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| **Authors(s)** | Reynolds-Feighan, Aisling J., Zou, Li, Yu, Chunyan |
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# Seasonality in European and North American air transport markets: network structures and implications for airline performance and recovery

Aisling Reynolds-Feighan[a], Li Zou[b] and Chunyan Yu[b]

[a] UCD School of Economics, University College Dublin, Belfield, Dublin 4, Ireland

[b] David B. O'Maley College of Business, Embry-Riddle Aeronautical University, 1 Aerospace Blvd., Daytona Beach, Florida, U.S.A.

## 1. Introduction

This note focuses on the seasonal variability in air traffic services and highlights the differences between air service capacity provision in Europe and North America. We explore the manifestations and measurement of seasonality, looking at the trends across airport communities and among airlines in the two continental regions. We argue that there are a complex set of drivers of the observed differences in air traffic seasonality and set out a research agenda for investigating these further.

Seasonality can be driven by demand and mitigated or aggravated by supplier responses. With air service liberalization and the continued growth of low-cost carriers (LCCs) and ultra-low cost carriers (ULCCs), air travel has become more affordable attracting an increasing number of leisure travellers taking vacations to tourist destinations or visiting friends and relatives (VFRs) during favourable weather or holiday seasons. Both activities have become more popular in recent years with the expansion of middle-class families particularly in emerging economies, generating increased seasonality in air travel demand. There are several similarities between tourism seasonality and air travel seasonality in terms of the seasonal pattern and the relevant social, cultural, economic, and weather conditions as driving forces (Rosselló and Sanso, 2017). However, the analysis of air travel seasonality and the implications for airline management strategies in dealing with this variability need to take account of several unique characteristics of the airline business in the areas of revenue management, operational characteristics, and network structures. Airlines have traditionally expanded their capacity to meet peak demand as well as rationing the fixed capacity using pricing mechanisms, and this phenomenon could aggravate the variability in seasonal capacity compared to other service providers in the hospitality industry such as hotels and restaurants where maximum capacity during high-demand season is fixed in terms of room or seat capacity. The focus on the leisure travel segment by LCCs and ULCCs has also stimulated more seasonal travel.

Airlines have different abilities to adapt operations, resources, and management strategies to deal with seasonal demand fluctuations. For example, some airlines (e.g., Aer Lingus, Vueling, TUI Group, Thomas Cook Group, and Royal Jordanian Airlines) employ wet leasing[1] to provide additional capacity during the summer vacation season to meet peak demand. In order to mitigate the negative effect of seasonality on fleet utilization, many airlines schedule heavy maintenance during the low-demand season (Merkert and Webber, 2018). Some airlines rely on intermediary agencies to outsource contracts with flight crews so as to maximize flexibility and better align operational costs with the varying revenue arising from seasonality effects. Some airlines are more cautious in selecting airports that are less affected by weather-related seasonal demand.

Seasonality has been measured and studied at the airport, airline, and regional level (Reynolds-Feighan, 2018 and 2021). Merkert and Webber (2018) develop an analytical model to investigate optimal pricing

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[1] Wet leasing involves the leasing of flight equipment and crews. Dry leasing refers to the leasing of just the equipment. Given that many airlines directly employ large numbers of operations staff on permanent contracts, wet leasing facilitates the lessor airline generating additional revenues during the off-peak season and allows the lessee airline to directly source equipment and crews to meet their (complimentary) peak period demand.

and seat load factor strategies that could help an airline achieve profit maximization during both the peak and off-peak traveling seasons. Under the assumption that travellers are more sensitive to airfare change during the off-peak season, Merkert and Webber (2018) suggest, counterintuitively, that airlines should lower the average airfare during the peak season, while raising the average airfare during the off-peak season, so that the ratio of the high-season load factor to the low-season load factor would be more inclined toward equalizing the marginal revenues during the peak and off-peak seasons, assuming that the fixed and unit variable costs do not vary between the high- and low-demand seasons.

Network structure is a critical component of an airline's operations and business model. However, there has been no published analysis of the role of network structure in moderating or attenuating air traffic seasonality. This research note fills a gap in the literature by providing a descriptive and exploratory analysis of the potential connection between seasonality and airline network properties. Based on our findings, we discuss several management implications and present a few promising new research avenues for future study.

## 2. Overview of Air Traffic Patterns in Europe and North America

There is a distinct difference in the monthly provision of scheduled airline seats between Europe and North America, with Europe exhibiting far greater seasonal variability between the single summer peak and winter trough than North America[2] as shown in Figure 1. The North American pattern consists of several minor peaks and a stronger summer peak, with a smaller winter trough. For both continental regions, the amplitude of the cycle has been increasing since 2009. Figure 1 also shows that the impact of Covid19 has been more severe in Europe: there was some recovery with a summer peak evident during 2020 and 2021, albeit at much lower capacity levels. In North America, however, while there were summer peaks during 2020 and 2021, there were larger winter (December) peaks.

Figure 1: Total scheduled jet departure seats available (domestic and international) in Europe and North America between January 2004 and December 2021

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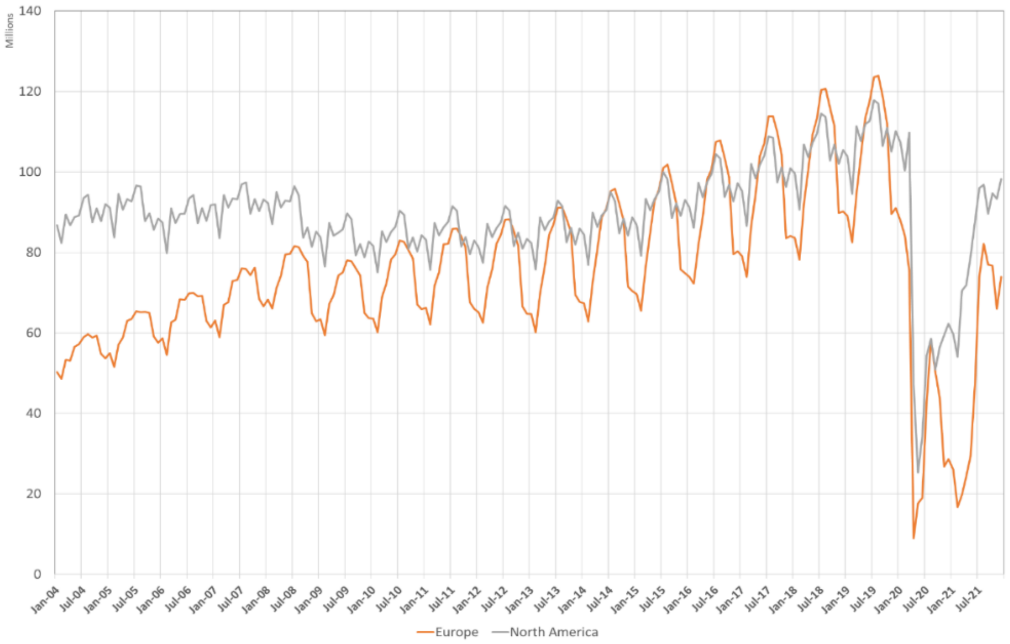
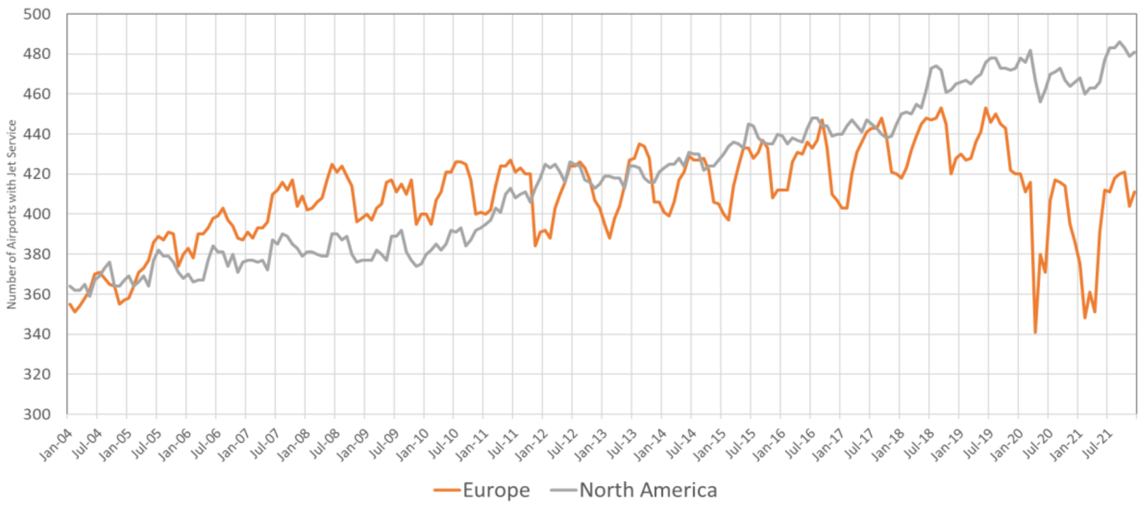
[2] According to Cirium nomenclature, Europe includes Albania, Andorra, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Gibraltar, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Macedonia, Malta, Moldova, Monaco, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine and United Kingdom; North America includes USA, Canada, Mexico and Greenland.



Data source: Cirium Diio Mi weekly schedules as of November 5th, 2021. Note that the November and December 2021 scheduled seats are those available for sale at this time and are subject to change prior to the date of departure (based on patterns of sales).

Figure 2 shows the steady and consistent growth in the number of North American airports receiving air services beginning in 2011-12, with relatively small numbers of seasonal airports (airports receiving less than year-round service). In Europe by contrast in the same figure, there is a strong seasonal pattern of variability in the number of airports receiving service with a substantial summer increase each year. Figures 1 and 2 highlight the key differences between the European and North American air transport markets. Following the liberalisation of the European air transport market in the 1992-97 period, the number of European airports receiving scheduled jet air services increased substantially as did the number of routes operated. For many routes, air services are often less than daily, and only offered in the summer peak or winter season to cater to sun or ski vacationers. Europe's air traffic distribution is more dispersed with low frequency services and predominantly point-to-point operations. In North America and particularly in the United States by contrast, the 1978 deregulation resulted in a reduction in the number of airports receiving scheduled jet air services and increasing concentration of air traffic through a relatively small number of hub airports. The focus by most airlines on hub-and-spoke network structures has given rise to high frequency concentrated air traffic corridors between the largest airports, with limited connections for smaller airports via operating carriers' hubs. This spatial concentration of air traffic has resulted in greater year-round stability for air services at the smaller airports.

Figure 2: Number of airports in Europe and North America receiving jet services between January 2004 and December 2021



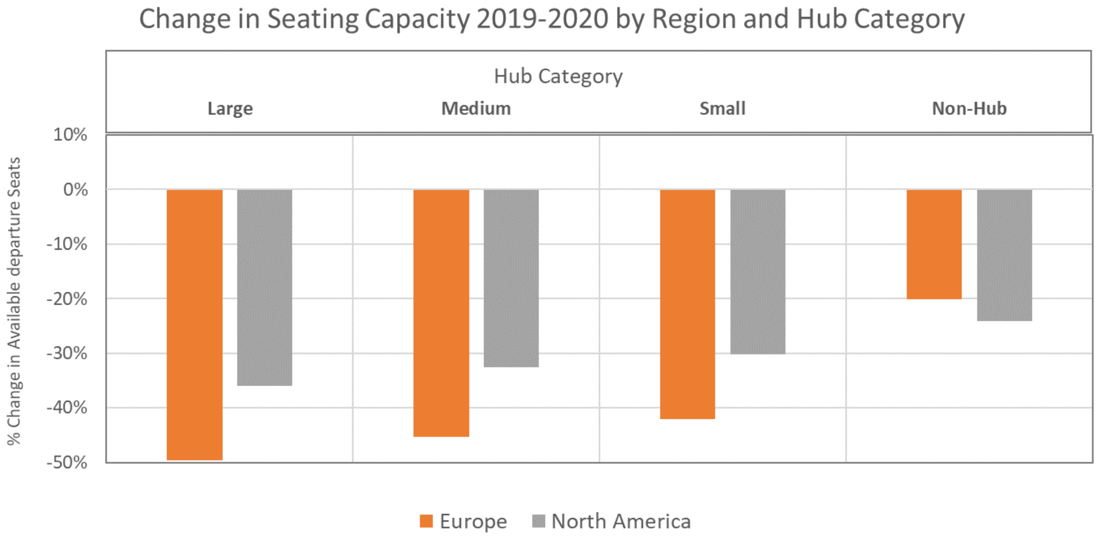
Data source: Cirium Diio Mi™

We categorize all airports based on the percentage of total continental scheduled seats in a 12-month period. Airports are distinguished as Large Hub (>1%), Medium Hub (0.25% - 1%), Small Hub (0.05% – 0.25%) or non-Hub (5,000 - 0.05%). Airports with fewer than 5,000 annual scheduled seats are not included. Table 1 shows the shares of scheduled departure seats by hub category for airports in Europe and North America in 2019 and highlights the greater spatial concentration of air traffic in the North American region, with 63% of all scheduled seats at large hubs compared to 52% in Europe. Figure 3 shows the change in scheduled seats by hub type between 2019 and 2020. For both Europe and North America, the biggest impact of COVID19 was at the large hub airports, with progressively lower impacts at medium and small hubs and non-hubs.

Table 1. Share of 2019 non-stop scheduled seats (domestic and international) by hub category

| **Region** | **Hub Category** | | | | **Grand Total** |
|---|---|---|---|---|---|
| | Large | Medium | Small | Non-Hub | |
| Europe | 52% | 30% | 14% | 4% | 100% |
| North America | 63% | 21% | 11% | 5% | 100% |

Figure 3: Change in scheduled seats 2019-2020 by region and hub category

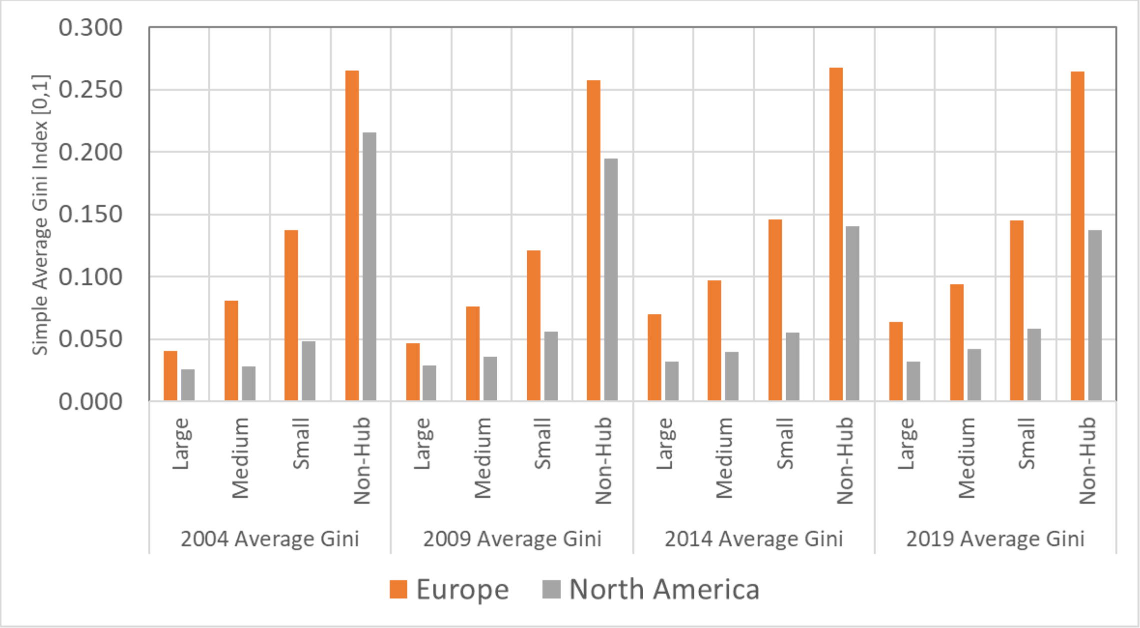


## 3. Air Traffic Seasonality Analysis

Most of the studies on seasonality associated with travel have focused on tourism flows, measuring and analyzing the changing pattern of tourism flows over different times during a year and across different geographical regions. Air transport enables and facilitates the flows of tourists (Reynolds-Feighan, 2021), and air passenger flows tend to follow a similar seasonal pattern as flows of leisure and vacation travellers. The Gini index is perhaps the most commonly used indicator to measure seasonality, such as in Fernández-Morales and Mayorga-Toledano (2008), Þórhallsdóttir and Ólafsson (2017), Reynolds-Feighan (2018), Marton, et al. (2019), and Šuštar and Ažić (2019).

We compute the yearly Gini index for each airport based on the monthly available seats. Figure 4 shows the higher degree of seasonal variability for all airport categories in Europe and a consistent pattern of higher seasonality as airport size decreases in both continental regions. Furthermore, Figure 4 shows that seasonal variability has been increased over time as air traffic has increased in both Europe and North America, with the exception of airports in the non-hub category.

Figure 4: Gini Index score by hub airport category for Europe and North America, 2004, 2009, 2014, 2019



We also examine the monthly air traffic patterns among a sample of the four largest Full-Service Carriers (FSCs) and the three largest Low-Cost Carriers (LCCs) in Europe and North America[3]. For each airline, the yearly Gini Index scores are computed based on the monthly scheduled departure seats across the full network for the period 2013 to 2021. Figure 5 shows the summary results for each region for these FSCs and LCCs for the 2013 – 2019 period. The high degree of seasonality in European LCCs monthly capacity is clearly evident in Figure 5 while European FSCs have significantly lower seasonal variation. In North America, the LCCs have lower seasonal variability than the FSCs beyond 2015[4].

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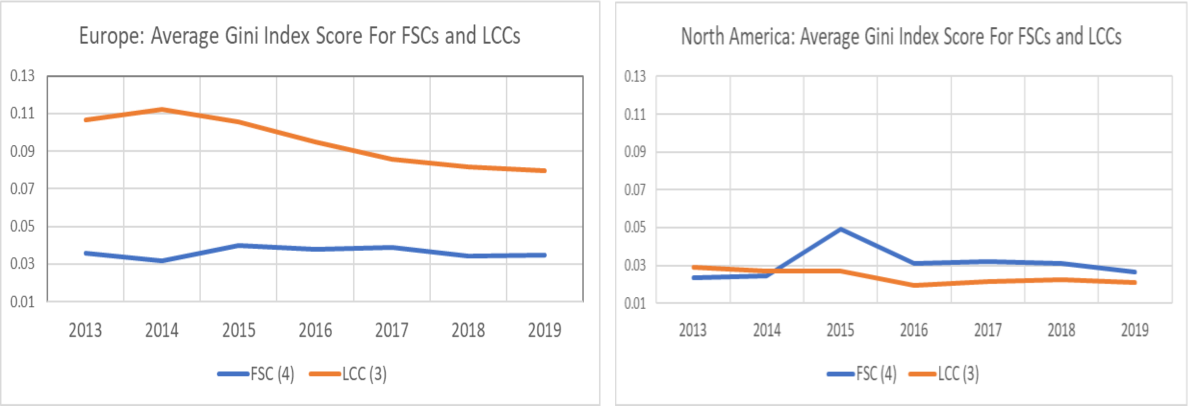
[3] The FSCs in Europe: Air France (AF), British Airways (BA), Lufthansa (LH), Turkish Airlines (TK); The LCCs in Europe: easyJet (U2), Ryanair (FR), Vueling Airlines (VY). The FSCs in North America: Air Canada (AC), American Airlines (AA), Delta Air Lines (DL), United Airlines (UA); The LCCs in North America: JetBlue Airways (B6), Southwest Airlines (WN), Spirit Airlines (NK).

[4] The high Gini score for FSCs in North America in 2015 is largely due to the distortion caused by the American Airlines – US Airways merger.

The difference in Gini scores between FSCs and LCCs is relatively small. European LCCs have larger networks compared to the North American LCCs, with the networks for the three largest European carriers consisting of 100-200 airports in 2019, whereas the North American LCC networks consist of between 60-100 airports in 2019. As discussed in the previous section, the number of airports served in Europe varies monthly with a pronounced cyclical pattern that became established after 2010, and the seat availability follows a strong single peak yearly pattern, with an additional capacity increase observed just for the month of August. This contrasts with the 'W' pattern observed for several US carriers including Southwest where there is a spring peak followed by capacity reduction and then a bigger summer peak in July each year.

Figure 5: Comparison of average Gini Index scores for selected full-service carriers (FSC) and low-cost carriers (LCC) in Europe and North America, 2013 – 2019



Note: Europe FSCs: AF, BA, LH, TK; European LCCs: U2, FR, VY. North America FSCs: AC, AA, DL, UA; North America LCCs: B6, WN, NK.

Air traffic flow patterns vary not only over time, but also across geographical regions. Therefore, analysis of air traffic seasonality must consider both the temporal dimension and the spatial dimension. Reynolds-Feighan (2021) presents a framework for analyzing spatial, temporal, and firm specific air traffic flows across major global regions and finds an exceptionally high degree of seasonality in European air traffic patterns and very low seasonality in North American traffic flows. Koo et al. (2016) establish a composite index to capture an individual airport's traffic distribution characteristics along spatial (i.e., city and country), temporal seasonality and industry dimensions.

Ferrante et al. (2018) propose a new index for measuring tourism seasonality that takes into account the ordinal and cyclical structures of seasonal variations. Their results show a strong connection between seasonal patterns and spatial distribution throughout European countries. Accordingly, airline spatial or network strategy may mitigate or exacerbate seasonal variation of air traffic flows. To explore the potential relationship between airline network structure and seasonality, we quantify and delineate the sample airlines' network structure using selected summary network metrics.

Although network structure is an integral part of airline operation, applying network metrics to quantify and evaluate airline network structure and connectivity has been relatively recent in airline research. Among the limited number of published studies, Lange and Bier (2019) use eight network metrics (network efficiency, transitivity, node strength, betweenness centrality, edge density, closeness, average edge weight, PageRank) to classify airline network structures in their effort to explore the relationship between airline network structures and business models. Wu et al. (2020) use four topological indexes and three network metrics (degree distribution, average path length, and clustering coefficient) to assess the network connectivity of individual LCCs in China. Mazzarisi et al. (2020) propose a new centrality metric to reflect the temporal and multi-layer structure of air transport network, and a causality metric to identify the propagation of extreme events in the network. The paper suggests that these metrics can be used to assess the effects of operational changes on airline network. To the best of our knowledge, there has not been any empirical analysis of the relationship between air traffic seasonality and airline network structure.  This paper fills the gap in literature.

Following the topology analysis methodology applied by Bombelli (2020), Bombelli et al. (2020), and Malighetti et al. (2019), we compute ten network metrics for the 14 sample airlines based on flight schedule data in 2019. The network characteristics for each airline include the number of nodes (i.e., airports) and edges (i.e., direct flight segments), the number of direct flight segments per airport, the network density, the average shortest path of the network, the share of non-stop shortest paths, and the concentration of the shortest paths via non-stop, one-stop, two-stop, and three-stop connections. For each airline, a set of airport-specific measures are also calculated that are then averaged across its network. These include the airport-specific degree of centrality, degree of betweenness, and seat-weighed eigenvector centrality, which represents the importance of an airport in an airline's network in terms of both system-wide connectivity and seat capacity it has to other airports in the network[5].

Of the 14 sample airlines studied, the overall average Gini value in 2019 is 0.039, and the three LCCs in Europe, Ryanair (FR), EasyJet (U2) and Vueling (VY), have above average Gini values. In contrast, among the three North American LCCs, Southwest (WN) and JetBlue (B6) have the lowest Gini values in 2019, while Spirit Airlines (NK) has the highest Gini value, compared to the other four leading FSCs in North America. The annual seat capacity for the sample airlines in 2019 ranges from the smallest at 33 million by Air Canada (AC) to the largest at 211 million by Southwest Airlines (WN).

While the comparison among the three European LCCs indicates that economies of scale may help mitigate the seasonality effect (i.e., the larger the network, the lower the degree of seasonal variability), the effect does not appear to be present for the three LCCs in North America and the European FSCs (Figure 6). For example, while the seat capacity of Vueling (40.6 million) is similar to Spirit Airlines (41.9 million), the Gini value of Vueling is more than three times as large as that of Spirit. Furthermore, while the seat capacity of Southwest (211 million) is more than four times as large as JetBlue (52.4 million), the Gini values are similar for these two U.S. LCCs.

In addition to seat capacity, we also explore whether network size, as measured by the number of airports, and flight segments, might impact the amplitude of seasonality. Excluding Vueling, the other two LCCs in Europe have the highest Gini values, and they are ranked, respectively, the 2nd and 4th in terms of the number of airports in their network, ranked the 1st and 2nd in terms of the number of flight segments making up the network, and also in terms of the number of flight segments *per* airport (node), among all the 14 airlines studied. However, despite bearing the highest seasonality in North America, Spirit Airlines has the smallest number of airports and is ranked 9th in terms of the number of flight segments. Southwest has the 3rd highest number of flight segments *per* airport (node), and the 2nd smallest Gini value only after JetBlue. These findings suggest that no single factor whether it is network size, or scale/scope, determine the amplitude of seasonality. In the next section, we will further investigate whether any of the network structural characteristics could impact seasonality.

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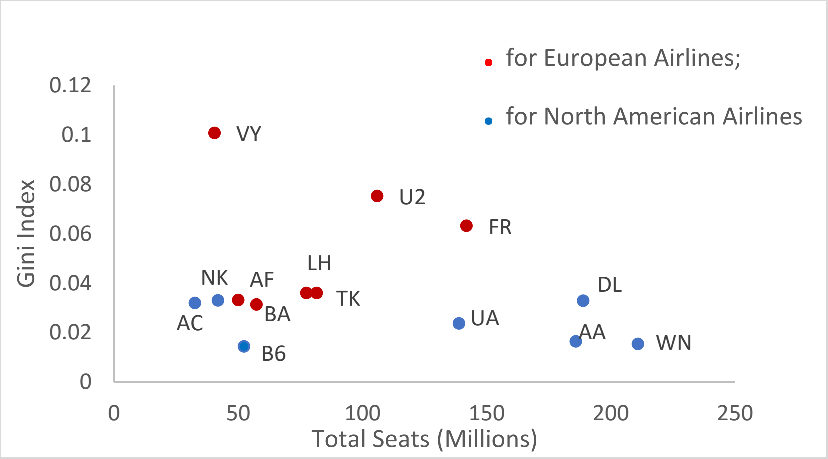
[5] For airline *i* that has *N* number of airports in its network, the degree of centrality for one of its airport *j* measures the number of airports in airline *i*'s network that have direct flights with airport *j*, scaled by the number of all other airports in the network, i.e., *N-1*; the betweenness centrality of airport *j* measures the importance of airport *j* in connecting other airports in the airline *i*'s network through serving as a node on the shortest paths between any other airport pairs; the eigenvector centrality represents the eigenvector corresponding to the largest eigenvalue of the distance matrix containing the number of seats available on the flight segment connecting any two airports in airline *i*'s network.

Figure 6: Gini index score and total available seats for 14 sample airlines in 2019



Consider an airline with its network consisting of $n$ airports (nodes) and $m$ flight segments (known as edges) that directly connect any of the two airports in the network. Network density measures the ratio of the existing flight segments $m$ relative to all the potential connections within the network, which is calculated by $n \times (n-1) \times \frac{1}{2}$ for non-direct flight segments. For an airline that adopts a hub-and-spoke structure, it will have fewer direct connections (i.e., edges) to connect the same number of nodes in its network, as compared to an airline that adopts a point-to-point structure. Therefore, the network density in a hub-and-spoke structure is expected to be lower than in a point-to-point structure for a network of any given size.

Of the fourteen airlines studied, we find that Southwest has the highest network density valued at 0.159, followed by Spirit at 0.112, EasyJet at 0.075, Ryanair at 0.069, JetBlue at 0.050, and Vueling at 0.043. The network density values for all six LCCs are higher than the values for the FSCs, indicating the LCCs' relatively greater reliance on point-to-point structure, as compared to the FSCs.  As shown in Figure 7, there seems to be a negative relationship between Gini value and network density for the LCCs, in particular the higher the network density, the lower the Gini values except for JetBlue. While the network density value for JetBlue is about a third of the value for Southwest, its Gini value (0.014) is similar to that of Southwest (0.015). For the FSCs, their network density values are not only similar to one another, but also consistently lower than those of LCCs, indicating the greater reliance on hub-and-spoke structures by FSCs.

When an airline develops a hub airport in its network, the traffic consolidation effects at the hub airport would help reduce the amplitude of seasonality effects arising from individual routes. Consistent with this proposition, the Gini values for the FSCs, as shown in Figure 7, are found to be lower than the Gini values for all the European LCCs including VY, U2 and FR. Despite the adoption of point-to-point structures, the lower seasonality experienced by Southwest might be attributable to its market entry strategy of favouring airports with greater connections and higher traffic as the airline has become more pivoted to the business passenger segment in recent years (Zou and Yu, 2020).

In addition to network density, the difference between the hub-and-spoke and point-to-point network structure can also be measured by using two other network metrics, the degree of centrality and the share of non-stop shortest paths in the total number of connections involving the shortest paths among all the possible nodes (airports) within the network.  These two metrics appear to follow the same pattern with respects to Gini values, thus only Gini versus the Degree of Centrality is shown is Figure 8.

Figure 7: Gini vs. Network Density

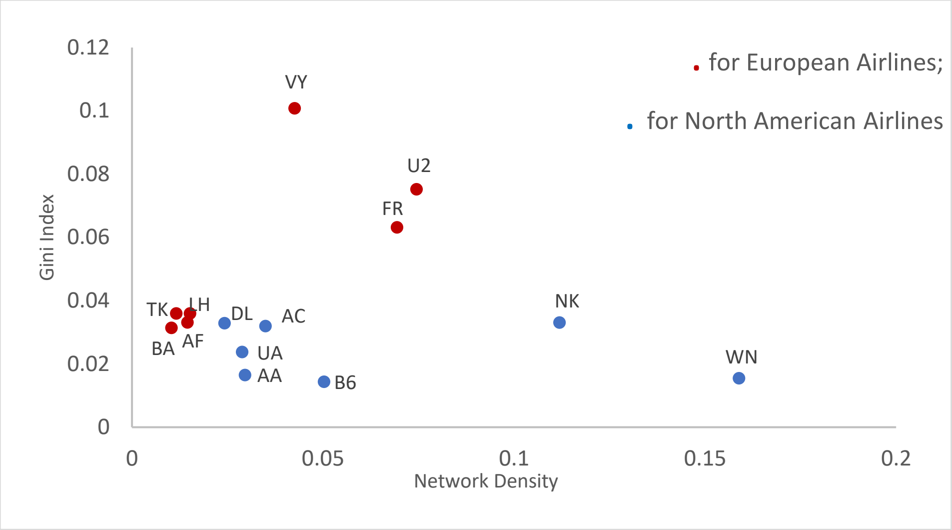
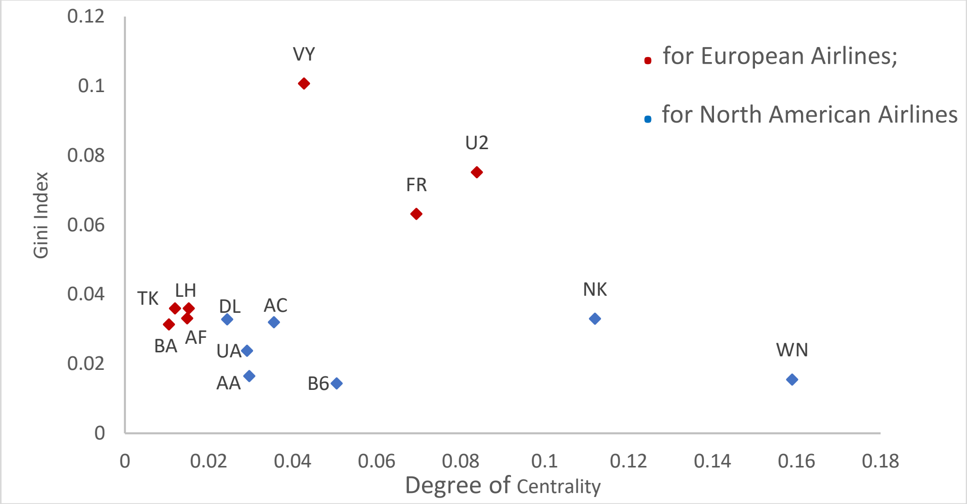


Figure 8: Gini vs. Degree of Centrality



The eigenvector centrality represents the importance of each airport in terms of both connectivity and seat capacity on the flight segments connected to all the other airports in an airline's network. We develop this seat-adjusted system-wide connectivity measure first at the airport level for an airline, and then calculate the average value across all the airports constituting the airline's network. It is expected that for a hub-and-spoke network airline, its hub airports are the most important airports within its own network. Consistent with this expectation, the seat-weighted eigenvalues for Delta Air Lines are found to be highest for its main hub airport, i.e., ATL (0.5822), followed by the value for MSP (0.2609), for DTW (0.2563), and for LAX (0.2192). Similarly, the seat-weighted eigenvalues can be used successfully to identify the three most important airports for American Airlines including DFW (0.4619), CLT (0.3411), and ORD (0.3186), while for United Airlines, its most important airports include SFO (0.3894), ORD (0.3763), EWR (0.3624), IAH (0.3427), and DEN (0.3328). Furthermore, the eigenvalues at other airports are found to be smaller than those of the hub airports, reconfirming the importance of the hub airports in terms of connectivity and capacity in the entire network.

When an airline adopts a point-to-point structure, although it may not have a primary hub airport, it is likely to develop several bases that are particularly important within its network. For example, Southwest Airlines has nine airports that have seat-weighted eigenvalues that are all above 0.2 including

DEN (0.2955), LAS (0.2947), MDW (0.2832), PHX (0.2734), DAL (0.2707), HOU (0.2394), LAX (0.2153), BWI (0.2118), and SAN (0.2107). Although the most important airport (DEN) for Southwest has a smaller eigenvalue than the most important airport (SFO) for United Airlines, Southwest has twenty-three airports with eigenvalues above 0.1, whereas United only has eight airports in its network with eigenvalues above 0.1. As shown in Figure 9, the system-wide eigenvalues across all the airports in the network for the largest FSAs in North America are found to be less than those for the largest LCCs.

When an airline's network consists of many airports that have high capacity and are highly linked to others, it could mitigate the system-wide seasonality effect as a result of traffic agglomeration effects[6], as shown by the three largest LCCs in North America. For example, the two airports that rank the highest for JetBlue are JFK (0.0498) and BOS (0.4161). Although these two airports are not typical hub airports for JetBlue, the high capacity and high connectivity out of these two airports will help smooth out the seasonality effect arising from individual routes. Similar to Southwest, Spirit Airlines also has nine airports in its network that have the seat-weighted eigenvalues that are above 0.2. Moreover, the highest-ranked airport by seat-adjusted eigenvalue for Spirit is FLL (0.4036), which is highly linked and has high capacity to other nodes in the network of Spirit.

As compared to the largest LCCs in North America, the largest LCCs in Europe have fewer such airports that are highly linked and have high capacity to other airports in the network. For example, Vueling has only three airports in its network that have their seat-adjusted eigenvalues above 0.2, although its most important airport (BCN) has an importance value at 0.6557. Similarly, Ryanair and Easyjet only have five airports in their respective networks that have the seat-adjusted eigenvalue being above 0.2, despite their having STN (0.4289) and DUB (0.3705) as the most important airports for Ryanair and having LGW (0.4537) for Easyjet.

In contrast, the reliance on a large number of airports that are highly linked and have high capacity to other airports in the network helps the largest LCCs in North America incur lower Gini values than their LCCs counterparts in Europe. Furthermore, the Gini values of Southwest and JetBlue are lower than all other FSCs, despite their adoption of a non-hub-and-spoke network structure.

Our findings suggest that seasonality could be mitigated by the adoption of hub-and-spoke network structure. Moreover, if an airline adopts a point-to-point structure, it could also mitigate seasonality through developing several airports that are highly linked and have high capacity to other airports in the network. The seasonality is expected to be most severe when an airline adopts a point-to-point structure consisting of a large number of airports that are not highly linked and do not have high capacity to other airports in the network. More rigorous empirical investigation using a larger sample of airlines would be needed to test the above hypothesis.

Examining several dimensions of network structure and the associated connectivity, we observe that while North American and European LCCs share a number of network characteristics, the European LCCs have exceptionally high variability in their capacity.

Figure 9: Gini vs. Seat-weighted Eigenvalue

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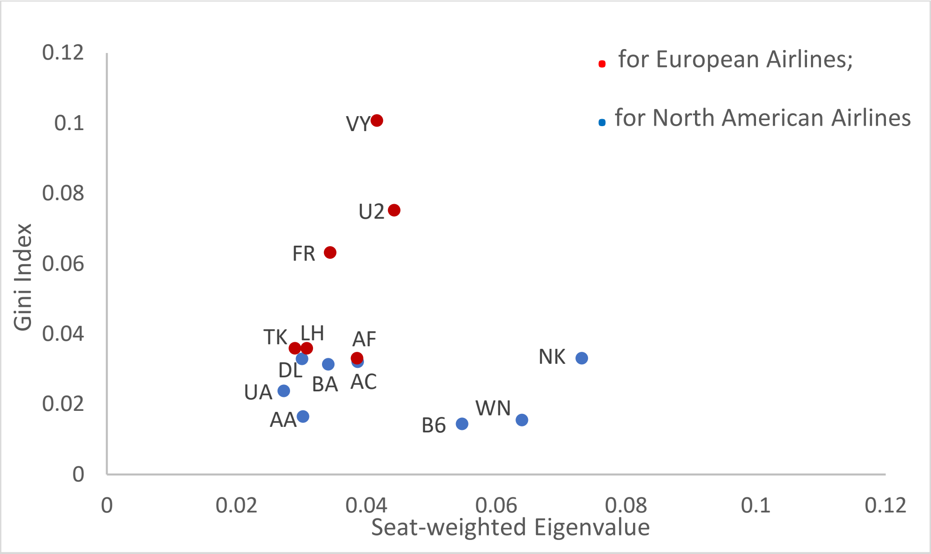
[6] The theoretical analogy of traffic agglomeration effect is statistical economies of scale, which says that the variation of the aggregated market demand is less than the sum of the variation of individual markets by a factor of the squared root of the number of markets, when the demand at individual markets is independent, and has identical standard deviation.



## 4. Discussion, Conclusions and Agenda for Further Study

The European LCCs and ULCCs seem to have driven the exceptionally high overall European capacity summer seasonal peak, contributing to the overall high seasonality of air traffic in Europe as compared to North America. The European LCCs operate relatively large networks with relatively low frequency and many seasonal airports, typically at Medium, Small and Non-hub airports. A closer examination of capacity deployment and management would give important insights into the adaptation strategies for different airlines (i.e., business model, network structure) in dealing with seasonality effects. The experience of airlines in other geographical regions would also provide useful insights in this regard. We set out a structured agenda for further study in Table 2.

Our exploratory analysis does not find any definitive evidence on the effects of airline network size on air traffic seasonality. However, our results indicate a negative relationship between Gini value and network density and the degree of centrality for the LCCs, suggesting that increasing network density and degree of centrality may help LCCs to mitigate the effects of seasonality. Conversely, our results indicate a positive relationship between the Gini value and seat-weighted eigenvalue for FSCs and European LCCs, suggesting that when an airline adopts a point-to-point network and when the network consists of fewer highly connected and high-capacity airports, it is more likely to be susceptible to seasonality than a hub-and-spoke network. Certainly, the different seasonality pattern experienced by airlines will not be fully explained by considering only the spatial dimension of network structure in terms of its centrality, connectivity, and density metrics. In Table 2, we suggest the development of databases supporting a multi-dimensional network structure in the context of social, cultural, economic, and geographic and climate characteristics and propose that this would be worthwhile studying to fully understand the confounding effects on seasonality.

Airports in the Medium, Small and Non-hub categories appear to have been impacted less by Covid19 restrictions and have been faster to recover in late 2020 and during 2021 as there has been some resumption in air travel in both Europe and North America. The LCCs in Europe operate predominantly short haul point-to-point services. Long haul air services, particularly on international/extra-EU routes have been slow to recover and European FSCs have had lower total capacity on offer in 2021 compared to LCCs. The ability of the LCCs to survive and recover from the pandemic will be closely monitored in the next couple of years: perhaps their dispersed network and experience with high seasonal capacity variability means that they are better placed to weather this exceptional global public health event.

Table 2 proposes study of the effects of seasonality on airline financial performance. Findings from studies examining the impacts of seasonality on hotel financial performance/survivability are not conclusive. Seasonality has negative impacts on hotel occupancy rates during the off-season, but high seasonality allows hotels to charge significantly high rates during the peak season, generating high overall revenues. Some studies find negative overall impacts on hotel financial performance, whereas other studies find positive overall impacts on hotel financial performance. For airlines, seasonality undoubtedly has negative effects on fleet utilization, but similar to hotels, air fares during the high season are significantly higher. Investigating airline financial performance explicitly taking account of the role of seasonality would provide important insights and as shown in Table 2, would require the development of a database of appropriate financial, operational and network indicators.

This note presents some evidence on the relationship between airline network structure and seasonality. However, the network metrics used in this note do not consider climate differences. Another area proposed in Table 2 for future research is to incorporate climate characteristics into the network metrics, the relationship between a “climate adjusted” network structure and seasonality might provide useful insights on the nature of air travel market demand (i.e., the composition of air passenger traffic including business, leisure, and VFR travellers) and climate zone diversification (or the lack thereof).

In Table 2, the final recommendation is for the development of simulation models to examine alternate approaches to supplying air traffic capacity in different geographical regions. The growing pressure on the aviation sector from climate change advocates raises questions about the long-term sustainability of short haul aviation particularly where surface transport alternatives (utilising non-fossil fuel energies) exist. This will particularly impact LCCs where network structures are focused on short haul routes. The excess capacity for many months of the year may point to a re-assessment of the traditional model of airlines continuously meeting peak demand, in favour of limiting capacity and rationing using pricing mechanisms during the peaks.

Table 2: An Agenda for Further Study of Air Traffic Seasonality

| **Tasks** | **Description** |
|---|---|
| Country & Regional comparisons of seasonality | Investigate high level (country and continental) trends in seasonality globally to understand the experience in different regions and countries of seasonal variability in air traffic. |
| Drivers of Seasonality | Develop a geo-referenced database of European and North American airports, capturing economic, demographic, social, cultural and climatic conditions associated with airport hinterlands. |
| Quantitative Depiction of Network Structures | Generate graph theory/network metrics to delineate airline network structure and investigate the influence of airlines on these measures across airport systems. |
| Airline Capacity and Financial Performance | Develop a financial performance database for North American and European airlines covering the period from 2010 onwards and include suitable graph theory/network metrics and capacity metrics. These metrics would be computed at the route and airport level and aggregated for different time periods (quarterly and annually) and airline nomenclatures (e.g. airline group operations; domestic versus international network operations; alliance and code sharing partnerships). |
| Covid19 Traffic Recovery | Track the recovery in air transport activity as countries emerge from the global pandemic and identify significant changes in pre and post pandemic traffic trends in relation to spatial and temporal distributions. |
| Causal links between seasonality and airline performance | Develop econometric models to quantify links between seasonality, climatic and environmental profiles, socio-economic and demographic indicators, and airline capacity and performance outcomes. |
| Alternate airline network structures to reduce seasonality | Develop simulation models to investigate alternate scenarios for supplying the European and North American markets under different network structures. |

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Appendix

Table A presents the summary of the aforementioned network metrics for the selected FSCs and LCCs in Europe and North America based on flight schedule data in 2019.

Table A. Comparison of Network Metrics among the leading airlines in NA and Europe, 2019

| | Nodes | Edges | Edges per Nodes | Network Density | Avg. Shortest Path | Share of non-stop shortest path | Concentration of the Shortest Path Connection | Degree of Centrality | Degree of Betweenness | Seat-weighted Eigenvalue |
|---|---|---|---|---|---|---|---|---|---|---|
| B6 | 107 | 571 | 5.34 | 0.050 | 2.115 | 5.04% | 0.647 | 0.050 | 0.011 | 0.055 |
| WN | 103 | 1670 | 16.21 | 0.159 | 2.002 | 15.90% | 0.535 | 0.159 | 0.010 | 0.064 |
| AA | 221 | 1439 | 6.51 | 0.030 | 2.222 | 2.97% | 0.581 | 0.030 | 0.006 | 0.030 |
| UA | 224 | 1443 | 6.44 | 0.029 | 2.332 | 2.91% | 0.525 | 0.029 | 0.006 | 0.027 |
| AC | 106 | 389 | 3.67 | 0.035 | 2.267 | 3.52% | 0.532 | 0.035 | 0.012 | 0.039 |
| DL | 251 | 1525 | 6.08 | 0.024 | 2.181 | 2.44% | 0.637 | 0.024 | 0.005 | 0.030 |
| NK | 76 | 638 | 8.39 | 0.112 | 2.052 | 11.19% | 0.565 | 0.112 | 0.014 | 0.073 |
| BA | 216 | 485 | 2.25 | 0.010 | 2.648 | 1.05% | 0.497 | 0.010 | 0.008 | 0.034 |
| AF | 178 | 460 | 2.58 | 0.015 | 2.182 | 1.48% | 0.718 | 0.015 | 0.007 | 0.039 |
| TK | 286 | 948 | 3.31 | 0.012 | 2.039 | 1.18% | 0.882 | 0.012 | 0.004 | 0.029 |
| LH | 205 | 637 | 3.11 | 0.015 | 2.055 | 1.53% | 0.843 | 0.015 | 0.005 | 0.031 |
| FR | 241 | 4016 | 16.66 | 0.069 | 2.263 | 6.95% | 0.473 | 0.069 | 0.005 | 0.034 |
| U2 | 283 | 5952 | 21.03 | 0.075 | 2.224 | 7.46% | 0.489 | 0.084 | 0.007 | 0.044 |
| VY | 150 | 716 | 4.77 | 0.043 | 2.058 | 4.27% | 0.745 | 0.043 | 0.008 | 0.042 |