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The monthly rhythms of aviation:

A global analysis of passenger air service seasonality

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Abstract

Aviation seasonality has been acknowledged for a long time, but no global picture is available. Our paper fills this gap by conducting a worldwide analysis of monthly passenger air services at the airport level, and discussing factors that shape this temporality. Our study found that 36% of airports worldwide (accounting for less than 12% of seats) experience a significant degree of seasonality, and that larger airports are less affected. On the one hand, diverse travel purposes related to larger cities, hubbing, physical geography, remoteness and appropriate weather throughout the year induce stable seat capacity. On the other hand, climate profiles and institutional factors are key factors of peaks. Aviation seasonality has impacts for airport funders and managers, regional development and scholars.

Keywords

Aviation seasonality; air services; temporal patterns; spatial patterns of seasonality

1. Introduction

Demand and supply seasonality is intrinsic to long-distance travel and aviation since the latter is dominated by leisure purposes (Doganis, 2010; Vasigh et al., 2013; de Neufville and Odoni, 2013). Aviation seasonality affects airports and airlines. Exactly as tourism seasonality challenges both the social and economic spheres of destinations, imbalances between demand and supply in the aviation industry could have negative effects for the airline industry. Some airports are extremely busy at some times of the year, while others operate well below their capacity. Furthermore, aviation seasonality involves short-term employment contracts, and thus no permanent salaries; fixed costs related to inflexible facilities shaped for peak volumes are not covered all year round, and resources and facilities are inefficiently used. However, it has been argued that off-peak times may be welcome, for instance for maintaining facilities (Butler, 1998). In addition, since fluctuations in demand are mostly predictable, airlines can adapt their output to some extent through price and capacity management (Merkert and Webber, 2018). Strategies include operating given routes only during some periods and adapting frequency and/or aircraft size (which practically means swapping aircraft between routes).

Seasonality also has important consequences for many aspects of social life. A striking example of this is the current outbreak of coronavirus disease. Firstly, before the quarantine of Wuhan (from January 23, 2020), the spread of the SARS-CoV2 coronavirus from the provincial capital of Hubei to other Chinese cities and abroad was very rapid because it took place during the first two weeks of the 40-day Spring Festival (Peeri et al., 2020). Indeed, this holiday period gives millions of Chinese people the opportunity to make domestic and international trips to celebrate the Lunar New Year (Du et al., 2020). Secondly, the temporal coincidence between the huge circulation of SARS-CoV2 in northern Italy and the Carnival (or winter) holiday in several western European states (e.g., during February in the various German Länder, from February 8 to March 1 in the various French regions, and from February 22 to March 1 in Belgium) has contributed to the massive spread of the virus in Europe (Rudan, 2020). In February 2020, people living in the large cities of northern Italy met tourists in the winter sports resorts of the Italian Alps, mainly from Germany, France, Switzerland and Belgium. The transmission of the virus, therefore, was likely to have been very active in these winter resorts between SARS-CoV2-positive Italians and foreign holidaymakers, which in turn contributed to the spread of the virus in their home countries.

Despite this, published research works interested in aviation seasonality have been restricted mostly to case studies to the detriment of global perspectives. As a result, academic research on aviation seasonality has remained limited, despite both heuristic and operational-related issues. Consequently, the patterns of aviation seasonality remain poorly known, and their factors still need to be explored in depth.

In this context, the aim of this paper is twofold. First, to assess the degree and spatiality of seasonality in air services; and second, to identify the factors related to monthly variations or constancy. In contrast with existing publications, the analysis is not restricted to a case study. It is geographically comprehensive, considering global data on all regular air services at the airport level. In this sense, it contributes, both heuristically and practically, to research on tourism and short-term mobility. In terms of knowledge on the one hand, it allows a better understanding of the seasonality of travel, particularly by highlighting factors that are not well known. On the other hand, on a practical level, it renews the approach to the impacts of seasonality by taking into account the diversity of the stakeholders concerned (airport funders and managers, regional policymakers, airline managers).

The remainder of this paper is as follows. Section 2 proposes a state of the art of seasonality in the air industry. Section 3 introduces the data and methods considered. Section 4 unveils the results and reflects on the factors influencing air service seasonality. Section 5 discusses the impacts, and Section 6 presents the conclusions.

2. Seasonality in aviation: A state of the art

2.1. Cases studies and temporal concentration indices

Scholars have acknowledged seasonality in aviation for a long time. For instance, Sealy (1966) and Charlier (1981) showed strong seasonal variations, respectively, for British European Airways traffic between 1963-1964 (a ratio of 2.33 between peak and low months) and for Lyon Airport in 1978 (a ratio of 1.34). In the same vein, books on aviation economics, aviation management and airport design (Doganis, 2010; Vasigh et al., 2013; de Neufville and Odoni, 2013) have recalled that the airline business is subject to travel seasonality. However, the typical research is restricted to case studies (rather than unveiling the global picture) and to degrees of seasonality indices rather than typologies of seasonality. Authors have considered either the supply or demand. Although this paper focuses on the supply, we also report research works interested in the demand, as far as they bring relevant findings for us.

On the supply side, several authors have tried to assess the degree of seasonality for a sample of airports, airlines or routes. Reynolds-Feighan (2021) considers a Gini index to assess the temporal concentration of air traffic (in monthly scheduled seats supplied by the airlines). To the best of our knowledge, this is the most ambitious research in terms of spatial coverage since she considers all airports worldwide. Results are shown at the scale of macro-regions and for selected airports only. Koo et al. (2016) also consider a Gini index to assess the temporal concentration of scheduled seats, considering 607 airports. However, the degree of seasonality is actually part of a composite index[1], and there is no comprehensive geographical analysis of the results. Neal (2014) completes traditional investigations of airline networks through the lens of the so-called complex network approach by notably adding a seasonal approach (winter vs. summer). Applied to the US domestic market, he finds that one third of edges are not operated during both seasons. Spatial patterns suggest links with climate patterns; Florida, for instance, accommodates several winter routes. All other published works have considered smaller samples. For instance, Kraft and Havlíková (2016) compare the number of flights operated from 10 of central Europe's airports in February and June. They find three main profiles at the airport level (namely, no seasonality, summer peak and winter peak), notwithstanding the fact that the number of seats can vary for the same number of flights. Their maps also compare routes and countries open to passengers in February and June. In addition, Reynolds-Feighan (2018) compares the three main US airlines and their regional sub-contractors acting as feeders. She uses two Gini indices to assess the extent to which air services are constant or not over months (in seats, at both network and route levels). She finds that most of the routes operated by regional feeders experience more seasonality than those operated by the main airlines. Southwest Airlines, considered for comparison purposes, also has a low seasonality profile. In addition, qualitative research based on interviews suggests the seasonality in tourism in Australia would be a factor of unprofitability at the route level, and thus of air route suspension (Lohmann and Vianna, 2016). If this scenario is in fact the case, it would mean that not all airlines could swap smaller and larger planes across their network to deal with temporal changes in demand.[2]

On the demand side, Fernández-Morales et al. (2016) investigate the seasonality of domestic and international tourism by air to Great Britain, notably through the Gini coefficient, using the monthly number of trips. Beyond low overall seasonality, domestic tourism is affected more by seasonality. However, if seasonality is disaggregated by country of origin and/or by travel purpose, one finds a wide range of patterns. Business travel is temporally more stable, followed by visiting friends and relatives (VFR) and by holidays. Coshall et al. (2015) perform a similar investigation but disaggregate the investigation by region of destination (in Scotland). Here too, the Gini coefficient varies by place and by travel purpose. Halpern (2011) also assesses the degree of seasonality through a Gini index, considering air passenger flows to Spain at the level of airports (34 largest terminals). There is a wide range of seasonality degrees, with more stable patterns, notably in large cities (including Madrid and Barcelona) and at tourist resorts with good weather all year round. Interestingly, the case of Ibiza (highest seasonality within the sample) shows that domestic seat capacity is the most stable while charter (vs. scheduled) and international (vs. domestic) passengers induce the highest level of seasonality.

Others scholars, like Merkert and Webber (2018), look into the interaction between supply and demand by analysing the influence of airline seasonal behaviour on pricing and capacity management. Their findings show that in most cases there is stronger seasonal variation in the average airfare than in the seat factor, and, based on their model, suggest that airlines should aim for more seasonality in the seat factor than the average airfare.

Finally, authors have also investigated whether the advent of low-cost airlines has decreased seasonality in tourist flows. Considering Jeju Island in Korea, Chung and Whang (2011) conclude that the effect is marginal.

In addition, it is worth noting that several authors working on air travel have considered splitting their results according to seasons, even though seasonality is not their main focus.

[1] Based on places, temporality and carriers.

[2] Either due to fleet mix or to the fact that all routes operated by a given airline would follow the same seasonal patterns.

For instance, Tsekeris (2009) builds a dynamic model of air travel demand in the context of sea/air intermodal competition in Greece. The econometric exercise is based on common factors such as airfares, population and the number of beds in legal accommodations for visitors, but the results are differentiated into a model in February and another one in August. The conclusion is that the estimators (and thus the magnitude of factors) significantly changes, which is notably interpreted by the fact that travellers travel more for mandatory purposes during winter.

2.2. The factors of seasonality

The above paragraphs suggest a strong link between leisure/tourism seasonality and aviation seasonality (Papatheodorou, 2002). Indeed, leisure or personal travel purposes, such as holidays and VFR, are often the dominant reasons for flying (Dobruszkes et al., 2019) and are seasonal in nature (BarOn, 1975; Baum and Lundtorp, 2001). Tourism seasonality is due to a range of push-and-pull factors that relate to the attributes of origins and destinations. These factors can be sorted according to natural elements (including the weather, hours of sunshine and presence of snow), institutional factors (including school and public holidays and religious events), while they also relate to social norms and habits (Koenig-Lewis and Bischoff, 2005). One understands from this that tourism seasonality also has a strong spatial dimension (Butler, 1998), with temporal profiles subject to strong variations across both emitting and attracting places subject to their natural, institutional and social attributes (see, e.g., Coshall et al., 2015; Fernández-Morales et al., 2016). Apart from leisure tourism seasonality, other factors could affect aviation seasonality across months, such as shorter but recurrent events (e.g., pilgrimages, meetings, congresses and fairs) or changes in the pace of business travel during the year. Conversely, it is likely larger/hub airports experience lower seasonality because of a wide variety of routes with various seasonality profiles, or even no significant seasonality, as suggested by Fernández-Morales et al.’s (2016) results.

As a conclusion, one understands that research on seasonality in aviation does exist and follows various pathways and approaches. However, existing publications, although quite interesting and stimulating, share two restrictions. First, there is almost no acknowledgement of various potential profiles of the temporal variations. In fact, no typology of seasonality has been proposed. Instead, the authors have considered indicators that render the degree of seasonality (typically through the Gini index based on monthly passengers or seat capacity, or the ratio between minimal and maximal monthly figures), which cannot render specific profiles. Second, a global assessment of seasonality is lacking, and the results of the only global assessment exist only at the macro-region level. Addressing these two points is the central focus of this paper.

3. Data and methods

3.1. Data

Our analysis is based on the provision of passenger regular air services at the airport level. The rationale for considering the supply is twofold. First, the supply is a good expression of airlines’ network strategies and of their ability to adapt supply to demand fluctuations. Second, no source details the temporal variation of demand over a year for a global set of airports. At best, data are available for a restricted range of countries, and usually after contacting relevant agencies one by one. In contrast, supply has become available in a comprehensive manner for more than two decades. As a result, there is a balance between sample size and spatial coverage, on the one hand, and demand-vs-supply focus, on the other hand.

As in Reynolds-Feighan (2021), data have been extracted from the 2019 OAG[3] Schedules Analyser, a commercial database of scheduled airline networks, seat capacity and timetables (among others), which is a very comprehensive source for analysing both the geography and temporality of worldwide air services. Information is disaggregated at the flight number and airport-pair levels and includes several key variables, such as each flight's frequency, number of seats, operating period, timetables and carrier. 2019 is the last "normal" year before the whole aviation industry was disrupted by the Covid19 crisis. For that year, the dataset includes no less than 797 airlines, 4,155 airports and 67,467 airport-pairs. An important restriction of the OAG Schedules dataset is that it does not include 'non-scheduled' (i.e., 'non-regular') flights. The main consequence is that full charter flights are supposed to be excluded. However, ICAO estimates that in 2019, non-scheduled revenue passengers accounted for only 3.8% of international revenue passengers-km (against 7.1% in 2009 and 12.8% in 1999).[4] Also, currently, a portion of charter passengers is carried on so-called scheduled or regular flights, notably in liberalised markets where the distinction between 'regular' (aka 'scheduled') and 'non-regular' (aka 'non-scheduled') has lost importance, and where charter airlines have become traditional leisure airlines (see Ramos-Pérez and Dobruszkes, 2019, for a detailed discussion). Such airlines are normally covered by OAG. As a result, seasonality due to chartered operations is only partially missed. Nevertheless, it would be underestimated for those tourist places (notably in Asia) that are still significantly served by charter flights (Wu et al., 2018).

3.2. Methodology

We first extracted from OAG the number of scheduled seats provided by airlines for each airport and month. This led to a matrix of 4,155 airports x 12 months. For each airport, we computed the share of seats of the airport's annual total. To avoid statistical noise (i.e., irrelevant patterns due to specific events), we then excluded airports with less than 260 flights per year, a threshold empirically found. Airports with supply that started during 2019 or ended somewhere in 2019 were also excluded. This left us with 3,303 airports, whose temporal profile could be considered complete and stable. These airports are spread all over the world (222 country codes).

Two quantitative analyses were then performed: a measure of temporal concentration and a typology of seasonality profiles. As for the former, we opted for the well-known Gini (G) index, which is clearly the most frequent metric in the academic tourism literature (Cisneros-Martínez et al., 2018). Although alternative indices also exist (see Duro, 2016), the Gini index makes our results comparable with previous research works cited in Section 2. Following Halpern (2011) after many other authors, the Gini index is obtained as:

$$G = \left| 1 - \sum_{i=1}^{N} (\sigma X_i - \sigma X_{i-1})(\sigma Y_i + \sigma Y_{i-1}) \right|$$

[3] Airline Official Guide.

[4] Source: ICAO annual reports, available at https://www.icao.int/about-icao/Pages/annual-reports.aspx (retrieved on November 10, 2021).

where σX is the cumulative share of months, σY is the cumulative share of seats and N is the number of months. G equals 0 in the case of a perfectly stable pattern over time, while it tends to be 1 along with an uneven temporal pattern.

Table 1**Erreur ! Source du renvoi introuvable.** illustrates selected temporal patterns based on breakdown values and the resulting Gini index, including extreme cases. It is clear from this table that airports experiencing capacity peaks (in the sense of one or several values that are higher than in other months) get higher Gini values. In contrast, airports with flatter temporal profiles get lower Gini values.
Such an index is useful for unveiling the degree of temporal concentration/dispersion of each airport and can be plotted against potential factors (e.g., airport size or spatial typology). However, it could not lead to a typology of seasonality profiles. Indeed, as in any dispersion index, various temporal patterns may give the same Gini index value. As a result, the matrix of monthly shares was submitted to a principal component analysis (PCA), a well-known factorial analysis technique (here performed through R). Its principle is to transform a large matrix of p variables into a smaller number of new axes named ‘principal components’ (or more generally, ‘factors’). This is done by seeking redundancy in the matrix, so the original variance can be condensed through an orthogonal transformation (see, e.g., Rogerson, 2001). The first principal component renders as much variance as possible; the second renders as much remaining variance as possible while being orthogonal to the first principal component; etc. PCA is often used as a means to explore data. Key results of PCA are factor loadings and scores, which will be explained in the next section, along with the results.

Airport	**Country**	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**	**GINI**
Korhogo	Ivory Coast	8.5%	8.2%	8.5%	7.9%	8.5%	8.2%	8.5%	8.5%	8.2%	8.5%	8.2%	8.5%	**0.0118**
Asyut	Egypt	7.4%	6.4%	7.5%	7.7%	8.5%	9.6%	8.9%	10.3%	8.5%	7.1%	8.2%	9.9%	**0.0780**
Kinshasa	D.R. Congo	7.8%	6.5%	6.9%	6.4%	7.1%	7.5%	8.0%	9.1%	9.7%	9.9%	10.1%	10.9%	**0.1008**
Parintins	Brazil	4.9%	6.3%	5.5%	4.1%	9.3%	12.3%	12.1%	9.1%	8.9%	9.1%	9.1%	9.3%	**0.1653**
Aurukun	Australia	10.3%	9.7%	10.0%	8.8%	10.9%	9.7%	11.2%	10.3%	10.3%	3.6%	2.7%	2.4%	**0.1889**
Tumushuke	China	0.3%	3.6%	4.8%	8.4%	9.3%	8.5%	9.6%	10.3%	10.7%	10.9%	11.6%	12.1%	**0.2179**
Juina	Brazil	4.8%	0.2%	4.8%	5.3%	5.5%	4.3%	11.3%	14.2%	10.6%	16.8%	11.3%	10.8%	**0.3089**
Karpathos	Greece	2.3%	2.0%	2.6%	3.2%	5.7%	14.7%	20.3%	22.3%	16.9%	4.9%	2.7%	2.5%	**0.4637**
Skiathos	Greece	0.4%	0.5%	0.5%	1.1%	10.3%	16.5%	24.8%	25.6%	17.0%	2.3%	0.5%	0.5%	**0.6020**
Plettenberg Bay	South Africa	35.3%	14.8%	12.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.0%	34.1%	**0.7268**

Table 1. Selected temporal distributions and resulting temporality indices (based on seats offered in 2019). SR: Seasonality Ratio.

4. Unveiling the diversity of seat capacity seasonality

4.1. The degree of seasonality

Figure 1 shows the cumulative distribution of the temporality index by airport. The mauve line is not weighted (each airport has the same weight). Most airports have low Gini values (for instance, the Gini index is lower than 0.1 for 73.4% of the airports), which means they experience rather constant seat capacity over the year. Interestingly, the curve is even more dissymmetric if results are weighted by seats supplied (see the green curve). This suggests that larger airports experience more stable seat capacity than smaller airports. Figure 2 confirms this by clearly showing that nearly all large airports have limited peaks. However, the opposite is not true: smaller airports can experience both constant supply and hard peaks.

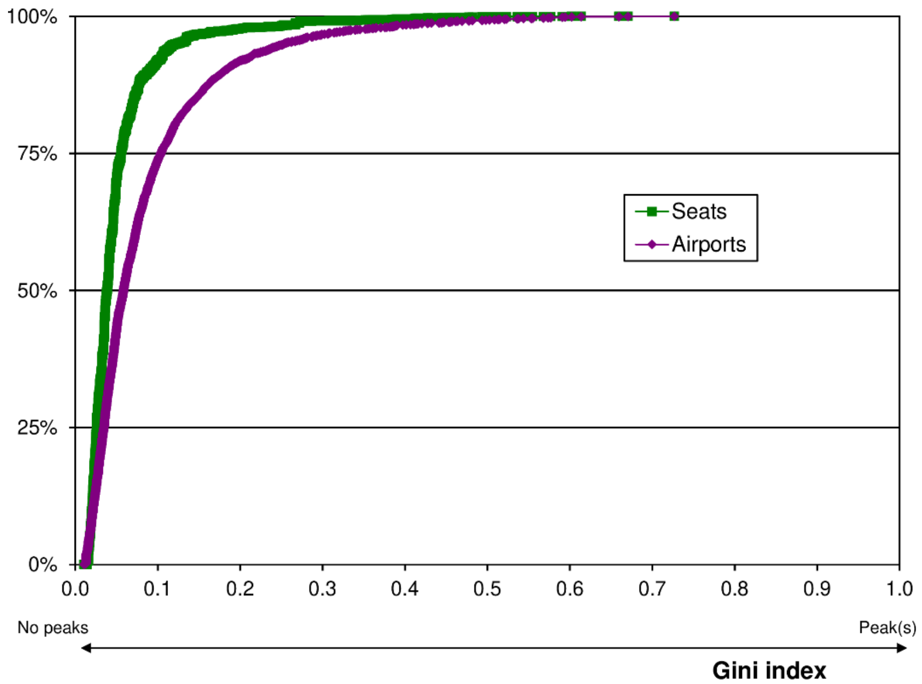

Figure 1. 2019 Temporality index cumulative distribution (1 dot = 1 airport, n=3,303)

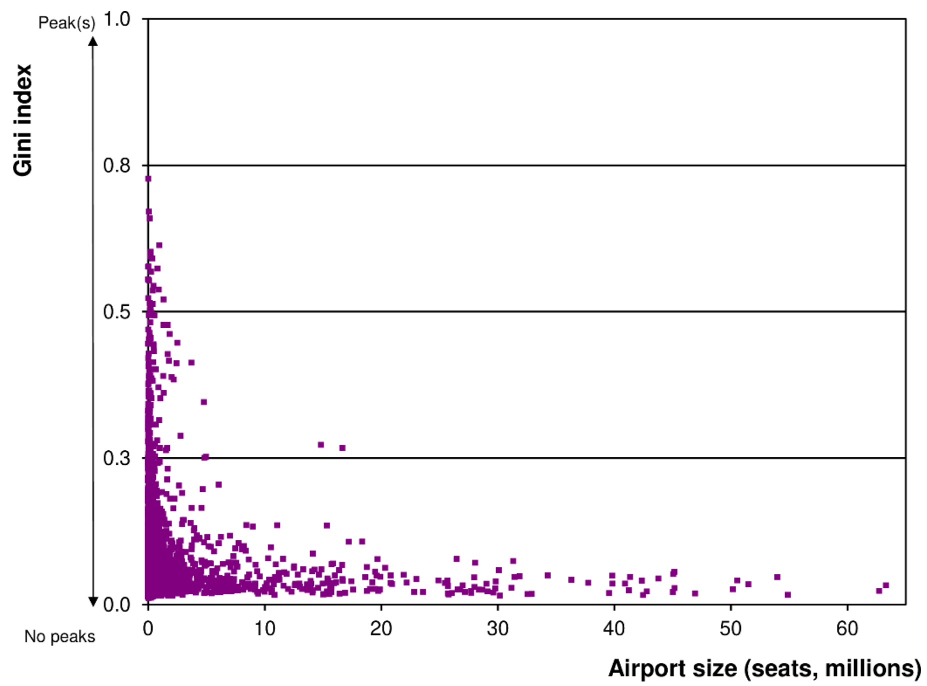

Figure 2. 2019 Temporality index against airport size (1 dot = 1 airport, n=3,303)

At this stage, it is desirable to find a threshold to draw a line between airports with peak(s) and airports with seat capacity that could be considered almost constant. To do so, the temporality index was submitted to a breakdown (aka natural breaks) analyser based on its cumulative distribution. Indeed, when proceeding with data clustering or selecting class intervals, it has long been considered that breakdowns are specific values that mean something (Mackay, 1955; Jenks and Coulson, 1963; Evans, 1977). The main breakdowns, along with the extreme values, are actually the selected cases shown in Table 1**Erreur !**

Source du renvoi introuvable.. From this table, the Gini value of 0.0780 is an indicative minimal threshold for uneven temporal distributions of seats. This value nearly coincides with the seasonality ratio value of 1.5, which is usually considered in the industry as a threshold for identifying the traffic of an airport as seasonal (ACI, 2018). On this basis, 63.9% of airports (2,111) accounting for 88.1% of the seats, are not significantly affected by temporality unevenness. And conversely, 36.1% of the airports (no less than 1,192 airports), accounting for 11.9% of the seats, significantly face peaks in terms of air services and thus seasonality effects.

4.2. Which seasonality profiles?

In order to investigate seasonality patterns, let us move to the PCA's key results. Table 2 shows that three PCs have an eigenvalue greater than 1, which means they restore more information than one single variable. With only the first two PCs, two thirds of the variance contained in the original matrix is restored. Figure 3 shows the PCA's factor loadings for PC1 and PC2. Factor loadings are the linear correlation coefficients (R) between the original variables (namely, the share of seats for each of the 12 months) and the PCs, and thus range between –1 and +1.[5] Factor loadings are a key result because they make it possible to interpret the PCs' meaning. PC1 clearly shows a contrast between winter and summer, with highly positive loadings for June to September and highly negative loadings for December to March (or November to April). As for PC2, it rather contrasts autumn with spring, with October to December on the one side and March to June on the other side. Table 3 makes the connection between PCs and seasons in each hemisphere.

Component	Eigenvalue	Variance	Cumulative variance
PC1	5.448	45.4%	45.4%
PC2	2.793	23.3%	68.7%
PC3	1.387	11.6%	80.2%

Table 2. Results of the PCA (I) – Principal components

[5] Factor loadings are significant (considering α=5%) if there are not between $-1.96/\sqrt{n}$ and $+1.96/\sqrt{n}$. With n=3,213, thresholds are thus ±0.035.

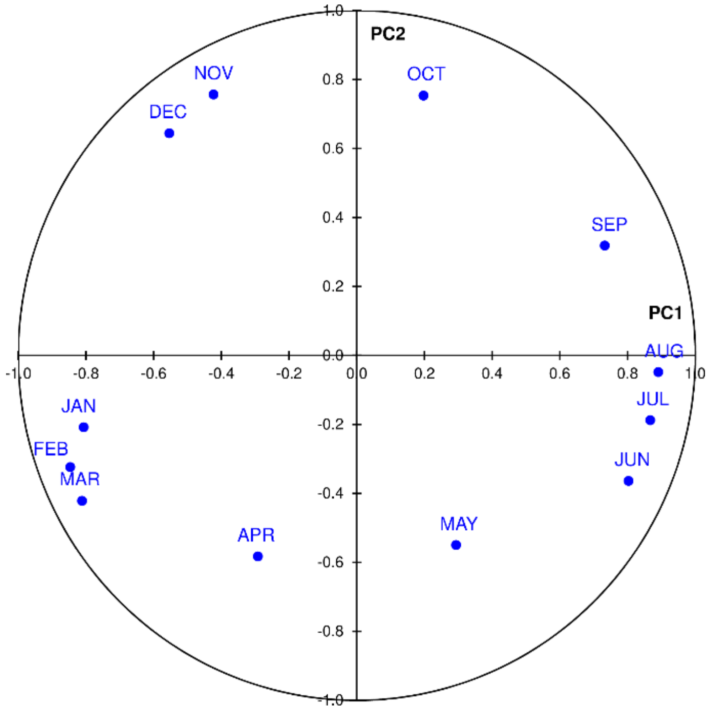

Figure 3. Results of the PCA (II) – Factor loadings (1 dot = 1 original variable)

	PC1 factor loadings		PC2 factor loadings	
	Positive	Negative	Positive	Negative
Northern Hemisphere	Summer	Winter	Autumn	Spring
Southern Hemisphere	Winter	Summer	Spring	Autumn

Table 3. Interpreting the PCs

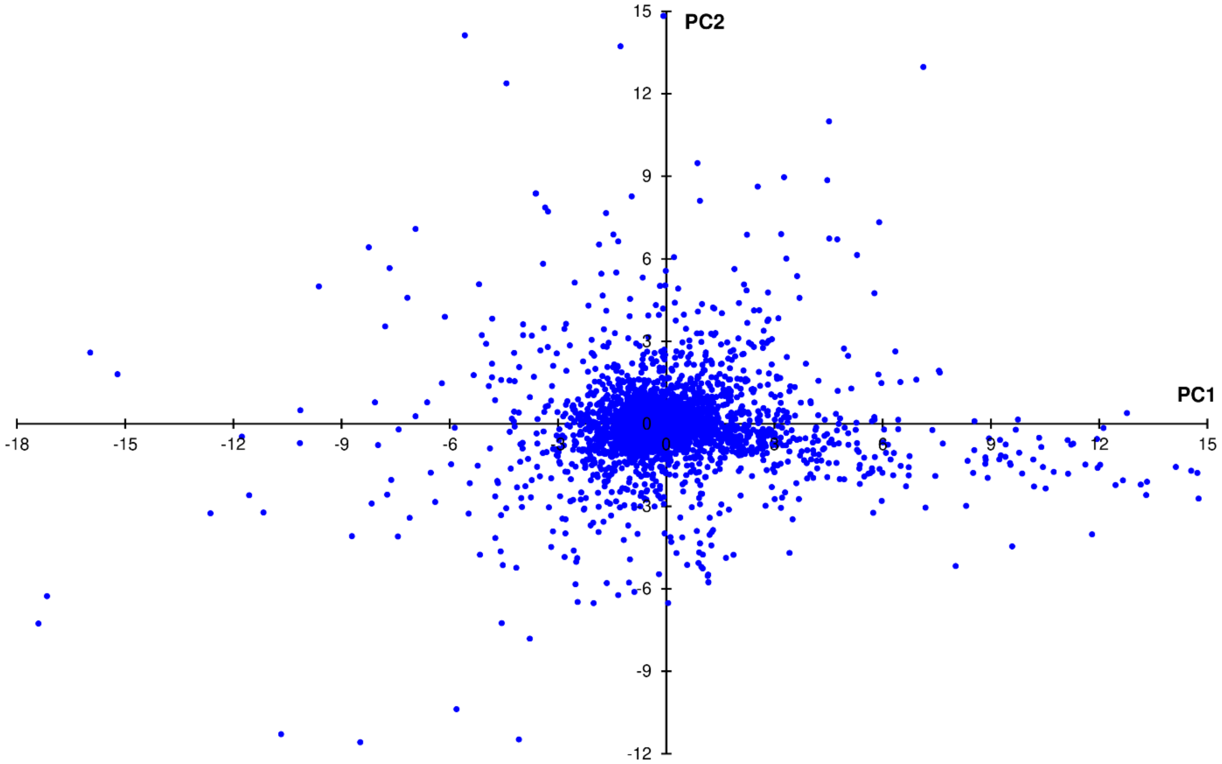

Figure 4. Results of the PCA (III) – Scores (1 dot = 1 airport)

Finally, Figure 4 shows the PCA's scores, which give the position of each airport on the PCs. This should be interpreted in line with PCs' meaning (Table 3). Scores are a standardised measure, so their mean equals zero. On a given principal component, a score of 0 means the airport has the same temporal profile as the whole sample, on average. And negative/positive scores mean that related airports are characterised more by variables that have negative/positive factor loadings, respectively.

As a result, scores on PC1 should be understood as follows:

- Higher positive scores involve a summer peak in the Northern Hemisphere and a winter peak in the Southern Hemisphere, stronger than for a whole sample.
- Higher negative scores involve a winter peak in the Northern Hemisphere and a summer peak in the Southern Hemisphere, stronger than for a whole sample.
- Scores close to zero involve either constant seat capacity across months or peaks in both summer and winter or erratic patterns.

Similarly, scores on PC2 should be understood as follows:

- Higher positive scores involve an autumn peak in the Northern Hemisphere and a spring peak in the Southern Hemisphere, stronger than for a whole sample.
- Higher negative scores involve a spring peak in the Northern Hemisphere and a spring peak in the Southern Hemisphere, stronger than for a whole sample.
- Scores close to zero involve either constant seat capacity across months or peaks in both autumn and spring and winter or erratic patterns.

The picture emerging from Figure 4 suggests a diversity of seasonality profiles, including no peak, one peak in one specific season, and one peak over two seasons (e.g., spring plus summer). Combining the Gini seasonality index and the PCA's scores (Figure 5), one notes most airports with peak(s) (G≥0.0780) have high PC score values (scores <-1 or >1), and thus do not combine winter and summer peaks or autumn and spring peaks. In addition, given the continuum of PC score values (see Figure 4), it is arguably vain to design a discrete typology through quantitative methods such as hierarchical classifications. However, mapping these scores will help us to consider seasonality patterns and related factors.

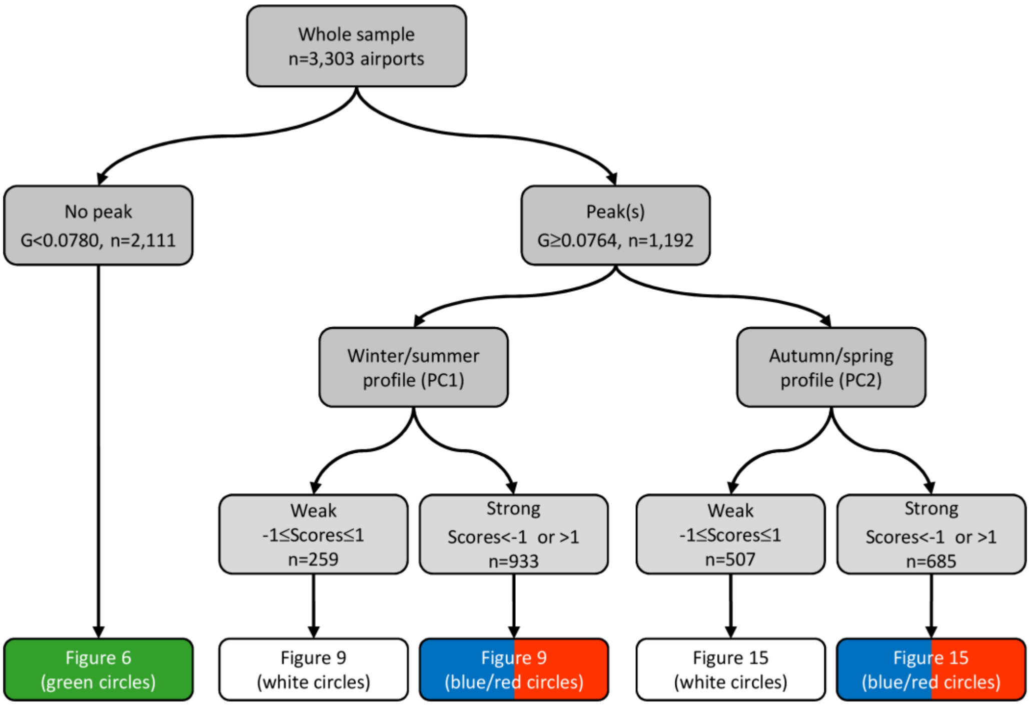

Figure 5. Combining the Gini seasonality index and the PCA's scores

4.3. The geography and factors of seasonality profiles

4.3.1. No-peak airports

Let us first discuss the geography of no-peak airports, highlighted by Figure 6. This group includes most of the largest airports but also many smaller ones. There are several factors shaping such stable temporality at the airport level.

First, there is a size effect, considering that most large airports are not significantly affected by seasonality patterns (see Figure 2). These airports usually serve big cities, including so-called global/world cities, which accommodate leading international firms and thus significant business travel, which is supposedly less affected by seasonality than leisure tourism. These cities also attract many immigrants (Sassen, 2005) who generate VFR travel. In addition, they often are major tourist destinations (e.g., New York, London, Paris, Amsterdam and Hong Kong). All together, this would induce a large range of travel purposes, and thus a high level of demand for air travel (and thus for airline seat capacity) at any time of the year. In addition, main airlines have mostly located their hub(s) at the largest cities' airports. This means transferring traffic is added to local traffic. By interconnecting a wide range of origins and destinations, a hub mixes various travel purposes, and this likely contributes to more stable seat capacity within the year. This is illustrated by the case of Beijing Capital Airport, the world's second busiest airport according to various metrics in 2019 (Figure 7).

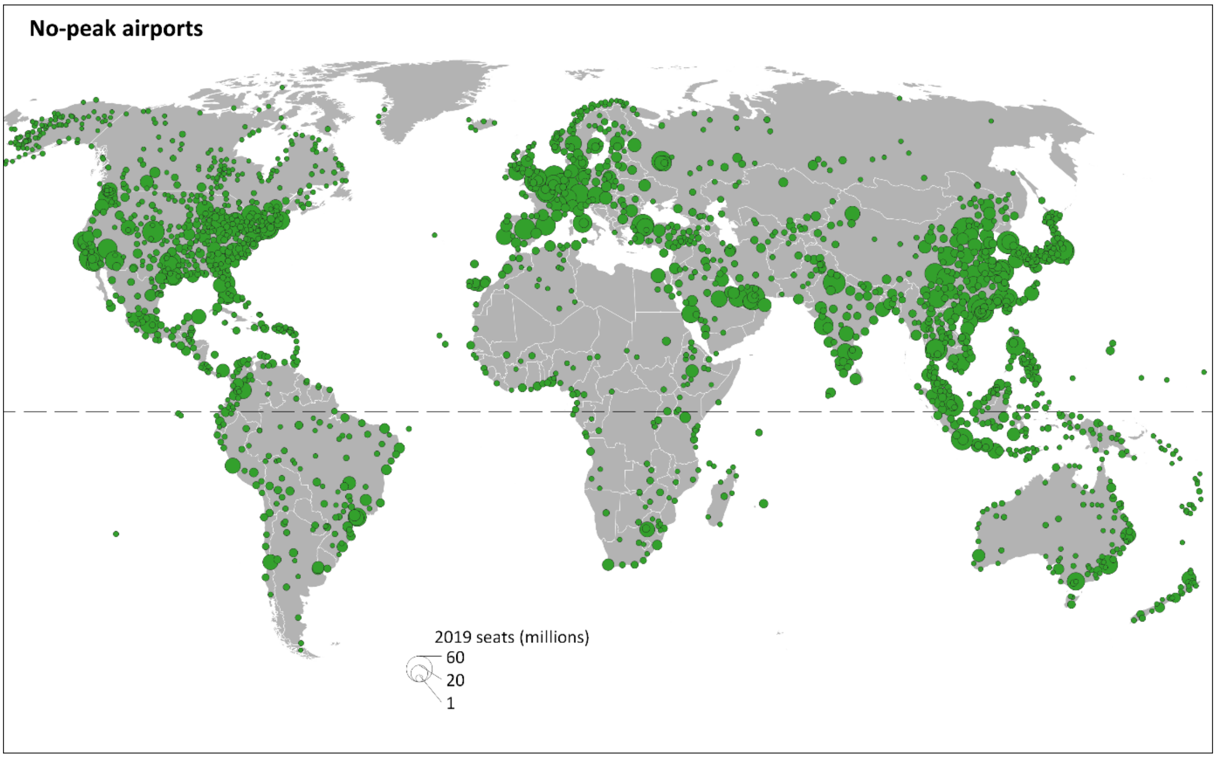

Figure 6. No-peak airports.

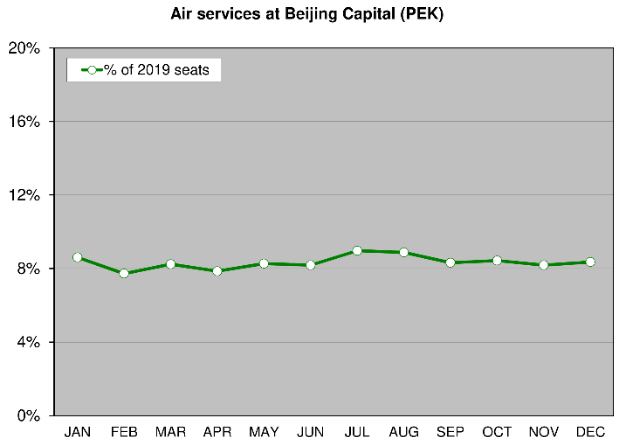

Figure 7. Monthly share of annual seat capacity at Beijing Capital Airport, 2019. Source: Authors' computations based on OAG.

Second, and beyond the airport size effect, lack of alternatives also appears as a key factor of no seasonality. When inter-city distances are rather long, more people are likely to fly (all other things being equal) and such effect would be reinforced in the case of weak passenger railways and the absence of high-speed rail (e.g., in the US and Australia) (Givoni and Dobruszkes, 2013). Beyond distance, the lack of alternatives is also related to the lack of reliable, safe and efficient surface options (e.g., in most of Africa) and in cases of insularity and adverse topography (such as in east and Southeast Asia). Countries' remoteness is also a major factor for those places that can only be reasonably accessed by plane (such as Australia and New Zealand) (Goetz and Budd, 2014).

Third, at medium- to small-sized airports, the lack of seasonality results from a low dependence on outbound or inbound leisure and VFR travellers. Industrial cities in developing countries provide good examples: the purchasing power of the population is not sufficient to generate outbound tourism flows, and the tourism offer is too weak to attract domestic or international tourists. In Argentina, for instance, the industrial city of Bahia Blanca has relatively constant air services, while Mar del Plata is a coastal resort with a clear seasonal profile (peak during the Southern Hemisphere's summer).

Fourth, airports that depend heavily on tourist, VFR or even pilgrim flows may nevertheless have a stable supply of seats throughout the year. This is the case first for tourist resorts with favourable weather throughout the year. As part of the Canary Islands in Spain, Tenerife is a typical example (Figure 8, left) in that it combines an appropriate climate (Figure 8, right), proximity to mainland Europe, belonging to the European passport-free Schengen area, political stability and security. There is only some more seat capacity in winter, when the weather in the Mediterranean basin is not suitable for sun-related tourism.

Fifth, apparent cases of a stable temporal pattern can relate to places where a peak is actually carried out by charter flights, which are not part of the OAG database. This includes airports near pilgrimage sites (e.g., Jeddah for Mecca) (Strale, 2009); airports in emerging tourist destinations served by charters before being served by regular airlines; and regional airports that are part of airport systems benefitting from charter services during peak holiday seasons (Jimenez et al., 2017).

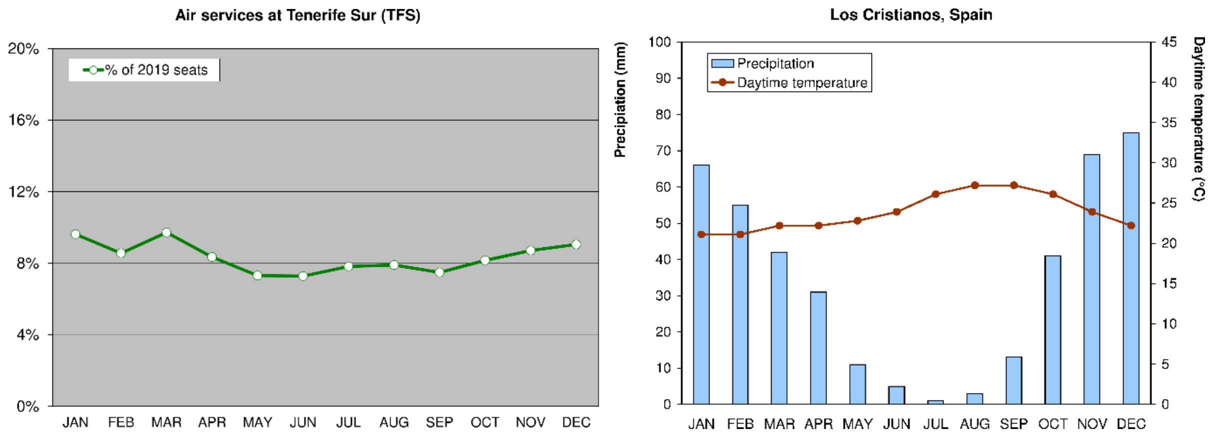

Figure 8. Monthly share of annual seat capacity at Tenerife Airport and climate data of a local resort.
Sources: Authors' computations based on OAG and www.weatherbase.com.

Finally, many small airports have a low service limited to one or two daily flights to the national capital and/or to a closer regional city. Such service can be regulated by public air services schemes, such as the US Essential Air Services scheme (see Fageda et al., 2018), which may facilitate the provision of air services notwithstanding temporal variations in demand.

4.3.2. The winter-summer and autumn-spring contrasts

Figure 9 shows the geography of the PCA's scores on PC1, and thus the geography of seasonality based on the winter/summer contrast. This map excludes stable airports, which are shown in Figure 6. The map contains useful information and should be interpreted having in mind the attributes of places and the fact that these places can be mostly emitting air traffic, mostly receiving air traffic or both, as our dataset cannot discriminate the directionality of air travel.

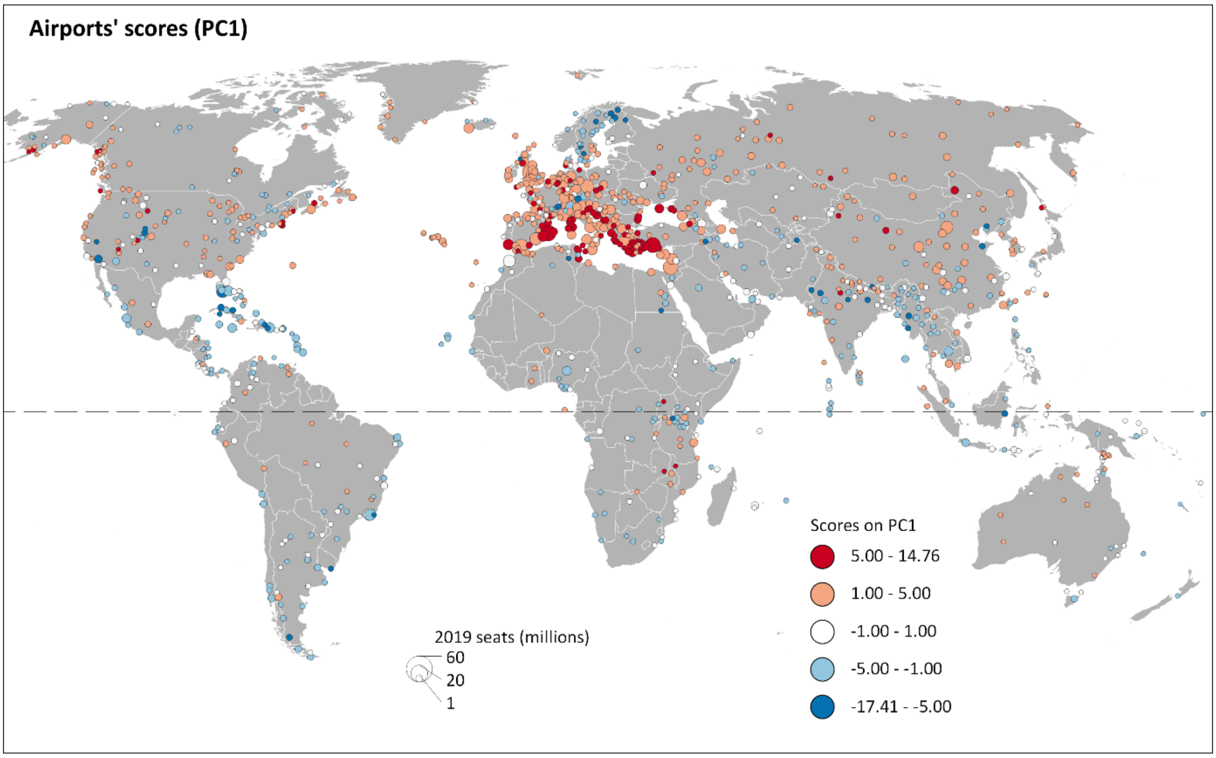

Figure 9. PCA scores (PC1), winter-summer contrast.
Reds highlight summer in the Northern Hemisphere and winter in the Southern Hemisphere.
Blues highlight winter in the Northern Hemisphere and summer in the Southern Hemisphere.
Airports without peaks have been excluded.

Figure 9 first shows a major division between two major tourist basins, namely the Florida-Caribbean (all blue on the map) and the Mediterranean (all red on the map). These basins are the quintessence of more general models related to climate at both destinations and origins. The Florida-Caribbean model offers mild or warm weather during the Northern Hemisphere's winter when it is cold or very cold at higher latitudes. The model includes resorts in Florida (e.g., Fort Myers), south California (e.g., Palm Springs), the Caribbean islands (e.g., La Romana in Dominica and Varadero in Cuba), Central America (e.g., Liberia in Costa Rica and Manzanillo in Mexico) and some resorts on or around the Red Sea (e.g., Luxor in Egypt). Figure 10 illustrates this group with La Romana, Dominica, and Palm Springs, USA. Note that part of these tourist spots can be too hot and/or too wet to accommodate tourists during the counter season (for instance, it is around 40°C in Palm Springs, California, in summer, see Figure 10).

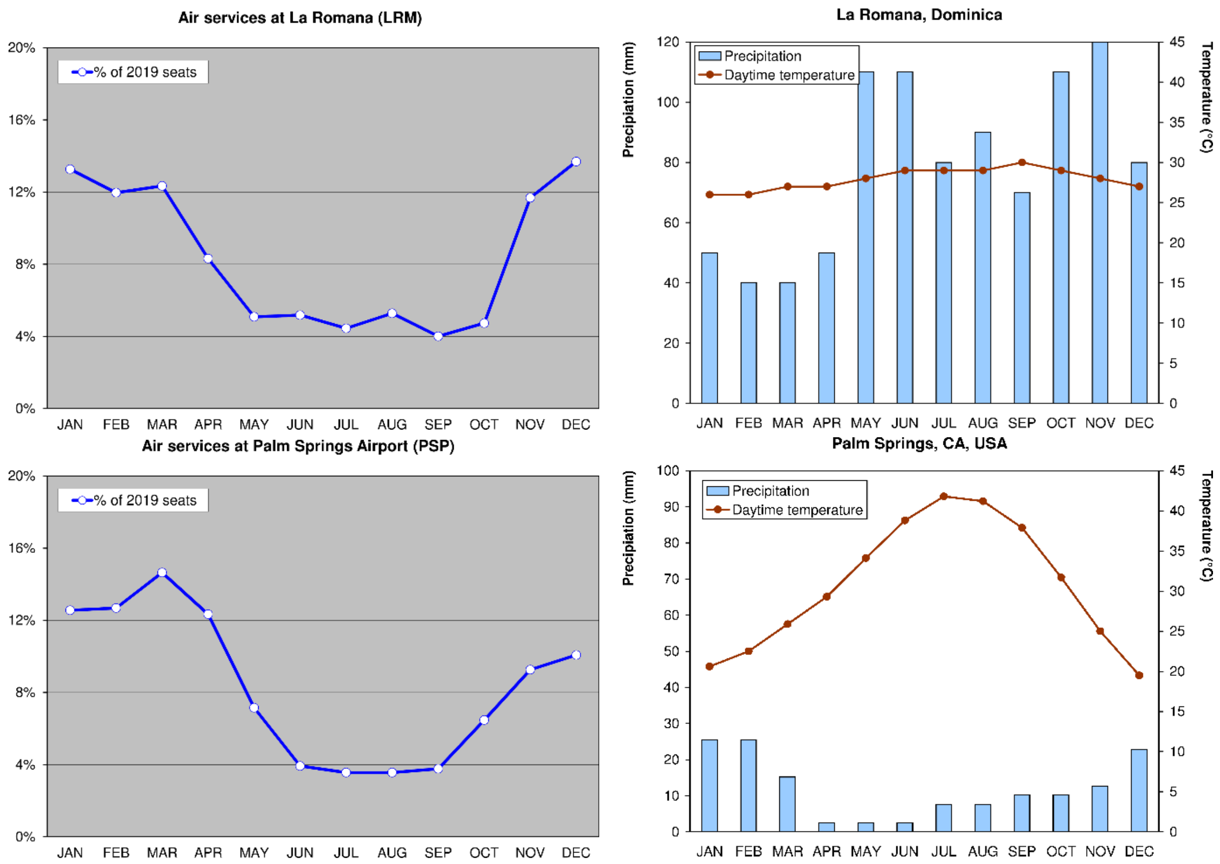

Figure 10. Monthly share of annual seat capacity at La Romana Airport and Palm Springs, and climate data of a local resort.
Sources: Authors' computations based on OAG and www.weatherbase.com.

The case of Hurghada in Egypt is an intriguing variant of this model. This is a typical winter/spring coastal resort for northern/western Europeans seeking to escape the cold winter (Vignal, 2010), but with an almost constant supply of seats throughout the year (Figure 11). This singularity is explained by the fact that in summer, very high temperatures can discourage northern/western European customers, who are replaced with lower purchasing power tourists. The latter come from (semi-)peripheral Europe and take advantage of cheaper summer deals. This result confirms that the role of climate at destinations and origins is mediated by social divides and development inequalities in the generating regions (Salazar and Zhang, 2013). This also suggests the airport-level seasonal pattern may actually hide strong seasonal patterns at the route level.

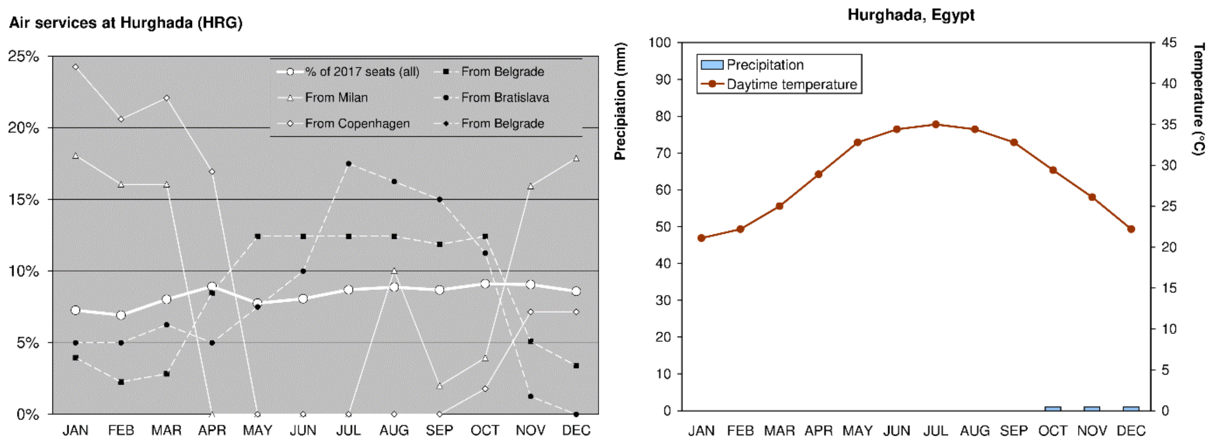

Figure 11. Monthly share of annual seat capacity at Hurghada Airport and climate data of local city. Routes from (semi)peripheral Europe in dashed lines.
Sources: Authors' computations based on OAG and www.weatherbase.com.

In addition to, and in contrast with, seeking wild or warm temperatures, ski resorts also induce peaks during winter. Cases with strong winter peaks include winter sport resorts around Chambery and Grenoble (France), Innsbruck (Austria), Kittilä Levi and Ivalo (Finland) and Vail/Eagle County (CO, USA). Because snow time can be short, the temporal profile of air services for such destinations can be sharper, as evidenced by the case of Grenoble Airport, which gives access to the French Alps' ski resorts (Figure 12). These results are in line with Suau-Sanchez and Voltes-Dorta (2019), who analyse scheduled airport traffic in ski tourism regions.

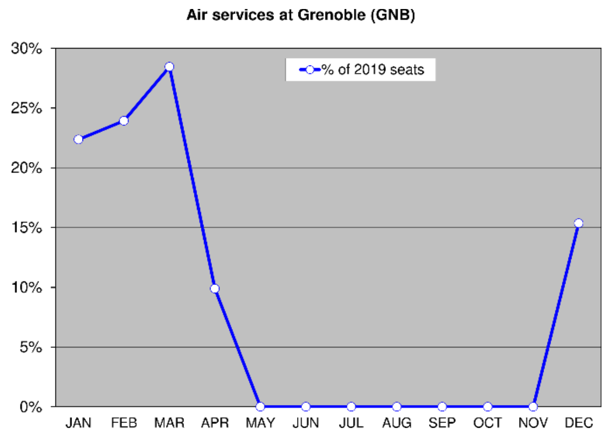

Figure 12. Monthly share of annual seat capacity at Grenoble Airport.
Sources: Authors' computations based on OAG and www.weatherbase.com.

In contrast, the Mediterranean model includes resorts where most of the tourism occurs during summer, when the weather is appealing and populations living on the same or nearby continents can thus travel over shorter distances. This model includes nearly all airports located around the Mediterranean, and thus, symbolic cases such as Mykonos and several other islands nearby (Greece), Burgas on the Black Sea, Dubrovnik (Croatia) on the Adriatic (Bulgaria), Costa Brava and the Balearics (Spain), the French Riviera, Corsica (France) and Sardinia (Italy), Bodrum (Turkey) and Monastir (Tunisia).[6] Figure 13 illustrates this group

[6] By extension, Faro, south of Portugal, can be considered a Mediterranean resort, despite the fact that it is on the Atlantic.

through Ibiza, Spain, as a typical case. Out of the Mediterranean, similar temporal patterns include resorts (including coastal resorts) in the northeast USA (e.g., Martha's Vineyard and Nantucket), in China (e.g., Burqin and Dunhuang) and in or on the Atlantic, although at higher latitudes than the Canaries (e.g., most of the Portuguese islands of Madeira and of the Azores, and La Rochelle in France), all in the Northern Hemisphere. In the Southern Hemisphere, coastal resorts in areas with a Mediterranean or temperate climate follow the same pattern. This includes, for instance, resorts in Uruguay (Punta del Este) and in Argentina (Mar del Plata and Puerto Madryn).

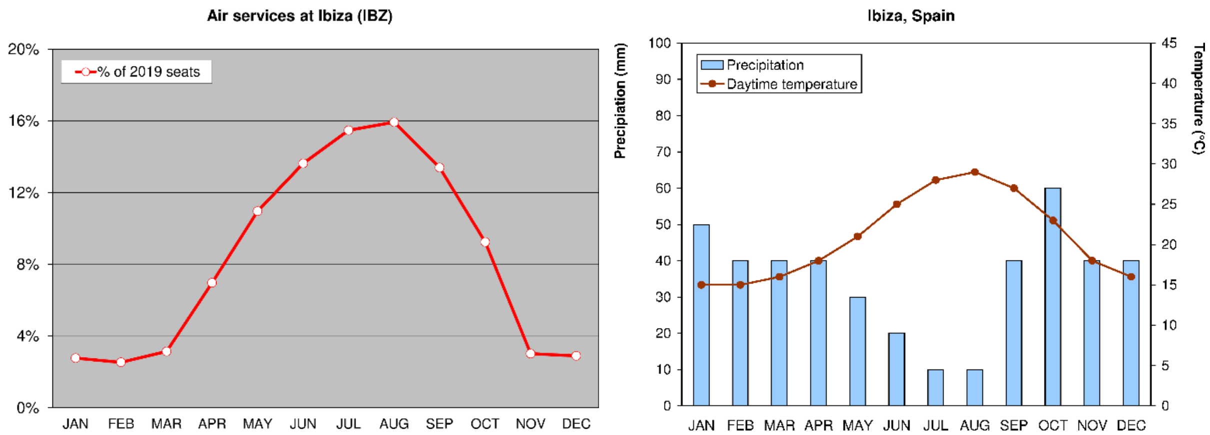

Figure 13. Monthly share of annual seat capacity at Ibiza Airport and climate data of local city.
Sources: Authors' computations based on OAG and www.weatherbase.com.

Beyond the weather at an intended destination, one should also consider the weather at one's origin. For instance, many regional airports in high-latitude countries, such as Sweden and Finland, show a winter peak, which suggests that inhabitants seek warmer weather. However, this pattern is certainly not systematic, as it is not that clear in Norway, as other forces related to Public Service Obligation (PSO) services could make the patterns more difficult to identify (see, for example, Bråthen and Eriksen (2018)).

Finally, Figure 9 also shows airports that are neither peak-less nor summer- nor winter-oriented (see white circles). This group includes some erratic cases but also airports with both summer and winter peaks, possibly because of policies aimed at developing counter-season tourism. Aspen, Colorado, is an example of a dual spot (Figure 14). As a ski resort, the place has been described as a "wintertime destination of choice for Hollywood celebs and those that follow them" (Schultz, 2015). But the place is also known for its Aspen [classical] Music Festival and School founded in 1949. The festival stretches over eight weeks, from June to late August, and includes more than 400 different events (including concerts, training and lectures) and attracts 100,000 visitors.[7]

[7] http://www.aspenmusicfestival.com (accessed 17 January 2019).

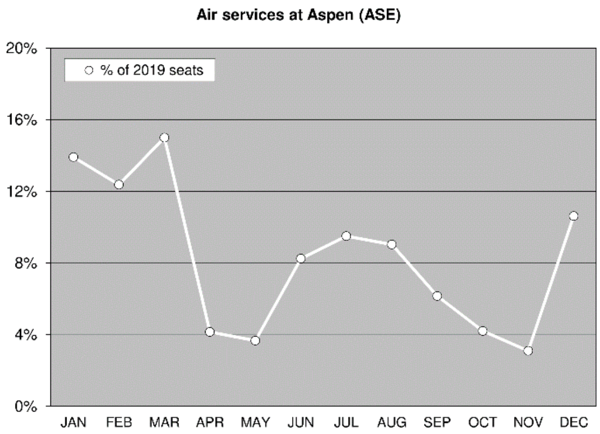

Figure 14. Monthly share of annual seat capacity at Aspen Airport.
Sources: Authors' computations based on OAG.

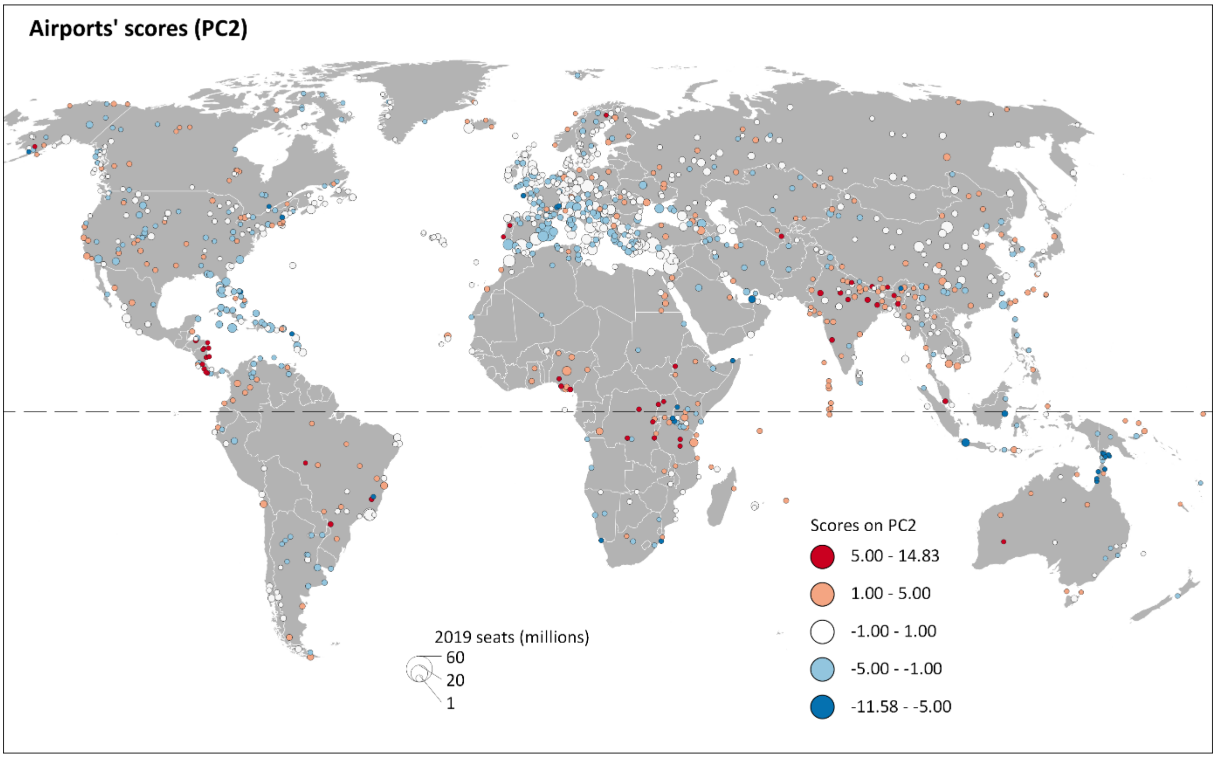

Figure 15. PCA scores (PC2), autumn-spring contrast.
Reds highlight autumn in the Northern Hemisphere and spring in the Southern Hemisphere.
Blues highlight spring in the Northern Hemisphere and autumn in the Southern Hemisphere.
Airports without peaks have been excluded.

Let us move to the autumn-spring contrast (Figure 15), still excluding stable airports shown in Figure 6. In this case, the contrast is less clear than with the summer-winter pattern, as more airports have scores close to zero (see Figure 5). A key conclusion is that the Mediterranean basin and the Caribbean/Florida basin now converge with a spring peak. This is mostly because the Mediterranean enjoys mild weather (see Figure 13) so it attracts tourists to some extent, notably during Easter holidays. In addition, various airports which serve tourist spots show a spring peak, subject to local weather – see, for instance, Jiuzhaigou in China (known for the eponym nature reserve and national park) and Chelinda in Malawi (safaris). In many cases, the spring peak is followed by a summer peak or follows a winter peak. A higher level of activity can also be observed in Nepal during the autumn. Indeed, October and November are the peak months for trekking in Nepal, when temperatures are mild, and the weather is quite stable.

4.3.3. Beyond climate profiles

The previous paragraphs have highlighted the role of climate at destinations and origins as a key factor related to air service seasonality for tourist resorts, although potentially mediated by social factors (see Hurghada). Three other kinds of factors could also play a role.

First, some destinations are characterized by a seasonal peak linked to a repeated hallmark tourist event. This is the case, for example, of Rovaniemi in Finland, a small town near the Arctic Circle, that is marketed as “the Official Hometown of Santa Claus”, a place where tourists are invited to come “for a genuine Christmas experience”, according to the nine-language municipal website.[8] As a result, many tourists flock there around Christmas time (Pretes, 1995; Rusko, 2013). This means something in that the only year-round route serving Rovaniemi is with its national capital, Helsinki. And among the 13 other routes operated in December 2019, only three are operated at some other times.

Second, several non-touristic places, known as areas of emigration, show a summer peak, arguably due to the VFRs. This case is well documented for the airports of Nador and Oujda, Morocco (Dobruszkes and Mondou, 2013). Based on the results obtained here, it could also occur in Al Hoceima (Morocco), Tlemcen (Algeria) and inland Turkey. Further investigation is needed, but one wonders whether VFR travellers would favour summer holidays so longer stays could be planned, and/or whether migrants would favour periods with warmer weather, just like any tourist.

Third, several European airports have a strong summer peak (for instance, East Midlands Airport in the UK, Liège and Oostende in Belgium, and Maastricht/Aachen in The Netherlands). It looks like these airports benefit from the spillover from congested airports to secondary airports (Gudmundsson et al., 2014) and accommodate peaks in demand when lots of people travel for summer holidays (including for VFR purposes). It could be that a threshold in demand is then reached, so airlines can add services that would not be profitable the rest of the year. Here, institutional factors (that is, school/industry vacations) would prevail over weather patterns. Figure 16 shows the case of East Midlands Airport (UK) as an example of such patterns. Out of the 84 routes operated in 2019 from this airport, only 29 were operated year-round and 47 during at least nine months. Among the routes operated all year, those to the main cities tend to have constant patterns, while outbound tourism routes can be very seasonal although subject to climate patterns, as evidenced by Table 4.

[8] https://www.visitrovaniemi.fi (accessed 17 January 2019).

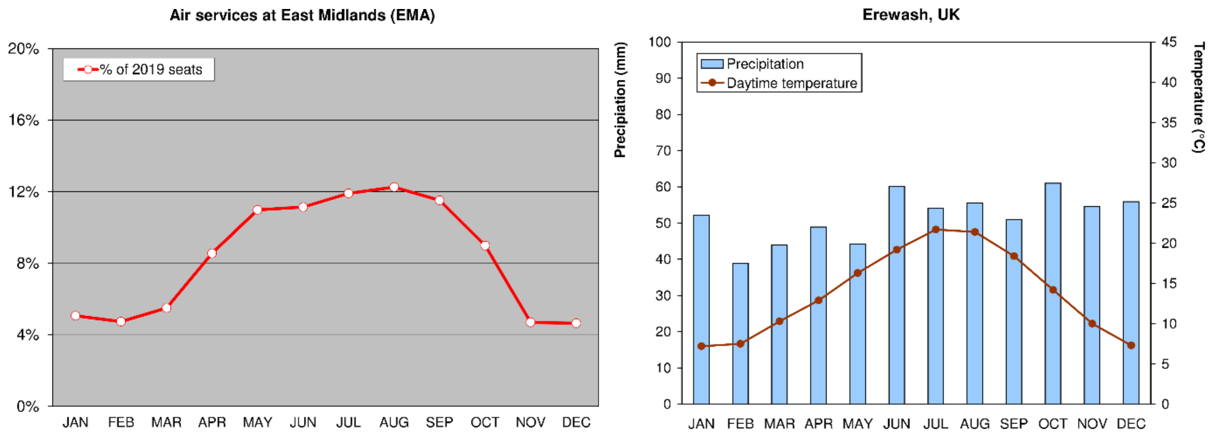

Figure 16. Monthly share of annual seat capacity at East Midlands Airport and climate data of local city.

Sources: Authors' computations based on OAG and www.weatherbase.com

	Amsterdam	Dublin	Tenerife	Malaga
Jan	2,106	9,072	15,836	6,870
Feb	2,184	8,694	14,324	5,948
Mar	2,418	9,450	16,276	7,642
Apr	2,340	8,883	15,616	16,329
May	2,418	9,261	14,454	17,643
Jun	2,340	8,883	14,045	17,750
Jul	2,418	9,072	14,454	18,087
Aug	2,418	9,261	15,399	19,057
Sep	2,340	9,072	14,234	17,454
Oct	2,418	8,883	13,239	17,775
Nov	2,184	9,072	12,351	8,473
Dec	2,262	8,694	12,877	8,136
Total	27,846	108,297	173,105	161,164
Max/min ratio	1.1	1.1	1.3	3.2

Table 4. The temporality of seat capacity on selected routes from East Midlands Airport, UK (2019). Tenerife includes both Tenerife North and Tenerife Sud airports. Source: Authors' computations based on OAG

5. Impacts

5.1. Planning for the peak limits the efficient management of infrastructure

The major issue related to seasonality for airport managers is the mismatch between airport infrastructure, which is long term and characterised by a high level of capital expenditure and sunk costs, and airline behaviour and passenger dynamics, which imply a high level of traffic fluctuation in the short term. That creates significant problems in terms of capital funding and the recovery of costs, as well as excessive costs during off-peak periods and problems of supply and level of service during peak periods.

In a context characterised by uncertainty and traffic fluctuations, airports tend to guide their level of investment on the basis of peak traffic. In other words, airport fixed costs are related mainly to short-term periods of high activity. Therefore, airports try to identify a Design Peak Day (DPD), which is usually identified by using the Average Day of the Peak Month (ADPM), the 15th or 30th busiest day of the year (ACRP, 2013) or the second busiest day of an average week of the peak month (IATA, 2016). For detailed planning and optimisation, airports also look into the Design Peak Hour, but that would be more useful for the larger and busiest airports. Indeed, generalisations are difficult or can be misleading, as highlighted by Wilken et al. (2011), for example, in 2008. In that year, London Stansted Airport handled 13.3% more ATMs than Palma de Mallorca Airport, but the peak week in Palma de Mallorca Airport was 8.3% busier than London Stansted Airport. Moreover, different typologies of cyclical variations overlap to create the actual traffic patterns: seasonal, monthly, weekly and daily fluctuations (de Neufville and Odoni, 2013). In that regard, the traffic fluctuations can be different depending on the type of airport. Whilst hub airports may have more weekly and daily fluctuations, smaller secondary airports might have more seasonal-level fluctuations, which can lead to different managing problems. For example, in the first case, human resources issues could be related to the planning of shifts, whilst in the second case they could be related to training and hiring staff beyond a fixed-term contract for a particular peak season.

Hence, there is the danger of ending up with overcapacity, which could challenge the airport's financial viability (Voltes-Dorta and Pagliari, 2012). That is why forecasting peak activity is so important. For example, in 1988 the Federal Aviation Administration (FAA) was one of the first to propose a straightforward relationship between annual passengers and the Design Peak Hour, based on coefficients that depend on annual passenger numbers (FAA, 1988).

Considering the above, our findings can contribute to the extant literature by adding some additional granularity and context. Beyond peak day and peak hour analyses, our results can help managers in profiling their airport and understanding which other airports they can turn to for comparison purposes. Furthermore, our seasonality worldwide-level benchmarking can be very useful to airport investors as they can quickly identify airports without seasonality and differentiate between the different airport seasonality profiles.

5.2. Seasonality can result in the inefficient use of the tourism and hospitality sector

In the same way that seasonality is a concern for airport managers, it is usually also a problem for a regional tourist service system (Rudihartmann, 1986). If the resulting rise in tourism demand is centred on a particular season (Jang, 2004; Vergori, 2012), tourism destination attractiveness policies might not lead to regional economic development (Saito and Romão, 2018). As in the case of airport infrastructure, the conjunction of the fixed nature of capacity and resources in the tourism and hospitality sector and the unevenness and seasonality of tourism demand can result in the inefficient use of fixed capital (Rosselló and Sansó, 2017), which significantly reduces the profitability of the tourism and hospitality sector (Cuccia and Rizzo, 2011), sacrificing growth or tax collection in the region (Koenig-Lewis and Bischoff, 2005). In that regard, previous research has identified important areas of interrelation between aviation and tourism, which include air route development, passenger experience and the different economic impacts of different types of passengers (Spasojevic et al., 2017).

Some well-known strategies to reduce seasonality include promoting independent tourism and stimulating business-related visitors and MICE (Meetings, Incentives, Conferences and Exhibitions) activities. But the impact of such strategies can sometimes be limited, since the positive relationship between income per capita, income elasticity of inbound tourism and exports shows some level of path dependency (Bahmani-Oskooee and Kara, 2005; Weldemicael, 2014). Indeed, seasonality in tourism is difficult to manage because some of its causes are natural and beyond the control of decision makers (e.g., climatic factors). Other causes are institutional and are partly under the control of decision makers – for example, the planning of cultural events and school holidays (Cuccia and Rizzo, 2011). Our findings indicate that beyond the classical winter-summer dynamics we can also identify an autumn-spring contrast that seems to be linked to specific economic activities in certain locations, such as safaris in Malawi or trekking in Nepal. Although these activities themselves can contribute to the local level of seasonality, they are good examples of how concrete activities can enhance the economic effects on the local economy by being outside of the typical annual seasonal pattern.

5.3. A two-season calendar is too rigid

One of the particularities of airline schedule planning is that it is organised in two seasons, i.e. summer and winter. The summer season runs from the last Sunday of March until the last Saturday of October. The winter season runs from the last Sunday of October until the last Saturday of March. This means that, from an institutional perspective, the aviation industry is organised in two clearly differentiated seasons, which structurally influence the global flows of passengers and tourists in a summer-winter contrast. In this regard, and with the aim of being prepared for each of the seasons, airlines, airports and tourism authorities meet before each season in the so-called Routes conferences. In these conferences, these three main stakeholders interact and try to persuade airlines to ensure that new routes are opened and more frequencies and capacities are offered on existing ones. This institutional organisation shows how airlines' decisions are a determining factor in the planning of tourism supply. This is especially true for regional airports with a smaller market, which may create problems in attracting the desired services. In this regard, local and regional tourism authorities sometimes take an active role by providing state aid or marketing aid to airlines (see, for example, Perboli (2015) and Ramos-Pérez (2016)). In other cases, the summer-winter contrast favours the winter season. That is the case of airports close to ski resorts. Some small mountain airports offer unparalleled accessibility to the resorts, but research shows this is not a guarantee of success in developing scheduled services, since other aspects such as competition, catchment area size and infrastructure requirements play a more important role as drivers of scheduled traffic at small mountain airports (Suau-Sanchez and Voltes-Dorta, 2019).

Another relevant aspect is that airlines tend to supply a more or less balanced number of seats and flights throughout a season. This means intra-seasonal seasonality is generally absorbed by airlines by simply having different load factor levels throughout the season. Nevertheless, it is true that since airlines have the capacity to move and transfer their assets (i.e., aircraft), on some occasions they would move some of their capacity to higher-yield markets for the peak months. For example, Sevilla Airport (Spain), which has grown significantly during the past few years and has a strong summer season, experiences a decrease in supply in August, just in the middle of the peak season, because some airlines move their assets to higher-yielding markets such as the Balearic Islands.

Our results, however, indicate that some airports show an autumn-spring contrast, which might suggest tourism airline scheduling planning cannot be conducted following the institutionalized summer-winter structure. Whilst this is not necessarily a problem for well-established destinations that follow the autumn-spring contract, it is indeed a problem for new destinations that might like to attract new services outside of the established summer-winter structure. Airlines would be more attracted to services that can be offered along an aviation season, instead of in between seasons as this would facilitate the slot request and coordination that is also managed following the summer-winter aviation season structure.

5.4. Potential bias for research

The existence of seasonal patterns in aviation suggests scholars need to be careful with the data they use. Because of cost or data-management issues, it is common to work on restricted data; for instance, one 'typical' week or month rather than annual data. However, because seasonality patterns involve selecting one period rather than any other can significantly impact the results. For instance, the importance of smaller airports, which are affected more by seasonality, on average, could be under- or overestimated. Similarly, any assessment of fleet use, airport ranking and typology of airline networks may not necessarily be an accurate representation. As an example of such potential issues, Table 5 unveils the top 10 airports by seats for three time frames. It is significant that even for a ranking that focuses only on the largest airports (thus with only little seasonality effect), both the rank and even the very fact of being part of the ranking are subject to important changes. Similarly, computing the share of international seats per airport in the same three periods opens up significant temporal gaps for several airports (Table 6), even though there are overall high correlations between the periods.[9] It is obvious that any map or typology of airports based on a specific week or month would be affected to some extent. In other cases, for instance, to compare airline networks or to investigate hubs' performance based on real schedules (e.g., Burghouwt and de Wit, 2005), a shorter period would make sense. Otherwise, there is a risk of mixing summer and winter seasonal routes, so indicators such as connectivity would be wrong.

Rank	Annual	January	August
1	Atlanta	Beijing Capital	Atlanta
2	Beijing Capital	Atlanta	Beijing Capital
3	Tokyo Haneda	Dubai	Dubai
4	Dubai	Tokyo Haneda	Tokyo Haneda
5	Los Angeles	Los Angeles	Los Angeles
6	Chicago O'Hare	London Heathrow	Chicago O'Hare
7	London Heathrow	Shanghai Pudong	London Heathrow
8	Shanghai Pudong	Hong Kong	Paris Charles de Gaulle
9	Hong Kong	Chicago O'Hare	Frankfurt
10	Frankfurt	Guangzhou	Shanghai Pudong

Table 5. Top 10 airports by seats (2019)

Airport	Annual	January	August
Aspen, USA	0%	0%	0%
Rovaniemi, Finland	9%	9%	0%
Atlanta, USA	12%	13%	13%
Mytilini, Greece	16%	0%	31%
Palm Springs, USA	17%	22%	8%
Ibiza, Spain	56%	6%	66%
Antalya, Turkey	72%	38%	81%
Tenerife Sur, Spain	88%	89%	85%
Dakar, Senegal	95%	95%	95%

Table 6. Share of international seats at selected airports (%, 2019)

6. Conclusions

This paper has assessed the degree and spatiality of seasonality of regular worldwide air services at the airport level. We also discussed the factors that shape these patterns. In contrast to most previous research, we then investigated seasonal patterns through a factorial analysis and the mapping and interpretation of the summer/winter and spring/autumn contrasts, considering worldwide airports served by regular air services. Engaging a very large sample of airports was only possible thanks to the focus on the supply rather than the demand, and

[9] $R>0.95$ for all combinations (annual vs. January, annual vs. August and January vs. August).

helped us to avoid biases, considering geographical diversity and the fact that smaller airports tend to be more affected by seasonality. Seasonality in aviation has significant impacts on the efficient use of airport capacity and capital. Seasonality creates problems in terms of capital funding and the recovery of costs, as well as excessive costs during off-peak periods and problems of supply and level of service during peak periods.

It has been found that 38.8% of worldwide airports (accounting for only 15.6% of seats) experience significant seasonal patterns. There is more stable seat capacity in the case of larger airports; diversity of travel purposes; hubs that mix various origins and destinations throughout the year; distance that makes flying the most reasonable (if not the only) option; lack of surface transport options; physical factors (including remoteness, relief); public service obligations; and appealing weather throughout the year.

For those airports with seasonality, this paper confirms the relevance of the climate–tourism/VFR travel nexus, as well as the impact of various forms of institutional factors. However, these traditional factors have been completed by social matters (see the case of Hurghada), places' attributes, travel purpose and the role of distance. Of course, seasonal patterns are often due to more than one single factor, so one should think in a multi-factorial perspective. And all factors should be considered at both the origin and destination, the combination shaping seasonal patterns.

This paper also implicitly shows that the relative weight of factors can change within the year. For instance, cold weather can invite tourists to seek sun far away (e.g., from Europe to the Red Sea or the Caribbean), so weather prevails on distance to some extent. But once appropriate weather is available not that far from the point of origin (for instance, in the Mediterranean for the Europeans), then distance becomes more important and closer resorts would be preferred over farther ones, all other things being equal.

All in all, this paper can serve as a warning about the temporality of data considered for aviation research (see the previous sub-section). However, our point is not to criticise colleagues who have used restricted data when annual data would have been more relevant. In many cases, this is due to data availability and cost issues. In this regard, there is a disparity in the resources available to research units, subject to their funding. Some have the resources to acquire comprehensive data more easily, while others would be obliged to restrict their ambitions and content themselves with partial data.

Finally, this paper paves the way for several further research works. Objectifying aviation seasonality patterns would be more robust if charter flights could be included. Unfortunately, given the lack of comprehensive data, this is clearly wishful thinking as long as one works globally. At best, data on charter seat capacity or traffic can be obtained for some specific airports or countries. And a common measure is then in flights rather than in seats. It would also make sense to develop similar research on a multi-year basis. Indeed, some seasonal patterns detected within a single year may actually be the result of longer-term increases or decreases. However, this raises the issue of the cost to access the data. Further investigations may also distinguish between domestic/international and intra-/intercontinental markets. It could be that having controlled for size, these dimensions also matter.

In addition, shifting from the supply (seats supplied) to the demand (passengers carried) would complement this paper. In our view, supply is not more or less relevant than demand. The supply says something about the strategies airlines pursue and their ability to adapt to seasonal demand. The supply perspective also poses critical issues in terms of aviation economics, management and marketing. The investigation of seasonality in demand makes sense in tourism, economy and destination-management perspectives. In addition, while supply is often viewed as a proxy for demand, one should not forget that tourism seasonality is partially absorbed by airlines by simply achieving higher load factors. In other words, load factors fluctuate and seasonality in air demand is expected to be higher than seasonality in air supply.

In the investigation of factors, directionality should be taken into account to help clarify the distinction between factors at the origin and factors at the destination. At this stage, at the airport level, one does not know whether traffic is dominated by inbound or outbound traffic, or if it is evenly balanced. MIDT demand data could partly solve the limitations of the current paper in terms of traffic directionality. Nevertheless, the point of sale and directionality of travel information in MIDT datasets is generally incomplete, and can sometimes be misleading. Furthermore, the analysis of seasonality in air services could be multiplied in several ways. For instance, would low-cost and ‘post-charter’ leisure airlines better adapt their services to seasonality? Are there specific seasonal patterns related to domestic, intra-continental international or intercontinental markets? And, of course, how much stable seat capacity at the airport level would actually hide seasonality at the route level?

References

ACI (2018). Airport markets and seasonal variations. Airports Council International Insights. URL: https://blog.aci.aero/airport-markets-and-seasonal-variations/

ACRP (2013). Guidelines for preparing peak period and operational profiles, Report 82, Washington: Transportation Research Board. URL: http://onlinepubs.trb.org/onlinepubs/acrp/acrp_rpt_082.pdf

Bahmani-Oskooee, M., Kara, O. (2005). Income and price elasticities of trade: some new estimates. The International Trade Journal 19 (2), 165-178.

BarOn, R. V. (1975). Seasonality in tourism. London: Economist Intelligence Unit.

Baum, T., Lundtorp, S. (Eds.) (2001). Seasonality in Tourism. Oxford: Elsevier.

Bråthen, S., Eriksen, K.S. (2018). Regional aviation and the PSO system – Level of Service and social efficiency. Journal of Air Transport Management 69, 248-256.

Burghouwt G., de Wit J. (2005). Temporal configurations of European airline networks, Journal of Air Transport Management 11(3), 185–198.

Butler, R. (1998). Seasonality in tourism: Issues and implications. The Tourist Review, 53(3), 18–24.

Charlier J. (1981). Le triptyque aéroportuaire lyonnais: une analyse géographique des installations, du trafic, des horizons aériens et de l'aire de desserte terrestre de l'aéroport de Lyon-Satolas. Revue de Géographie de Lyon 56(2), 115–163.

Chung J. Y., Whang T. (2011), The impact of low cost carriers on Korean Island tourism, Journal of Transport Geography 19(6), 1335–1340.

Cisneros-Martínez, J. D., McCabe, S., Fernández-Morales, A. (2018). The Contribution of Social Tourism to Sustainable Tourism: A Case Study of Seasonally Adjusted Programmes in Spain. Journal of Sustainable Tourism 26(1) 85–107.

Coshall, J., Charlesworth R., Page S. (2015). Seasonality of Overseas Tourism Demand in Scotland: A Regional Analysis, Regional Studies, 49(10), 1603–1620.

Cuccia, T., Rizzo, I. (2011). Tourism seasonality in cultural destinations: Empirical evidence from Sicily. Tourism Management 32, 589–595.

de Neufville, R. and Odoni, A. (2013). Airport Systems. Planning, Design and Management. Second Edition. New York: McGraw-Hill.

Dobruszkes, F. and Mondou, V. (2013). Aviation liberalization as a means to promote international tourism: The EU–Morocco case. *Journal of air transport management*, 29, 23-34.

Dobruszkes F., Ramos-Pérez D., Decroly J.-M. (2019), Reasons for Flying, in Graham A. & Dobruszkes F. (Eds), Air Transport: A Tourism Perspective, Elsevier, pp. 23–39.

Doganis R. (2010). Flying Off Course: Airlines Economics and Marketing. Fourth Edition, London: Routledge.

Du, Z., Wang, L., Cauchemez, S., Xu, X., Wang, X., Cowling, B. J., & Meyers, L. A. (2020). Risk for Transportation of Coronavirus Disease from Wuhan to Other Cities in China. Emerging Infectious Diseases, 26(5), 1049-1052.

Duro, J. A. (2016). Seasonality of hotel demand in the main Spanish provinces: Measurements and decomposition exercises. Tourism Management 52, 52–63.

Evans, I. (1977). The Selection of Class Intervals. Transactions of the Institute of British Geographers, 2(1), 98–124.

FAA (1988). Planning and design guidelines for airport terminal facilities. Advisory Circular AC 140/5360-13. Washington.

Fageda, X. Suárez-Alemán, A., Serebrisky, T., Fioravanti, R. (2018), Air connectivity in remote regions: A comprehensive review of existing transport policies worldwide, Journal of Air Transport Management 66, 65–75.

Fernández-Morales, A., Cisneros-Martínez, J. D., McCabe, S. (2016). Seasonal concentration of tourism demand: Decomposition analysis and marketing implications. Tourism Management 56, 172–190.

Givoni M., Dobruszkes F. (2013). A review of ex-post evidence for mode substitution and induced demand following the introduction of High-Speed Rail, Transport Reviews 33(6), 720-742.

Goetz A., Budd L. (Eds) (2014), Geographies of Air Transport, Farnham: Ashgate.

Gudmundsson, S., Paleari, S. and Redondi, R. (2014). Spillover effects of the development constraints in London Heathrow airport, Journal of Transport Geography 35, 64-74.

Halpern, H. (2011). Measuring seasonal demand for Spanish airports: Implications for counter-seasonal strategies, Research in Transportation Business & Management 1, 47–54.

IATA (2016). Airport Development Reference Manual. 4th Release. Montreal: International Air Transport Association.

Jang, S., 2004. Mitigating tourism seasonality: A quantitative approach, Annals of Tourism Research 31, 819-836.

Jenks, G. F., Coulson, M. R. C. (1963). Class Intervals for Statistical Maps. International Yearbook of Cartography, 3, 119–133.

Jimenez, E., Claro, J., Pinho de Sousa, J., de Neufvile, R. (2017). Dynamic evolution of European airport systems in the context of low-cost carriers growth. Journal of Air Transport Management 64, Part A, 68-76.

Koenig-Lewis, N., Bischoff, E. (2005). Seasonality Research: The State of the Art, International Journal of Tourism 7(4-5), 201–219.

Koo, T., Halpern, N., Papatheodorou, A., Graham, A., Arvanitis, P. (2016). Air transport liberalisation and airport dependency: developing a composite index. Journal of Transport Geography 50, 83–93.

Kraft S., Havlíková D. (2016). Anytime? Anywhere? The seasonality of flight offers in Central Europe, Moravian Geographical Reports 24(4), 26–37.

Lohmann, G., Vianna, C. (2016). Air route suspension: The role of stakeholder engagement and aviation and non-aviation factors. Journal of Air Transport Management 53, 199–210.

Mackay, J. (1955). An Analysis of Isopleth and Choropleth Class Intervals. Economic Geography, 31(1), 71–81.

Merkert, R. and Webber, T. (2018). How to manage seasonality in service industries – The case of price and seat factor management in airlines, Journal of Air Transport Management, 72, 39–46

Neal, Z. (2014). The devil is in the details: Differences in air traffic networks by scale, species, and season, Social Networks 38, 63–73.

Papatheodorou, A. (2002). Civil aviation regimes and leisure tourism in Europe, Journal of Air Transport Management 8(6), 381–388.

Peeri, N. C., Shrestha, N., Rahman, M. S., et al. (2020). The SARS, MERS and novel coronavirus (COVID-19) epidemics, the newest and biggest global health threats: what lessons have we learned?. *International journal of epidemiology*, 2020 (doi: 10.1093/ije/dyaa033).

Perboli, G., Ghirardi, M., Gobbato, L., Perfetti, F. (2015). Flights and their economic impact on the airport catchment area: an application to the Italian tourist market. *Journal of Optimization, Theory and Application* 164, 1109–1133.

Pretes, M. (1995). Postmodern tourism: the Santa Claus industry. *Annals of Tourism Research*, 22(1), 1-15.

Ramos-Pérez, D. (2016). State aid to airlines in Spain: An assessment of regional and local government support from 1996 to 2014. Transport Policy 49, 137-147.

Ramos-Pérez D., Dobruszkes F. (2019). The End of European Charter Airlines: Myths and Realities, in Graham A. & Dobruszkes F. (Eds), Air Transport: A Tourism Perspective, Elsevier, pp. 143–162.

Reynolds-Feighan A. (2018). US feeder airlines: Industry structure, networks and performance, Transportation Research Part A 117, 142–157.

Reynolds-Feighan, A. (2021). The Role of Air Transport in Tourism Market Access: A Framework for Capturing Spatial, Temporal and Industry Variability in Air Traffic Flows. In Mauro Ferrante, Olivier Fritz, özge öner (Eds), Regional Science Perspectives on Tourism and Hospitality, pp. 103-124, Cham: Springer.

Rogerson, P. (2001). Statistical Methods for Geography. London: SAGE.

Rosselló, J., Sansó, A. (2017). Yearly, monthly and weekly seasonality of tourism demand: A decomposition analysis. Tourism Management 60, 379-389.

Rudan, I. (2020). A cascade of causes that led to the COVID-19 tragedy in Italy and in other European Union countries. *Journal of Global Health*, 10 (1) (doi: 10.7189/jogh.10.010335).

Rudihartmann. (1986). Tourism, seasonality and social change, Leisure Studies 5, 25-33.

Rusko, R., Merenheimo, P., & Haanpää, M. (2013). Coopetition, resource-based view and legend: Cases of Christmas tourism and city of Rovaniemi. *International Journal of Marketing Studies*, 5(6), 37.

Saito, H., Romão, J. (2018). Seaonality and regional productivity in the Spanish accommodation sector, Tourism Management 69, 180-188.

Salazar, N. B., Zhang, Y. (2013). Seasonal lifestyle tourism: The case of Chinese elites. Annals of Tourism Research, 43, 81–99.

Sassen, S. (2005). Global City: Introducing a Concept. Brown Journal of World Affairs 11(2), 18–43.

Schultz, P. (2015). 1,000 Places to See Before You Die. Revised Second Edition. New York: Workman Publishing Company.

Sealy, K. (1966). The Geography of Air Transport. 2nd Ed. London: Hutchinson University Library, 198 p.

Spasojevic, B., Lohmann, G. and Scott, N. (2017). Air transport and tourism – a systematic literature review (2000-2014). Current Issues in Tourism 21, 975-977.

Strale M. (2009). Organiser les flux vers La Mecque, Fumey G., Varlet J. and Zembri P. (Eds), Mobilités contemporaines. Approches géoculturelles des transports, Ellipses, pp. 153–163.

Suau-Sanchez, P., Voltes-Dorta, A. (2019). Drivers of airport scheduled traffic in European winter tourism areas: Infrastructure, accessibility, competition and catchment area. Journal of Air Transport Management 81, 101723.

Tsekeris, T. (2009). Dynamic analysis of air travel demand in competitive island markets, Journal of Air Transport Management 15(6), 267–273.

Vasigh B., Fleming K., Tacker T. (2013). Introduction to Air Transport Economics: From Theory to Applications, Second Edition, Farnham: Ashgate.

Vergori, A. (2012). Forecasting tourism demand: The role of seasonality. Tourism Economics 18, 915-930.

Vignal, L. (2010). The new territories of tourism in Egypt: a local-global frontier? Cybergeo: European Journal of Geography, available at http://journals.openedition.org/cybergeo/23324 (DOI: 10.4000/cybergeo.23324).

Voltes-Dorta, A. and Pagliari, R. (2012). The impact of recession on airports' cost efficiency. Transport Policy 24, 211-222.

Weldemicael, E. (2014). Technology, trade costs and export sophistication. The World Economy 37 (1), 14-41.

Wilken, D., Berster, P. and Gelhausen, M. C. (2011). New empirical evidence on airport capacity utilisation: relationships between hourly and annual air traffic volumes, Research in Transportation Business & Management 1, 118– 127.

Wu, C., Jiang, Q., Yang, H. (2018). Changes in cross-strait aviation policies and their impact on tourism flows since 2009. Transport Policy 63, 61–72.