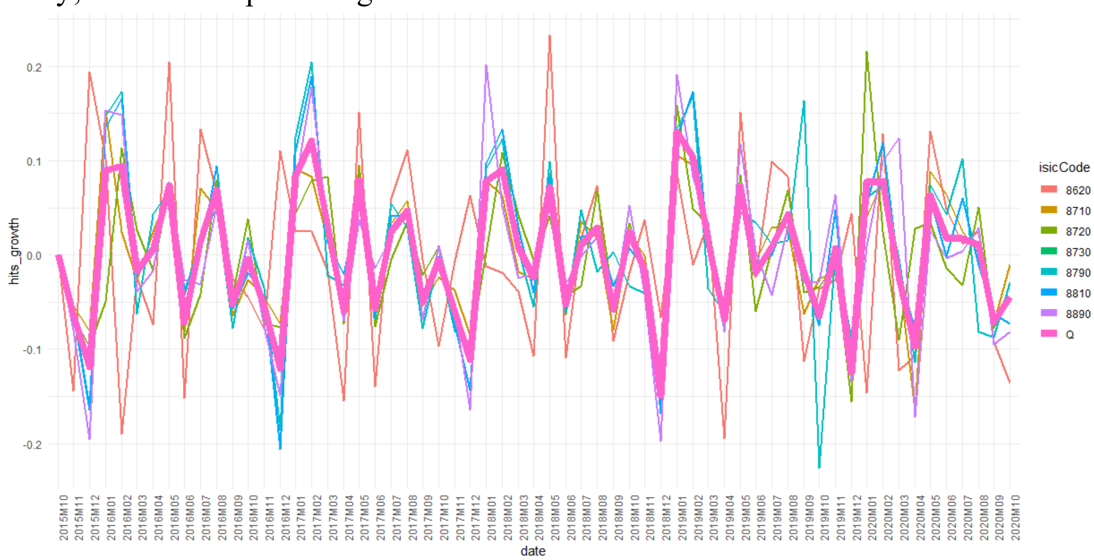


Figure 2: Monthly growth SVIs (hits_growth) at ISIC Rev 4 4-digit and section levels for section Q: Human health and social work activities, from October 2015 to October 2020

<u>Bias and noise reduction</u>

By using this bottom-up approach we achieve a more robust measure of each sector in the economy. Individual searches may be biased towards a negative or positive sentiment. SVIs measure how popular a specific search is and, to remove the sentiment bias, it would need to be complemented by using several SVIs from related words. Fortunately, this is already taken care of by Google's Trends categories, which is the focus of our study. Still, if we only target one category to measure a specific aspect of the economy, we may be getting a biased sample. This is where our approach could be useful to reduce the noise associated with the

SVIs of an individual category by using a combination of several categories to produce an estimate at the *ISIC* section level.

Even with the above methodology, there still may be significant sampling noise for smaller countries for certain categories. Taking multiple samples on a weekly basis and taking the average of SVIs as the current SVI may reduce this variance as suggested in Woloszko (2020)[24]

Chaining and rescaling

Moving beyond a one-time Google Trends data collection to a production system where we update SVIs regularly poses some questions which are discussed in this section. For example, some of the questions we need to consider if we start with an initial 5-year weekly SVIs and intend to update the data on a weekly basis include:

- Do we query new 5-year data every week for the same countries & categories (T-2 weeks of overlap), or do we aim at querying, say, 1-month worth of data (4 weeks, 3 weeks of overlap) at a daily frequency, which we aggregate to weekly?
- What is the best way to chain 2 SVIs time series? There are different ways we can rescale the SVIs resulting from the new data, calculating the difference, the ratio, the ratio between ranges, etc. Does this matter? Do we need to rescale the whole series or just add the new data point at the end based on one of the rescaling options?

According to Woloszko (2020), the rescaling needs to be multiplicative. The definition of an SVI is: #searches ("car")/#searches (all) * const., where the constant is here to ensure that the max = 100. So, two SVIs covering different time ranges may have different const, as the max of the relative search intensities can occur at two different points in time:

SVI_a = #searches ("car")/#searches (all) * const_a

in theory:

SVI_a * SVI_b/SVI_a = #searches ("car")/#searches (all) * const_b.

But this is only true in theory, because each SVI is computed over a fixed-rate sample of the universe of Google Searches. That is the second cause of existing differences between SVI_a and SVI_b. As a result, rescaling SVI_a over SVI_b using the ratio between the two series based on only one observation is probably not a good idea. A possible solution would be to multiply SVI_b by the mean of the ratio of SVI_a/SVI_b taken over all common observations.

[24] "Tracking activity in real time with Google Trends," OECD Economics Department Working Papers, No. 1634, OECD Publishing, Paris, https://doi.org/10.1787/6b9c7518-en.

Annex II. Data and Methods with the *imfgoogle* R Package

This annex explains how to install and use the '*imfgoogle'* package in R, which the authors created to implement the techniques used in this working paper.

A. Install and load *imfgoogle*

Place the binary source package in the R library folder of your local computer, typically: C:/R/R-3.6.3/library/. You need to have R installed in your local computer and the location of your R library folder may be different, depending on the R version or the operative system. Next start R or RStudio and run:

```
> install.packages("C:/R/R-3.6.3/library/imfgoogle_0.1.0.tar.gz",
repos = NULL, type="source")
> library(imfgoogle)
```

B. Available datasets

imfgoogle includes several datasets used throughout the paper. To access any of them simply run:

```
> data("name_of_dataset")
```

The following datasets are included in the R package:

- Trends_categories_codes_full_hierarchy
  Google Trends categories with indentation and full hierarchy

```
category                              indentation categCode full_categCode
All categories: 0                              1         0             ;0
Arts & Entertainment: 3                        2         3             ;3
Celebrities & Entertainment News: 184          3       184         ;3;184
Comics & Animation: 316                        3       316         ;3;316
…
```

- ISIC_4d_full_hierarchy
  ISIC Rev. 4 complete hierarchy

```
isicCode      Description                                               indentation
full_isicCode
A          Agriculture, forestry and fishing                                2   A
01  Crop and animal production, hunting and related service activities      3   A;01
011        Growing of non-perennial crops                                   4   A;01;011
0111       Growing of cereals (except rice), leguminous crops and oil seeds 5
A;01;011;0111
…
```

- Google_Places_types_ISIC_NAICS
  Google Places types matched with *ISIC* and *NAICS* products

```
type             isic_codes   isic_code_label                                  isic_secti
on
bakery              1061     1062 Manufacture of starches and starch products       C
roofing_contractor  4100     410 4100 Construction of buildings                     F
plumber             4322     4322 Plumbing, heat and air-conditioning installation  F
car_dealer          4530     453 4530 Sale of motor vehicle parts and accessories   G
…
```

- mapping_isic4d_trendsCategories
  ISIC Rev. 4 products matched to Google Trends categories as used in the paper to compute Google Trends SVIs at *ISIC* section level

```
isicCode categoryCode dist_full  dist_top dist_bottom
0111           749     0.8849943 0.9223012   0.8423424
0112           621     0.8711644 0.9223012   0.7637744
0113           749     0.8592794 0.9223012   0.7195353
0114           621     0.8631717 0.9223012   0.7358893
…
```

- match_Trends_categories_ISIC_products
  Distances (cosine similarity) between Google Trends categories and *ISIC Rev. 4* products greater or equal than 0.8

```
category            isic_product                                                      dis
t
arts entertainment  arts entertainment recreation                                     0.9
53
arts entertainment  arts entertainment recreation creative arts entertainment        0.9
85
arts entertainment  arts entertainment recreation libraries archives museums cultural 0.8
73
…
```

- cities_places
  List of select cities used to collect Google Places API

C. Methods

Operating Status Indicators

The Google Places API permits users to extract the operating status of each place identified on the Google Places platform. Places are given the status of "Open", "Temporarily Closed" or "Permanently Closed". This information can be used to produce several useful business dynamic indicators.

Operational Indicator

The operational index represents the share of Places in a given geographic region that are operational at a given point in time weighted by the number of reviews. The R function below generates the indicator as described in the paper:

```
biz_status_places(
  in_data_path = ".",
  out_data_path = ".",
  file_prefix = "sample_Google_places_",
  city_pop_limit = 1e+06,
  sample_freq = "month",
  write_out = TRUE
)
```

The following example saves an Excel file to the specified *out_data_path* parameter location:

```
biz_status_places(in_data_path = "C:/Users/<MyUserName>/Box Sync/Google
Places API/data/", out_data_path = "<output_directory>")
```

Here is an excerpt:

```
  status      city    placetype period     statuso statuswo
  <chr>       <chr>   <chr>     <chr>        <dbl>    <dbl>
1 OPERATIONAL Atlanta Total     2020-05-30    93.4     90.6
2 OPERATIONAL Atlanta Total     2020-07-26    96.1     96.5
3 OPERATIONAL Atlanta Total     2020-08-26    98.3     98.1
4 OPERATIONAL Atlanta Total     2020-09-17    98.5     97.5
5 OPERATIONAL Atlanta Total     2020-10-17    98.8     98.6
6 OPERATIONAL Atlanta Total     2020-11-25    98.6     98.4
…
```

Business Re-opening Indicator

This indicator is used to track the path and pace at which businesses that are temporarily closed in a region re-open. The R function below generates the indicator as described in the paper:

```
biz_reopening_places(
  in_data_path = ".",
  out_data_path = ".",
  exclude_periods = c("2020-06-29"),
  select_cities = NULL,
  longitudinal = FALSE,
  groupby_var = "city",
  method = "reopening",
  interpolate = FALSE,
  min_sample_size = 50,
  write_out = TRUE
)
```

The following example returns a data.frame with the reopening indicator for the select group of cities as illustrated in the table in Figure 4 of the paper:

```
reopening_isicSection <- biz_reopening_places(in_data_path =
"C:/Users/<MyUserName>/Box Sync/Google Places API/data/")
```

This indicator can be generated for different aggregations: by Google Places type, *ISIC* or *NAICS*. For example, running the following will generate the reopening indicator aggregated at *ISIC Rev. 4* section: A, B, C, …

```
reopening_isicSection <- biz_reopening_places(in_data_path =
"C:/Users/<MyUserName>/Box Sync/Google Places API/data/",
                    groupby_var = "ISIC_section")
```

And this will aggregate by Google Places business type for a specific city:

```
reopening_isicSection <- biz_reopening_places(in_data_path =
"C:/Users/<MyUserName>/Box Sync/Google Places API/data/",
                    groupby_var = "type", select_cities = "Manila")
```

Business Activity Indicators

Google Trends capture the interest in a topic relative to all other topics at a given point in time. If we assume that there is a relationship between changes in interest in a topic(s) and changes in business activity the Google Trends could be used as a proxy for business activity (at least in the short term). Similarly, the Google Places API permits users to extract reviews from the Google Places platform.

Google Reviews as an indicator of business activity

For this indicator, the rating was used to adjust the number of reviews such that a Place with 100 poorly rated reviews would have a lower weight than a Place with 100 highly rated reviews. Since the maximum score for a review is 5 the "adjusted" number of reviews was calculated as (average rate / 5) *(number of reviews).

```
biz_reviews_places(
  in_data_path = ".",
  out_data_path = ".",
  file_prefix = "sample_Google_places_",
  city_pop_limit = 1e+06,
  sample_freq = "month",
  write_out = TRUE
)
```

To generate the underlying data for Figure 5 outlined in the paper simply run:

```
biz_reviews_places(in_data_path = "C:/Users/<MyUserName>/Box
Sync/Google Places API/data/", out_data_path = "<output_directory>")
```

Here is an excerpt of the output file:

```
city         placetype         wr2020-04-24S1 wr2020-05-30S1 wr2020-05-30S2 wr2020-06-
20S2
Baghdad       accounting        206.76         209.50           NA             NA
Baghdad       airport           1946.30        2018.96          NA             NA
Baghdad       amusement_park    3946.60        3996.86          NA             NA
Baghdad       aquarium          10714.18       10826.10         NA             NA
…
```

Google Trends as an indicator of activity

Calculates Google Trends for *ISIC Rev. 4* different industry levels. This method allows users to generate Tables 12, 13 and Figure 6 as shown in the paper.

```
biz_activity_trends(
  out_data_path = ".",
  select_countries = NULL,
  select_categories = NULL,
  select_isic_sectors = NULL,
  select_keyword = NA,
  only_interest = FALSE,
  time_span = "today+5-y",
  write_out = TRUE
)
```

The following example calculates weekly SVIs and related topics and queries for *ISIC Rev.4* sector "A" (Agriculture, forestry and fishing), for the past 5 years from Spain's web searches:

```
biz_activity_trends(out_data_path = "C:/Users/<MyUserName>/Box
Sync/Google Places API/data/", select_isic_sectors = c("A"),
select_countries = c("ES"))
```

As described in the paper, this approach “links” the textual information underscoring a specific Google category / topic with the textual information associated with a specific *ISIC* class. Readers may find the file mapping categories and *ISIC* codes by loading the *mapping_isic4d_trendsCategories* dataset included in the *imfgoogle* package by running:

```
> data(“mapping_isic4d_trendsCategories”)
```

This file already selects the best matches according to criteria explained above. However, the package also includes a dataset with the distances (cosine similarity) between Google Trends categories and *ISIC Rev. 4* products greater or equal than 0.8. To load this dataset:

```
> data(“match_Trends_categories_ISIC_products”)
```

Finally, users also have the possibility to run alternative mappings using the *imfgoogle* package. The following function returns, in its default choice of parameter values, the mapping dataset described above and utilized in this paper as reference:

```
match_categ_trends(
  refresh = FALSE,
  dist_threshold = 0.8,
  custom_dist_threshold = 0.85,
  removeDup = FALSE,
  keepTop_n = 5,
  weight_score = 4,
  count_score = 3
)
```

However, by setting the refresh parameter to TRUE and selecting different values for the rest of the parameters, it is possible to obtain an alternative mapping file. See technical annex above for a full explanation of this method.

D. References

Some of the methods and datasets included in this annex benefited from the following valuable sources:

- World cities: https://simplemaps.com/data/world-cities. Free version under Creative Commons Attribution 4.0
- Pre-trained word vectors from Wikipedia 2014 + Gigaword5: glove6B under Public Domain Dedication and License v1.0. For more information on GloVe: Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. [pdf] [bib]
- googleway R package. Under MIT + file LICENSE
- gtrendsR R package. Under GPL-2 | GPL-3 [expanded from: GPL (≥ 2)]

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OECD Issue Note:1: The OECD Weekly Tracker of activity based on Google Trends.