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Winners and Losers from COVID-19

Global Evidence from Google Search

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Abstract

As COVID-19 continues to wreak havoc across the world, researchers are attempting to quantify the economic fallout from the pandemic as it continues to unfold. Estimating the economic impacts of a prevailing pandemic is fraught with uncertainties about the epidemiology of the disease and the breadth of disruption of economic activities. This paper employs historical and near real-time Google search data to estimate the immediate impacts of COVID-19 on demand for selected services across 182 countries. The analysis exploits the temporal and spatial variations in the spread of the virus and finds that demand for services that require face-to-face interaction, such as hotels, restaurants and retail trade, has substantially contracted. In contrast, demand for services that can be performed remotely or provide solutions to the challenges of reduced personal interactions, such as information and communications technology (ICT), and deliveries, has increased significantly. In a span of three months, the pandemic has resulted in a 63 percent reduction in demand for hotels, while increasing demand for ICT by a comparable rate. The impacts appear to be driven by supply contractions, due to social distancing and lockdown measures, and demand shocks as consumers shelter in place, with the latter dominating for most services. The magnitude of the changes in demand varies considerably with government responses to the pandemic..

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Winners and Losers from COVID-19: Global Evidence from Google Search

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1. Introduction

COVID-19 is adversely affecting the lifestyle, health, and livelihoods of billions of people around the world. Early forecasts and simulations show that, besides grave health consequences, the pandemic will contract global economic growth, increase global poverty and unemployment (ILO, 2020; Mahler et al., 2020; Vos et al., 2020; Sumner et al., 2020;). However, estimating the overall health and economic costs of COVID-19 is challenging for various reasons. First, the sheer magnitude of the pandemic in terms of confirmed cases and fatalities, the speed at which the virus has been spreading, and the number of economies it has impacted are unprecedented since the Spanish Flu pandemic in 1918. Second, while various government measures to contain the virus and limit economic damages are still evolving, there is limited understanding of how economic agents behave under such a large-scale pandemic, further complicating the mechanisms through which COVID-19 impacts economies across the world. Third, data on standard economic indicators for the real sectors, such as earnings, consumption, profits, and losses, are not yet available for much of the developing world to assess the impacts globally. Estimating the economic consequences of COVID-19, therefore, requires new sources of information and novel empirical approaches. Our paper investigates the impacts of COVID-19 on consumer demand using historical and near real-time Google search data. The Google search data have global coverage and are instantaneously available, permitting timely policy analyses.

As COVID-19 continues to wreak health, economic and social havoc across the world, governments and development financing agencies have rolled out rescue packages and large-scale measures to save jobs and livelihoods. For instance, about 193 countries around the globe have already implemented various policy measures and rescue packages, in addition to aid packages from the World Bank and International Monetary Fund (IMF).[1] The effectiveness of these measures in weathering the impacts of the pandemic depends on the ability to assess the effects on different sectors of the economy and target the most impacted ones. This is particularly imperative for governments with limited fiscal space and, which, thus, have been forced to allocate their limited resources among competing needs. Understanding the sectoral distribution of the impacts is also important to inform COVID-19 policy responses that have potential welfare and redistributive implications.

[1] https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

Using historical and near real-time data from Google Trends, this paper provides fresh evidence on the immediate impacts of COVID-19 on selected sectors of economies. We quantify the impacts of the pandemic on consumer demand for services involving face-to-face interactions – such as travel and tourism, hotel and restaurant, retail trade – and services that require less physical interaction, such as ICT and delivery services. Google search data measure the search intensity or popularity of a search term submitted to the Google search engine. These search queries are submitted by billions of users around the world each day and capture consumer interests, perceptions, and demands for different services and products. With the increasing penetration of the internet across the world, the application of "big data" – such as search queries, social media, and web-scraping – to understand human behavior is becoming prominent in finance, economics, and many other disciplines.

Google search data accurately predict the present and future economic outlooks, including consumer demand (Vosen and Schmidt, 2011; Choi and Varian, 2012; Gilchrist and Sands, 2016). Google search data have been used to forecast macroeconomic indicators such as GDP (Narita and Yin, 2018); evaluate firm and stock market performances (Da et al., 2010; Bordino et al., 2012); predict demand for automobiles and consumer confidence (Choi and Varian, 2009); forecast house prices (Wu and Brynjolfsson, 2015); understand consumer behavior and quantify demand for information (Goel et al., 2010; Drake et al., 2012); predict unemployment rates (Pavlicek and Kristoufek, 2015); measure job search (Baker and Fradkin, 2017) and racial bias (Stephens-Davidowitz, 2014; Chetty et al., 2020). Google search data have also been used for predicting the outbreak and spread of epidemics (Ginsberg et al., 2009) and election outcomes (Metaxas and Mustafaraj, 2012). More recently, these data are used to assess the impact of COVID-19 on mental health (Brodeur et al., 2020), economic anxiety (Fetzer et al., 2020) and religiosity (Bentzen, 2020). Google search data also has some advantages because Google the dominant internet search provider with more than 87 percent of the global online search engine market share in 2019.

COVID-19 is expected to have a broader negative impact on economies while also inducing reallocation of activities across sectors, where some sectors gain, and others lose. The magnitude of the aggregate impact and the potential reallocation of economic activities is likely to depend on the structure and composition of economies. Sectors that are functionally dependent on the internet and offer remote work options are likely to be less affected, relative to those involving face-to-face interactions (Dingel and Neiman, 2020). The economic impact is also expected to depend on government responses and mitigating strategies (Koren and Peto, 2020). For instance, government restrictions and shutdowns disrupt supply chains and the labor market. Layoffs, furloughs, and wage cuts, in turn, affect consumer demand for various services through income and wealth effects. Consumers could also cut back spending on certain goods and services and increase precautionary saving due to elevated economic uncertainty.

To gauge the role of supply and demand-driven shocks, we interact data on government responses, such as social distancing and lockdown restrictions, with information on the spread of the pandemic. Government responses are correlated with the spread of the pandemic, with highly affected countries expected to implement stricter measures. However, variations in the timing and spread of the pandemic and government measures across countries allow us to identify the impact of the pandemic before and after government measures are put in place. This will provide important evidence on how much of the effects are driven by supply-side restrictions arising from social distancing and lockdown measures and demand-driven changes in economic activities.

We employ fixed effects models and exploit the temporal and spatial variations in the spread of COVID-19, as measured by the number of confirmed cases and deaths, across 182 countries that are currently affected by the disease.[2] As of May 20, over 5 million people have been infected by COVID-19, and over 320,000 people have deceased from the disease. While the spread of the pandemic is relatively swift, there are spatial and temporal variations in the exposure and intensity of the pandemic, which allows us to identify the impacts of the pandemic.

We find that demand for some services jumped (dipped) immediately as countries experienced COVID-19 and associated business closures and lockdowns. As countries detect their first case of COVID-19 in March 2020, we observe significant spikes and dips in demand for some services. Demand for services that require face-to-face interaction, such as transport, hotel and restaurant, tourism, and retail, has substantially contracted, with hotel and restaurant services worst hit. On the contrary, demand for services that require less face-to-face interaction or provide solutions to reduced personal interaction, such as ICT and delivery, has increased. For instance, countries that have recorded 10 or more confirmed cases saw a 63-79 percent decline in demand for hotel and restaurant services, and a 46-77 percent increase in the demand for ICT services.

[2] We have dropped 13 small island nations and territories from our analysis sample owing to high volatility in their internet search data, which makes identifying search trends problematic.

The magnitude of change in demand varies with government response to the pandemic. Countries with a higher number of cases and stricter social distancing and lockdown measures experience the largest drop in demand for services. Both supply disruptions due to business closures and demand-driven changes in economic activities are at play, with demand-side factors playing a greater role in most services. The varying impacts we find across sectors point to the need for targeted public policies that ease the economic burden of the pandemic on the sectors that are hit heavily. Finally, the paper shows the value of using near real-time "big data" to rapidly assess the impacts of the pandemic at a more granular level to inform immediate and medium-term policy responses.

Our paper is related to recent studies on the impacts of COVID-19 on consumer demand and spending. Andersen et al. (2020) and Baker et al. (2020) used high-frequency transaction-level data to study the impacts of the pandemic on household spending in Denmark and the United States (U.S.), respectively. Both studies report a sharp decline in spending in a range of consumption categories as COVID-19 spread. While these results are informative, it is difficult to replicate or extrapolate the findings to other countries or globally, mainly because such transaction-level data are difficult to find in several other countries.

Our paper also relates to a burgeoning body of macroeconomic studies that attempt to quantify the impacts of COVID-19 on national and global economies (Breisinger et al., 2020; Gourinchas, 2020; Eichenbaum et al., 2020; Guerrieri et al., 2020; Fornaro and Wolf, 2020). Many of these studies provide evidence on the macroeconomic implications of the pandemic, drawing largely on historical data, macroeconomic models, and simulations. A significant challenge in estimating the impact of the pandemic, as highlighted in these early studies, is a lack of reliable data on the spread of the pandemic and associated economic and health damages. These data are needed to design alternative containment policies at minimum economic cost (Stock, 2020). Moreover, high-frequency cross-country data on consumer spending are lacking to assess the global impacts of the pandemic. Our paper fills this gap by using near real-time Google search data that reasonably predict consumer demand.

The remainder of the paper is organized as follows. Section 2 provides a detailed description of the Google Trends data, which capture consumer demand in near real-time, and the search terms that we carefully selected for each service. Section 3 lays out our empirical specification and identification strategies, while Section 4 presents and discusses the results. We discuss potential mechanisms in Section 5, and we present a range of robustness checks in section 6. Section 7 provides concluding remarks.

2. Data

2.1 Data Sources and Descriptions

To understand the potential win or loss in demand for various services and potential reallocation of economic activities, we carefully choose Google search terms that can capture demand for major economic activities. The choice of sectors is informed by the relative importance of the sector to employment and GDP.[3] We also focus on services for which representative Google search terms that capture demand for a particular service can be found. For example, the manufacturing sector is a major employer, but finding representative search terms has been difficult, and thus not included in this study. Therefore, we focus on six service categories within the broader services sector: (i) hotels and restaurants, (ii) transport, (iii) tourism, (iv) retail trade, (v) ICT, and (vi) delivery services.

The Google search data provide both historical and near real-time data on search intensity for a given term or topic going back to 2004. Google makes these search data publicly available by transforming them into search intensity or popularity index, which measure the relative popularity of a search term in a specific geographic area and over a specific period. Google applies a two-layer normalization to calculate the popularity index for a given search term. First, it calculates the ratio of the total volume of search for a given search term to all searches in a geographic region and over a given period. Then, the highest ratio is normalized to be 100, and the remaining ratios are scaled relative to this maximum data point to obtain the search index. Because of these normalizations, the index always assumes a number between 0 and 100. This normalization across time facilitates a comparison of search intensity of a given term across time. Besides capturing spatio-temporal variation, the data are available at a granular level, such as district and city. These time-series data are available, on a weekly basis, for the period starting January 1, 2004. We downloaded these data on May 1, 2020, for 182 countries.[4]

[3] For instance, the travel and tourism sectors were estimated to account for more than 10 percent of global GDP (travel bookings alone amounting to 1.6 trillion USD) in 2017, and the aggregate retail trade revenue of the top 250 retailers around the world was estimated at 4.4 trillion USD (Deloitte, 2018a, 2018b).

[4] https://support.google.com/trends/answer/4365533?hl=en. We used R Google Trends Application Program Interface (API) gtrendsR to access the platform (https://cran.r-project.org/web/packages/gtrendsR/gtrendsR.pdf).

Google Trends data and their usage require some caveats. First, the Google Trends platform calculates comparable search indices for a maximum of five search terms and five geographic areas only. This technical restriction forces users to download search volume indices for multiple countries – 182 countries in our case – and multiple terms separately, rendering them incomparable across geographic areas and terms. Therefore, users need to renormalize the indices with a reference country to make them comparable across geographic areas. While there are different approaches to do so, we use the approach suggested by Narita and Yin (2018) to make the search index for our terms comparable across countries.[5] See Appendix A for a detailed description of the renormalization.

Second, potential differences in search language across countries call for a more careful approach to extracting the Google search data. In a given geographic area, some people could submit their search queries in local (non-English) language and others in English. In order to best capture search popularity for our selected terms in countries where English is not the main language, we request search terms in English and in a local language that is widely spoken in the country. We mass translate our search terms from English to the respective local languages using Google Translate API for all countries and terms.[6] We extract sector-specific search queries both in English and the most dominant local language. For the United States, for example, search intensity is measured in English, whereas in Japan, it is measured both in English and Japanese.

The COVID-19 data on confirmed cases and deaths are extracted from the Johns Hopkins University Center for Systems Science and Engineering for the period from January 22, 2020 to April 30, 2020. We aggregate the number of daily new cases and deaths to create weekly confirmed cases and deaths for each country. This allows us to link the weekly Google Trend data with COVID-19 cases and deaths. The number of COVID-19 cases and deaths are expected to inform consumer behavior and government policy responses to reduce the spread of the virus and the economic cost of the pandemic. These may impact demand for services through different, but related channels.

The aggregate impact of COVID-19 on consumer demand for services is the combined effects of (i) a reduction in the supply of services due to social distancing and lockdowns measures,

[5] We have also applied the renormalization method by Stephens-Davidowitz (2014), but it makes no difference to our results. Results from this approach are available upon request.
[6] We mass translate our search terms from English to the respective local languages using Google Translate API for all countries and terms. See also at https://github.com/MarkEdmondson1234/googleAnalyticsR

and (ii) a reduction in demand due to adverse shocks to household incomes, increased economic anxiety and the associated increase in precautionary savings and reduced economic activities due to the spread of the pandemic. To understand the extent to which supply-side shocks and demand-side responses drive our results, we use data on government responses to the pandemic to further inform our analysis. These data are collected on a real-time basis by the Assessment Capacities Project (ACAPS) and cover major travel restrictions, social distancing, and lockdown measures for 192 countries.[7] The data are compiled from various publicly available sources on the internet, including governments (official sites and embassies), media, United Nations agencies, and other organizations. Whenever available, the ACAPS prioritizes official/ governmental sources in collecting and assembling these data. Because each government measure is dated, we construct time-varying indicators of government responses, mainly social distancing and lockdown measures.

2.2 Economic Sectors, Services, and Associated Google Query Terms

In addition to the relevance of search terms to demand in specific service categories, the quality of the information relayed by Google search data also depends on the comparability and representativeness of selected search terms. To make the search terms comparable across countries, more general terms such as "hotel" and "restaurant" are used to capture changes in demand for hotel and restaurant services. We use two search terms for each service category to enhance the robustness of the search query results. For instance, we measure temporal variations in demand for transport services, more specifically air travel, using "flight" and "airport" search terms. Slowdowns in the transport sector have ramifications for the tourism sector. Such spillovers, combined with social distancing and lockdown measures, could put a brake on tourist flows. We track the search terms "tourist" and "museum" to gauge changes in demand for tourism services. We use "mall" and "shopping" to measure changes in demand for the retail sector.

While economic sectors that require face-to-face interaction are expected to suffer, sectors that provide solutions to the challenges of reduced face-to-face interaction are likely to prosper. Some of the candidates for potential winners include ICT and delivery services. As more people are forced to work from home due to lockdowns and stay-at-home orders, internet-based group communication mediums have grown in popularity. We use the search terms "zoom" and "skype"

[7] https://www.acaps.org/

to trace demand in the ICT sector in the pre- and COVID-19 periods. To measure demand for delivery services, we use the term "delivery," which can effectively capture demand for takeout and delivery of food, groceries, and other items.

2.3 Temporal Evolution of Demand for Services

The Google search intensity data are expected to exhibit some form of seasonality. For instance, demand for transport and tourism services have seasonal patterns, with peaks during the summer and holiday months. To disentangle the effects of seasonality, we use three years of data (2018-2020) and compare search trends in the COVID-19 period (January–April 2020) with the same time window in the previous two years (2018 and 2019). Once seasonality is removed, structural breaks in Google search trends during the COVID-19 period would reflect the impacts of the pandemic.

Figures 1 and 2 present the global temporal evolution of demand for various services in the last five years, as captured by global Google search data. The search trends demonstrate an interesting mix of secular trend and seasonality in the pre-COVID-19 period. Figure 1 shows that demand for hotel services has remained stable, but with significant seasonal variation, whereas demand for delivery services has been steadily rising with little seasonality. The other services exhibit varying degrees of the two dimensions.

Since the first confirmed COVID-19 cases in China in late December 2019, demand for some services has dipped while demand for others has gone up. Demand for hotels and restaurants, transport and tourism has sharply dived to their lowest levels. On the other hand, demand for ICT and delivery services have peaked following the outbreak. The scale of the fall or rise in demand for these services is much greater during the pandemic than seasonal variations in demand. For instance, while demand for hotels and restaurants peaks in the summer months (July-August), air travel peaks around December-January. In the five pre-COVID-19 years, Google search queries for hotel and restaurant, transport, and tourism key terms dropped 15-20 percentage points on average between peak and trough. This is significantly lower than the over 60 percentage points fall during COVID-19. Likewise, the popularity of search queries for ICT and delivery services rose by over 75 percentage points during COVID-19 compared to the pre-COVID-19 averages. These facts demonstrate the scale of changes in demand for these services due to COVID-19, and the need to account for seasonality in our analysis.

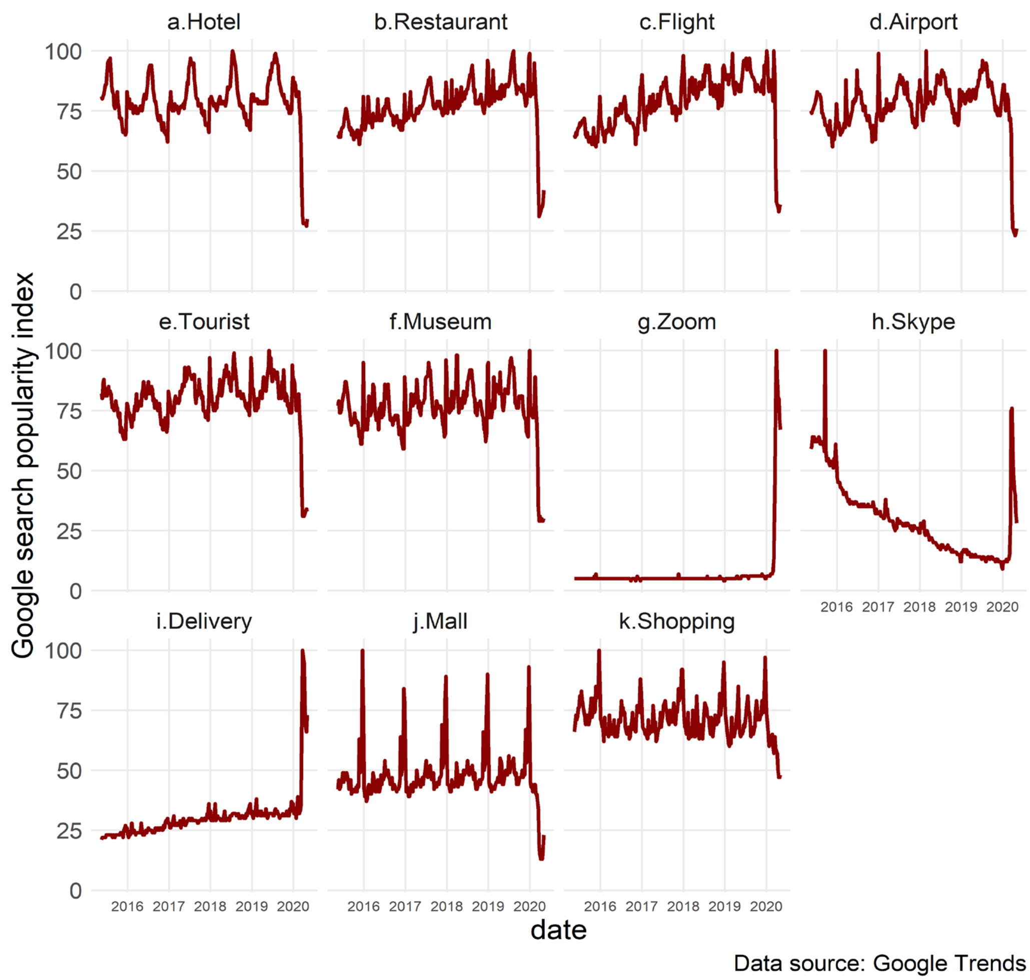
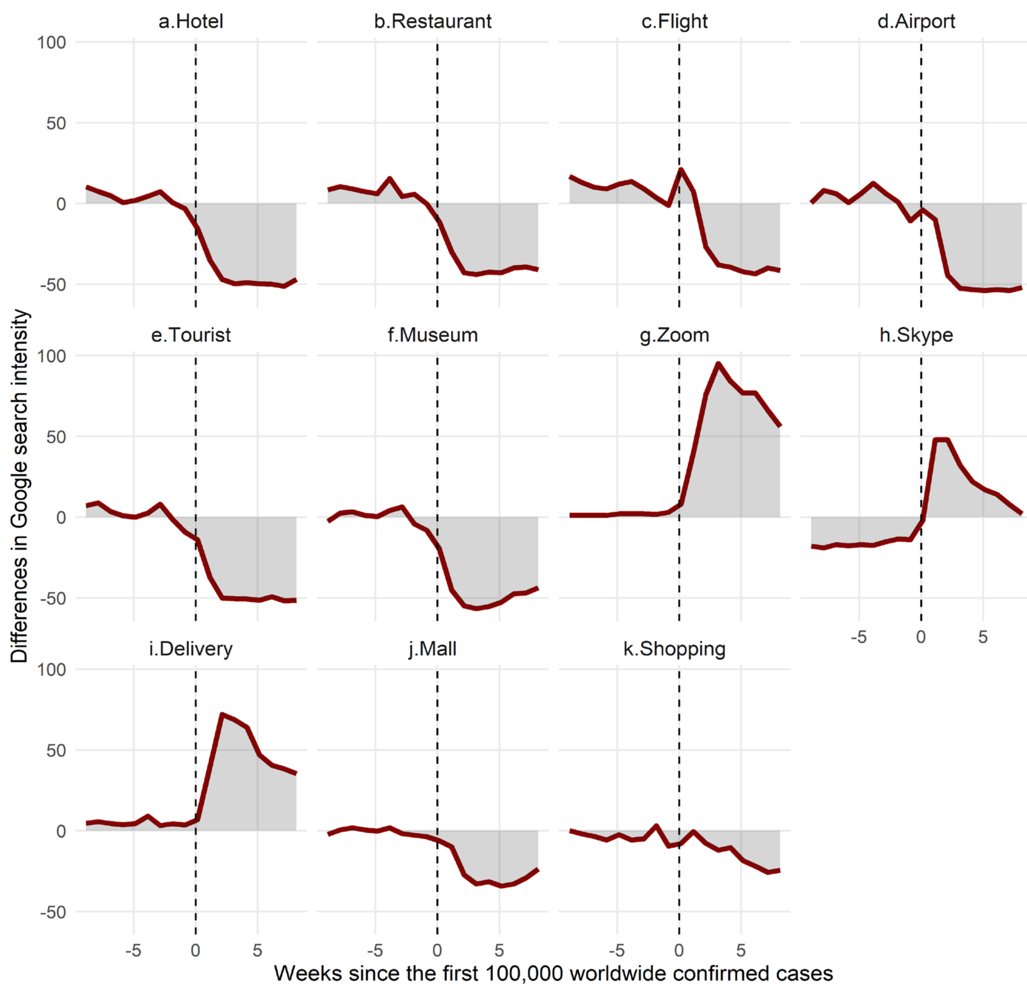


Figure 1: Worldwide Google search trends of key search terms

Figure 2 reports the deviations of normalized weekly Google search intensity from the historical average for the selected search terms. Weekly deviations for each search term are calculated using the corresponding weekly average search for the four years preceding COVID-19 (2016-2019). Because the search intensity for most of the search terms had been trending upwards prior to COVID-19, deviations from the historical mean may underestimate the actual drop in search intensity in recent weeks. The values on the vertical axis show changes in search intensity relative to historical averages. The horizontal axis measures the number of weeks since the week the global COVID-19 cases reached 100,000 (the first week of March 2020). This date corresponds with the introduction of strict measures, including movement restrictions and business closures in several countries. The figure shows that demand for “losing” sectors, indeed, experienced large and rapid fall starting around this milestone, while it takes a sharp upturn for the "winning" sectors.



Note: Dashed vertical lines represent the week (first week of March 2020) worldwide confirmed COVID-19 cases surpassed 100,000. The deviation is calculated by subtracting the search index values for a specific week in 2020 from the historical (long-term) average corresponding to the week. For each search term and week, the historical averages represent the average Google search index for particular weeks in 2016-2019.

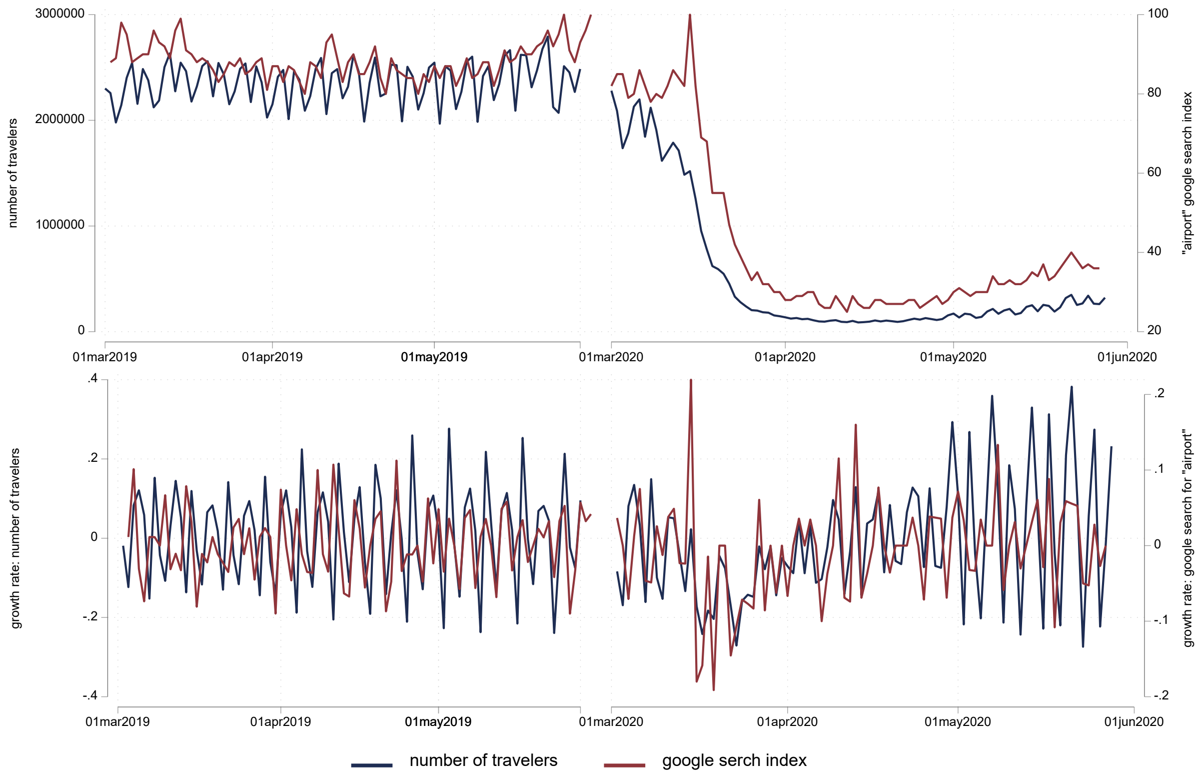
Figure 2: Deviation of COVID-19 period Google search intensity from the historical (2015-2019) averages

2.4. Google Search Data Validation

Several studies have used Google search data to predict economic activities, demand, and several other consumer behaviors. More importantly, the potential of Google search data to capture actual economic activities and demand for services has been validated in several studies. Google search data are shown to capture macroeconomic performance (GDP), even in low- and middle-income countries (Narita and Yin, 2018). Google search data and relevant queries are shown to realistically capture actual unemployment trends (e.g., Pavlicek and Kristoufek, 2015). Others have demonstrated the potential of Google search indices to measure actual consumption spending, sometimes outperforming common survey-based indicators (e.g., Vosen et al., 2011). Some recent studies have already validated some of the search queries we are employing in our study, those related to air transport and tourism services (e.g., Rivera, 2016; Havranek and Zeynalov, 2019). Table B.1 in Appendix B provides a list of selected studies that use Google search data to investigate various topics.

Nonetheless, we conduct alternative validation exercises to show that Google search data are indeed strong predictor of consumer demand for the services that we study in this paper. Because high-frequency data are not available for all services and countries covered in this study, we focus on countries and services for which relevant data are publicly available. The first dataset is the daily number of passengers screened at the Transportation Security Administration (TSA) checkpoints in the U.S. from March to May 2019 and the same period in 2020.[8] Figure 3 compares the number of passengers arriving in the U.S. with the Google search index for the term "airport" for these months. The top panel presents the daily volume of passengers and Google search intensity, and the bottom panel shows the growth rate of the number of passengers and Google search intensity. From visual inspection, the Google search index strongly traces out both the actual number of passengers and the variability in the volume of passengers for both years. We also run some linear regressions (Table B.2 in Appendix B) and find that the Google search indices associated with our search terms, "flight" and "airport," explain over 90 percent of the variations in the daily number of travelers.

[8] https://www.tsa.gov/coronavirus/passenger-throughput



Note: The TSA passenger throughput data cover daily arrivals for March 1-May 28, 2019 and March 1-May 28, 2020. The top panel compares raw daily passenger volumes to the Google search index for "airport". The bottom panel shows how the daily growth rates in passenger volumes at U.S. checkpoints compare with the growth rate of Google search intensity for "airport."

Figure 3: Daily passenger volumes at U.S. TSA checkpoints and Google search data for March-May 2019 and 2020

We conduct a similar validation exercise for hotel and restaurant services using restaurant reservations data from OpenTable.[9] The dataset contains information on daily restaurant reservations at OpenTable network restaurants in seven countries (Australia, Canada, Germany, Ireland, Mexico, the United Kingdom, and the United States). The OpenTable data for 2020 are given in percentage changes relative to the same day in 2019. To make these data comparable with the Google search data, we convert the daily records into weekly averages. Figure B.1 (in Appendix B) plots daily percentage changes in Google search index for restaurant and percentage changes in actual restaurant reservations for the seven countries. The graphs in Figure B.1 (in

[9] https://www.opentable.com/state-of-industry

Appendix B) clearly show that reductions in Google search index for the term "restaurant" strongly traces out actual percentage changes in restaurant bookings for all seven countries. As shown in Table B.3 (in Appendix B) weekly Google search indices explain about 60 percent of the variations in actual restaurant reservations.

Finally, we use monthly retail data from the U.S. Census Bureau to assess the validity of our retail-related Google search terms ("shopping" and "mall"). We compare actual trends in monthly retail spending and Google search indices associated with retail services. Figure B.2 indicates that our search terms and associated indices indeed mimic the trends in actual monthly retail spending. Table B.4 (in Appendix B) shows that these indices are strong predictors of actual retail spending.

These pieces of evidence, along with previous validations in the literature, confirm that Google search data strongly capture actual consumer demand for the services that we investigate in this paper. This is particularly encouraging as traditional economic data are not available in a timely manner or with high frequency to inform immediate policy responses in times of emergency such as the COVID-19 pandemic.

3. Empirical Strategy

The Google search data and COVID-19 data provide spatial and temporal (weekly) variations in the search intensity for services and COVID-19 cases and deaths, respectively. We exploit these dimensions of variation to identify the impacts of additional COVID-19 cases and deaths on demand for various services. We estimate the following fixed effects specification to quantify the impacts of COVID-19:

$$D_{ct} = \alpha_c + \beta_1 Cases_{ct} + \delta_t + \varepsilon_{ct}, \qquad (1)$$

where D_{ct} stands for the demand for various services, as captured by Google search intensity index, for country c and week t, α_c captures country fixed effects, $Cases_{ct}$ represents the number of confirmed COVID-19 cases for each country and week, δ_t stands for weekly time dummy, and ε_{ct} is an error term assumed to be uncorrelated with the number of COVID-19 cases/ deaths conditional on government measures and country and week fixed effects. The country fixed effects in equation (1) capture time-invariant heterogeneities across countries, while the weekly time dummies capture aggregate trends in demand for services.

Our identifying variations come from within-country temporal dynamics in COVID-19 cases/ deaths. The capacity of health systems to respond to the pandemic, sectoral composition of economic activities, degree of urbanization and population density influence the spread of the pandemic. They are also likely correlated with the level of development of countries, hence demand for services. Such time-invariant differences across countries will be absorbed by country fixed effects. Heterogeneities in government responses to the pandemic present another challenge to our identification. These responses, which include mobility restrictions and business closures, are direct consequences of COVID-19 and hence are likely to amplify the impacts of the spread of the pandemic. To isolate the effects of government measures, we interact the spread of the pandemic with government responses, by generating dummy variables for the weeks during which government measures have been in place. As the spread of the pandemic has been swift, conditional on government responses, such temporal dynamics in COVID-19 cases/ deaths are likely to be exogenous. Thus, our coefficient of interest, β_1, captures the causal impact of a unit increase in the number of cases. We also estimate the impacts of COVID-19 deaths by replacing the number of confirmed cases in equation (1) by confirmed deaths.

The effects of COVID-19 cases and deaths are likely to be non-linear. The first 100 confirmed cases/deaths, for instance, are probably more impactful than the subsequent additional 100 cases due to behavioral heuristics. Thus, we consider slightly different measures of the spread of the pandemic by constructing "milestone" event indicator variables for the number of confirmed cases and deaths. For each country, three dummy variables are constructed for: (i) the first confirmed case/death, (ii) the first 10 confirmed cases/deaths, and (iii) the first 100 confirmed cases/deaths. We re-estimate equation (1) by replacing the number of confirmed cases and deaths by these "milestone" dummy variables, which also assume time-varying values.

A country's contribution to changes in global demand for services, as captured by the Google search index, depends on its population size and internet penetration. To adjust for such factors, we weight our regressions using countries' population with internet access. To uncover potential heterogeneities in the impacts due to policy harmonization, geographic proximity, or similarity in level of development across regions, we estimate our model separately across continents. To probe the robustness of our results, we also estimate our models only for the

COVID-19 months in 2020. Because demand for services in each country could be correlated across time, standard errors are clustered at the country level.

Observed changes in demand for services during the COVID-19 period could be due to: (i) lower consumer spending due to income losses, precautionary savings and reduced shopping due to fear of contracting the virus, and (ii) government restrictions on movement, business closures, and lockdowns. Government responses to the pandemic, therefore, may compound the economic fallout and lead to a greater decline in demand. To isolate the impact of government measures on demand, we construct two indicator variables for the introduction of social distancing and lockdown measures. These variables reflect spatial and temporal variations in the implementation of government measures and take the value one for weeks in which government measures were in place and zero otherwise. We estimate the following fixed effects specification to quantify the compounding impacts of government measures on demand for services:

$$D_{ct} = \alpha_c + \gamma_1 Cases100_{ct} \times measures_{ct} + \delta_t + \varepsilon_{ct}, \quad (2)$$

Where $Cases100_{ct}$ is a dummy variable that switches from zero to one in the week in which the number of confirmed cases surpassed 100, and $measures_{ct}$ is a dummy variable for the introduction of social distancing or lockdown measures. By combining data on the spread of the pandemic and government measures, we can assess the compounding effect of social distancing and lockdown measures on consumer demand for services. This estimation can inform the extent to which impacts are driven by government-imposed (supply) restrictions and/or demand-driven contractions in economic activities.

4. Results and Discussion

We present two sets of evidence on the effects of COVID-19 on demand for various services. Our first results use a continuous measure of COVID-19 confirmed cases/deaths to gauge countries' exposure to the pandemic. For the second set of results, we use dummy variables for the first, tenth, and hundredth confirmed cases/deaths to reflect potential non-linearity in the impacts of the spread of the pandemic.

Table 1 provides regression results for weekly confirmed cases by service type and associated search terms. Given the sudden outbreak and rapid growth in the number of COVID-

19 cases and deaths, the logarithmic transformation would make the interpretation of estimated coefficients more convenient. However, in the weeks preceding December 2019, when the first COVID-19 cases were reported, and for part of the COVID-19 period, the number of cases/deaths was zero. Thus, the weekly cases and deaths are transformed using inverse hyperbolic sine transformation, while the Google search data are transformed using logarithmic transformation. The estimated coefficients from these transformed data can be interpreted as elasticities. Panel (a) presents results for hotels and restaurants, transport and tourism, while Panel (b) presents results for ICT solutions, delivery services, and retail trade sectors.

The results in Panel (a) of Table 1 show that demand for hotels and restaurants, transport and tourism have contracted due to COVID-19. A 1 percent increase in confirmed weekly cases leads to a 0.09 percent decrease in demand for hotels and restaurants, a 0.04-0.07 percent decrease in demand for transport, and a 0.01-0.04 percent decrease in demand for tourism. Panel B shows that a similar rise in weekly cases is associated with a 0.03-0.09 percent decrease in demand for retail services. On the other hand, ICT (Zoom and Skype) services have enjoyed a positive demand shock because of the pandemic. A 1 percent increase in weekly confirmed cases induces a 0.05-0.07 percent increase in demand for Zoom and Skype. As we show in our next sections, the demand for delivery services also jumped, but only in countries that implemented lockdown measures. This is intuitive as delivery services are expected to increase in the presence of restrictions of movements. We find similar results using the number of confirmed deaths (see Table B.5 in Appendix B).

Table 1: The impacts of Covid-19 confirmed cases on demand for services

a) Hotel and restaurant; transport, tourism

	Hotels and restaurant		Transport		Tourism	
	hotel	restaurant	flight	airport	tourist	museum
IHS (cases)	-0.09^{***}	-0.09^{***}	-0.04^{***}	-0.07^{***}	-0.01^{**}	-0.04^{***}
	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
R-squared	0.92	0.92	0.91	0.87	0.84	0.9
Observations	8,160	8,160	8,160	8,160	7,344	7,344

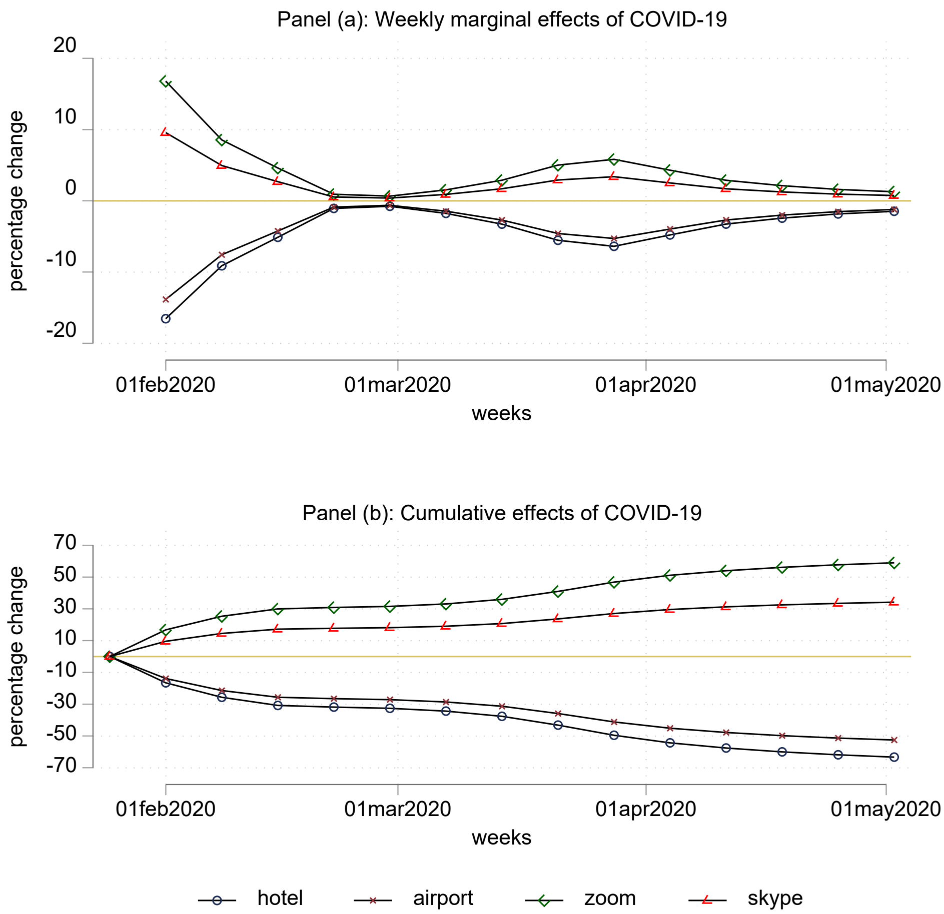
b) ICT, delivery, and retail trade

	ICT		Delivery	Retail trade	
	Zoom	Skype	delivery	mall	shopping
IHS (cases)	0.07^{***}	0.05^{***}	-0.01	-0.09^{***}	-0.03^{**}
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
R-squared	0.87	0.75	0.88	0.92	0.91
Observations	8,208	8,208	7,872	7,776	7,968

Note: the data used cover January-April of 2018-2020. For every country where Google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. IHS stands for inverse hyperbolic sine transformation. Standard errors, clustered at country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The magnitude of the impact we find is quite large. And it is important to put our results in perspective. Unlike previous pandemics, COVID-19 has been spreading quickly, increasing by over 100 percent weekly, on average. The sheer magnitude of the pandemic and the speed at which it transmitted translates into substantially large reductions (increases) in demand for services. Figure 3 presents the weekly marginal (Panel (a)) and cumulative (Panel (b)) impact of COVID-19 on demand for selected services. At the margin, the pandemic has led to a 4.2 and 3.5 percent weekly decline in demand for hotels and travel. The corresponding impacts on demand for Zoom and Skype are 4 and 2.3 percent, respectively. The impact is particularly greater in the earlier stages of the pandemic. The sharp drops (rises) in demand for services stabilize after week five of the pandemic.

As shown in Panel (b) of Figure 3, the cumulative impacts for the three months (January 25 to April 30, 2020) amount to 63 and 52 percent drops in demand for hotel and travel, and 59 and 34 percent increases in demand for Zoom and Skype, respectively. These rates are comparable to evolving estimates in other studies on the impacts of the pandemic on consumer spending (e.g., Andersen et al., 2020) and U.S. Commerce Department monthly retail sales reports (U.S. Census Bureau, 2020).



Note: Weekly change in demand is calculated by applying the size of the effect identified in Table 1 to the weekly global growth in the number of confirmed cases.

Figure 3: Weekly changes in global demand for services due to COVID-19

In Tables 2a and 2b, we report results using indicator variables for country-specific "milestones" with regards to the spread of the pandemic. In this exercise, we focus on the differential implications of the first, 10th and 100th confirmed cases. Such "milestones" influence the behavior of individuals and induce governments into action by making the spread of the pandemic more salient, thereby impacting demand for various services.

Table 2a shows that hotels and restaurants, transport and tourism services experience a significant fall in demand as the number of confirmed cases reaches 10. While the demand starts falling when countries register their very first case, the effect becomes statistically significant for 10 or more cases. Columns 1-6 show that demand for hotel and restaurant services decreases by about 63-79 percent compared to weeks with fewer than 10 cases. The impact size increases to 90-94 percent when countries register 100 confirmed cases.[10] We find similar results consistently across most sectors.[11] We also find that the number of confirmed deaths has a greater impact on demand than confirmed cases (see Table B.6 in Appendix B). This is intuitive, as deaths are more likely to induce fears and stricter government responses than confirmed cases.

The results in Table 2b show that demand for ICT services received a significant boost as COVID-19 related mobility restrictions and business closures shift a considerable chunk of economic activities online, and individuals stay indoors for fear of contracting the virus. As face-to-face interactions become increasingly difficult with the spread of the pandemic, substitutive ICT services have seen a spike in demand. On average, as the number of confirmed cases exceeds 10, countries experience a 46-77 percent increase in demand for ICT services. The effect is bigger when the 100 confirmed cases milestone is reached, with demand for ICT services rising by 55-84 percent, on average, compared to the weeks with fewer than 100 cases.

[10] Percentage changes are calculated as $(e^{\beta_1} - 1) \times 100$.

[11] Interestingly, in the early stages of the spread of the virus, there is an uptick in search for "flight", perhaps as people scramble to catch flights back to their home countries and cities before travel becomes difficult.

Table 2a: The impacts of COVID-19 confirmed cases and deaths on demand for losing services

	Hotels and restaurant						Retail					
	hotel	hotel	hotel	restaurant	restaurant	restaurant	mall	mall	mall	shopping	shopping	shopping
First case	-0.23			-0.32			0.03			-0.03		
	(0.19)			(0.20)			(0.06)			(0.06)		
First 10 cases		-0.49**			-0.58**			-0.13***			-0.23***	
		(0.24)			(0.23)			(0.04)			(0.06)	
First 100 cases			-0.64***			-0.66***			-0.23***			-0.40***
			(0.21)			(0.21)			(0.06)			(0.06)
R-squared	0.88	0.89	0.91	0.89	0.91	0.91	0.90	0.90	0.90	0.83	0.84	0.85
Observations	8,208	8,208	8,208	8,112	8,112	8,112	8,160	8,160	8,160	8,160	8,160	8,160
	Transport						Tourism					
	flight	flight	flight	airport	airport	airport	tourist	tourist	tourist	museum	museum	museum
First case	0.03			-0.03			-0.06			-0.11		
	(0.06)			(0.06)			(0.06)			(0.10)		
First 10 cases		-0.13***			-0.23***			-0.17***			-0.23***	
		(0.04)			(0.06)			(0.05)			(0.09)	
First 100 cases			-0.23***			-0.40***			-0.19***			-0.29***
			(0.06)			(0.06)			(0.05)			(0.05)
R-squared	0.90	0.90	0.90	0.83	0.84	0.85	0.84	0.84	0.84	0.89	0.89	0.89
Observations	8,160	8,160	8,160	8,160	8,160	8,160	7,344	7,344	7,344	7,584	7,584	7,584

Table 2b: The impacts of COVID-19 confirmed cases and deaths on demand for wining services

	ICT						Delivery		
	Zoom	Zoom	Zoom	Skype	Skype	Skype	delivery	delivery	delivery
First case	0.25			0.21			-0.13***		
	(0.22)			(0.13)			(0.04)		
First 10 cases		0.57**			0.38***			-0.06	
		(0.24)			(0.13)			(0.06)	
First 100 cases			0.61***			0.44***			-0.01
			(0.22)			(0.06)			(0.10)
R-squared	0.86	0.87	0.87	0.74	0.75	0.75	0.88	0.88	0.88
Observations	8,208	8,208	8,208	8,208	8,208	8,208	7,872	7,872	7,872

Note: The data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. Standard errors, clustered at country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Potential Mechanisms and Heterogeneity in Impacts

The observed changes in aggregate demand for various services due to the pandemic reflect a combination of demand and supply shocks. As we highlighted earlier, there are three major channels through which the coronavirus pandemic can affect demand for services. First, as the pandemic began to take hold in much of the world, governments have introduced multiple measures, including travel restrictions, social distancing, and lockdowns, to reduce the spread of the virus. These measures directly affect the supply of some services, while inducing demand for substitutes such as remote working. These business closures limit the availability of some services, such as international flights, which effectively put a total hold on air travel and tourism.

Second, the pandemic could affect consumer demand through income and wealth channels as workers get laid off or experience cuts in wages and salaries due to business closures and economic slowdowns. Third, as the pandemic takes hold, consumers will reduce economic activities and alter their demand for certain services (such as hotels, restaurants, local malls, and shopping centers, and travel and leisure) for fear of contracting the virus. Besides such fear-induced withdrawal of demand, people may also reduce the consumption of some services deemed non-essential due to economic anxiety and elevated uncertainties about the future under the shadow of the pandemic. Such anxieties and negative economic sentiments are known to reduce consumer confidence and aggregate spending. In this regard, early studies from Europe and the United States show a significant decline in consumer spending across various sectors. Using daily transaction-level data from Denmark, for instance, Andersen et al. (2020) find a 25 percent decline in overall household spending following lockdown.

To identify whether supply-side or demand-side shocks drive our results, we interact with the number of weekly confirmed cases with the implementation of social distancing and lockdown measures. More specifically, we interact with social distancing and lockdown implementation indicators with an indicator variable for whether a country has registered the first 100 cases. However, we cannot disentangle the change in demand due to income losses from that driven by anxieties. Similarly, the breadth and implementation of these policies vary across countries. But the variations in the spread of the pandemic and government responses give us some latitude to isolate the relative roles of demand- and supply-side factors in driving the average effect.

Panel A of Table 3 provides results on the impacts of the spread of the pandemic in the absence or presence of social distancing measures. In contrast, Panel B provides similar results by interacting with the spread of the pandemic with lockdown measures. Countries with higher confirmed cases and that have imposed mobility restrictions experience greater loss (gain) in demand for services. For most services, the "milestone" of registering 100 cases has a significant impact even in the absence of social distancing and lockdown measures. For most services, comparison of the treatment effects in the absence and presence of government responses suggests that demand-driven impacts are larger than those driven by supply-related shocks. The largest decrease (increase) in demand is observed in countries that have confirmed cases (deaths) above 100 and have imposed lockdown measures. For instance, demand for restaurant services shrunk by 60 percent for countries with 100 plus confirmed cases and have lockdown in place, while demand for ICT services increased by 92 percent. Overall, the results in Table 3 suggest that both supply-side restrictions and demand contractions drive the changes in demand for services.

Table 3: The impacts of COVID-19 confirmed cases on demand for services

	Panel A: The implication of the pandemic in the presence (absence) of social distancing measures										
	Hotel and restaurant		Transport		Tourism		Retail		ICT and delivery		
	hotel	restaurant	flight	airport	tourist	museum	mall	shopping	Zoom	Skype	delivery
100 cases(0)*social distance(1)	-0.35***	-0.38**	-0.03	0.00	-0.16**	-0.15**	-0.08	-0.05	0.59***	0.31**	-0.16***
	(0.12)	(0.15)	(0.07)	(0.08)	(0.08)	(0.06)	(0.09)	(0.06)	(0.20)	(0.13)	(0.06)
100 cases(1)*social distance(0)	-0.42***	-0.60***	0.46**	0.26	-0.07	-0.19	-0.30***	-0.06	0.81***	0.54***	-0.10*
	(0.10)	(0.15)	(0.20)	(0.20)	(0.07)	(0.15)	(0.10)	(0.06)	(0.15)	(0.13)	(0.06)
100 cases(1)*social distance(1)	-0.82***	-0.82***	-0.36***	-0.52***	-0.28***	-0.37***	-0.62***	-0.19*	0.81***	0.54***	-0.06
	(0.22)	(0.21)	(0.09)	(0.08)	(0.05)	(0.04)	(0.16)	(0.10)	(0.23)	(0.06)	(0.10)
No. observations	8160	8160	8160	8160	8160	8160	8160	8160	7344	7344	7344
	Panel A: The implication of the pandemic in the presence (absence) of lockdown measures										
100 cases(0)*lockdown(1)	-0.33***	-0.62***	-0.16	-0.12	-0.27**	-0.24*	-0.30***	0.00	0.51**	0.38***	0.11*
	(0.08)	(0.18)	(0.12)	(0.09)	(0.12)	(0.12)	(0.10)	(0.12)	(0.24)	(0.13)	(0.05)
100 cases(1)*lockdown(0)	-0.67***	-0.67***	-0.26***	-0.45***	-0.19***	-0.33***	-0.58***	-0.18*	0.66***	0.42***	-0.08
	(0.23)	(0.23)	(0.06)	(0.07)	(0.04)	(0.05)	(0.17)	(0.11)	(0.19)	(0.05)	(0.11)
100 cases(1)*lockdown(1)	-0.67***	-0.90***	-0.18***	-0.26**	-0.32**	-0.24***	-0.57***	-0.06	0.62*	0.65***	0.28***
	(0.11)	(0.15)	(0.05)	(0.10)	(0.13)	(0.08)	(0.12)	(0.08)	(0.35)	(0.19)	(0.07)
No. observations	8208	8208	8208	8208	7872	7872	7776	7776	7968	7968	

Note: the data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. Standard errors, clustered at country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Robustness Checks

We probe the robustness of our results against some alternative scenarios and threats to identification. First, as we combine pre-and post-COVID-19 data, one may suspect that this can increase the treatment effects associated with the number of confirmed cases and deaths. We thus apply a more conservative approach by restricting our sample to the COVID-19 period, January-April 2020, and exploit the intensive margin of variation in the spread of the pandemic only. Second, our main results could be driven by a few influential countries and regions. To gauge whether a few countries and regions influence our results, we, therefore, split our sample by continent and estimate disaggregate treatment effects. As different regions have varying levels of access to the internet and use different languages in their Google search queries, such disaggregation can inform whether our results hold for several regions and different languages. We estimate our main empirical specifications for countries in the four main continents in our sample: Africa, the Americas, Asia, and Europe.

The results in Table B.7 (in Appendix B) show similar effects of a weekly increase in confirmed cases and deaths. The sizes of the coefficients are comparable with those based on the larger sample. The impacts of the pandemic on some services are even more visible in this smaller sample and conservative approach. For example, demand for delivery services appears to have significantly increased because of the pandemic in this smaller sample. Overall, this exercise confirms that our results are not affected by specific periods and sampling. This is not surprising as much of the variation in the intensive margin arises from the COVID-19 period.

The disaggregated results generally confirm that most of our results hold across all the four continents covered (see Table B.8 in Appendix B). As expected, there exist some differences in the size of the effects across continents. The impact of the pandemic on consumer demand in Africa, for instance, is smaller compared to other regions of the world. This is owing, presumably, to the lowest confirmed cases and deaths that the continent has registered and the relatively lax movement restrictions that African governments implemented compared to other regions. The most notable and statistically significant effect of the pandemic is on hotel and restaurant services, which is higher in Latin American and Asian countries. In comparison, the effect of the pandemic on the airline industry is much higher in Europe than the rest of the world. These are likely to be driven by the differences in government responses, including social-distancing, travel restrictions, and lockdowns, across countries and regions. Overall, the evidence suggests that the patterns of effects hold across most continents, reassuring that a few countries and regions do not drive the average impacts. In particular, these findings confirm that our search terms and languages are relevant to all regions and hence can capture demand for the important sectors and services we are studying.

7. Concluding Remarks

To uncover the impacts of the COVID-19 pandemic on various services, we assemble Google search data that capture the temporal and spatial evolution of consumer demand for a carefully selected list of services. These novel data provide a unique opportunity to estimate the impacts of the pandemic in contexts where other types of conventional data sources are not available. These data are used to predict human preferences, and responses to fast-shifting events and pandemics (Choi and Varian, 2009; Goel et al., 2010; Pavlicek and Kristoufek, 2015). We use fixed effects specifications to quantify the impact of the COVID-19 spread across countries. We exploit temporal variations in the spread of COVID-19, both confirmed cases and deaths, across 182 countries that are currently affected by the pandemic.

We find that demand for some services has significantly increased because of the pandemic, while some services experienced significant loss. Most importantly, we quantify the impact of the additional spread of the burden on winning and losing sectors economies. More specifically, we find that the spread of the pandemic has significantly reduced demand for services that require face-to-face interactions while boosting demand for services involving less in-person interactions. The size of the impacts is quite large. For instance, countries with at least 10 confirmed cases are likely to experience a 63-79 percent reduction in demand for hotel and restaurant services while enjoying a comparable increase in demand for ICT services. Most of these patterns are observed in all four continents (Africa, Americas, Asia, and Europe) in our sample. Our estimates suggest that the impacts are driven both by supply-side shocks due to social distancing and lockdown measures and demand-driven contractions (expansions), with the latter dominating in most of the services we study.

These findings can inform policy efforts and responses to the pandemic. More importantly, such evidence on the relative impacts of the pandemic on various sectors and services of economies can improve governments' ability to identify and target the most impacted sections of the economy. This is particularly imperative for governments with limited fiscal space, which hence are usually forced to allocate their limited resources among competing needs. Our findings can also help understand potential sectoral productivity shifts due to the COVID-19 pandemic, crucial information that governments may employ for designing redistributive public policies. Finally, we argue that national and sub-national governments can employ the types of data we employ in this study to inform their context-specific policies in near real-time.

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Online Appendix to

Winners and Losers from COVID-19: Global Evidence from Google Search

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Appendix A: Renormalizing the Google search popularity index for spatio-temporal comparability

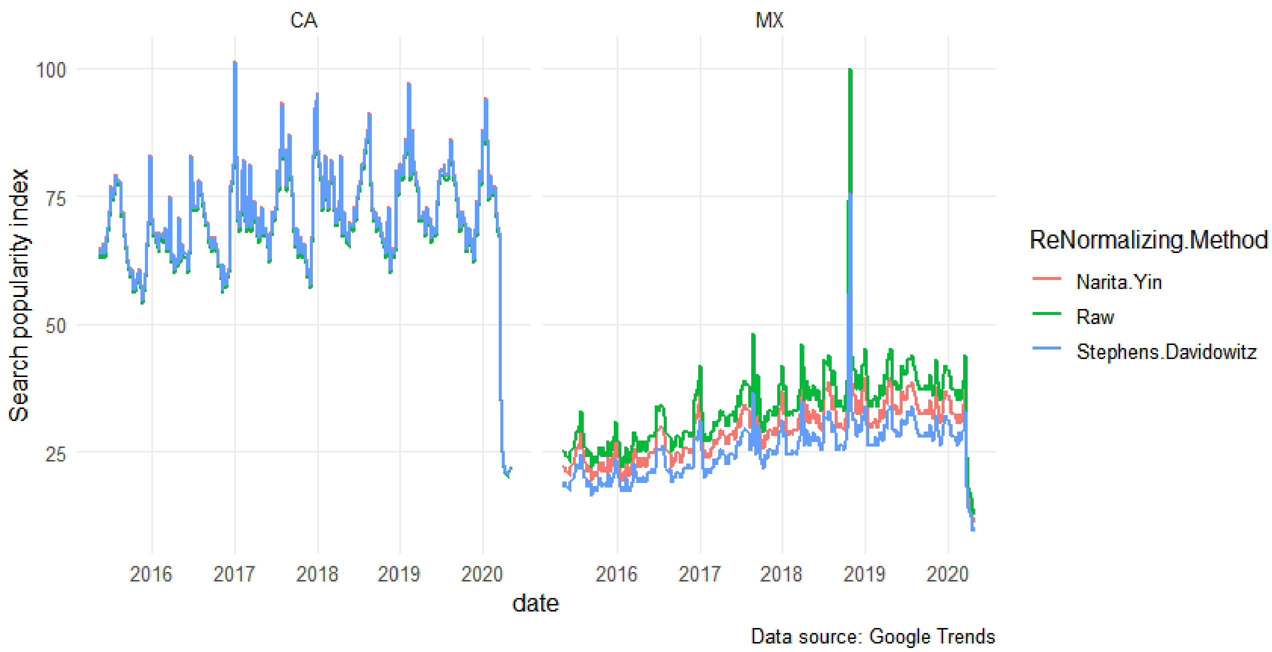
One of the limitations of the Google search popularity index is that it is not directly comparable across terms and geographic areas. For instance, search indices requested in a single submission (for a maximum of five countries) are comparable. In contrast, the search index for the sixth country that is obtained through a second request is not comparable with the indices downloaded in the previous request. Therefore, the raw Google search indices are not comparable across countries. In the literature, there are a couple of suggested adjustments to make the indices comparable across space and time. In this paper, we follow two approaches suggested by Stephens-Davidowitz (2014) and Narita and Yin (2018).

The approach suggested by Stephens-Davidowitz (2014) is to renormalize the indices by a geographic reference (in our case, the U.S.). We pull the data for a given search term in multiple requests for a pair of countries: the U.S. and country j, i.e., in each request for country j we include the U.S. Then, we renormalize the index for country j as follows: $\frac{Index_{j,t}}{\max_{t \in T}(Index_{u.s,t.})} = \widetilde{Index}_{j,t}$, where $\widetilde{Index}_{j,t}$ is the renormalized search popularity index that is comparable both across countries and time. The renormalized search popularity index could take any positive value.

The approach suggested by Narita and Yin (2018) is to renormalize search indices for two separate search terms in a given geographic area and time window. We use their suggested renormalization approach to make the search popularity indices comparable across countries. Let $Index_{j,t}$ is search popularity index for a given term pulled for country j, and $Index_{u.s.,j,t}$ is search popularity indices for the same term but pulled for a pair of countries, $u.s.$ and j, where $u.s.$ is our reference country, and $Index_{u.s.,t}$ is search popularity index for the same term pulled for the reference country ($u.s.$) only. The renormalized search popularity index for country j is given by:

$$\widetilde{Index}_{j,t} = Index_{j,t}\left[\frac{avg(Index_{j,t})}{avg(Index_{u.s.,t})}\right]\left[\frac{avg(Index_{-u.s.,j,t})}{avg(Index_{u.s.,-j,t})}\right],$$

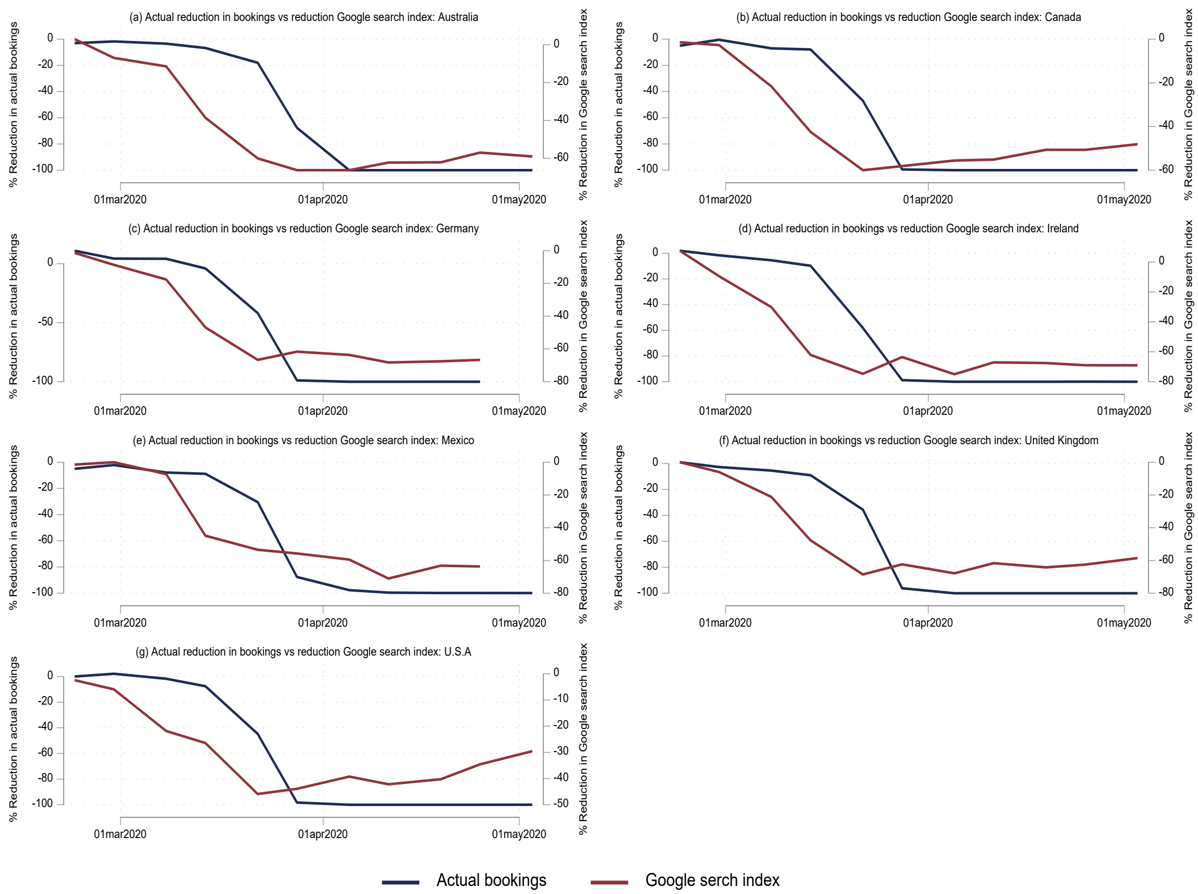
where $\widetilde{Index}_{j,t}$ is the renormalized search popularity index that is comparable between the $u.s.$ and country j, $avg(Index_{j,t})$ and $avg(Index_{u.s.,t})$ are the average popularity indices calculated using data that were pulled separately for country j and $u.s.$, $avg(Index_{-u.s.,j,t})$ is the average popularity index for country j using data pulled jointly for the pair, and $avg(Index_{u.s.,-j,t})$ is the average popularity index for the $u.s.$ using data pulled jointly for the pair. We repeat this process for all countries and terms by setting the U.S. as a reference country ($u.s.$). These indices are normalized with respect to the reference country, and they are comparable both across countries and time (see Narita and Yin (2018) for more detail). For illustration purposes, figure A.1 shows the raw search popularity indices for the term "airport" before normalization and after renormalization using Stephens-Davidowitz (2014) and Narita and Yin (2018) methods for Canada (CA) and Mexico (MX) with the U.S. as the reference country.



Note: reference country is U.S. "Narita.Yin" and "Stephens.Davidowitz" represent renormalized values using suggested renormalization approaches by Narita and Yin (2018) and Stephens-Davidowitz (2014), respectively. "Raw" represents the search popularity index without renormalization. Given the primary language is Spanish in Mexico, our term for airport is submitted as "aeropuerto+airport".

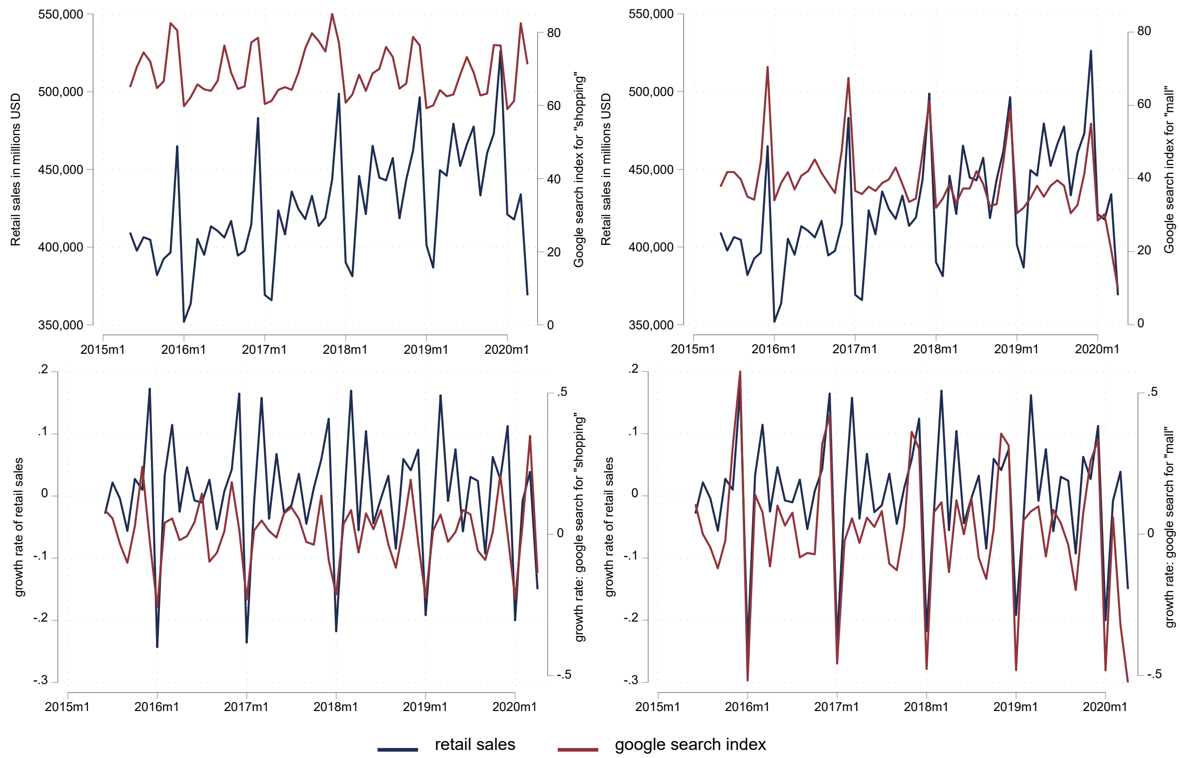
Figure A.1: Raw and renormalized Google search popularity indices of the term "airport" for Canada (CA) and Mexico (MX)

Appendix B. Additional Figures and Tables



Note: The graphs in this figure compare actual reductions in restaurant bookings versus reductions in the Google search index for "restaurant" for the seven countries where these data are available. The bookings data come from OpenTable, https://www.opentable.com/state-of-industry.

Figure B.1: Comparison of actual reductions in restaurant bookings versus reductions in Google search index for "restaurant"



Note: The data used in this figure covers May 2015-April 2020. The top panel compares total monthly retail sales with the corresponding Google search index for "shopping" and "mall". The bottom panel shows monthly growth rates in retail sales and the growth rate of google search intensity for "shopping" and "mall".

Figure B.2: Monthly U.S. retail sales and Google search index for "shopping" and "mall"

Table B.1: Selected Studies that Used Google Search Data

Author	Topic
Afkhami et al. (2017)	Energy price volatility
Baker and Fradkin (2017)	unemployment insurance on job search
Beer et al. (2012)	Investor sentiment and stock market
Bentzen (2020)	religiosity
Bloom et al. (2015)	skin cancer
Bordino et al. (2012)	stock market
Brodeur et al. (2020)	mental health
Chetty et al. (2020)	Racial bias
Choi and Varian (2009)	firm and stock market performances
Choi and Varian (2012)	consumer demand
D'Amuri and Marcucci (2017)	Unemployment
Da et al. (2010)	investor attention
Donadelli, M. (2015)	Uncertainty and macroeconomic conditions
Drake et al. (2012)	quantify demand for information
Fetzer et al. (2020)	economic anxiety
Ginsberg et al. (2009)	predicting the outbreak and spread of epidemics
Goel et al. (2010)	consumer behavior
Hand, C., & Judge, G. (2012)	Cinema
Jackman and Naitram (2015)	Tourist arrival
Joseph et al. (2011)	stock returns and trade volume
Li et al. (2015)	Oil prices
Metaxas and Mustafaraj (2012)	election outcomes
Narita and Yin (2018)	GDP
Naritomi (2019)	Tax compliance
Pavlicek and Kristoufek (2015)	predict unemployment rates
Stephens-Davidowitz (2014)	race and election outcomes
Vosen and Schmidt (2011)	consumer demand
Wu and Brynjolfsson (2015)	forecast house prices
Xu et al. (2017)	Forecasting influenza
Yang et al. (2015)	estimation of influenza epidemics
Yelowitz and Wilson, M. (2015)	Bitcoin

Table B.2: Actual number of air travelers and Google search index for "flight" and "airport"

	(1) Log (actual daily number of travelers)	(2) Log (actual daily number of travelers)	(3) Log (actual daily number of travelers)	(4) Log (actual daily number of travelers)
Google index "flight"	0.05^{***}			
	(0.00)			
L1. Google index "flight"		0.05^{***}		
		(0.00)		
Google index "airport"			0.05^{***}	
			(0.00)	
L1. Google index "airport"				0.05^{***}
				(0.00)
R-squared	0.89	0.89	0.97	0.97
No. observations	177	176	177	176

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Actual restaurant reservations and Google search index for hotel and restaurant

	(1) Percentage change in actual bookings	(2) Percentage change in actual bookings	(3) Percentage change in actual bookings	(4) Percentage change in actual bookings
Percentage change in search index for "restaurant"	1.43^{***}	1.54^{***}		
	(0.14)	(0.14)		
Percentage change in search index for "restaurant"			1.27^{***}	1.54^{***}
			(0.09)	(0.05)
Country dummies	No	Yes	No	Yes
R-squared	0.59	0.64	0.63	0.78
No. observations	75	75	75	75

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Monthly U.S. retail sales and Google search index for “shopping” and “mall”

	(1) Log(retail)	(2) Log(retail)	(3) Monthly percentage change in retail	(4) Monthly percentage change in retail
Google index “shopping”	0.006***			
	(0.001)			
Google index “mall”		0.004***		
		(0.001)		
Monthly change in Google index “shopping”			0.008***	
			(0.001)	
Monthly change in Google index “mall”				0.007***
				(0.001)
R-squared	0.205	0.249	0.408	0.722
No. observations	60	60	59	59

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: The impacts of COVID-19 confirmed deaths on demand for services

a) Hotel and restaurant, transport, and tourism						
	hotel	restaurant	flight	airport	tourist	museum
IHS (deaths)	-0.09***	-0.09***	-0.06***	-0.09***	-0.01	-0.05***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
R-squared	0.91	0.91	0.91	0.87	0.84	0.9
Observations	8160	8160	8160	8160	7344	7344

b) ICT, delivery, and retails					
	Zoom	Skype	delivery	mall	shopping
IHS (deaths)	0.06***	0.04**	-0.02	-0.10***	-0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R-squared	0.86	0.74	0.88	0.92	0.91
Observations	8208	8208	7872	7776	7968

Note: the data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. Standard errors, clustered at the country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: The impacts of COVID-19 confirmed cases and deaths on demand for losing and winning services

	Hotels and restaurant						Retail					
	hotel	hotel	hotel	restaurant	restaurant	restaurant	mall	mall	mall	shopping	shopping	shopping
First death	-0.60***			-0.61***			-0.20***			-0.38***		
	(0.22)			(0.22)			(0.07)			(0.07)		
First 10 deaths		-0.54**			-0.55***			-0.26***			-0.45***	
		(0.23)			(0.21)			(0.09)			(0.08)	
First 100 deaths			-0.57**			-0.48***			-0.35**			-0.55***
			(0.23)			(0.17)			(0.14)			(0.15)
R-squared	0.90	0.90	0.91	0.91	0.91	0.90	0.90	0.91	0.91	0.85	0.86	0.87
Observations	8,208	8,208	8,208	8,112	8,112	8,112	8,160	8,160	8,160	8,160	8,160	8,160

	Transport						Tourism					
	flight	flight	flight	airport	airport	airport	tourist	tourist	tourist	museum	museum	museum
First death	-0.20***			-0.38***			-0.17***			-0.26***		
	(0.07)			(0.07)			(0.05)			(0.08)		
First 10 deaths		-0.26***			-0.45***			-0.08**			-0.24***	
		(0.09)			(0.08)			(0.04)			(0.06)	
First 100 deaths			-0.35**			-0.55***			0.00			-0.23***
			(0.14)			(0.15)			(0.05)			(0.05)
R-squared	0.90	0.91	0.91	0.85	0.86	0.87	0.84	0.84	0.84	0.89	0.89	0.89
Observations	8,160	8,160	8,160	8,160	8,160	8,160	7,344	7,344	7,344	7,584	7,584	7,584

	ICT						Delivery		
	Zoom	Zoom	Zoom	skype	skype	skype	delivery	delivery	delivery
First death	0.50**			0.40***			-0.05		
	(0.25)			(0.08)			(0.07)		
First 10 deaths		0.50***			0.33***			-0.04	
		(0.19)			(0.04)			(0.11)	
First 100 deaths			0.33**			0.23***			-0.10
			(0.16)			(0.08)			(0.12)
R-squared	0.87	0.87	0.86	0.75	0.75	0.74	0.88	0.88	0.88
Observations	8,208	8,208	8,208	8,208	8,208	8,208	7,872	7,872	7,872

Note: the data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. Standard errors, clustered at the country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: The impacts of COVID-19 confirmed cases (deaths) on demand for services (COVID-19 period only)

a) Hotel and restaurant; transport, tourism												
	Hotels and restaurant				Transport				Tourism			
	hotel	hotel	restaurant	restaurant	flight	flight	airport	airport	tourist	tourist	museum	museum
IHS (cases)	-0.08***		-0.09***		-0.04***		-0.06***		-0.02*		-0.03***	
	(0.02)		(0.02)		(0.01)		(0.01)		(0.01)		(0.01)	
IHS (deaths)		-0.07**		-0.06*		-0.07**		-0.09***		-0.02		-0.03**
		(0.03)		(0.03)		(0.03)		(0.02)		(0.01)		(0.01)
No. observations	2736	2736	2736	2736	2720	2720	2720	2720	2448	2448	2448	2448
b) ICT and delivery, and retails												
	ICT				Retails							
	Zoom	Zoom	Skype	Skype	delivery	delivery	mall	mall	shopping	shopping		
IHS (cases)	0.12***		0.08***		0.08***		-0.08***		-0.00		-0.08***	
	(0.03)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
IHS (deaths)		0.09***		0.06***		0.06***		-0.09***		-0.02		
		(0.03)		(0.02)		(0.02)		(0.02)		(0.02)		
No. observations	2736	2736	2736	2736	2736	2736	2430	2430	2430	2430	2430	

Note: the data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. Standard errors, clustered at the country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Disaggregated impacts of COVID-19 across continents

	Africa	Americas	Asia	Europe
		Hotel and restaurant (hotel)		
IHS(confirmed cases)	-0.09***	0.08***	-0.11***	-0.05*
	(0.02)	(0.02)	(0.01)	(0.03)
Observations	2208	1392	2064	1920
		Transport services (flight)		
IHS(confirmed cases)	-0.04	-0.04**	-0.05***	-0.08***
	(0.03)	(0.02)	(0.01)	(0.01)
Observations	2160	1392	2064	1920
		Tourism (museum)		
IHS(confirmed cases)	-0.04	-0.06***	-0.04***	-0.05***
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	1632	1392	2016	1920
		ICT services		
IHS(confirmed cases)	0.08	0.05	0.09***	0.05
	(0.07)	(0.05)	(0.02)	(0.03)
Observations	2208	1392	2064	1920
		Retail trade		
IHS(confirmed cases)	-0.08	-0.03***	-0.09***	-0.07**
	(0.06)	(0.01)	(0.01)	(0.03)
Observations	1920	1392	2064	1872

Note: the data used covers January-April of 2018-2020. For every country where google trends data is available, the search index reflects searches in English and the most dominant local language. Each regression includes weekly dummies to capture aggregate temporal trends. IHS stands for inverse hyperbolic sine transformation. Standard errors, clustered at the country level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.