Changes in air passenger demand as a result of the COVID-19 crisis: using Big Data to inform tourism policy

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Abstract

This paper develops a methodology for the early detection of reactivation of tourist markets to help mitigate the effects of the COVID-19 crisis, using Skyscanner data on air passenger searches (>5,000 million) and picks (>600 million), for flights between November 2018 and December 2020, through ForwardKeys. For future travel during the May to September 2020 period, the desire to travel (based on the number of flight searches) has dropped by about 30% in Europe and the Americas, and by about 50% in Asia, while intention to travel (the number of flight picks, the final selections amongst flight searches) has dropped a further 10-20%. Most source markets remain optimistic about air travel during the last quarter of 2020, suggesting a U shape recovery. However, optimism has dwindled as time passes, suggesting a flatline L shape. A traffic light dashboard for domestic and inbound air travel demand to Spain shows how destination managers might use Big Data relating to the early recovery of key source markets to develop targeted marketing strategies. We show how Big Data provides timely granular data essential in highly volatile situations, and we argue that destination management organisations must improve their Big Data analytical and evidence-based, decision-making skills.

Keywords: COVID-19, tourism, risk, Big Data, forecast, impact.

Introduction

The current pandemic has clearly shown how a lack of knowledge constrains the tourism industry's ability to plan for, and manage, risks and uncertainty (Williams & Baláž, 2015). Most pandemic research has focused on the measures that airports should take to contain health pandemics, not on the economic consequences to the travel and tourism industries (Chung, 2015; Gössling, Scott, & Hall, 2020). Economists typically detect the impact of structural breaks on tourism crises ex-post (Cró & Martins, 2017). While this may allow us to allocate negative shocks in tourism demand to crises, it is insufficient in terms of enabling us to proactively manage the impact of such crises. Historic data is a form of tacit knowledge that works relatively well to inform decisions where there is limited environmental change. In situations with low risk, future tourism patterns closely follow recent-past patterns, and therefore Destination Management Organisations (DMOs) use historical data as indication of future tourism demand. However, in situations where we have limited knowledge to inform decision-making, such as those that result from extraordinary exogenous events, the tourism industry faces unsystematic risk for which they are not prepared (Williams & Baláž, 2015).

Pandemics, nowadays, spread through aviation (Chung, 2015; Gössling et al., 2020). In March to May 2003, efforts to mitigate the spread of SARS reduced passenger volumes in key affected airports by between 57.0% - 77.6%, and in March to May 2009, due to Swine Flu, by 4.12% - 7.88%; however, there were increases of between 9.04%- 16.0% in May to July 2006 despite Avian Influenza (Chung, 2015). In all three pandemics, airports generally deployed large-scale, temperature screening using thermo-imaging cameras, followed by containment of passengers showing symptoms. However, differences between the pathogens' lifecycles (e.g. incubation periods, severity of symptoms), among other aspects, determine the effectiveness of such airport screening procedures to contain them. Despite the unknown efficacy of the measures, previous pandemics did not have a significant impact on the continuous growth of international travel. As a result, the tourism industry in 2020 may not have been sufficiently prepared for the COVID-19 pandemic (Gössling et al., 2020).

COVID-19 differs from previous pandemics by having a longer incubation period and less discernible symptoms, making its spread easier (Chinazzi et al., 2020). Despite this, default government responses and advice from the Collaborative Arrangement for the Prevention and Management of Public Health Events in Civil Aviation (CAPSCA) followed lessons learned in earlier pandemics (Shaw, Kim, & Hua, 2020; Sohrabi et al., 2020). Consequently, initial statistical models estimated that the impact of travel reduction would be small on three key variables: (i) the number of exported cases, (ii) the probability of a major epidemic, and (iii) the time delay to a major epidemic (Anzai et al., 2020). The United Nations World Tourism Organization (UNWTO) grossly underestimated the impact of COVID-19 on the tourism industry, when it initially forecasted a 2-3% reduction in international travel in 6th March 2020, compared to 2019 figures. In less than a month, it had readjusted its expectations to a 20-30% reduction, announced by 26th March 2020 (Gössling et al., 2020). Although, to date, there have not been further estimates released by UNWTO during April or early May 2020, it is difficult to foresee that only a 20-30% reduction has taken place, especially since a UNWTO report dated 28 April 2020 stated that every surveyed tourist destination in the world has COVID-19-related travel restrictions and that 83% of them have had those restrictions for four weeks or more (UNWTO, 2020a). Both Anzai et al. (2020) and UNWTO (2020a) warned about the need to balance the estimated epidemiological impact and predicted economic fallout from controlling travel volume through restrictions on mobility.

In less than six months, COVID-19 has proven to be a much greater pandemic than any other in recent history, with the COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University reporting 4,716,965 cases and 315,248 deaths on 18 May 2020 (Dong, Du, & Gardner, 2020). There is a clear connection between tourism consumption and health disaster risk and, accordingly, governments have been forced to impose travel bans to manage transmission risks (Gössling et al., 2020; Yang, Zhang, & Chen, 2020). A dynamic stochastic general equilibrium COVID-19 tourism model shows how "longer and greater risk of health disasters pushes the tourism sector and the overall economy into an abyss" (Yang et al., 2020:5). Earlier travel restrictions would have had a substantial effect on delaying the spread of the virus (Sohrabi et al., 2020), although even 90% restrictions on international travel would not manage to control the spread of COVID-19 alone, without the inclusion of localised measures of social distancing and hygiene (Chinazzi et al., 2020). Nowhere was the tourism industry's contribution to spreading COVID-19 more evident than in the now–well-reported case of the Diamond Princess cruise, where one passenger carrying the virus led to 619 passengers and crew testing positive. A study of this case showed how the conditions on board clearly amplified a highly transmittable disease (Rocklöv, Sjödin, & Wilder-Smith, 2020), and showed how the travel and tourism industry was a key sector responsible for the transmission of the virus and, as a result, was going to be disproportionately impacted by actions designed to mitigate the pandemic (Gössling et al., 2020).

As a result of the pandemic, the sudden changes to mobility mean that DMOs and businesses alike need to rethink not only the expected demand for 2020 but, also, their longer-term business models and, to do so, requires the use of new data sources that do not depend on historical data. This will have implications for the business models that these destinations adopt, and the economic, social and environmental impacts that they generate. The objective of our research is to develop a methodology for the early detection of reactivation of tourist markets, so that tourist destination managers can make decisions to help mitigate the effects of the crisis in their tourist destinations. In doing so, we show the benefits of DMOs using Big Data to take policy decisions as an adaptive process to reduce their vulnerability to unsystematic exogenous risks such as natural disasters (Williams & Baláž, 2015). The increasing importance of air passenger movement to the tourism industry has led us to focus on this sector, as 59% of international tourist arrivals were by air in 2016 and, until COVID-19, this percentage was expected to increase to 61% by 2030 (UNWTO, 2019b), an increase which reflects the reliance of tourist destinations in international mobility and that subsequently alarms many give the detrimental impacts aviation has on the environment.

First, we summarise how we have accessed data for seat capacity, air passenger searches and picks conducted in Skyscanner, for flights between November 2019 and December 2020, to show the accessibility to current data available to the tourism industry. Second, we outline key findings available at 30 April 2020 with regards to how COVID-19 has affected flight cancellations, as well as the interest and choices of consumers with regards to travel, at a global and sub-continent level. Third, we drill down on the data to analyse variations in online flight searches and picks per source market for one specific tourism-dependent region in Spain, in order to provide a case study on how such data can be used to take policy decisions to support strategies for economic recovery. Finally, we reflect on how, in situations of uncertainty, Big Data can help us acquire knowledge to reduce risk (Williams & Baláž, 2015).

Methodology

Our study aims to identify leading indicators on the behaviour of demand at the time the pandemic is occurring, without the need to wait for historical data for it or to develop complex econometric models (Kuo, Chen, Tseng, Ju, & Huang, 2008). Big Data is the means of exploration to achieve this objective, since it allows us to work with real data in real time. This is not without its difficulties, since the capture, management and processing of the data cannot be carried out using conventional technologies. For this, there are payment platforms (Adara, Amadeus, Expedia, ForwardKeys, Mabrian, Sojern, etc.) that carry out all this procedure and make the data available in a more accessible environment for the analyst. Operational transaction data (web searches, webpage visits, online bookings and purchasing) is frequently used by DMOs to predict demand, although, within tourism research, it is the least used source of Big Data due to reasons of privacy, commercial sensitivity and cost (Demunter, 2017; Li, Xu, Tang, Wang, & Li, 2018). Specifically, for this article we work with the data platform offered by ForwardKeys (2020), a big data company that monitors the aviation industry. Below, we provide a description of the databases and variables used, as well as the steps and assumptions taken to construct indicators that allow destination managers to make informed decisions.

Our first step was to identify two data sets in ForwardKeys that would offer complementary perspectives. First, we analysed the supply using the dataset of *global air capacity,* which is fed weekly with Schedule Reference Service data from Cirium and includes information on both historical scheduled capacity (as of January 2010) and future scheduled capacity up to one year ahead. Second, we analysed the demand, in terms of the daily updated flight searches conducted through the travel meta-search engine and fare aggregator Skyscanner, with more than 100 million unique visitors per month, servicing consumers globally in more than 30 languages (Skyscanner, 2020); the dataset available includes search information from January 2016 to one year ahead. For the demand dataset, in order not to report Skyscanner's confidential business performance, ForwardKeys (2020) performs a daily sample of records sufficient to adequately show the behaviour of the markets. It is relevant to note that despite the fact that Skyscanner is one of the main metasearch engines in the world, its presence varies significantly by country – it reaches a market share of more than 80% in countries such as Greece, Italy, Singapore and Thailand, but does not reach even 10% in countries such as the United States or Canada, where Kayak or Google Flights prevail. ForwardKeys takes into account these limitations in the way that data is sampled, and provides a dataset that is large enough to present no problems regarding statistical representativeness.

Once the databases were analysed, the second step was to select the most appropriate variables to use for our research. Two different units were provided to quantify air capacity: number of seats and number of flights. Since the objective was to obtain indicators for the volume of demand, the chosen variable was the number of seats. Next, the flight search database offered us two variables of interest: “search”, which showed consumer preferences, and “flight picks”, which identified their final selection. Ideally, each search should lead to a "flight pick" but, in reality, the number of searches is much higher due to mismatches between the options displayed and the consumers’ preferences for reasons such as a lack of nonstop routes, expensive fares, inappropriate departure / arrival times, journey times, and waiting time between flights. It was these second units of analysis (searches and picks) that provided substantial depth to our understanding of market demand. Before booking a flight, travellers look for the best options, focusing on attributes (itinerary, schedules, fares, etc.) that maximise the precision of their purchase decision (Jun, Vogt, & MacKay, 2010), regardless of actual availability of that service by airlines. Therefore, this showed us the consumer’s desire to travel (search) and helped us to understand their real intentions. Then, through data on flight picks, we learned of the final choice selected (out of all the possibilities available in the search), prior to purchase, by the consumer, which provided us with an indicator of the traveller’s final intention to travel. The prospective data for these variables comes from the searches and flight selections actually made by the demand to travel in future months, it does not require estimates or predictive models.

The third step in our research was data extraction. For this, it was necessary to define the territorial and temporal units of analysis. One of the great advantages of Big Data is the granularity of the information. The most granular unit of analysis that our chosen databases allowed was to search data by day, by origin and by destination airports, which allowed us to evaluate the negative impacts of specific jolts on demand (e.g. news of new policies from outbound markets to present the spread of COVID-19) as well as positive impacts of marketing campaigns (e.g. promotions to promote demand for particular flight routes). For the two studies of our research, we chose to aggregate data differently, as follows: i) Study 1, data aggregated monthly and by sub-continent, and ii) Study 2, data aggregated monthly and by country / region. More details are given in the following sections.

It was also necessary to take into account the time of data extraction, given that the databases were updated continuously (weekly for airline seat capacity and daily for consumer searches). Taking into account the volatility of the data, due to the high uncertainty caused by the health crisis, continuous updates in the datasets were required. For the development of the empirical part of this article, we worked with an extraction dated 30 April 2020, which generated a large volume of data for each variable (see Table 1). It should be noted that both databases worked with real quantitative data, that is, they were not based on estimates or extrapolations. This ensured that we could obtain reliable conclusions about the real behaviour of the demand. No database enables you to have a complete picture of tourism demand, but they can be used as indicators to understand part of the reality (Chevalier et al., 1992). In our case, the limitation of the dataset was that it captured airline travel data but did not capture tourism travel through other forms of transport.

Table 1. Volume of data used in the empirical analysis for flights between November 2018 and December 2020 (as of 30 April 2020)

Variables	***Data (million)***
Seat capacity	73
Flight searches	5,465
Flight picks	667

Source: Authors, based on ForwardKeys (2020)

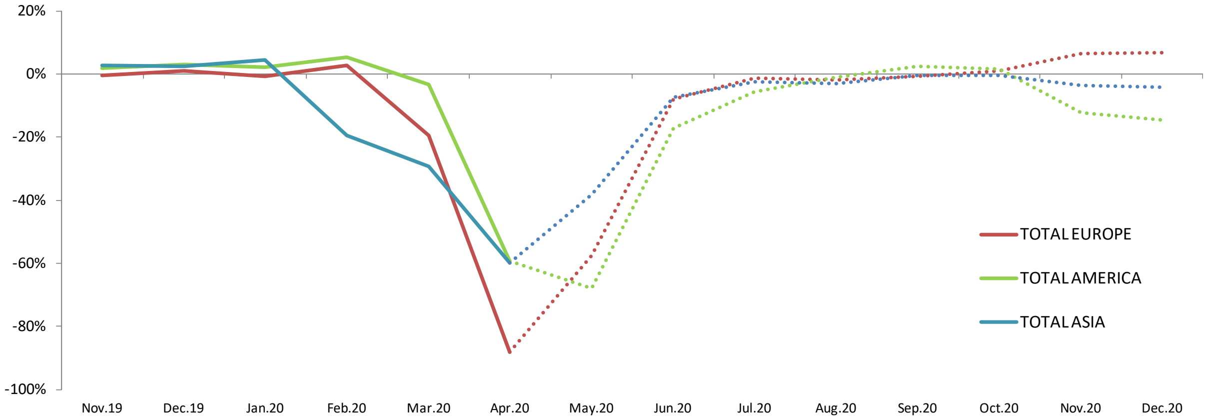
Finally, we use year-on-year variation of each of the variables listed above as an indicator of early detection of reactivation of tourist markets. The chosen start date for this year-on-year variation was November 2019, the month that the pandemic was first detected in Wuhan, China (Shaw et al., 2020; Sohrabi et al., 2020). This date allowed us to observe variations within the time period, and also across destinations as the pandemic spread.

Study 1: Global impact of COVID-19 on air passenger intention to travel

Study 1 analyses change in air capacity by destination, based on the number of seats offered by airlines. This analysis tells us about the reaction of airlines to this crisis and enables us to monitor their business decisions and how those decisions affect destinations, both from the point of view of flight cancellations and future reactivations. Graph 1 presents real data up to April 2020, and shows the time lag in the reaction of the airline industry to the crisis by continent. For Study 1 we choose to use data for Asia, Europe and the Americas to trace the geographical spread of COVID-19 across three continents. The data shows a sharp reduction in airline seats offered, starting in February in Asia, followed by Europe in March and America in April. Specifically, in April, the last month for which real data is available, it is observed that the negative effects on air capacity are more pronounced in Europe (-88.0%) than in Asia (-60.0%) or America (-59.4%). The data shows that the closure of air transport hubs and routes followed the spread of COVID-19 globally, rather than preceded it. This reactive behaviour is worrisome. We know that the risk of a flu-type virus becoming a pandemic can be reduced by up to 37% by increasing hand-hygiene measures in 10 global airports (Nicolaides, Avraam, Cueto-Felgueroso, González, & Juanes, 2019). This knowledge demonstrates how easy it is for a virus to spread as a result of delays or inconsistencies in measures introduced; all it takes for a pandemic to spread exponentially is authorities in some key locations delaying taking measures.

Graph 1 also offers very useful information to DMO managers regarding the commercial strategies of airlines, as it allows them to understand their vulnerability to these decisions and it provides data to support contract negotiations with airports and airlines in order to maximise the competitiveness of their tourist destination (Gallego & Font, 2019). However, this data has limitations as a predictive indicator and should be analysed with caution for three reasons: i) *data management* - there is a delay in airlines sending reports on flight cancellations to the data provider Cirium, which causes actual data on flight operations and capacity to be inaccurately reflected; ii) *commercial policy* - as airlines avoid cancelling flights until the last minute; and iii) *legislative changes* - the rules on slots, take-off and landing permits (that airlines have to have to operate at airports) have been modified, a response to avoid that airlines need to fly without passengers (ghost flights) in order to maintain their slots, with a view to alleviating the delicate situation that the airline sector is going through due to COVID-19 and their environmental impact; for example, in Europe, there has been a temporary suspension (from March 1 to October 24, 2020) of the slot usage requirements under EU law, which requires airlines to use at least 80% of their take-off and landing slots if they are to maintain them the following year (European Council, 2020). For all these reasons, flight forecasts seen in Graph 1 for May to December 2020 are unreliable and they may give a false sense of recovery of the supply of air services.

Graph 1. SUPPLY | Year-on-year variation rates. Air capacity (number of seats) by continent. [Data as of 30 April 2020]



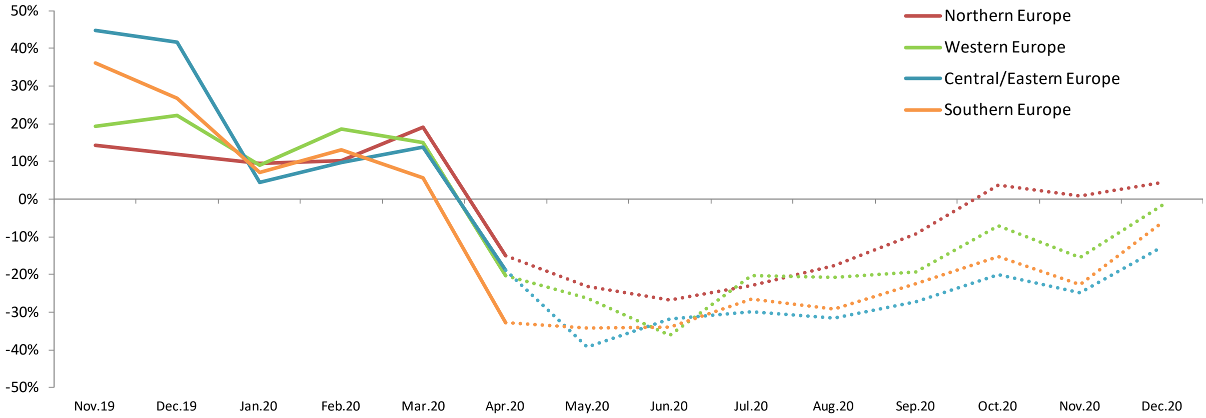
Source: Authors, based on ForwardKeys (2020)

Due to the limitations in supply data, it was necessary to analyse demand data in order to develop valid predictive indicators that were sensitive to change and could be used to forecast travel patterns. We used two indicators: i) changes in the desire to travel (*search*), based on searches carried out by Skyscanner users, and ii) changes in the intention to travel (*picks*), based on the final selection of flights made in the metasearch engine. In both cases, we analysed demand for international and domestic flights. For both indicators, two time horizons had to be established; first, the period in which the trip would take place and we chose to analyse the data in months. Second, the search period in which the potential traveller had searched for that trip. For trips that had already occurred, we opted to analyse searches conducted in the twelve months before the month of travel, for example, if the month of the trip was January 2020, the searches carried out from 1 January 2019 to 31 January 2020 were considered. This criterion, however, does not make sense for future travel (May - December 2020) since we only know the searches that have occurred up to the last real month (April 2020). In these cases, the criterion taken is to include data from the same month of the previous year, but ends in all cases on April 30th, 2020, e.g. for a search to travel in October 2020, the search period considered is October 1st, 2019 to April 30th, 2020. Obviously, to calculate the interannual variation rates for these months, the same time intervals are applied in the previous year with which it is compared, thus ensuring that the figures for both years show the same reality and that their results are consistent.

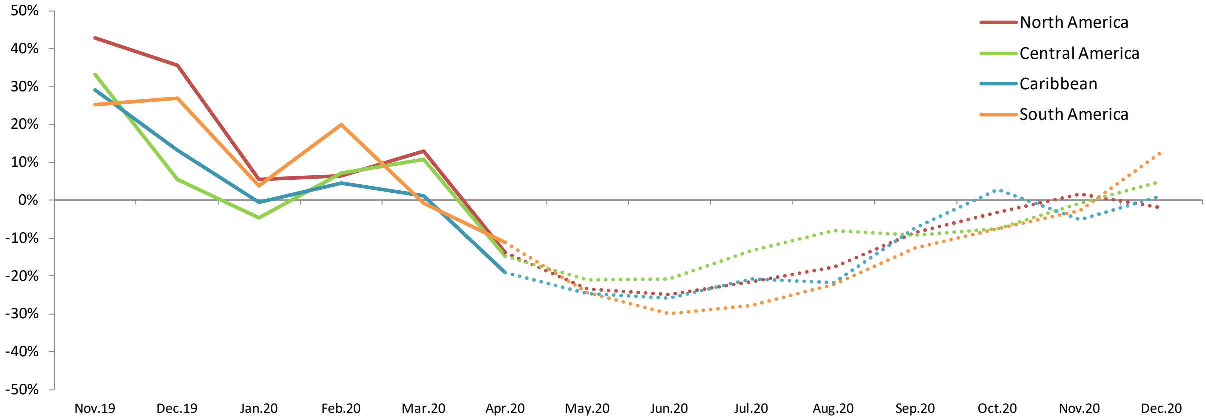
The rapid spread of COVID-19 is partly due to our mobile lifestyles (Shaw et al., 2020). Graphs 2a, 2b and 2c confirm that COVID-19 is a global crisis, where all the European, American and Asian sub-continents present similar trends. All the regions analysed showed a substantial increase in customer desire to travel at the end of 2019 compared to the previous 12 months. In the beginning of the year 2020, there were still no signs of a decline in the demand for travel to the European and American subcontinents, which continued to achieve growth demand rates in the first quarter. As expected, it was Asia where the decline line showed a steeper slope and where negative rates began earlier. In April 2020, the last month for which we have real data available, there was a widespread and profound decline in flight searches globally and, most pronounced, for Asian destinations.

At a predictive level, if we use the data in Graphs 2a, 2b and 2c alone, we conclude that the American sub-continents are likely to start recovering earlier and, also, in a more homogeneous way than other parts of the world, reaching rates in the last months of 2020 close to recovery in demand, compared to the same period of the previous year. This does not occur in the recovery of the desire to travel to the European and Asian subcontinents, which present a less homogeneous trend and record higher and more continuous negative rates over time, especially in the case of Asia. Only Northern Europe and Middle East reach rates of close to 0% towards the end of 2020. The difference in searches between the sampled regions can likely be explained by the date when the epidemic reached a peak in each location, first in Asia, then Europe and finally the Americas (UNWTO, 2020a).

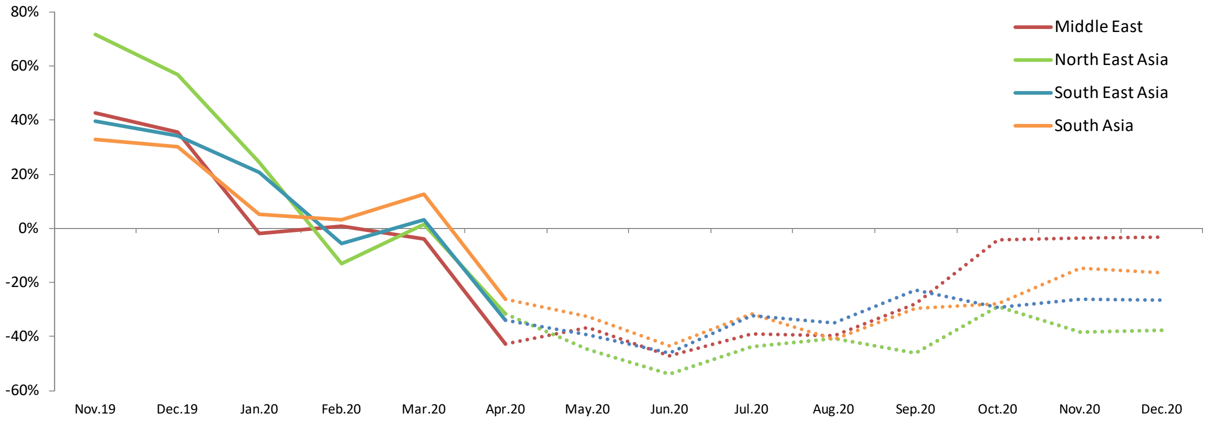
Graph 2a: DEMAND | Year-on-year variation rates. Desire (*Search*) to travel to Europe. [Data as of 30 April 2020]



Graph 2b: DEMAND | Year-on-year variation rates. Desire (*Search*) to travel to the Americas. [Data as of 30 April 2020]



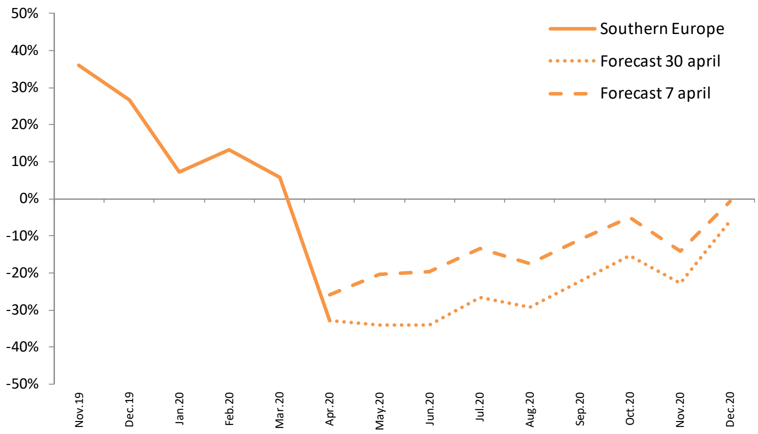
Graph 2c: DEMAND | Year-on-year variation rates. Desire (*Search*) to travel to Asia and the Middle East. [Data as of 30 April 2020]



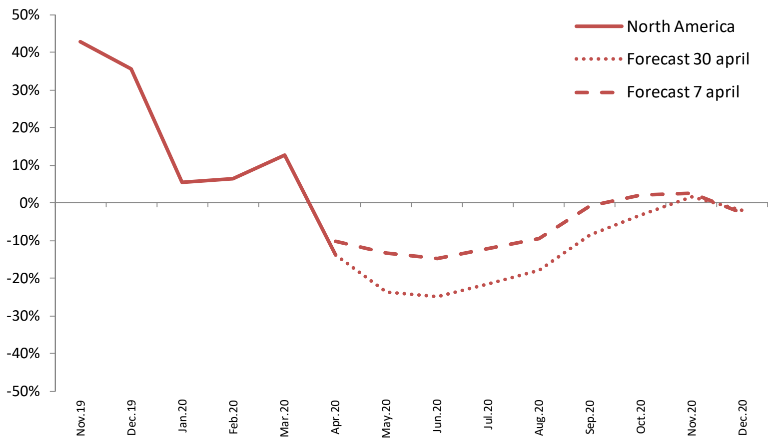
Source: Authors, based on ForwardKeys (2020)

Ongoing analysis of data is essential due to the uncertainty surrounding COVID-19 and the resulting variations in demand, in response to short term changes due to news of deaths and lockdown procedures. Although airport and tourist destination have managed to rebound after a pandemic in the past (Chung, 2015; Gössling et al., 2020), the novel conditions of COVID-19 mean that past experience is not a good indicator of future performance. Graphs 3a, 3b and 3c show the importance of the point in time at which data is analysed, for the three sub-continents most affected by COVID-19 out of the continents we analysed in our research (Southern Europe, North America and North East Asia). Taking as reference two cut-off points (information extracted on 7 April and 30 April, 2020), Graphs 3a, 3b and 3c show that the course of events caused a significant setback in searches and, therefore, a loss in the desire to travel short term, although this difference is less notable in longer term forecasts. Analysis of the data and its give predictions for the volume of travel in coming months vary significantly, although trends with regards to the relative recovery of some months compared to others remain relatively constant.

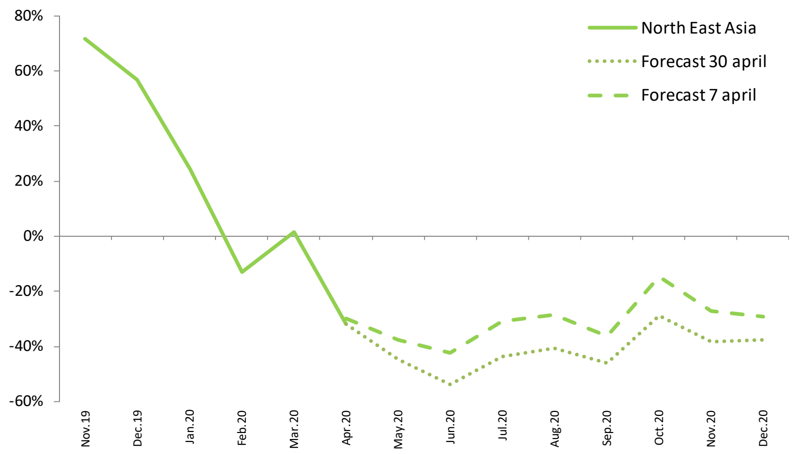
Graph 3a: DEMAND | Year-on-year variation rates. Flight *searches* to Southern Europe: a comparison of forecasts from 7 April 2020 and 30 April 2020. [Data as of 30 April 2020]



Graph 3b: DEMAND | Year-on-year variation rates. Flight *searches* to North America: a comparison of forecasts from 7 April 2020 and 30 April 2020. [Data as of 30 April 2020]



Graph 3c: DEMAND | Year-on-year variation rates. Flight *searches* to North East Asia: a comparison of forecasts from 7 April 2020 and 30 April 2020. [Data as of 30 April 2020]

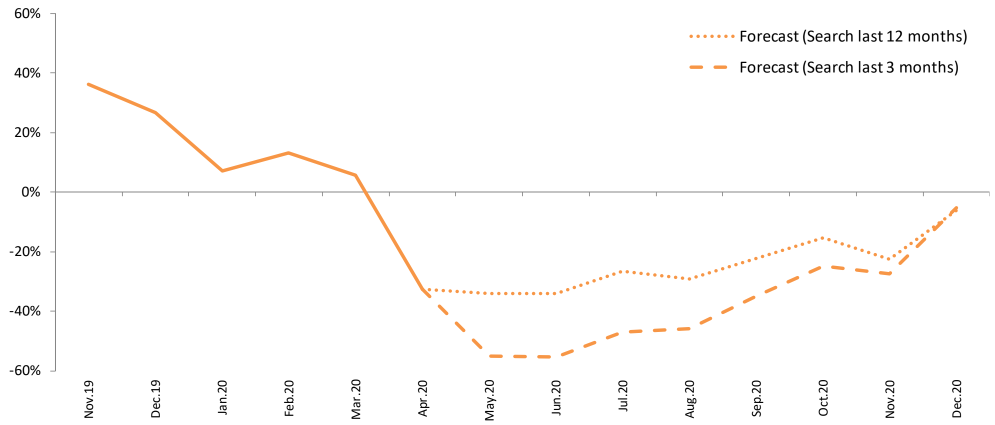


Source: Authors, based on ForwardKeys (2020)

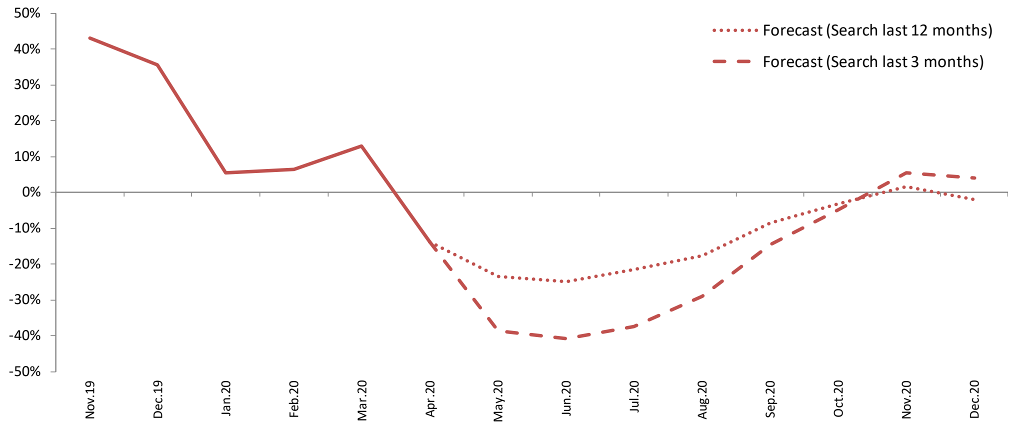
It is not only necessary to analyse data regularly, but to consider the time horizon used, and for what purpose each analysis is conducted. For example, in Graphs 4a, 4b and 4c we compare searches conducted over the previous twelve months, the default time horizon for this whole study, with searches specifically conducted three months before departure. Hence, to forecast travel in May 2020, a twelve months horizon would use searches carried out from 1 May 2019 to 30 April 2020, while a three months horizon for any month from May to December 2020 uses searches from 1 February 2020 to 30 April 2020, the last period for which we have search data (see explanation provided for the search periods for Graphs 2a, 2b and 2c to understand the reference months for future searches).

The data from three subcontinents shows that both time horizons follow the same trends. As expected, we register higher falls with a forecast that is directly based on searches conducted in the three months from 1 February 2020 to 30 April 2020. We understand that many searches conducted prior to the COVID-19 outbreak to travel in spring or summer 2020, captured by our twelve months horizon, will have resulted in cancelled bookings. We argue, however, that while a three months horizon is helpful to detect sudden changes in demand, it is less appropriate than a twelve months horizon to take strategic decisions at DMO level. A twelve months horizon in flight searches evidences that your destination is within an evoked set of travel destinations that the demand has an interest to travel to, even if this trip does not finally occur. This information is very interesting for DMO managers, since through appropriate marketing strategies they can reinforce the positioning of the destination and influence that this trip takes place, even if it is in another period. Given that the objective of this article is to help DMO managers in their decision-making, it is considered more useful to define the searches carried out in the last twelve months as the reference period.

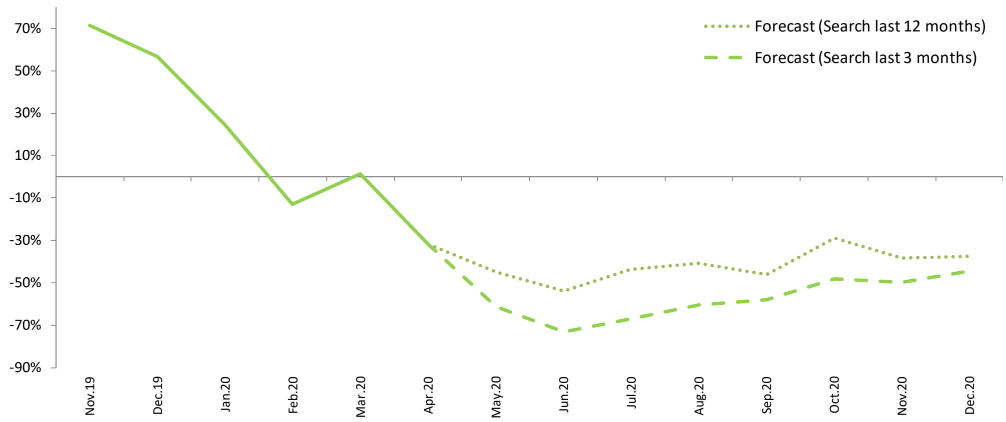
Graph 4a: DEMAND | Year-on-year variation rates. Flight *searches* to Southern Europe: a comparison of forecasts based on searches over 12 months and 3 months. [Data as of 30 April 2020]



Graph 4b: DEMAND | Year-on-year variation rates. Flight *searches* to North America: a comparison of forecasts based on searches over 12 months and 3 months. [Data as of 30 April 2020]



Graph 4c: DEMAND | Year-on-year variation rates. Flight *searches* to North East Asia: a comparison of forecasts based on searches over 12 months and 3 months. [Data as of 30 April 2020]

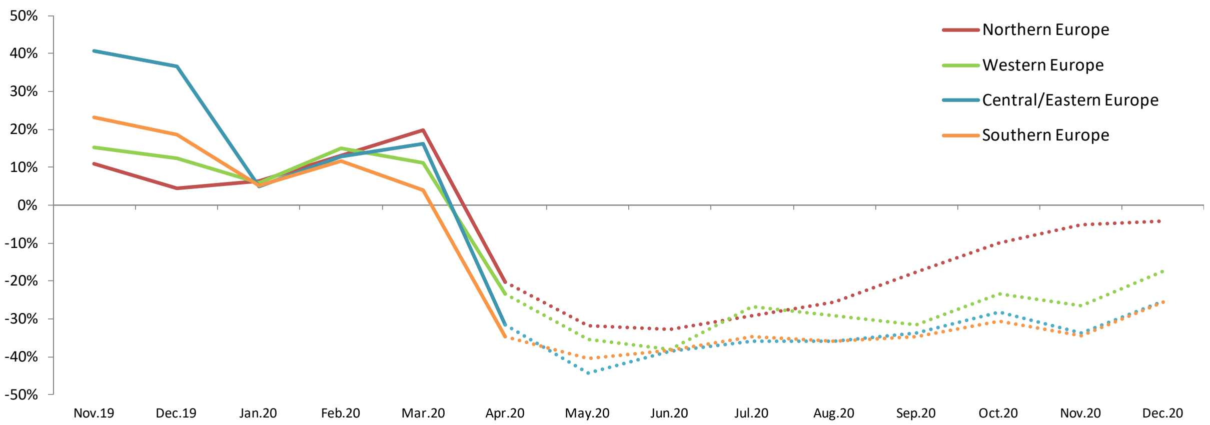


Source: Authors, based on ForwardKeys (2020)

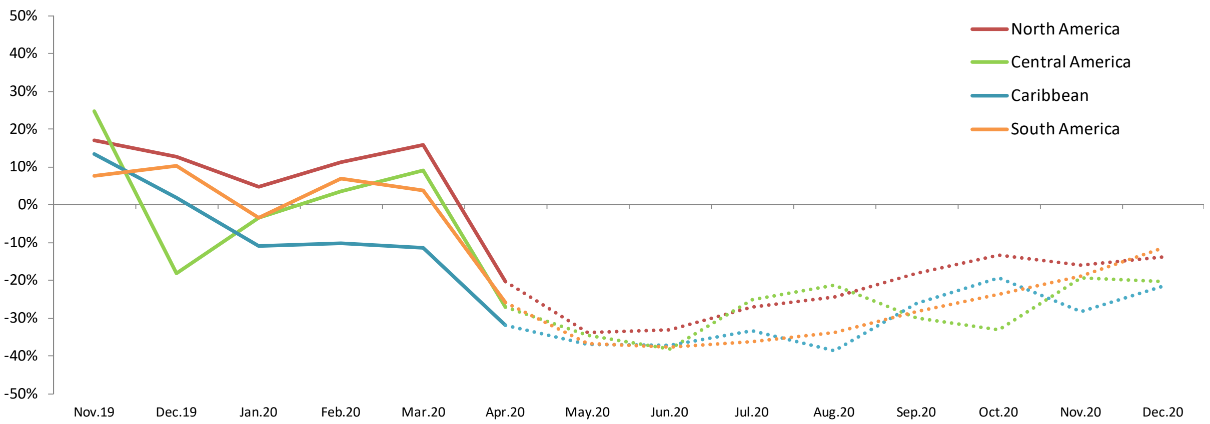
We now move on to analyse the customers' "*picks*", i.e., the selections they made from all the options offered by the metasearch engine in response to a "*search*" they initiated. Graphs 5a, 5b and 5c show the monthly flight picks in Europe, the Americas and Asia respectively, based on the intended travel dates. Year on year comparisons show a drop of typically between 40 and 60% in spring 2020, with a gentle upwards curve for intended travel during the remainder of 2020. Flight picks follow closely the spread of COVID-19 and travel restrictions subsequently introduced by governments between February and April 2020. The percentage of picks attributed to repatriations does not severely affect the results, as the percentage of one-way flight picks remains relatively consistent around 20% throughout the study period for Europe, America and Asia (there is a spike to 27.6% in March 2020 that drops to 17.4% for April 2020). As expected, the number of flight picks for North East Asia and Southern Europe dropped earlier (i.e. in February and March 2020) and more quickly than the numbers for other destinations, as they were the destinations most affected by the virus early on. Flight picks to the Caribbean dropped sooner than elsewhere in the Americas, probably because the Caribbean is more sensitive to fluctuations in intercontinental leisure demand than other destinations within the Americas, i.e., destinations that have a greater proportion of domestic or intra-continental travel.

Initial expectations from UNWTO and IATA, of a short lived crisis, suggested that flight picks would follow a V shape, but the second press release from UNWTO suggested a U shape (Gössling et al., 2020). Our results herein suggest that it is closer to an L shape, implying that the impact of COVID-19 on parts of the tourism industry that rely heavily on air travel is likely to be devastating.

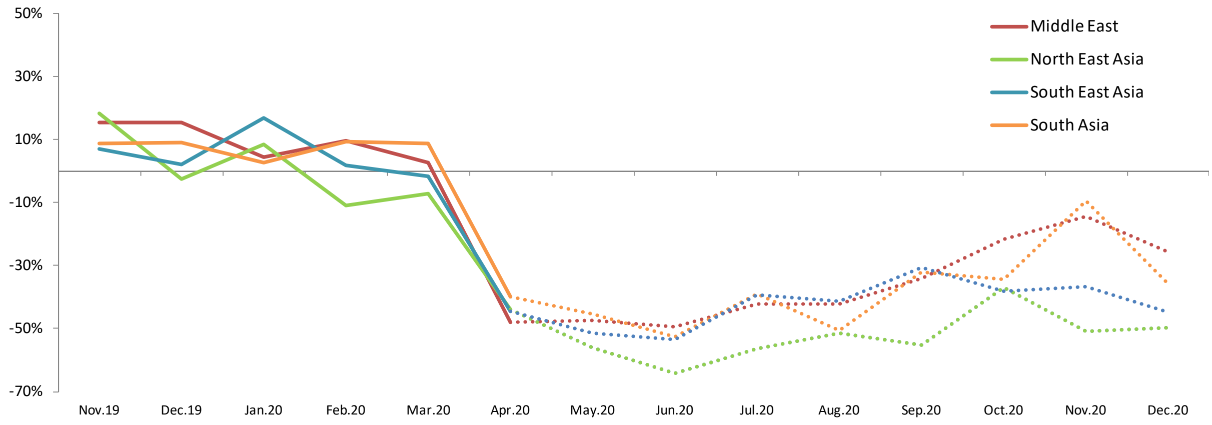
Graph 5a: DEMAND | Year-on-year variation rates. Intention (*Picks*) to travel to Europe. [Data as of 30 April 2020]



Graph 5b: DEMAND | Year-on-year variation rates. Intention (*Picks*) to travel to America. [Data as of 30 April 2020]



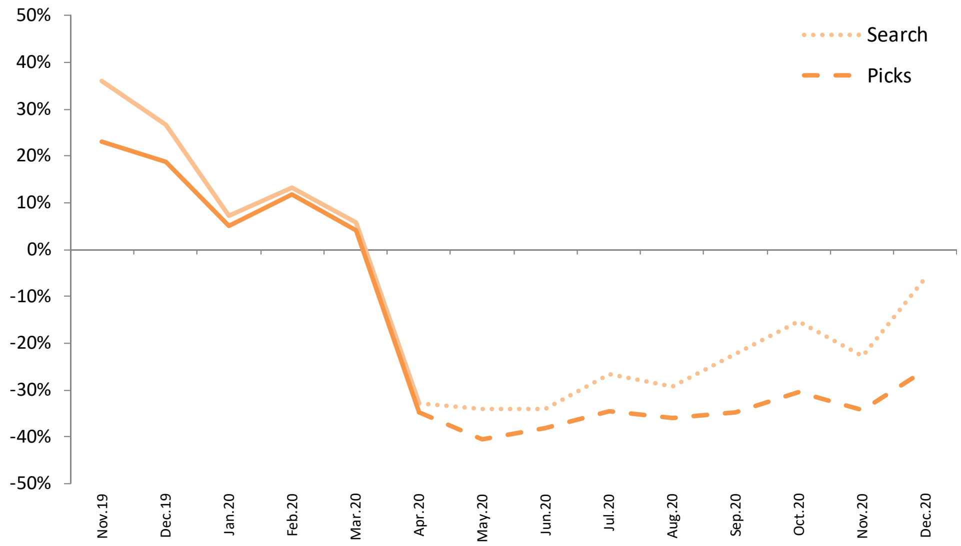
Graph 5c: DEMAND | Year-on-year variation rates. Intention (*Picks*) to travel to Asia and the Middle East. [Data as of 30 April 2020]



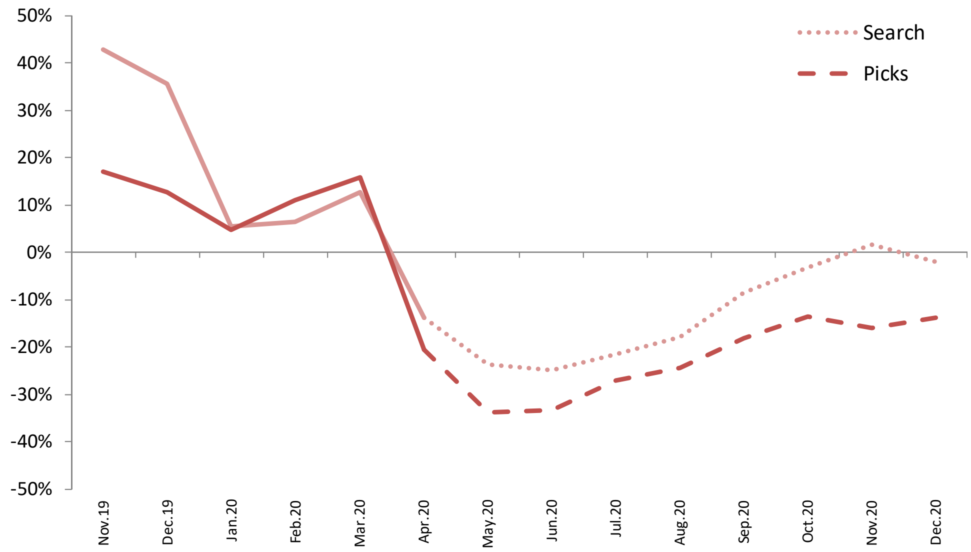
Source: Authors, based on ForwardKeys (2020)

It would be beneficial to conduct a more detailed comparison of the variation between the consumers' desires to travel (*searches*) and their flight selections (*picks*). As explained in the earlier Methodology section, typically, we would expect to see a mismatch between the number of customer searches and the number of customer picks, as for example, consumers find that the flight options displayed in response to their searches do not fulfil their needs, amongst other reasons. This expectation is confirmed in Graphs 6a, 6b and 6c particularly for November and December 2019. We can see that Asia is one month ahead of Southern Europe and North America (March vs April 2020) in this pattern. Looking at the forecasted behaviour for May 2020 to December 2020, we see that searches recover faster than picks although, in each of the three cases, the numbers of both remain substantially below previous year data due to the uncertainties associated with future travel due to travel restrictions (UNWTO, 2020a).

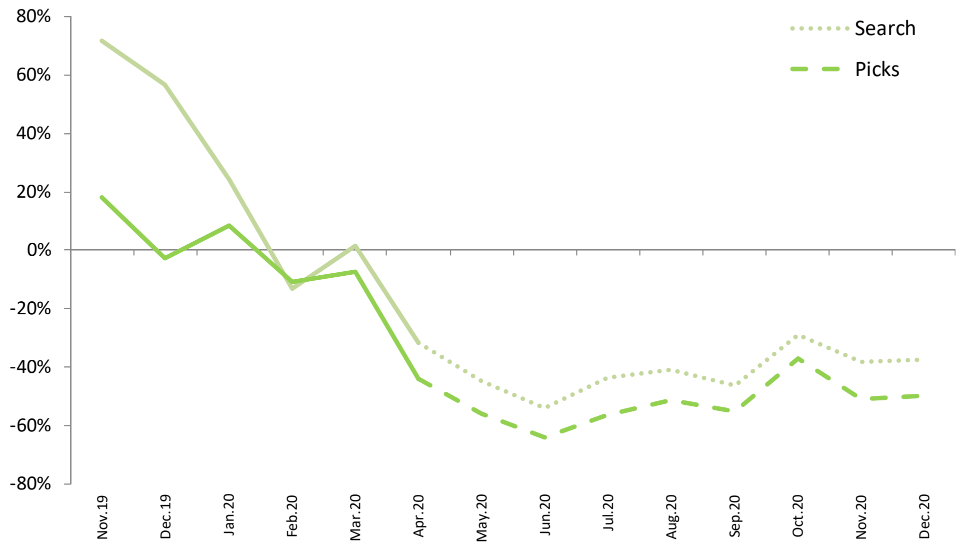
Graph 6a: DEMAND | Year-on-year variation rates. Desire (Search) and intention (Picks) to travel to Southern Europe. [Data as of 30 April 2020]



Graph 6b: DEMAND | Year-on-year variation rates. Desire (Search) and intention (Picks) to travel to North America. [Data as of 30 April 2020]



Graph 6c: DEMAND | Year-on-year variation rates. Desire (Search) and intention (Picks) to travel to North East Asia. [Data as of 30 April 2020]



Source: Authors, based on ForwardKeys (2020)

Study 2: Destination specific use of Big Data to inform policy

Tourism is a strategic sector for the Spanish economy that accounts for 12.3% of the country's GDP (Instituto Nacional de Estadística, 2019). In 2019, Spain received a total of 83.7 million foreign tourists, of which 82% used air travel as a means of transport to access Spain; the main markets of origin being the United Kingdom, Germany and France, which together represented almost half of the total foreign tourists received by the country (Instituto Nacional de Estadística, 2020b), as shown in Table 2.

Table 2: Distribution of foreign tourists to Spain according to markets of origin, 2019

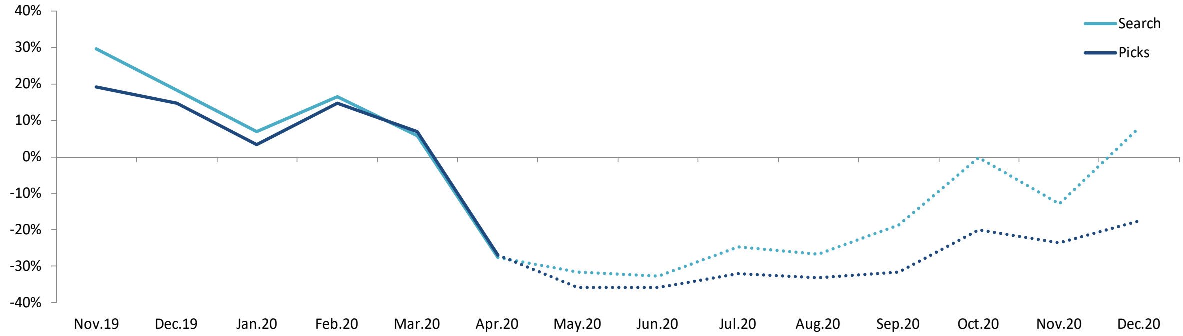
	Nº tourists	Share (%)
United Kingdom	18,078,076	21.6%
Germany	11,176,545	13.4%

France	11,156,671	13.3%
Nordic countries	5,548,745	6.6%
Italy	4,542,709	5.4%
Netherlands	3,701,944	4.4%
USA	3,332,654	4.0%
Belgium	2,538,829	3.0%
Portugal	2,440,746	2.9%
Ireland	2,177,106	2.6%
Switzerland	1,824,839	2.2%
Rest of the world	17,182,147	20.5%
Total	*83,701,011*	*100%*

Source: Authors, based on Instituto Nacional de Estadística (2020)

Graph 7 shows the flight demand indicators (both *searches* and *picks*) for Spain over a period of 14 months. Before the health crisis began, Spain was a destination in high demand, registering growth rates for both indicators. It is from March 2020, as we saw in Study 1 for the rest of the European continent, that Spain suffers the effects of the pandemic. Graph 6 suggests that the maximum fall in demand will take place in June 2020, with a drop of 32.7% in searches and 35.9% in picks, compared to the same month of the previous year. After June, the declines become less pronounced and it is notable that potential tourists are predicted to increase (over last year) their searches for flights towards the very end of 2020, even though the data suggests that they will not then pick those flights - this suggests that they are not booking ahead but simply scanning the availability of flights.

Graph 7: DEMAND | Year-on-year variation rates. Desire (Searches) and intention (Picks) to travel to Spain. [Data as of 30 April]



Source: Authors, based on ForwardKeys (2020)

Study 2 demonstrates the value of a methodology to detect, early, the reactivation of tourist markets, and enable DMOs to develop policy actions to help mitigate the effects of the crisis on their tourist destinations. Both of the indicators (*searches* and *picks*) already used in Study 1 offer DMO managers valid information about the behaviour of the markets and their moment of reactivation. If used wisely, such information should enable DMO marketing strategies to be more effective and efficient, since the data helps to define target markets and to determine the best timing for marketing actions. The number of *searches* indicates the desire to travel to the destination and, therefore, identifies a potential client who is in the initial phase of their travel decision, while *picks* shows a client who has already progressed further into the decision-making process. Having this knowledge enables managers to define better strategies targeted to the phase and level of decision of the potential market.

In order to foresee and identify the reactivation of markets, and understand when it will take place, a dashboard was developed (see Figure 1) to enable managers to interpret the results in an intuitive way. For this, a traffic light system was used, using green for interannual variation rates that showed positive results, yellow for negative variation rates of up to -30%, and red for the most extreme cases with falls of more than -30%. This cut-off point has been statistically determined through a percentile analysis for the case study, but it could also be defined by the managers or experts of the destination according to their objectives. In addition, two specific periods were chosen for the prospective analysis, namely, the summer months (June - September 2020) and the fourth quarter (October - December 2020); these two periods present very different tourist characteristics and are of special interest to managers in their strategic decision-making.

The dashboard in Figure 1 shows the results for the destination Spain, where the main inbound markets (see Table 2) and the domestic market, are included; although, in the latter case, the indicators are less representative, as only 11.6% of domestic trips are made by plane, compared to private cars, which amount to 75.6% of trips (Instituto Nacional de Estadística, 2020a). Two different, but complementary, analyses are also included: i) the general behaviour of each market (global vision), and ii) the behaviour of each market towards Spain (destination vision). A comparison of the results of the two analyses will alert DMO managers to whether a market is reactivating globally earlier than towards Spain, which could lead to a loss of opportunities and competitiveness for the Spanish tourist destination.

The presentation of results on the dashboard allow DMO managers to efficiently observe that the summer season, both overall and towards Spain specifically, will suffer major falls in demand compared to previous years, since all year-on-year variations present negative results (see Figure 1). Obviously, this lack of interest in air-based travel is influenced both by short-term uncertainty and by the administrative closures of borders (UNWTO, 2020a). However, some markets are already showing signs of reactivation for the fourth quarter of 2020, although there are significant variations. For example, the Portuguese market shows a desire to travel generally by aeroplane but not to neighbouring Spain (highly accessible by road), while the Irish show the opposite behaviour, demonstrating an increased desire to fly to Spain but not towards flying in general. The German and the US markets have a desire to travel both generally and to Spain, of equal intensity in the case of the German market, but of less intensity towards Spain for the Americans, possibly due to the distance. The United Kingdom is the only market that presents both desire and intention to travel globally and to Spain, and it is the only market with a marked increase in demand for travel.

Monthly data presents a first snapshot. Once DMO managers have identified broad brush patterns, they can use Big Data to drill down to more granular changes, focusing, for example, on daily changes in searches and picks in response to specific announcements reducing lockdown procedures in source markets. In the case of Spain, DMO managers could identify increased desire to travel (following the data seen for Germany, USA or Ireland), and could conduct more advanced searches for those markets that have shown a greater propensity to recover and pick flights, such as can be seen for the UK.

Figure 1: Traffic light dashboard for travel by market to Spain.

		Short-term SUMMER (JUN. - SEP. 2020)		Medium-term OCT. - DEC. 2020	
		GLOBAL	SPAIN	GLOBAL	SPAIN
TOTAL	Desire to travel (search)	-29.7%	-26.9%	-15.0%	-0.9%
	Intention to travel (picks)	-37.3%	-33.4%	-27.7%	-20.3%
Spain	Desire to travel (search)	-29.2%	-28.1%	-1.2%	-1.6%
	Intention to travel (picks)	-36.3%	-36.1%	-23.2%	-23.8%
United Kingdom	Desire to travel (search)	-6.8%	-0.9%	27.5%	55.5%
	Intention to travel (picks)	-14.9%	-16.3%	15.1%	27.5%
Germany	Desire to travel (search)	-10.6%	-14.2%	8.8%	8.3%
	Intention to travel (picks)	-25.2%	-25.6%	-19.0%	-22.5%
France	Desire to travel (search)	-25.3%	-31.6%	-8.4%	-11.2%
	Intention to travel (picks)	-34.5%	-42.8%	-31.0%	-41.1%
Nordic countries	Desire to travel (search)	-33.2%	-30.8%	-18.2%	-18.7%
	Intention to travel (picks)	-40.6%	-35.3%	-34.5%	-37.4%
Italy	Desire to travel (search)	-30.7%	-39.3%	-14.8%	-24.3%
	Intention to travel (picks)	-39.4%	-42.5%	-36.0%	-47.2%
Netherland	Desire to travel (search)	-23.5%	-26.2%	-5.3%	-9.2%
	Intention to travel (picks)	-24.9%	-27.3%	-16.4%	-24.8%
USA	Desire to travel (search)	-17.8%	-23.1%	7.4%	2.8%
	Intention to travel (picks)	-25.7%	-29.8%	-9.1%	-16.2%
Belgium	Desire to travel (search)	-27.7%	-32.0%	-4.9%	-5.8%
	Intention to travel (picks)	-28.6%	-29.5%	-19.2%	-26.3%
Portugal	Desire to travel (search)	-25.2%	-32.1%	9.3%	-7.4%
	Intention to travel (picks)	-34.7%	-47.3%	-17.6%	-36.7%
Ireland	Desire to travel (search)	-23.9%	-21.6%	-0.6%	23.1%
	Intention to travel (picks)	-26.8%	-18.6%	-17.9%	4.7%
Switzerland	Desire to travel (search)	-29.3%	-37.4%	-14.4%	-17.7%
	Intention to travel (picks)	-29.5%	-41.0%	-26.0%	-23.4%
Rest of the world	Desire to travel (search)	-44.7%	-33.9%	-26.9%	-24.2%
	Intention to travel (picks)	-52.4%	-38.4%	-37.3%	-30.1%

Source: Authors, based on ForwardKeys (2020)

Likewise, the granularity of the information offered by Big Data makes it possible to analyse which Spanish regions will benefit the most from the reactivation of a market and, even, which will be the most demanded cities of origin / destination. As an example, we can disaggregate the information geographically for the United Kingdom, since it is a key source market, to show the most favourable indicators for Spain. Table 3 highlights that the British intend to fly (*picks*) to the main Spanish tourist regions in the last quarter of the year, highlighting growth above the Spanish average for the regions of Valencia (+ 37.0%) and the Canary Islands (+ 34.5%), and that the most demanded origin-destination routes are: London (all airports) - Tenerife (9.4% picks) and Manchester - Tenerife (8.9% picks). This information will help DMO managers to make better action plans by defining more targeted and profitable marketing strategies.

Table 3: Most popular routes from origin (UK) - destination (Spain) (based on searches and picks) for October to December 2020

Origin (UK) ▶ Destination (Spain)	Search (%)	Picks (%)
London ▶ Tenerife (Canary Islands)	6.3%	9.4%
Manchester ▶ Tenerife (Canary Islands)	7.5%	8.9%

London ▶ Lanzarote (Canary Islands)	3.3%	3.8%
Manchester ▶ Alicante (Valencia)	3.4%	3.8%
London ▶ Málaga (Andalusia)	2.5%	3.6%
London ▶ Alicante (Valencia)	2.3%	3.4%
Manchester ▶ Lanzarote (Canary Islands)	3.1%	3.4%
London ▶ Las Palmas (Canary Islands)	2.3%	2.9%
Edinburgh ▶ Tenerife (Canary Islands)	2.4%	2.4%
London ▶ Barcelona (Catalonia)	1.6%	2.3%
Manchester ▶ Málaga (Andalusia)	1.9%	2.0%
Birmingham ▶ Tenerife (Canary Islands)	1.8%	1.8%
Glasgow ▶ Tenerife (Canary Islands)	2.5%	1.7%
Manchester ▶ Las Palmas (Canary Islands)	1.5%	1.6%
Newcastle ▶ Tenerife (Canary Islands)	1.8%	1.4%
Others (UK) ▶ Others (Spain)	55.7%	47.7%
Total	100.0%	100.0%

Source: Authors, based on ForwardKeys (2020)

Discussion

There are 7-Vs currently identified as the characteristics that define Big Data: volume, velocity, variety, variability, veracity, visualisation and value (El Alaoui, Gahi, Messoussi, Todoskoff, & Kobi, 2017; Gandomi & Haider, 2015). This article exemplifies each of these characteristics as follows: *Volume*, working with a total of 6,205 million data that allow a high level of representation; *Velocity*, through rapid data processing with which it is possible to offer daily results; *Variability*, referring to the variation in data flow rates, was avoided thanks to the consistency of the data sources used; *Veracity,* taking real data, and not estimates or extrapolations that may offer imprecise and inaccurate results; *Visualisation*, the results have been presented intuitively to the end user; *Value*, demonstrating the validity and usefulness of the data in times of crisis for early detection of the reactivation of tourism demand. We acknowledge that our data has limitations with respect to *Variety*, as the use of flight information only paints a partial picture of tourism demand (our research uses only data for international flights, hence DMO manages will need to complement with similar datasets for accommodation searches and picks), hence, to obtain a completer picture, it would be necessary to incorporate new sources and new data formats to the crisis management dataset and, subsequently, to create data systems that offer a more complete vision of tourism to DMO managers.

Having said that, there is evidence that governments are not prepared to upgrade their traditional tourism statistical methods with Big Data models, even though Christophe Demunter, Head of Section at Eurostat, recommended that DMOs develop mixed-source, national tourism statistics that combine surveys and Big Data, and unequivocally stated that “ignoring innovation will push statistical authorities out of the information market” (Demunter, 2017:3). Governments can only take policy decisions based on available data (Lozano-Oyola, Blancas, González, & Caballero, 2012) and tourist surveys are currently used as the main source of data to develop national and regional tourism statistics (Saluveer et al., 2020). Eurostat’s current version of the “Methodological manual for tourism statistics” was published in 2014 and assumes that data will be collected through surveys, without a role for Big Data (Eurostat, 2014). However, tourist surveys are costly and most importantly in times of rapid change, collect data retrospectively.

At present, the market of Big Data sources is highly fragmented, including numerous private data providers that can provide valid tourism information (such as mobile telephony, banking sector through credit cards, online purchase of accommodation and flights, sentiment analysis in RRSS, etc.) (Demunter, 2017). This situation is a disadvantage for tourist destinations, which encounter technical, capacity and budgetary difficulties in accessing the necessary information. Tourist boards are experimenting with technologies such as tourist tracking, because of the latter's accuracy, immediacy and cost benefits (Shoval & Ahas, 2016). However, although Big Data has been used to calibrate, complement and provide greater accuracy to, traditional statistics (Batista e Silva et al., 2018; Demunter, 2017), it is still considered unconventional. Data is seldom collected systematically by offices of tourism statistics, and its use by DMOs and policy makers to inform decision-making is limited (Batista e Silva et al., 2018; Demunter, 2017). Policy prescriptions constrain the process of knowledge creation in public organisations (Hartley & Skelcher, 2008; Rashman, Withers, & Hartley, 2009) and this is most evident when policy objectives change and organisational systems are not able to adapt to the changes in an agile way (Pee & Kankanhalli, 2016; Sutcliffe & Court, 2005).

Although indicator systems can facilitate the work of managers (Holman, 2009; Lozano-Oyola, Blancas, González, & Caballero, 2019), for them to be useful, they must provide answers to a managers' real needs, integrating the academic approach and the political (Tanguay, Rajaonson, & Therrien, 2013) while not losing their usability to the managers (Bauler, 2012), who do not have to be experts in the field (Gallego & Font, 2019). This is a challenge for Big Data because, by definition, its results come from a large volume of data, extracted from a wide variety of sources and formats that require complex treatment processes. Furthermore, the granularity of the information that these sources allow, despite having a great analytical advantage, also makes it easy to deviate from the main objective. In most cases, efforts to develop and use Big Data have ended in intangible benefits (discussion forums, relationship building, greater awareness, etc.) (Gahin, Veleva, & Hart, 2003), while few cases have led to the development of new policies based on the evidence. Only one case of new policy is reported in academic journals, that of the use of mobile positioning data in Estonia to accurately generate national tourism statistics (Saluveer et al., 2020); information shared at the UNWTO's International Network of Sustainable Tourism Observatories shows that Estonia's National Institute for Statistics are complementing their national travel statistics with credit card details (Austria, France), and mobile phone data (Spain) (Demunter, 2017; UNWTO, 2019a).

Tourism administrations at different levels (national, regional and local) should draw up a common plan for working with the data providers, in order to avoid duplication of efforts. They should also demand the involvement of official statistical agencies in the use and dissemination of these new sources, as has been done with traditional statistics. Along these lines, it is worth highlighting the initiative of the European Commission (2020) that has reached a historic agreement with Airbnb, Booking, Expedia Group and TripAdvisor on the exchange of data through Eurostat. This involvement of official statistical agencies in members of the European Commission with online travel agencies would also favour the establishment of methodological standards, hitherto non-existent, that would favour comparability between destinations and guarantee the transparency and rigor of the process, along with the credibility of its results.

Recognising the relevance of these new sources has highlighted a lack of data analysts within DMOs and a need to train staff in new skills (Struijs, Braaksma, & Daas, 2014). Initially, the entire effort of DMOs was focused on direct purchase of Big Data or subscriptions to Big Data-based business intelligence platforms, but little time was spent on defining a work plan (with clear objectives and trained personnel) for what to do with the data once it was received. DMOs need to reassess what forms of evidence they consider valid to take policy decisions (Nutley, Walter, & Davies, 2003), as policy decisions are often based on inertia, ideology or short term financial considerations (Bowen & Zwi, 2005; Innes & Booher, 2000; Walker, 2000). It is important to remember that simply *having* data is not relevant; the value of the data lies in its ability to inform management and decision-making effectively. We need to apply user-oriented thinking to design tourism statistics (Demunter, 2017) and ensure that we clearly define the objective of gathering statistics, which is to provide timely and relevant information that managers can rely on for decision-making.

Conclusions

In this article, we have demonstrated the power of using operational Big Data: i) to acquire knowledge in order to reduce risk in situations of uncertainty (Williams & Baláž, 2015), and ii) to improve public sector organisational effectiveness (Pee & Kankanhalli, 2016). We have done this through the analysis of airline search and pick data from Skyscanner, thus creating a methodology for the early detection of reactivation of tourist markets. The aim is to support DMOs to take evidence-based, policy decisions to mitigate the effects of the crisis in their tourist destinations. In this crisis, DMO managers have understood that it is necessary to understand market behaviour and act quickly to restore confidence and stimulate demand. Thus, systems or methodologies, such as the one presented in this article, give managers powerful tools to monitor markets in real time, to anticipate their reactivation and to act accordingly by adjusting their strategies.

An extreme situation, that of the health crisis of COVID-19, has made Big Data become more relevant than ever in the tourism sector. UNWTO (2020b) states that it is essential that decisions and strategies adopted have an empirical basis, especially in times of crises, and proposes, as one of the measures to mitigate the socio-economic impact of COVID-19 and accelerate recovery, to invest in data, analysis and alliances that will allow for detailed and short-term monitoring of tourism development and its impact. However, while technical DMO staff may be able to generate valuable evidence through Big Data, the lack of common ground between their staff and the policy makers, who are supposed to take decisions based on such data, creates barriers to the use of Big Data (Nutley & Davies, 2000). The introduction of Big Data for DMO decision-making is constrained by how well the newly acquired data fits with an organisation's structure and values (Nutley et al., 2003). Therefore, the ability of a DMO to proactively respond to a pandemic such as COVID-19 will be determined, in part, by how much of an overhaul of organisational structures is required (Guenther, Williams, & Arnott, 2010), which will in turn require an overhaul in the values of those who manage such organisations.

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References

Anzai, A., Kobayashi, T., Linton, N. M., Kinoshita, R., Hayashi, K., Suzuki, A., . . . Akhmetzhanov, A. R. (2020). Assessing the impact of reduced travel on exportation dynamics of novel coronavirus infection (COVID-19). *Journal of clinical medicine, 9*(2), 601.

Batista e Silva, F., Herrera, M. A. M., Rosina, K., Barranco, R. R., Freire, S., & Schiavina, M. (2018). Analysing spatiotemporal patterns of tourism in Europe at high-resolution with conventional and big data sources. *Tourism management, 68*, 101-115.

Bauler, T. (2012). An analytical framework to discuss the usability of (environmental) indicators for policy. *Ecological indicators, 17*, 38-45.

Bowen, S., & Zwi, A. B. (2005). Pathways to "evidence-informed" policy and practice: a framework for action. *PLoS medicine, 2*(7), e166.

Chevalier, S., Choiniere, R., Bernier, L., Sauvageau, Y., Masson, I., & Cadieux, E. (1992). *User guide to 40 community health indicators*. Retrieved from Ottawa, Canada:

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., . . . Sun, K. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science*.

Chung, L. H. (2015). Impact of pandemic control over airport economics: Reconciling public health with airport business through a streamlined approach in pandemic control. *Journal of Air Transport Management, 44*, 42-53.

Cró, S., & Martins, A. M. (2017). Structural breaks in international tourism demand: Are they caused by crises or disasters? *Tourism management, 63*, 3-9.

Demunter, C. (2017). *Tourism statistics. Early adopters of big data? : 2017 edition. Doi 10.2785/762729*. Retrieved from Luxembourg:

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet infectious diseases, 20*(5), 533-534.

El Alaoui, I., Gahi, Y., Messoussi, R., Todoskoff, A., & Kobi, A. (2017). *Big Data Analytics: A Comparison of Tools and Applications.* Paper presented at the Proceedings of the Mediterranean Symposium on Smart City Applications.

European Commission. (2020). Commission reaches agreement with collaborative economy platforms to publish key data on tourism accommodation. Retrieved from: https://ec.europa.eu/commission/presscorner/detail/en/ip_20_194.

Eurostat. (2014). *Methodological manual for tourism statistics https://ec.europa.eu/eurostat/documents/3859598/6454997/KS-GQ-14-013-EN-N.pdf*. Retrieved from Luxembourg:

ForwardKeys. (2020). ForwardKeys. Retrieved from https://forwardkeys.com/

Gahin, R., Veleva, V., & Hart, M. (2003). Do indicators help create sustainable communities? *Local Environment, 8*(6), 661-666.

Gallego, I., & Font, X. (2019). Measuring the vulnerability of tourist destinations to the availability of air transport, using multi-criteria composite indexes. *Journal of Destination Marketing & Management, 14*, 100382.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International journal of information management, 35*(2), 137-144.

Gössling, S., Scott, D., & Hall, C. M. (2020). Pandemics, tourism and global change: a rapid assessment of COVID-19. *Journal of Sustainable Tourism, DOI: 10.1080/09669582.2020.1758708*.

Guenther, J., Williams, E., & Arnott, A. (2010). *The politics of evaluation: evidence-based policy or policy-based evidence.* Paper presented at the NARU Public Seminar Series, Darwin.

Hartley, J., & Skelcher, C. (2008). The agenda for public service improvement. In J. Hartley, C. Donaldson, C. Skelcher, & M. Wallace (Eds.), *Managing to Improve Public Services* (pp. 1–24). Cambridge: Cambridge University Press.

Holman, N. (2009). Incorporating local sustainability indicators into structures of local governance: a review of the literature. *Local Environment, 14*(4), 365-375.

Innes, J. E., & Booher, D. E. (2000). Indicators for sustainable communities: a strategy building on complexity theory and distributed intelligence. *Planning theory & practice, 1*(2), 173-186.

Instituto Nacional de Estadística. (2019). *Cuenta Satélite del Turismo de España. Revisión estadística 2019. (Spanish Tourism Satellite Account. 2019 Statistical revision) Retrieved from: https://www.ine.es/prensa/cst_2018.pdf*. Retrieved from Madrid:

Instituto Nacional de Estadística. (2020a). *Encuesta de Turismo de Residentes ETR/FAMILITUR (Domestic tourism survey ETR/FAMILITUR). Retrieved from: https://www.ine.es/daco/daco42/etr/etr0419.pdf*. Retrieved from Madrid:

Instituto Nacional de Estadística. (2020b). *Estadística de Movimientos Turísticos en Fronteras-FRONTUR. (Tourism Movement Border Statistics- FRONTUR) Retrieved from: https://www.ine.es/daco/daco42/frontur/frontur1219.pdf*. Retrieved from Madrid:

Jun, S. H., Vogt, C. A., & MacKay, K. J. (2010). Online information search strategies: A focus on flights and accommodations. *Journal of Travel & Tourism Marketing, 27*(6), 579-595.
Kuo, H.-I., Chen, C.-C., Tseng, W.-C., Ju, L.-F., & Huang, B.-W. (2008). Assessing impacts of SARS and Avian Flu on international tourism demand to Asia. *Tourism management, 29*(5), 917-928.
Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism management, 68*, 301-323.
Lozano-Oyola, M., Blancas, F. J., González, M., & Caballero, R. (2012). Sustainable tourism indicators as planning tools in cultural destinations. *Ecological indicators, 18*, 659-675.
Lozano-Oyola, M., Blancas, F. J., González, M., & Caballero, R. (2019). Sustainable tourism tags to reward destination management. *Journal of Environmental Management, 250*, 109458.
Nicolaides, C., Avraam, D., Cueto-Felgueroso, L., González, M. C., & Juanes, R. (2019). Hand-Hygiene Mitigation Strategies Against Global Disease Spreading through the Air Transportation Network. *Risk Analysis, https://doi.org/10.1111/risa.13438*.
Nutley, S., Walter, I., & Davies, H. T. (2003). From knowing to doing: a framework for understanding the evidence-into-practice agenda. *Evaluation, 9*(2), 125-148.
Pee, L. G., & Kankanhalli, A. (2016). Interactions among factors influencing knowledge management in public-sector organizations: A resource-based view. *Government Information Quarterly, 33*(1), 188-199.
Rashman, L., Withers, E., & Hartley, J. (2009). Organizational learning and knowledge in public service organizations: A systematic review of the literature. *International Journal of Management Reviews, 11*(4), 463-494.
Rocklöv, J., Sjödin, H., & Wilder-Smith, A. (2020). COVID-19 outbreak on the Diamond Princess cruise ship: estimating the epidemic potential and effectiveness of public health countermeasures. *Journal of travel medicine*.
Saluveer, E., Raun, J., Tiru, M., Altin, L., Kroon, J., Snitsarenko, T., . . . Silm, S. (2020). Methodological framework for producing national tourism statistics from mobile positioning data. *Annals of Tourism Research, 81*, 102895.
Shaw, R., Kim, Y.-k., & Hua, J. (2020). Governance, technology and citizen behavior in pandemic: Lessons from COVID-19 in East Asia. *Progress in Disaster Science, 6*(April 2020), 100090.
Shoval, N., & Ahas, R. (2016). The use of tracking technologies in tourism research: the first decade. *Tourism Geographies, 18*(5), 587-606.
Skyscanner. (2020). Skyscanner. Retrieved from https://www.skyscanner.com/about-us.
Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., . . . Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). *International Journal of Surgery*.
Struijs, P., Braaksma, B., & Daas, P. J. (2014). Official statistics and big data. *Big Data & Society, 1*(1), 2053951714538417.
Sutcliffe, S., & Court, J. (2005). *Evidence-based policymaking: What is it? How does it work? What relevance for developing countries*. Retrieved from London:
Tanguay, G. A., Rajaonson, J., & Therrien, M.-C. (2013). Sustainable tourism indicators: Selection criteria for policy implementation and scientific recognition. *Journal of Sustainable Tourism, 21*(6), 862-879.
UNWTO. (2019a, 22-23rd October 2019). *2019 Global INSTO Meeting*, Madrid.
UNWTO. (2019b). *Transport-related CO2 Emissions of the Tourism Sector. Modelling Results. Retrieved from https://www.e-unwto.org/doi/pdf/10.18111/9789284416660*. Retrieved from Madrid:
UNWTO. (2020a). COVID-19 travel restrictions https://www.unwto.org/news/covid-19-travel-restrictions.
UNWTO. (2020b). *Supporting jobs and economies through travel & tourism. Call for Action to Mitigate the Socio-Economic Impact of COVID-19 and Accelerate Recovery*. Retrieved from

https://webunwto.s3.eu-west-1.amazonaws.com/s3fs-public/2020-04/COVID19_Recommendations_English_1.pdf:
Walker, W. E. (2000). Policy analysis: a systematic approach to supporting policymaking in the public sector. *Journal of Multi-Criteria Decision Analysis, 9*(1-3), 11-27.
Williams, A. M., & Baláž, V. (2015). Tourism risk and uncertainty: Theoretical reflections. *Journal of Travel Research, 54*(3), 271-287.
Yang, Y., Zhang, H., & Chen, X. (2020). Coronavirus pandemic and tourism: Dynamic stochastic general equilibrium modeling of infectious disease outbreak. *Annals of Tourism Research*, 102913.