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Airline Seasonality: an Explorative Analysis of Major Low-Cost Carriers in Europe and the United States

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Abstract

We develop two air traffic seasonality indices to complement the traditional Gini index. These measurements are adopted to assess the variability of air traffic over time and across the route network of low-cost carriers (LCCs) in Europe and the United States and to estimate the impact of seasonality on fleet utilization. Using panel data for nine LCCs in Europe and the United States from 2004 to 2017, we find that higher seasonality results in lower fleet utilization after controlling for stage length, network size, aircraft size, and fleet standardization. Moreover, we find that seasonality is negatively associated with spatial and climate zone diversification of airline route networks. These results suggest that airlines may be able to reduce seasonal traffic variability through diversifying their networks geographically and consequently mitigating the negative fleet utilization impact.

Keywords: Seasonality, Fleet Utilization, Low-cost Carriers
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1. Introduction

Demand for air travel is derived from demand for activities such as business, visiting friends and family, and tourism. Because demand for tourism and holiday travel tends to be seasonal, air transport demand by leisure and vacation travelers also tends to vary seasonally. However, airline capacity, particularly the fleet and employee components, has limited flexibility within each seasonal cycle. Balancing demand and capacity poses a major challenge for airlines with significant seasonal markets. Airlines have adopted different strategies to deal with the seasonal demand. While peak load pricing can contribute to management of demand fluctuations, some airlines, e.g., Ryanair and easyJet, offer only seasonal services to certain airports in their network, and may park "surplus airplanes" during the off-peak season. In contrast, other airlines, such as Southwest, are more cautious about the airports they serve, and minimize or even avoid serving seasonal airports[1] in their networks.

Anecdotal evidence indicates that Ryanair grounds about 20% of its aircraft during the low-season months in a typical year, leading to a lower annualized fleet utilization than other low-cost airlines including its archrival, easyJet. Based on daily airline schedule data from OAG, Reynolds-Feighan (2018 & 2021) calculates the system-wide seasonality at airports in the three years of 1996, 2006, and 2016, and finds the presence of lower seasonality (measured by Gini Index Scores) in the United States as compared to Europe and other regions. Moreover, Reynolds-Feighan (2018) provides an in-depth study investigating the regional carrier operations in the U.S. air travel market and finds that regional carriers play a significant role in helping the mainline airlines mitigate seasonality and achieve higher fleet utilization as compared to airlines in other regions of the world.

Although there has been a movement toward hybridization of airline business models in the recent years (Birolini et al., 2021, Morlotti et al., 2020, Klophaus et al. 2012), our exploratory analysis of European airline schedules indicates that there is relatively little seasonality in terms of scheduled seats among the traditional full-service network carriers (FSCs), which is consistent with the findings of anna.aero (2015). On the other hand, scheduled flights/seats for low-cost

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[1] Seasonal airports are defined in this paper as an airport where at least one airline has less than one full-year operation that is not related to market entry or exit during the year concerned. If an airline enters or exits from an airport during a given year, the operation at this airport will not be full year, but this airport will not be identified as a seasonal airport.

carriers (LCCs)[2] tend to show significant seasonal variations. This may be explained by the fact that LCCs continue to focus largely on leisure travelers with seasonal demand and generally operate in the short and medium haul markets. With the continued expansion of LCCs, it remains unclear how the route network structure unique to many LCCs impacts the seasonality they may experience. Moreover, as many LCCs, such as Ryanair, easyJet, and Allegiant Air, have targeted and entered tourism routes including destinations that are particularly popular during holiday seasons, the impacts of seasonality on airline performance are of significant importance to airline management. This paper focuses on seasonality and fleet utilization of LCCs in Europe and the United States.

Using panel data for nine LCCs over the 2004 - 2017 period, we quantify both the temporal and spatial dimensions of airline routes and traffic dispersion patterns over time and across the route network using three alternative seasonality measures. The traditional Gini index and our proposed Concentration Index focus on temporal dimension of seasonality, whereas our proposed SES Pooling Index incorporates the spatial as well as temporal dimensions of traffic variability by measuring the aggregation effect across all airports in an airline's network. Furthermore, we use *Köppen* values to depict climate diversification of airline route network in order to analyze their effects on air traffic seasonality. This paper addresses two key research questions: (1) How does the geographic and climate diversification of LCCs' route networks affect their traffic seasonality? and (2) What are the effects of seasonality on airlines' fleet utilization? Our empirical results suggest that higher seasonality results in lower fleet utilization, and seasonality is negatively associated with spatial and climate zone diversification of airline route network. While these findings are drawn in the context of LCCs in Europe and the United States, the implications are also relevant to full-service airlines that have pivoted their route network toward leisure travel markets during the COVID-19 pandemic period.

Our study contributes to the aviation seasonality literature in three aspects. First, we develop two alternative seasonality measures describing the temporal-spatial characteristics of air traffic variability. Second, we empirically explore the potential relationship between climate

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[2] Low-cost carriers in this paper also include the so-called ultra-low cost carriers (ULCC), namely Spirit, Frontier, and Allegiant.

diversification and airline seasonality. Finally, we find empirical support for the effects of seasonality on airline fleet utilization.

The rest of the paper is organized as follows. Section 2 reviews the literature on seasonality, focusing on how it is measured. Section 3 describes our research design and presents several measures to capture temporal and spatial aspects of air travel seasonality as well as measures of climate diversification of airline route networks. Section 4 describes the data sources and sample selection, and examines the seasonality trends among the sample airlines. Section 5 sets out our empirical models and discusses the estimation results. Section 6 summarizes our conclusions and discusses their implications for airline management and further research.

2. Literature Review

Seasonality has been extensively studied in the context of the tourism industry. Koenig-Lewis and Bishoff (2005) provide a good review of works in the area of tourism seasonality research including both methodology and empirical findings. Several measures of seasonality have been developed and applied in the literature. The Gini index is perhaps the most commonly used indicator of seasonality, such as in Fernández-Morales and Mayorga-Toledano (2008), Þórhallsdóttir and Ólafsson (2017), Marton et al. (2019), Šuštar and Ažić (2019), and Reynolds-Feighan (2018 & 2021). The Gini Index was introduced in 1912 by Corrado Gini (Ceriani and Verme, 2012), and has been applied in many disciplines to study inequality and variability. Many researchers choose the Gini index because of its stability and lack of sensitivity to outliers (Turrion-Prats and Duro, 2018).

Lundtop (2001) discusses several other seasonality measures, including the coefficient of seasonal variations, Seasonality ratios, and Seasonality indicator. The Seasonality ratio is considered as a measure of amplitude, as it measures the relation between the maximum value and the average value. The Seasonality indicator is the inverse of the Seasonality ratio and measures the occupancy rate when applied to hotels. Studies using these measures include Bigovic (2011), Petrevska (2015) and Duro and Turrion-Prats (2019). Duro and Turrion-Prats (2019) use the Coefficient of Variation to measure and analyze the temporal concentration of worldwide tourist demand during the 2008-2013 period. The study finds that the highest seasonality is concentrated in the

Mediterranean countries, and the world seasonality shows an inverted U-shape pattern (indicating a distinctive summer peak). Lundtop (2001) points out that these measures do not take account of the skewness of the distributions and are influenced by extreme values. Some studies use multiple indicators to measure seasonality of tourist demand. Coshall et al. (2015) disaggregate quarterly numbers of overnight stays in the regions of Scotland by vacation tourists, overseas visiting friends and relatives (VFR) and business visitors, and examine the seasonality patterns of each group using amplitude ratios and Gini Coefficients.

Duro (2016) proposes to use Theil Index and the Coefficient of Variation (in addition to the Gini Index) and decomposes hotel monthly seasonality based on results from the Theil index. The Theil Index is shown to be more sensitive to changes in the months with lower demand. Rossello and Sanso (2017) propose to use entropy and relative redundancy as alternative tourism seasonality indicators to the Gini index. Entropy is derived from the Theil Index, and relative redundancy is directly derived from entropy "as a way of indexing a measure from 0 to 1." Rossello and Sanso (2017) state that the entropy measure is computationally simple, and easily decomposable into multiple dimensions. Ferrante et al. (2018) propose a general approach for the analysis and measurement of seasonality in tourism, based on two key-aspects of seasonality, its pattern and amplitude. The study proposes a new index for measuring tourism seasonality in order to measure seasonal amplitude, which takes into account the ordinal and cyclical structures of seasonal variations. Their results show a strong connection between seasonal patterns and the spatial distribution throughout European countries. Martín et al. (2019) propose to use a distance method (DP2) to aggregate Gini indices measured in terms of different variables (such as domestic travelers, foreign travelers, etc.) to form a "synthetic" seasonality indicator.

Seasonality of air travel, however, has attracted limited attention among academics. Reynolds-Feighan (2007a) presents a framework for analyzing spatial and industry dimensions of air transport activity and utilizing Gini decomposition approaches to track between micro-level and macro-level changes in air transport activity, and this has been extended to include a temporal dimension of seasonality in Reynolds-Feighan (2021). This application compares major global regions and identifies the exceptionally high degree of seasonality in European air traffic patterns and very low seasonality in North American air traffic flows.

Koo et al. (2016) present an airport dependency index (ADI) and argue that the composite index captures an individual airport's traffic distribution characteristics along spatial (i.e., city and country), temporal seasonality and industry dimensions. Their ADI is a linear combination of four Gini sub-indexes relating to traffic distributions across cities, countries, airlines, and time, with weights determined by average results from a survey of industry experts' Likert scores. Raju et al. (2020) apply the HEGY method (Hylleberg, et al.,1990) to monthly air traffic data at six major airports in India, and their results indicate the presence of seasonality at all six airports albeit with different patterns.

Instead of using any seasonality indicators, Garrigos-Simon et al. (2010) estimate two separate autoregressive models to analyze airlines' pricing behavior in the Alicante-London market: one for April and one for August. Kraft and Havlíková (2016) examine the monthly patterns of flights at 10 selected airports in Central Europe in 2014 in relation to types of carriers providing services at the airports and the geographical distribution of non-stop destinations from the airports. The study simply observes monthly flight fluctuations in traffic bar charts generated from data collected from flightstats.com. No seasonality measure is used. Merkert and Webber (2018) develop a model of airline seasonal pricing and seat load factors that include two independent airfare equations: high season and low season, assuming the same seat capacity in both seasons. Some studies have included time dummies or time fixed effects in their analysis to capture certain seasonality issues. Rupp et al. (2006) include 3 seasonal dummies (Winter, Spring, and Summer) to capture the seasonal differences in their investigation of the effects of route competition on airline on-time performance. Although not intended for seasonality, Forbes (2008) includes two time dummies, *Post1* (second and third quarter of 2000) and *Post2* (last quarter of 2000), to represent the expansionary period and the containment period following the Aviation Investment and Reform Act for the 21st Century (AIR-21) being enacted in April 2000 and to study the effects of delays on airline prices.

As the discussions above attest, there is a gap in the literature with respect to analysis of air travel seasonality and lack of consensus on the seasonality measures. This paper contributes to the literature by (i) defining and proposing appropriate metrics of seasonality for air transport studies;

(ii) exploring the extent of the impact of airline network climate diversification on air traffic seasonality; and (iii) analyzing the effects of seasonality on airline fleet utilization.

3. Research Design

To empirically investigate the potential effect of climate and geographic diversification of an airline's network on its traffic seasonality, and the impact of seasonality on fleet utilization, we develop two seasonality measures, SES Pooling Index and Concentration Index, to complement the traditional Gini index, which enables us to assess multiple aspects of the variability of monthly air traffic throughout an airline's network.

Whereas previous studies have used dummy variables to represent different geographical locations (such as Vowles, 2000; Morrison, 2001), this study constructs a set of climate variables to measure the climate diversification of airline network based on Köppen Climate Classification (Chen & Chen, 2013). Our study attempts to quantify the relationship between these climate variables and airline traffic seasonality. A logical conjecture would be that airlines with geographically diversified networks may have seasonal services during different times of the year in different regions, allowing them to retain a level of overall traffic stability throughout the year. Thus, we hypothesize that there is a negative association between an airline's route network geographical diversification and air traffic seasonality.

Fleet utilization has been included as a factor that may affect airlines' performance in previous studies such as Amizadeh et al. (2016) and Mantin and Wang (2012). However, there has been limited research that examines factors that affect airline fleet utilization, apart from those on fleet planning and aircraft assignment. As stated in the Introduction section, airlines have limited flexibility to adjust fleet capacity within each seasonal air travel cycle, and thus high seasonality is expected to result in low fleet utilization. This common belief, however, has not been empirically investigated in existent literature. To fill this gap, we hypothesize that seasonality has a negative effect on an airline's fleet utilization. Our study provides empirical analysis assessing the impact of air traffic seasonality on fleet utilization.

3.1 Seasonality Indices

As discussed in the previous section, air traffic seasonality not only have a time dimension, but also a spatial dimension. Therefore, the seasonality measures that are often used in tourism studies, such as coefficient of seasonal variations, seasonality ratios, seasonality indicator, may not be able to adequately reflect the seasonality of air travel as these measures are sensitive to extreme values and do not consider the likely unevenness of traffic fluctuations (Lundtop, 2001). Therefore, we propose a unique measurement for assessing the spatial seasonality effect, drawing upon the concept of “statistical economies of scale” (SES) in the supply chain management literature. To provide a complete profile of the seasonality of low-cost airlines’ services, we also develop a traffic concentration index based on the Herfindahl-Hirshman Index (HHI). Air traffic seasonality patterns depicted by the SES Pooling Index and the Concentration Index are compared with those derived from the most commonly used Gini Index.

3.1.1 SES Pooling Index

Eppen and Schrage (1981) and Evers (1994) discuss the existence of the so-called ‘statistical economies of scale’ which is defined as the advantages that firms could derive from markets pooling or through inventory consolidation, thereby reducing demand uncertainty and thus safety stock requirements. In the context of airline operations, such potential “pooling” effects may arise if airlines can reassign their aircraft across airports with seasonal services during different season(s) of the year and at different locations. The number of seasonal airports and their geographic locations will both affect the magnitude of such “pooling” effects. To the extent that airports are complementary in terms of seasonality of demand occurrence, the opportunities and advantages will increase for airlines from aircraft reassignment across airports within its network. A spatial seasonality measure, namely the SES Pooling Index, can be constructed based on either the number of scheduled seats or the number of scheduled flights.

Consider airline *i* in year *t,* we first calculate the standard deviation of scheduled seats it has at airport *j* over the 12 months of the year *t*, denoted as $SD\ of\ Seats_{ijt}$. The sum of the standard deviations is calculated for this airline across all the airports it operates in year *t*, and is the denominator in the index formula (Eq. 1). We also aggregate the scheduled seats across all the airports for airline *i* in year *t*, and calculate the standard deviation of the aggregated seats over the 12 months of the year *t*. According to the ‘statistical economies of scale’ rule, the ratio of the standard deviation of the aggregated seats to the sum of the standard deviation of seats across the airports is expected to be less than 1. The lower the ratio value, the stronger the "pooling" effect, i.e., an airline can better reallocate the aircraft in its network for higher utilization rates. Similarly, the SES Pooling Index can be calculated based on scheduled flights. The formula for the SES Pooling Index by scheduled seats and scheduled flights are the following.

$$\text{SES Pooling Index}_{it} \text{ by Seats} = \frac{Std.\ Dev.\ of\ (\sum_{j=1}^{Nit} Seats_{ijt})}{\sum_{j=1}^{N} SD\ of\ Seats_{ijt}} \qquad \text{Eq. (1)}$$

$$\text{SES Pooling Index}_{it} \text{ by Flights} = \frac{Std.\ Dev.\ of\ (\sum_{j=1}^{Nit} Flights_{ijt})}{\sum_{j=1}^{N} SD\ of\ Flights_{ijt}} \qquad \text{Eq. (2)}$$

3.1.2 Gini Index

As stated earlier, the Gini index is a commonly used seasonality measure (Yizhaki and Schectman, 2013). Following Reynolds-Feighan (2018), we calculate the Gini Index for the overall airline traffic as well as at each airport in an airline's network based on monthly (quarterly) scheduled seats and scheduled flights. Specifically, the following Gini Index scores are calculated.[3]

(i) Day-adjusted monthly traffic at network level for each airline. Airline system-wide monthly traffic (seats and flights) is used to calculate a yearly Gini index score, adjusting for the number of days in each month.

(ii) Quarterly traffic at network level for each airline. Airline system-wide quarterly traffic (seats and flights) is used to calculate a yearly Gini index score.

(iii) Disaggregated airline-specific, airport-level Gini index. Day-adjusted airport traffic is used to calculate a Gini Index score for each year, adjusted for the number of days in each month.

3.1.3 Concentration Index

To further explore and compare the extent of airline seasonal variability, we develop the Monthly Concentration Index at the airline level and at the airline-airport level based on the concept of the

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[3] We also explore the possible effects of calendar year (January to December) on seasonality measures, by computing 'rolling Gini index scores' where we compare the index values as we vary (roll) the 12 months included in the calculations. That is, Gini Scores are computed for different sets of 12 consecutive months over a two-year period for a sample of airlines. Extensive testing of airline traffic trends using the rolling Gini index revealed that there was no material impact on the calculated Gini Index scores. Therefore, all the analysis including the concentration measures in this paper uses January – December monthly traffic for the calendar year indicated.

Herfindahl-Hirshman Index (HHI). HHI has been widely used for measuring market concentration among firms. For example, Zhang et al. (2020) use both the unweighted HHI and weighted HHI to measure competition in the Chinese domestic air transport market. Manuela et al. (2019) use the HHI to assess market power of airlines at SeaTac (Seattle Tacoma International Airport). HHI has also been used as a measure of concentration in other studies. For example, Suau-Sanchez and Burghouwt (2011) use HHI to analyze the geographical concentration pattern of seat capacity at Spanish airports. Chi (2016) applies HHI to investigate the citation concentration characteristics of journal articles and books in Web of Science (WoS). Lee et al. (2020) develop a concentration index for industrial accidents based on the Herfindahl-Hirshman Index.

Seasonality means uneven traffic distribution over time, indicating there is some degree of concentration of traffic during certain periods. Naturally, HHI provides a good indicator of temporal concentration of traffic. At the airline level, we use the aggregated monthly scheduled seats across all the airports for airline *i* in year *t* to calculate the degree of the concentration of the scheduled seats over months in the year.[4]

$$Monthly\ Seat\ Concentration\ Index_{it} = \sum_{M=1}^{12}\left(\frac{Number\ of\ Seats_{iM}}{Number\ of\ Seats_{it}}\right)^2 \qquad \text{Eq. (3)}$$

3.2 Climate Diversification Indices

The widely used Köppen Climate Classification is based on the relationship between climate and vegetation and divides climates into five main climate groups, denoted by letters $A - E$: A for tropical area, B for arid area, C for temperate area, D for continental area, and E for polar area. Table 1 provides a reference for the Köppen values in letter codes and the corresponding Köppen grid codes for each of the climate groups. Köppen Climate Classification, therefore, allows us to compile detailed climate information including Köppen Climate Zone values, precipitation, and temperature for seasonal airports in an airline's network. In particular, the following four climate variables[5] are constructed to measure climate diversification:

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[4] Similar to the development of SES Pooling Index and Gini Index, we also calculate the HHI concentration measures using monthly scheduled flight data, which is highly correlated with seat-based HHI concentration index.

[5] Initially, we also constructed two other climate variables, $COV\_KPV\ I_{it}$ - the coefficient of variation of climate zones, as indicated by Köppen Category I letter codes ; and $COV\_KPV\ II_{it}$ - the coefficient of variation of climate zones, as indicated by Köppen Sub-category II letter codes, where airline *i*'s airports are located in year *t*. Since they are highly correlated with COV_KPV_{it}, they are not included in the empirical analysis.

Insert Table 1

(1) NUM_KPV_{it}: Number of climate zones, as indicated by the Köppen values, where airline *i*'s airports are located in year *t*;

(2) COV_KPV_{it}: The coefficient of variation of climate zones, as indicated by Köppen numerical values, where airline *i*'s airports are located in year *t*;

(3) $HHI\_KPV\_Seasonal\_Airport_{it}$: The concentration of seasonal airports of airline *i* in year *t* across different climate zones, as indicated by Köppen values, of the airline *i*'s network. It is calculated by the following three steps. First, the number of seasonal airports in each climate zone is counted for airline *i* in year *t*. Second, the percentage of seasonal airports in each climate zone is calculated in the total number of seasonal airports for airline *i* in year *t*. Last, the squared percentage values are calculated, and then added up across all the climate zones that airline *i* has in year *t*.

(4) *Number of Seasonal Airports per* KPV_{it}: The number of seasonal airports that airline *i* has in year *t* per climate zone, as indicated by Köppen values. It is calculated by the following formula.

$$Number\ of\ Seasonal\ Airports\ per\ \mathrm{KPV_{it}} = \frac{Number\ of\ Seasonal\ Airport_{it}}{Number\ of\ KPV\ Zones_{it}} \qquad \text{Eq. (4)}$$

4. Data and Preliminary Analysis

4.1 Data Sources and Sample Airlines

Our primary data source is airline monthly schedules retrieved from Cirium Diio Mi/SRS Analyser.[6] Our initial sample includes 5 major LCCs in Europe, Ryanair (FR), easyJet (U2), Air Berlin (AB), Vueling Airlines (VY) and WOW Air (WW); and 6 major LCCs in the United States, Southwest (WN), Frontier (F9), AirTran Airways (FL), JetBlue (B6), Spirit (NK), and Allegiant Air (G4). Due to lack of data, Vueling and WOW are excluded from the study. Therefore, the final dataset includes 9 LCCs over the 2004 to 2017 period. Table 2 summarizes the basic information of our sample airlines.

Insert Table 2 herein.

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[6] SRS Analyser is now part of the LexisNexis Risk Solutions Group subscription product offerings and gives daily airline schedules for global airlines and include rostered equipment.

We do not include the full service or network carriers in our analysis for two reasons. First, in both Europe and the United States, the large FSCs have gone through several rounds of mergers in the past two decades and these airlines were significantly different entities between the start and end of our analysis period. In exploring the relationship between climate and seasonality, and seasonality and fleet utilization, we track the evolution of carrier networks as airlines enter and exit routes. The merger events of FSCs and their regional feeder carriers distort the data and would detract from the focus of our research. Second, for network carriers in both Europe and the United States., there is significant subcontracting of air services within the large airline groups. In Europe, the large network carriers retain their national brands. For example, Lufthansa Group owns Lufthansa, Austrian Airlines and Brussels Airlines but operates them as distinct brands.[7] In the United States, while there are single brands among the three large network carriers, each carrier subcontracts a significant share of domestic capacity to mostly independently owned regional feeder carriers. Adding more complexity to the issue is the fact that large regional carriers have contracts with more than one of the network carriers. For example, SkyWest provides feeder services to all four network carriers in the United States (Alaska Air, American Airlines, Delta Air Lines and United Airlines). The ownership arrangements for the LCCs, on the other hand, do not have such complex arrangements in the marketing and operation of the schedules during our analysis period, and with the exception of Southwest Airlines, did not engage in significant mergers or acquisitions over the study period. We include provision for the Southwest merger with AirTran in our empirical analysis.

Figure 1 shows the monthly number of airports served by the three European LCCs from August 2003 to January 2019. Ryanair has the largest network serving more than 200 airports for much of 2018, followed by easyJet with around 150 airports. Air Berlin's network was of similar size to that of easyJet prior to 2008 but had become smaller until its operations ceased in October 2017. The variability in the number of airports served by the three European LCCs shows a clear cyclical pattern especially after 2008 with more airports served during the summer months compared to winter months each year. Figure 2 shows the monthly number of airports served by the U.S. LCCs over the same period. The U.S. LCCs' networks are generally smaller than those of their European

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[7] There were 13 brands within the Lufthansa group in 2018 and a complex set of subcontracting/code share arrangements between a total of 39 airlines operating Lufthansa Group services in 2018.

counterparts and show less variability in a given year. The U.S. LCCs appear to fall into two groups. Group One consists of Southwest, Spirit, and JetBlue showing a gradual increase in their network size over time and having a very small number of seasonal airports. The overall network size is small with less than 100 airports in 2018. The second group includes Frontier and Allegiant. There is higher seasonal variability in the number of airports served by Allegiant, while Frontier has experienced significant restructuring and network reorganization during the 2004-2017 period.[8] Both airlines have shown a pronounced trend of seasonal variability since 2006, with Allegiant showing less variability in the period after 2015.

The comparison of the number of airports served by European LCCs and that by the U.S. LCCs indicates that European LCCs tend to have more seasonal services than their U.S. counterparts. This finding is consistent with the results of Reynolds-Feighan (2021) that shows the aggregate air traffic in Europe is more seasonal than in the United States.

Insert Figure 1 and 2 herein.

Figure 3 shows the spatial distribution of the seasonal airports served by the three major European LCCs during the study period. We can see that the summer seasonal airports in Europe are concentrated in the "sun-sand" holiday resorts surrounding the Mediterranean Sea and Adriatic Sea coastal areas including Spain, Italy, Croatia, Greece, and Turkey. During the winter months, seasonal airports are located in the Alps and French/Swiss/Italian mountain resorts for skiing and other winter sport recreation. In contrast, the seasonal airports in the United States, as shown in Figure 4, are agglomerated in two broader regions – the Rocky Mountains in the west, and the Heartland and Southern Appalachian regions in the mid-west. There are also some airports with seasonal services operated by LCCs in Southern California, Cape Cod/Massachusetts Bay area, and coastal Mexican resorts such as Cancun and Acapulco.

Insert Figure 3 and 4 herein.

By tracking the entry and exit patterns of each carrier and categorizing airports in terms of levels of service, we are able to identify differences in the entry strategies adopted by different carriers. After an airline enters a new airport with seasonal services, in due course it has three options: (1)

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[8] Frontier was sold by Republic Airways Holdings to Indigo Partners, and it refocused as an ultra-low-cost carrier with a smaller network from 2014 to 2017.

extending the operation at the airport to year-around services; (2) keeping the operation as seasonal; or (3) terminating the services if it does not meet the expected performance level.

During the 2005 – 2016 period, a total of 1,854 entry events are identified for the nine low-cost airlines in our sample. Figure 5 presents the number of airports identified as seasonal in the first year after entry. Clearly, the LCCs in Europe entered more airports with seasonal services during the study period than the LCCs in the United States. Figure 6 shows the three entry strategies adopted by the airlines in the second year after an entry and indicates that the LCCs in the United States tend to convert seasonal operation to year-round operation in the second year after an entry. Air Berlin is shown to have dropped many of its seasonal airports in the second year after entry, reflecting its less coherent and more rapid network and route strategy changes during the period, which probably had contributed to its persistent losses and ultimate demise in 2017. Like Air Berlin, Frontier also appears to show a lack of prudence in terms of its entry decisions, as indicated by its relatively high percentage of airports being dropped in the second year of entry.

Insert Figure 5 and 6 herein.

We also collect and compile a secondary dataset consisting of the operating characteristics of the nine sample airlines, including total revenue passenger-miles, fleet size and composition, number of airports in an airline's network, average stage length, and average number of scheduled seats in a given year, as well as annual aircraft flight hours. The data are collected from Airline Monitor and individual airline annual reports. The dataset has an unbalanced panel with a total of 114 observations[9] over the 2004-2017 period.

4.2 Seasonality Trend and Comparison

The nine sample airlines collectively served a total of 485 seasonal airports during the 2004-2017 period, and these airports vary in size and are dispersed over wide geographic regions. Our study focuses on the spatial and temporal variations of air passenger traffic at these seasonal airports.

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[9] Air Berlin (AB) ceased operations in October 2017, thus has no observation in 2017. AirTran Airways (FL) officially started to merge its operations with Southwest (WN) in May 2011, and flew the last flight under its code in December 2014. AirTran's observations from 2011 to 2014 were excluded to avoid any potential double counting. Allegiant Air (G4) had very limited operations prior to 2008, and was not included between 2004 and 2007.

The three seasonality indices, SES Pooling Index, Gini Index and Concentration Index, discussed in Section 3 are applied to the sample airlines' monthly and quarterly flights and monthly seats during the study period. Since LCCs tend to have uniform fleets, it is not surprising to see that the seasonality indices based on flights are highly correlated with the indices based on seats, with correlation coefficient at 0.9874 for the SES Pooling Index and 0.985 for Gini Index,[10] respectively. Therefore, our analysis focuses on the seasonality indices computed from scheduled seats. The SES Pooling index calculated using Eq. (1) are presented in Figure 7, showing an increasing trend for the two major European LCCs, Ryanair (FR) and easyJet (U2), which have been consistently higher than those of Southwest (WN) and JetBlue (B6) in the more recent years.

Insert Figure 7 herein.

Figure 8 presents the average Gini index scores for the U.S. LCCs versus European LCC, and shows that the U.S. carriers, on average, have lower Gini Index scores than the LCCs in Europe, and are more consistent over time, whereas the Gini Index scores for European LCCs had increased substantially since the Great Recession of 2008. Figure 9 compares the Gini Index scores (by seats) across airlines. We can see that the Gini index scores for AB, G4, FR, and U2 are consistently higher than those of WN, B6, FL, NK, and F9. Moreover, WN, B6 and FL have shown relatively constant Gini scores during the study period. In contrast, Gini scores for NK and F9 have shown pronounced fluctuation over the same period. Figure 10 compares the Gini Index scores by seats for selected airlines using quarterly vs. monthly data. The Gini scores calculated using quarterly data broadly follow the same trend as those using monthly data, but tend to have lower values reflecting the data smoothing of aggregation effects. Gini Index scores and SES Pooling index scores are correlated with a correlation coefficient of 0.7 as shown in Figure 11.

Insert Figure 8 herein.

Insert Figures 9, 10 and 11 herein.

Eq. (3) is used to calculate the Monthly Concentration index, and Figure 12 shows an upward, concave relationship between the Gini Index and Monthly Concentration Index scores across all

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[10] Gini scores are similar if not identical when computed using scheduled flights and available seats. As the fleet variants increase, the differences between the two sets of Gini scores increase.

the airports for selected airlines in a given year. For the four selected LCCs, the correlation coefficients between these two indices ranges from 0.8 to 0.9.

Insert Figure 12 herein.

4.3 Climate Diversification of Sample Airlines' Network

As described in Section 3, Köppen Climate Classification is used to construct climate diversification variables. Table 3 summarizes the Köppen values including both numerical and letter codes for each of the sample airlines over the study period. Air Berlin's network appears to have covered all five climate zones, whereas the other airlines' services are spread over four climate zones.

Insert Table 3 herein.

5. Model Estimations and Discussion of Results

5.1 Empirical Models

Having undertaken preliminary and descriptive analysis of our suite of variables, we select four climate variables and the three measures of seasonality along with the operating characteristics for our sample of LCCs. Table 4 presents the summary statistics for all the variables included in the empirical estimation. Table 5 provides their correlation coefficients based on the nine sample airlines over the 2004-2017 period with a total of 114 observations.[11] It is noted that the Gini Index has the highest correlation (0.94) with Overall Monthly Concentration Index, indicating the similarity and convergence of these two indices in measuring the temporal-dimension of seasonality of aggregated air services by an airline across its network. In comparison, the SES Pooling Index has lower correlations with the other two indices, revealing the distinct characteristics of this measurement in assessing the spatial dimension of seasonality, and its potential as a complementary measurement to the Gini Index and Monthly Concentration Index. It is further noted that the correlations among the four climate diversification measures are low to moderate,[12] as shown in Table 5.

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[11] Because there is no seasonal airport in the route network for B6 in 2006, and for WN in 2004-2012, and in 2015, the number of observations for calculating the summary statistics of HHI_KPV_Seasonal_Airport drops to 103.

[12] The two highest correlations among the climate variables are the correlation (i.e., -0.3598) between HHI_KPV_Seasonal_Airport and Number of Seasonal Airport per KPV, and the correlation (i.e., -0.3625) between COV_KPV and Number of Seasonal Airport per KPV.

Insert Table 4 and 5 herein.

5.1.1 Climate and Seasonality

To examine the relationship between an airline's traffic seasonality and its route network diversification in terms of geographic coverage and climate heterogeneity, we estimate the following equation using three measurements for *Seasonality Index,* namely the *SES Pooling Index*, the *Gini Index*, and the *Overall Monthly Seat Concentration Index,* as the three alternative dependent variables, as shown on the left-side of Eq. (5).

$$\text{Seasonality Index}_{it} = \beta_0 + \beta_1 \textit{Climate Diversification}_{it-1} + X_{it}\beta + \sum_{t=2}^{14} \delta_t \textit{ Year Dummy}_t + u_i + \epsilon_{it} \qquad \text{Eq. (5)}$$

where $Seasonality\ Index_{it}$ is the seasonality index of airline *i* in year *t*. This dependent variable is regressed on *Climate Diversification* as the independent variable, and a set of control variables X_{it}, including *Number of Origin Airports, Fleet Size, and total Revenue Passenger-miles* (denoted as $Num\ of\ Origin_{it}$, $Fleet\ Size_{it}$, and $Total\ RPM_{it}$) for airline i in year t to control for airlines i's network size, fleet size, and traffic volume effects. Because of the high correlation between $Fleet\ Size_{it}$, and $Total\ RPM_{it}$, only one is used in a particular estimation. We also include year dummy variables to represent time-specific effects, and airline-specific error term is denoted as u_i. The correlation structure between u_i and other explanatory variables is examined by the results from Hausman tests. The remaining error term, ϵ_{it} is assumed to have zero mean, and to have no correlation with other explanatory variables or autocorrelation with itself.

Four alternative variables are used to reflects the degree of *climate diversification* of airline network, namely the number of climate zones (i.e., *Num of KPV*), the coefficient of variation of climate zones (i.e., *KPV COV*), the concentration of seasonal airports across different climate zones (i.e., *HHI of Seasonal Airports*), and the average number of seasonal airports per climate zone (i.e., *Seasonal Airports per KPV*). Equation 5 is estimated with each of these climate diversification variables separately, and we focus on the results of using *Seasonal Airports per KPV* as *climate diversification* variable for its having significant and positive coefficients consistently across all three models using alternative measurements for *Seasonality Index* as dependent variable, including *SES Pooling Index*, the *Gini Index*, and the *Overall Monthly Seat*

Concentration Index. Because of the potential endogeneity concern,[13] we use the lagged value of climate diversification as instrument variables in estimating Eq. (5). The choice of lagged climate diversification can be justified by the fact that any route network restructuring taken by an airline in the current year for mitigating the seasonality effect should not impact the climate diversification characteristics of its route network in the previous year. In searching for the proper lag length of the instruments, we estimate the model using a generalized linear model (GLM) and test lags ranging from one to three years. The Akaike's Information Criterion (AIC) values are calculated to compare models with different lag periods. Based on the AIC results, we select the one-year lagged instruments as it has the minimal AIC values adjusted for sample size.

To assess the potential multicollinearity problem among the explanatory variables, we calculate the variance inflation factor (VIF) values for all the predicting variables based on the OLS estimation of Eq. (5) with three alternative dependent variables (DV): *SES Pooling Index* as DV in Model I, *Gini Seat Index* in Model II, and *Overall Monthly Seat Concentration Index* in Model III. The mean VIF value is found to be 2.22 and the VIF values for all those predictive variables across the three models range from 1.60 to 2.95, indicating that multicollinearity is not a major concern. We estimate Eq. (5) using both fixed-effect and random-effect model, and select the appropriate model based on Hausman tests. The estimation results are presented in Table 6, and will be discussed in Section 5.2.1.

5.1.2 Seasonality and Fleet Utilization

Seasonality in demand impacts an airline's capacity commitments over the course of a given year. We hypothesize that an increasing degree of seasonality will lead an airline to experience reduced utilization of its fleet. However, seasonality is not the only factor that affects an airline's fleet utilization. Therefore, to empirically examine the relationship between fleet utilization and seasonality, we also consider several other factors including the coefficient of variation of stage length, average aircraft size, and the coefficient of variation of daily seats, and construct a set of

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[13] For example, when an airline experiences an increased seasonality, it may diversify its route network to mitigate the potential seasonality effect. Therefore, climate diversification variables could be endogenous variables, and such an endogeneity may exist simultaneously. We perform the Durbin-Wu-Hausman test and Davidson-MacKinnon test and both tests reject the exogeneity assumptions. Following the suggestion in Lu et al. (2018), we use the lagged variables as instruments for climate diversification variables to address the endogeneity concern, and also estimate the Arellano and Bond (1991) dynamic GMM model for robustness check. The results are similar to the key findings.

fleet standardization indices as control variables. Average stage length is expected to have a positive relationship with fleet utilization, as longer flights likely reduce the aircraft time on ground. Coefficient of variation of stage length is an indicator of network diversification. Fleet standardization has been shown to provide significant cost advantages for airlines in studies such as Kilpi (2007), West and Bradley (2008), Brüggen and Klose (2010), Zuidberg (2014), Zou et al. (2015), and Narcizo et al. (2020). Built upon the combination of DEA efficiency score method and Tobit regression analysis, Merkert and Hensher (2011) and Merkert (2022) find empirical evidence suggesting the cost efficiency benefits for airlines from fleet standardization in terms of not only aircraft types but also its engine equipment. Despite the aforementioned literature, what remains empirically unexplored is the effect of fleet standardization on fleet utilization.

Although a standardized fleet is often cited as a key element of LCC business model, not all LCCs have completely standardized fleet. For example, Frontier Airlines' fleet comprises of Airbus 319s, Airbus 320s and Airbus 321s, and Spirit Airlines operates both Airbus 320s and Airbus 321s. Zou et al. (2015) develop a set of fleet standardization indices at three levels, i.e., Model, Family, and Manufacturer, based on the Herfindahl-Hirshman Index (HHI). Following Zou et al. (2015), we calculate the fleet standardization index at family level, *FSI_family*[14] as follows:

$$FSI\_family = \sum_{j=1}^{F}\left(\frac{Number\ of\ Aircraft\ of\ Family\ j}{Number\ of\ Aircraft\ in\ Fleet}\right)^2 \qquad \text{Eq. (6)}$$

The higher the values for *FSI_family*, the greater the degree of fleet standardization in terms of its composition of aircraft families. The following equation (Eq. 7) is then estimated to quantify the effects of seasonality on fleet utilization:

$$Fleet\ Utilization_{it} = \alpha_0 + \alpha_1 Seasonality_{it} + X_{it}\alpha + \alpha_4 Time\ Trend_t + \alpha_5 GFC + u_i + \tau_{it} \qquad \text{Eq. (7)}$$

where $Fleet\ Utilization_{it}$ is the fleet utilization of airline *i* in year *t*, and it is measured by average flight hours per day (Alamdari and Fagan, 2005). The dependent variable is regressed on *Seasonality* as the independent variable, and a set of control variables X_{it}, including *Number of*

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[14] Family Examples: Boeing 737 family vs Boeing 787 family or Airbus 320 family vs Airbus 350 family; Model Examples: Boeing 737-200 vs Boeing 737-800 or Airbus 350-900 vs Airbus 350-1000.

Origin to represent an airline's route network size, the average stage length (i.e., *Stage Length*) and its coefficient of variation (*COV of Stage Length*), *Aircraft Size*, the coefficient of variation of daily seats (i.e., *COV of Daily Seats*) as well as *fleet standardization index*, notably *FSI_family*. In addition to the above airline-related control variables, we also include the time trend variable[15], $Time\ Trend_t$, to estimate whether there is a general trend of fleet utilization by LCCs over time. The value for $Time\ Trend_t$ ranges from 1 (for the year of 2004) to 14 (for the year of 2017). *GFC* is a dummy variable representing the 2008/09 period to control for the effect on fleet utilization due to this external shock. The right-side of Eq. (7) also includes u_i for airline-specific error term, and τ_{it} as the remaining error term with zero mean, and uncorrelated with other explanatory variables or itself.

Seasonality in Eq. (7) is measured by three alternative variables, namely the *SES Pooling Index*, the *Gini Index*, and the *Overall Monthly Seat Concentration Index*. We estimate three models using each of these three seasonality measurements as independent variables, respectively. The models are estimated using fixed-effect and random effect methods, and the model selection is based on Hausman test results. The estimation results of Eq. (7) are presented in Table 7, and will be discussed in Section 5.2.2.

5.2 Discussion of Estimation Results

5.2.1 Effects of Climate Diversification on Seasonality

Table 6 presents the estimation results for Eq. (5). Model I is estimated with the *SES Pooling Index* as the dependent variable, Model II has *Gini Seat Index* as the dependent variable, and Model III has the *Overall Monthly Seat Concentration Index* as the dependent variable. We use each of the four climate diversification variables as an independent variable to estimate its potential impact on airline seasonality. Of the four climate diversification variables, the coefficient on *Number of KPV Zones* and *Concentration (HHI) of Seasonal Airports per KPV Zone* are found to be insignificant across Model I to III, and the *COV of KPV* are not consistently significant across the three models.

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[15] As a robustness check, we estimate Eq. (7) replacing the Time Trend and GFC variables with a set of year-dummy variables. The coefficients on all the independent and control variables are consistent with those from using the Time Trend variable. We prefer using the model with Time Trend since it leads to a higher degree of freedom than using a set of year dummy variables. The results of using year-dummy variables are available upon request.

Therefore, we focus on *Number of Seasonal Airports per KPV Zones* as the climate diversification variable and report the estimation results of Eq. (5) in Table 6.

Because of the high correlation between *Fleet Size* and *Total RPMs*, we choose to use these two variables separately in model (a) and (b), along with other control variables including *Number of Origin Airport*, and year dummy variables[16]. The Hausman test results for Model I-III provide support for the use of fixed-effect model, indicating that when using *SES Pooling Index, Gini Seat Index*, and *Overall Monthly Seat Concentration Index* to measure seasonality, the airline-specific error terms u_i in Eq. (5) are all correlated with the explanatory variables, and therefore the estimators from using airline-specific dummy variables to control for unobserved cross-sectional heterogeneity in the fixed-effect model are unbiased and consistent (Judge et al. 1988).

Among the climate diversification variables, the coefficients on *Number of Seasonal Airports per KPV Zone* are found to be the most consistent in all the alternative model estimations; thus, we use it for measuring climate diversification in our final models. As shown in Table 6, the *Number of Seasonal Airports per KPV Zone* variable has positive and highly significant coefficients across all three models, suggesting that an airline with a higher number of seasonal airports per KPV zone tends to have greater air traffic seasonality as measured by all three alternative seasonality indices. This result implies that when seasonal airports are more concentrated in fewer climate zones, an airline will experience a higher degree of traffic seasonality. Moreover, we find that the *Number of Origin Airports* has negative and significant coefficients throughout Model I to III, suggesting that there is an inverse relationship between the route network size, and airline seasonality as measured by *SES Pooling Index*, *Gini Index*, and *Overall Monthly Seat Concentration Index*. In addition, the coefficients on *Fleet Size* and *Total RPMs* are positive and significant, suggesting a positive association between an airline's operation scale and its seasonality after controlling for the network size effect.

The comparison of R^2 values across the three models indicates that the estimation has the best overall goodness of fit in Model I where *SES Pooling Index* is used as dependent variable (R^2=0.33), the second-best model is Model II, in which the dependent variable is *Gini Seat Index* (R^2=0.25),

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[16] Since we are using a lagged value as the dependent variable, the first year dummy variable is for 2006.

whereas Model III using *Overall Monthly Seat Concentration Index* as dependent variable has the worst goodness of fit, as shown by having the lowest R^2 value (0.19), and insignificant *F-test* statistics. The different goodness of fit shown across Model I, II and III provides further evidence suggesting that the three alternative seasonality measurements are not full substitutes for each other[17]. In sum, the positive and significant coefficients on the *Number of Seasonal Airports per KPV Zone* variable provide consistent evidence suggesting that an airline's traffic seasonality is negatively associated with its route network structure, as measured by the degree of location concentration of seasonal airports across different climate zones.

Insert Table 6 Herein.

5.2.2 Effects of Seasonality on Fleet Utilization

Table 7 presents the estimation results for the effects of air traffic seasonality on fleet utilization based on Eq. (7). Seasonality is measured by the *SES Pooling Index* in Model (a), the *Gini Index* in Model (b), and the *Overall Monthly Seat Concentration Index* in Model (c). We conduct Hausman tests for all three models to compare the results between fixed-effect models and random-effect models, and the results are all significant across Model (a) to (c), providing support for using fixed-effect estimators.

As shown in Table 7, the coefficients for the *SES Pooling Index* in Model (a) and the *Gini Index* in Model (b) are both negative, and highly significant in Model (a) and (b). For Model (c), the coefficient for the *Overall Monthly Seat Concentration Index* is negative, but not significant. This finding, again, implies the similarity and differences among the three seasonality measurements. The lack of variation of the *Overall Monthly Seat Concentration Index*, as compared to *SES Pooling Index* and *Gini Index*, might help explain its insignificant effect on fleet utilization. Overall, the results from Model (a) and (b) suggest that there is a negative association between seasonality and fleet utilization.

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[17] Of the three seasonality measures, *Overall Monthly Seat Concentration Index* has the smallest coefficient of variation, as measured by the ratio of the overall standard deviation (0.0016), between-airline standard deviation (0.0012), and within-airline standard deviation (0.0011), relative to the mean value (0.0846). The intraclass correlation coefficient is more similar between *SES Pooling Index* (0.6002), and *Overall Monthly Seat Concentration Index* (0.5884), and both of them are less than the ICC for *Gini Seat Index* (0.7972).

The estimation results for other control variables are summarized as follows. First, the *Number of Origin Airport* has negative and significant coefficients throughout Modal (a) to (c), suggesting there is a negative association between fleet utilization and network size. Second, the coefficients for the *Average Stage Length* variable are all positive and significant, suggesting that fleet utilization is likely to increase with the average stage length. That is, the longer the route distance, the higher the block hours per flight, as expected. Third, the results from Model (a) to (c) show that the *Fleet Standardization* index at family level has positive and statistically significant coefficients, suggesting that there is a positive association between fleet standardization and fleet utilization. Consistent with the finding of Zou et al. (2015), these positive effects imply that the operation of a standardized fleet of the same aircraft family may help airlines improve fleet utilization resulting from the greater interchangeability among aircraft in a highly standardized fleet. Finally, the positive and significant coefficient on the time trend variable suggests an increase of fleet utilization by LCCs over time, and it is more pronounced during the 2008/09 global financial crisis.

Insert Table 7 Herein.

6. Conclusions, Implications, and Future Research

Several recent studies have presented detailed seasonality characteristics across locations in Europe and focused on variations in airport traffic. The focus of our paper is to investigate traffic seasonality by incorporating airline route network structure and operational characteristics. Using panel data consisting of nine low-cost carriers in the United States and Europe from 2004 to 2017, our empirical analysis reveals that there is stronger seasonal demand variability for the LCCs in Europe as compared to those in the United States. This result is consistent with Reynolds-Feighan (2021) who finds that the aggregate air traffic distribution in Europe is more seasonal than that in the United States.

Our study contributes to the previous literature of airline seasonality in three aspects. First, we present a variety of measures of air traffic seasonality and demonstrate the application of the alternative measurements of seasonality at both the airline level and airline-airport level including the new SES Pooling Index, the Gini Index, and the Overall Monthly Seat Concentration Index. These measures capture different aspects of the variability in monthly air traffic and aggregate traffic in different ways across the airline's network. The Gini Index is the most widely used measure in the literature on tourism and captures the total pairwise variability across monthly or quarterly traffic in a 12-month period. The Concentration Index is based on HHI and captures the squared monthly shares of traffic in a 12-month period and thus gives greater weight to the busiest month. HHI is widely used in a variety of applications, and the Overall Monthly Seat Concentration index is highly correlated with the Gini Index as both of these measures represent the temporal distribution of air travel over a 12-month period. As a complementary measure to the aforementioned seasonality indices, the SES pooling index is drawn from the supply chain literature and its inclusion into seasonality metrics can help assess, more directly, the spatial distribution of air traffic seasonality across all airports in an airline's route network, which is similar to the 'statistical economies of scale' effect well known in the inventory management area. That is, the SES Pooling Index captures the spatial complementarity in an airline's network consisting of a set of airports that in aggregate may counter-balance the extent of local seasonal traffic variability. We employ these three measures in our empirical investigation to better understand and quantify the magnitude of air traffic seasonality across time and space dimensions.

Second, we use Köppen values to measure climate diversification of airline network. The climate characteristics of an airline's route network have not been well studied in the field of air transport research. In our study, we develop a set of alternative indicators to assess the degree of climate diversification in an airline's network. We find the presence of significant network structural differences in terms of climate characteristics and route entry/exit development strategies adopted by LCCs in Europe and the United States. These differences contribute to the consequence that European low-cost carriers tend to have more seasonal services than their U.S. counterparts. Finally, our estimation results suggest a negative association between an airline's traffic seasonality and the degree of climate diversification based on the airport locations within its route network. This is the first empirical finding, as far as we know, regarding the negative relationship between climate diversification of airline's route network and its air traffic seasonality. To develop a theoretical framework in future research, we need to conduct a more micro-level analysis of individual airlines and scheduling dynamics across the route network for additional insights and understanding of this relationship.

The drivers of the exceptionally strong European seasonality in tourism flows and air traffic should be investigated further. Factors such as labor market considerations (number, uptake and distribution and concentration of paid vacation days), school holiday cycles, duration and impacts, government paid holiday leave distributions as well as regulatory constraints are worthy of detailed comparative examination for different global regions and may add further insights. We believe that the measurements we develop in our paper for quantifying the multi-level climate diversification indicators could be added to those social-economic factors and applied in future research studying the determinants of tourist travel demand, and its implication on air travel seasonality. We hope that our development of climate diversification measures and the temporal and spatial dimensions of seasonality indices will help generate more interest among aviation researchers in the study of climate and seasonality characteristics of air transport networks in regional and global contexts.

Our results demonstrate the negative impact of seasonality on aircraft utilization, which has not been empirically studied in existent literature. This finding not only contributes to aviation research, but also provides management implications considering that fleet utilization is an important determinant of an airline’s cost structure. A higher fleet utilization is expected to have a positive effect on airlines’ profitability. Our results imply that through lowering the concentration of seasonal airports per climate zone, an airline may experience less traffic seasonality, thereby increasing its fleet utilization throughout a year. Moreover, we have demonstrated that air traffic seasonality has been increasing in the post-GFC period for both the U.S. and European carriers but is consistently higher for European carriers. The GFC had a disruptive impact on travel and air traffic patterns, with air traffic showing increasing seasonal variability in the years following 2008/9. Given the scale and duration of the COVID-19 pandemic, it will take many years for the full structural impacts on airline operations to be fully appreciated. However, there has been some indications that airlines now focus more on leisure markets which tend to have higher seasonal variations. Full-service carriers (FSCs) have traditionally experienced lower seasonal variability in demand compared to the LCCs. As the global air transport industry emerges from the pandemic, FSCs are experiencing increased demand for leisure and VFR travel and reduced demand for business travel. The management of fleets and the availability and scheduling of flight crews and ground staff between the peak and off-peak periods is a significant challenge for airlines. FSC management will have to deal with greater volatility in management of aircraft, crew, and labor rotations as they experience greater seasonal variation in demand. It will be important to monitor and measure seasonal variability patterns and network changes in the immediate pandemic aftermath as air travel resumes.

Given the increasing prominence of environmental impacts of air transport, and particularly of excess capacity, optimal fleet utilization strategies will be an increasingly important focus for airlines. Managing traffic demand and supply across space and over time will continue to be the major challenge for airlines in the difficult trading environment of the 2020s and during the recovery stage of the post-pandemic period. For future research, we need to expand the small sample of nine LCCs included in our study beyond the United States and Europe, and to continue exploring and investigating the driving forces of traffic seasonality, managerial implications for different airline business models, and some differential social and cultural drivers of traffic seasonality in a global context.

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Table 1. Köppen Values: Numerical vs. Letter Categorization

Category I	Category II
A (Tropical): 1, 2, 3	A (Tropical): 1, 2, 3
B (Arid): 4, 5, 6, 7	B1 (Arid & Hot): 4, 6;
	B2 (Arid & Cold): 5, 7
C (Temperate): 8, 9, 10, 11, 12, 13, 14, 15, 16	C1 (Temperate & Hot Summer): 8, 11, 14,
	C2 (Temperate & Warm summer):9, 12, 15
	C3 (Temperate & Cold summer): 10, 13, 16
D (Continental): 17-28	D1 (Continental & Hot Summer): 17, 21, 25
	D2 (Continental & Warm Summer): 18, 22, 26
	D3 (Continental & Cold Summer): 19, 23, 27
	D4 (Continental & Very Cold Winter): 20, 24, 28
E (Polar): 29, 30	E (Polar): 29, 30

Table 2. Description of Sample Airlines

Europe						
Airline	IATA Code	Country of Registration	Year Founded	Average Number of Airports Served 2018	Number of Available Seats 2018	Significant milestones
Air Berlin	AB	Germany (1991)	1978	103 (2017)	21,775,255 (2017)	Ceased in 2017
Ryanair	FR	Ireland	1985	205	144,002,294	
EasyJet	U2	UK	1995	135	100,076,459	
USA						
Southwest Airline	WN	USA	1971	97	207,226,407	Merged with AirTran in 2013
JetBlue	B6	USA	2000	98	51,560,080	
Allegiant Air	G4	USA	1998	117	16,175,614	
Spirit	NK	USA	1983	63	35,296,772	
AirTran	FL	USA		40 (2014)	10,867,809 (2014)	Merged with Southwest in 2013
Frontier	F9	USA	1994	81	23,412,520	Part of Republic Airways Holdings until 2014 when sold to Indigo Partners

Table 3. Köppen Values for the Airports in the Network of Selected Airlines during the 2004-2017 period

Airline	Köppen values for all the airports (KPV)	Category I: Köppen Letters for all the airports (*KPV_i*)	Category II: Köppen Letters for all the airports (*KPV_ii)*
AB	1, 2, 3, 4, 5, 6, 7, 8, 9, 14, 15, 18, 25, 26, 27, 29	A; B; C; D; E	A; B1; B2; C1; C2; D1; D2; D3; E
B6	1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 14, 19, 25, 26	A; B; C; D	A; B1; B2; C1; C2; D1; D2; D3
F9	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 14, 15, 18, 19, 25, 26, 27	A; B; C; D	A; B1; B2; C1; C2; D1; D2; D3
FL	1, 2, 3, 4, 6, 7, 9, 12, 14, 25, 26	A; B; C; D	A; B1; B2; C1; C2; D1; D2;
FR	4, 5, 6, 7, 8, 9, 14, 15, 26, 27, 29	B; C; D; E	B1; B2; C1; C2; D2; D3; D4; E
G4	1, 3, 4, 5, 6, 7, 8, 9, 14, 17, 18, 25, 26	A; B; C; D	A; B1; B2; C1; C2; D1; D2;
NK	1, 2, 3, 4, 6, 7, 9, 12, 14, 25, 26	A; B; C; D	A; B1; B2; C1; C2; D1; D2;
U2	4, 5, 6, 7, 8, 9, 14, 15, 26, 27, 29	B; C; D; E	B1; B2; C1; C2; D2; D3; E
WN	1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 14, 18, 25, 26	A; B; C; D	A; B1; B2; C1; C2; D1; D2;

Table 4. Summary Statistics for Seasonality, Climate and Other Key Variables

Variable	Number of Obs.	Mean	Std. Dev.	Min.	Max.
Gini Seat Index	114	0.0531	0.0348	0.0082	0.2095
SES-Pooling Index by Seat	114	0.5858	0.1638	0.2821	0.9215
Overall Monthly Seat Concentration Index	114	0.0846	0.0016	0.0834	0.0956
Num_KPV	114	11.1316	2.1014	7	17
COV_KPV	114	0.6102	0.1546	0.3819	1.0624
HHI_KPV_Seasonal_Airport	103	0.3727	0.2515	0.1056	1
Number of Seasonal Airports per KPV	114	1.4302	1.4701	0	6.4286
Number of Origin Airports	114	91.2193	42.0972	18	208
Aircraft Utilization	114	9.4113	1.7449	4.32	12.53
Stage Length	114	864.8596	189.6844	486	1345
COV of Stage Length	114	0.4545	0.1556	0.2693	1.0322
Aircraft Size	114	153.3561	19.4910	117.7	200.1
COV of Daily Seats	114	1.9848	0.6249	0.8875	3.8725
Fleet Standardization	114	0.8095	0.2162	0.3648	1
Fleet Size	114	182.6404	180.3854	28	723
Total RPMs	114	31902.62	29139.55	3832.9	129045.2

Table 5. The Correlation among Seasonality, Climate and Other Key Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Gini Index (1)	1.00															
SES Pooling Index (2)	0.71* (0.00)	1.00														
Overall Monthly Concentration Index (3)	0.94* (0.00)	0.64* (0.00)	1.00													
Num_KPV (4)	-0.03 (0.74)	-0.03 (0.75)	-0.01 (0.92)	1.00												
COV_KPV (5)	-0.19* (0.04)	-0.45* (0.00)	-0.17 (0.07)	-0.12 (0.22)	1.00											
HHI_KPV_Seasonal_ Airport (6)	-0.38* (0.00)	-0.15 (0.13)	-0.28* (0.00)	-0.19 (0.06)	0.21* (0.03)	1.00										
Number of Seasonal Airports per KPV (7)	0.74* (0.00)	0.47* (0.00)	0.64* (0.00)	0.19* (0.04)	-0.26* (0.00)	-0.47* (0.00)	1.00									
Number of Origin Airports (8)	0.47* (0.00)	0.58* (0.00)	0.37* (0.00)	0.27* (0.00)	-0.51* (0.00)	-0.31* (0.00)	0.68* (0.00)	1.00								
Aircraft Utilization (9)	-0.18 (0.06)	-0.13 (0.17)	-0.13 (0.18)	0.04 (0.69)	0.27* (0.00)	0.09 (0.38)	0.06 (0.51)	0.02 (0.85)	1.00							
Stage Length (10)	0.22* (0.02)	-0.17 (0.06)	0.19* (0.05)	0.22* (0.02)	0.59* (0.00)	0.13 (0.18)	0.02 (0.82)	-0.22* (0.02)	0.08 (0.39)	1.00						
COV of Stage Length (11)	0.46* (0.00)	0.29* (0.00)	0.39* (0.00)	0.16 (0.09)	0.09 (0.36)	-0.04 (0.69)	0.53* (0.00)	0.28* (0.00)	0.36* (0.00)	0.38* (0.00)	1.00					
Aircraft Size (12)	0.39* (0.00)	0.29* (0.00)	0.30* (0.00)	-0.24* (0.00)	-0.16 (0.09)	-0.27* (0.01)	0.29* (0.00)	0.53* (0.00)	-0.12 (0.20)	-0.09 (0.33)	-0.22* (0.02)	1.00				
COV of Daily Seats (13)	0.03 (0.75)	-0.24* (0.00)	0.00 (0.96)	0.39* (0.00)	-0.00 (0.97)	-0.19* (0.05)	0.00 (0.99)	0.00 (0.92)	0.04 (0.67)	0.31* (0.00)	0.35* (0.00)	-0.29* (0.00)	1.00			
Fleet Standardization (14)	-0.19* (0.04)	-0.05 (0.59)	-0.14 (0.12)	-0.03 (0.75)	0.00 (0.99)	-0.08 (0.41)	-0.15 (0.12)	0.01 (0.94)	-0.02 (0.84)	-0.38* (0.00)	-0.53* (0.00)	0.29* (0.00)	-0.14 (0.14)	1.00		
Fleet Size (15)	-0.31* (0.00)	0.19* (0.03)	-0.21* (0.02)	0.27* (0.00)	-0.26* (0.00)	0.43* (0.00)	-0.23* (0.01)	0.22* (0.02)	0.02 (0.81)	-0.42 (0.00)	-0.27* (0.00)	-0.08 (0.42)	-0.51* (0.00)	0.21* (0.02)	1.00	
Total RPMs (16)	-0.21* (0.02)	0.26* (0.00)	-0.13 (0.15)	0.31* (0.00)	-0.23* (0.01)	0.36* (0.00)	-0.09 (0.33)	0.37* (0.00)	0.12* (0.21)	-0.33 (0.00)	-0.15 (0.11)	0.02 (0.80)	-0.47* (0.00)	0.20* (0.04)	0.97* (0.00)	1.00
Note: The numbers in parenthesis are p-values. * Significant at 0.05 level.																

Table 6. The Estimation Results of the Climate Diversification Effects on Seasonality Index

	Model I SES Pooling Index		Model II Gini Index		Model III Concentration Index	
Independent Variables	(a)	(b)	(a)	(b)	(a)	(b)
Number of Seasonal	0.0544***	0.0523**	0.0106**	0.0103**	0.0004*	0.0004*
Airports per KPV Zone$_{it-1}$	(0.0204)	(0.0205)	(0.0040)	(0.0040)	(0.0002)	(0.0002)
Number of Origin Airport$_t$	-0.0026**	-0.0026**	-0.0005**	-0.0005**	-0.00003**	-0.00003**
	(0.0010)	(0.0010)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
Fleet Size$_t$	0.0011***		0.0002***		6.87e-06*	
	(0.0003)		(0.0001)		(3.45e-06)	
Total RPM$_t$		5.33e-06***		8.18e-07***		3.20e-08*
		(1.35e-06)		(2.66e-07)		(1.62e-08)
Year_2006	-0.0459	-0.0405	-0.0166*	-0.0159*	-0.0013**	-0.0012**
	(0.0476)	(0.0477)	(0.0094)	(0.0094)	(0.0006)	(0.0006)
Year_2007	-0.1436***	-0.1418***	-0.0144	-0.0144	-0.0009	-0.0009
	(0.0504)	(0.0505)	(0.0099)	(0.0098)	(0.0006)	(0.0006)
Year_2008	-0.1063**	-0.1067**	-0.0096	-0.0099	-0.0010	-0.0010
	(0.0528)	(0.0529)	(0.0104)	(0.0104)	(0.0006)	(0.0006)
Year_2009	-0.0995*	-0.0907*	-0.0082	-0.0072	-0.0006	-0.0006
	(0.0526)	(0.0525)	(0.0105)	(0.0103)	(0.0006)	(0.0006)
Year_2010	-0.1398**	-0.1217**	-0.0218**	-0.0197*	-0.0013**	-0.0012*
	(0.0536)	(0.0528)	(0.0106)	(0.0104)	(0.0006)	(0.0006)
Year_2011	-0.0851	-0.0740	-0.0111	-0.0102	-0.0009	-0.0009
	(0.0589)	(0.0583)	(0.0117)	(0.0114)	(0.0007)	(0.0007)
Year_2012	-0.0740	-0.0694	-0.0064	-0.0064	-0.0006	-0.0006
	(0.0607)	(0.0606)	(0.0120)	(0.0119)	(0.0007)	(0.0007)
Year_2013	-0.0714	-0.0734	-0.0045	-0.0055	-0.0004	-0.0004
	(0.0631)	(0.0635)	(0.0125)	(0.0124)	(0.0008)	(0.0007)
Year_2014	-0.0813	-0.0954	-0.0047	-0.0075	-0.0005	-0.0006
	(0.0632)	(0.0642)	(0.0125)	(0.0126)	(0.0008)	(0.0007)
Year_2015	-0.0682	-0.0822	-0.0009	-0.0038	-0.0003	-0.0003
	(0.0654)	(0.0667)	(0.0129)	(0.0131)	(0.0008)	(0.0008)
Year_2016	-0.1158*	-0.1345*	-0.0104	-0.0143	-0.0007	-0.0008
	(0.0668)	(0.0688)	(0.0132)	(0.0135)	(0.0008)	(0.0008)
Year_2017	-0.1445*	-0.1652**	-0.0134	-0.0178	-0.0007	-0.0008
	(0.07507)	(0.0774)	(0.0149)	(0.0152)	(0.0009)	(0.0009)
Constant	0.6260***	0.6698***	0.0640***	0.0702***	0.0860***	0.0863***
	(0.0612)	(0.0602)	(0.0121)	(0.0118)	(0.0007)	(0.0005)
Num. Obs.	105	105	105	105	105	105
Hausman test	χ^2= 20.92	χ^2= 20.94	χ^2= 28.80	χ^2= 29.27	χ^2=24.11	χ^2=23.96
(Prob> χ^2)	(0.0019)	(0.0019)	(0.0001)	(0.0001)	(0.0005)	(0.0005)
F-value	2.68	2.64	1.76	1.86	1.26	1.25
(Prob>F)	(0.0023)	(0.0027)	(0.0561)	(0.0401)	(0.2475)	(0.2517)
Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3318	0.3282	0.2454	0.2561	0.1891	0.1883

Standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01);

Table 7. The Estimation Results of the Seasonality Effects on Fleet Utilization

	Model (a)	Model (b)	Model (c)
Independent Variables	Fixed-effect	Fixed-effect	Fixed-effect
SES Pooling Index	-1.4660^{**}		
	(0.7133)		
Gini Index		-10.3582^{**}	
		(4.1347)	
Overall Monthly Seat Concentration Index			-104.56
			(68.61)
Number of Origin Airport	-0.0167^{***}	-0.0173^{***}	-0.0187^{***}
	(0.0058)	(0.0057)	(0.0058)
Avg. Stage Length	0.0031^{**}	0.0030^{**}	0.0027^{**}
	(0.0013)	(0.0013)	(0.0013)
COV of Stage Length	-0.2618	-0.0428	-0.6515
	(1.3427)	(1.3382)	(1.3325)
Avg. Aircraft Size	-0.0032	0.0003	-0.0003
	(0.0084)	(0.0083)	(0.0084)
COV of Daily Seats	0.3315	0.2583	0.4278
	(0.3377)	(0.3383)	(0.3338)
Fleet Standardization (Family)	0.9662^{*}	1.2165^{**}	1.0483^{*}
	(0.5359)	(0.5509)	(0.5611)
Time Trend	0.0785^{**}	0.0864^{**}	0.0917^{**}
	(0.0355)	(0.0353)	(0.0367)
GFC	0.3216	0.4051^{**}	0.3660^{*}
	(0.2008)	(0.1995)	(0.2025)
Constant	7.6197^{***}	6.7596^{***}	15.5705^{**}
	(1.8442)	(1.7986)	(5.9454)
Num. Obs.	114	114	114
F-value	2.82	3.10	2.57
(Prob>F)	(0.0055)	(0.0026)	(0.0109)
R^2	0.2093	0.2251	0.1940
Hausman test	χ^2=63.45	χ^2=77.51	χ^2=76.28
(Prob> χ^2)	(0.0000)	(0.0000)	(0.0000)

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

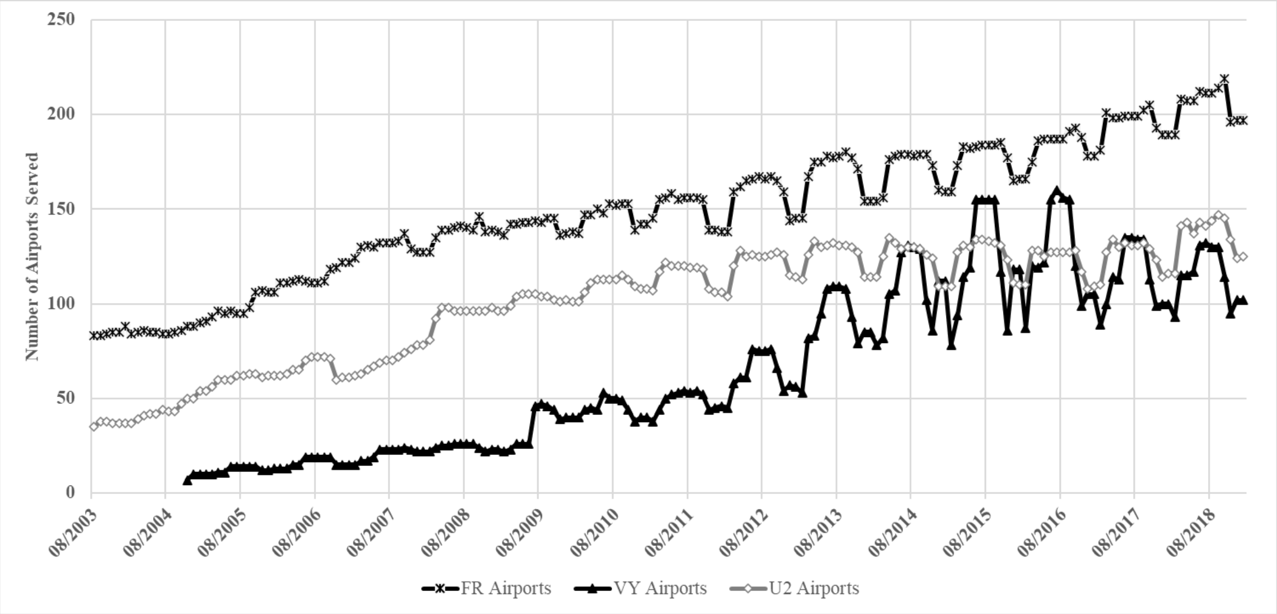

Figure 1. Number of Airports Served by European LCCs on a Monthly basis, Aug. 2003 – Jan. 2019

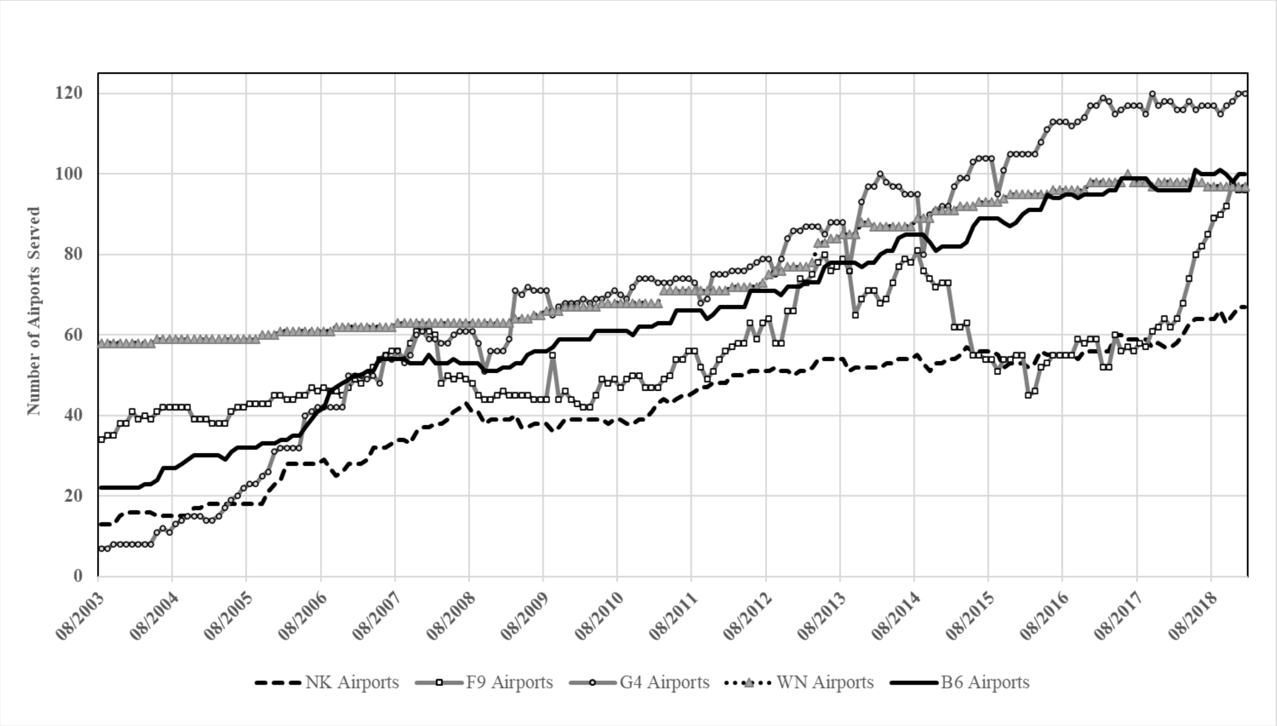

Figure 2. Number of Airports Served by US LCCs and ULCCs on a Monthly basis, Aug. 2003 - Jan. 2019

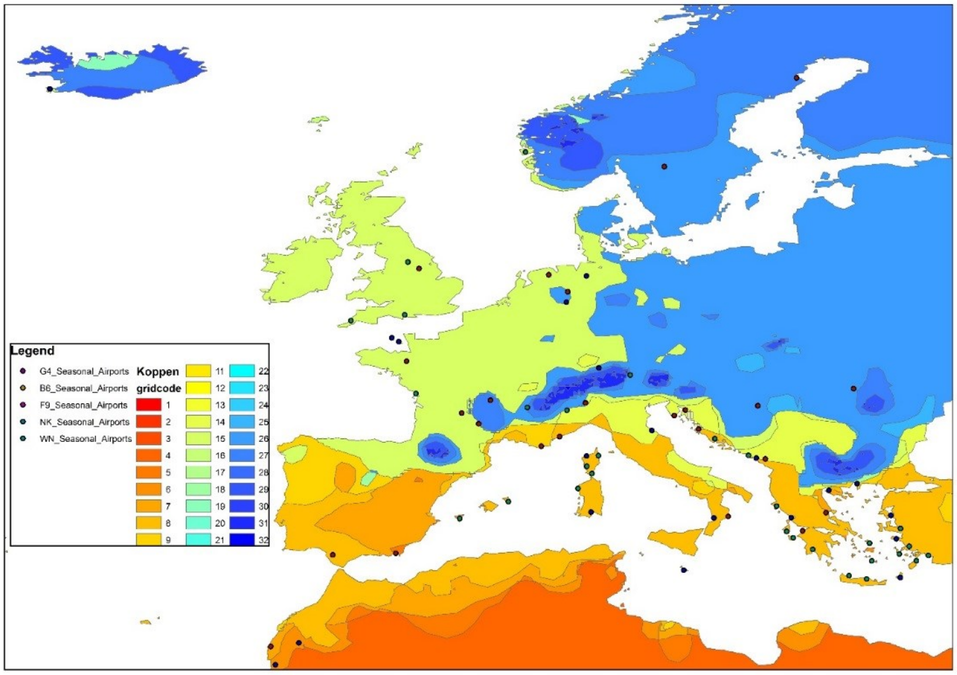

Figure 3. The Spatial Distribution of Seasonal Airports of LCCs in Europe

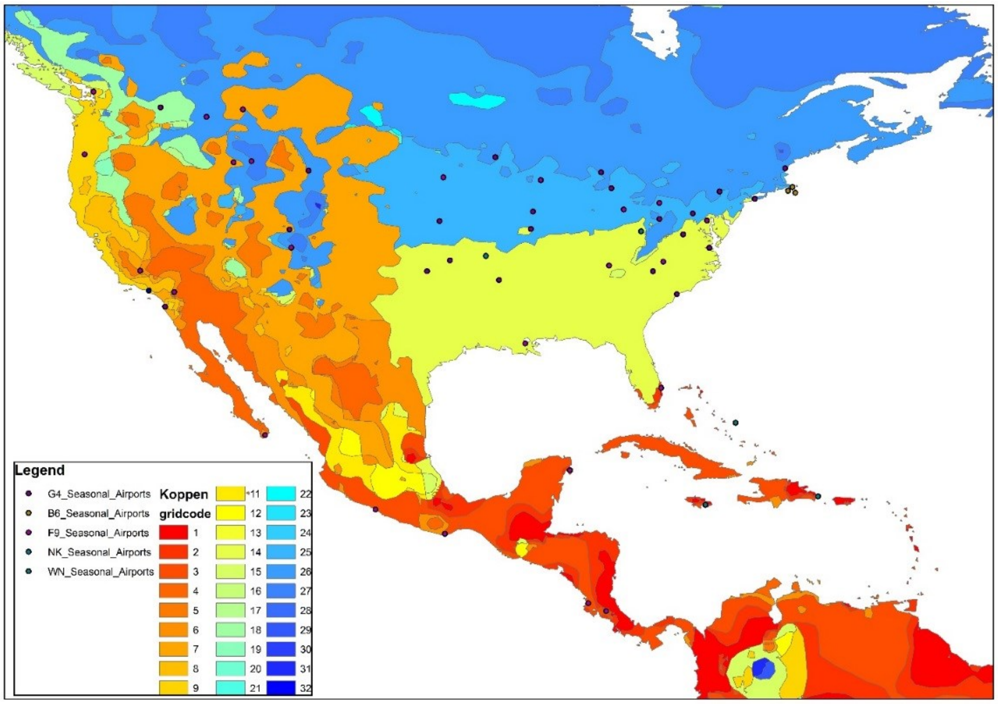

Figure 4. The Spatial Distribution of Seasonal Airports of US LCCs

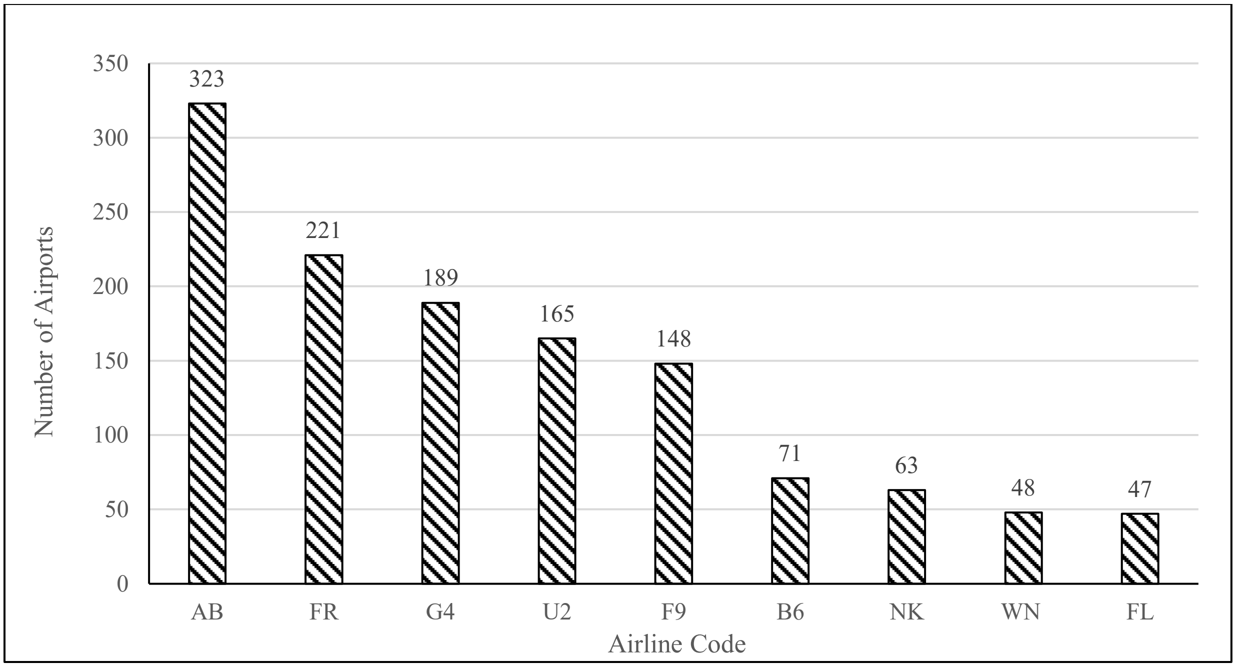

Figure 5. Number of Airports with Less Than 12 Months Operation in Year t+1

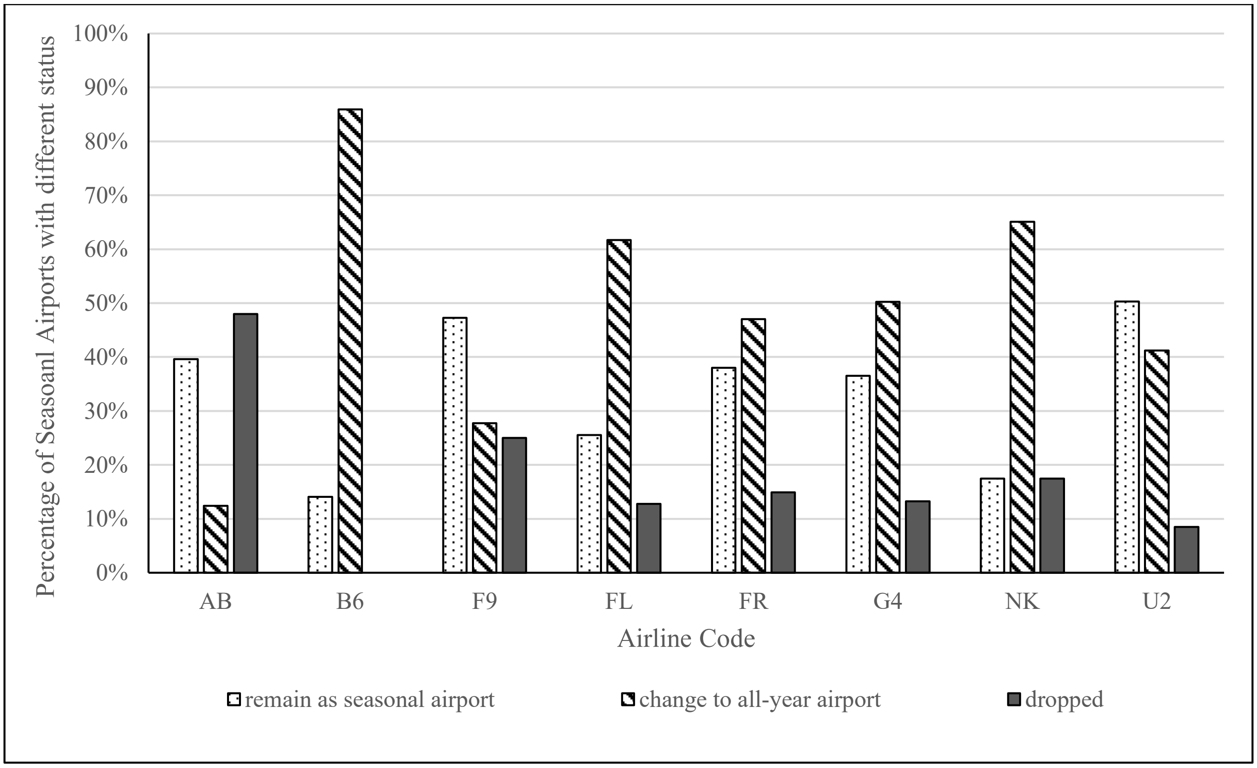

Figure 6. Three Alternative Status of Newly Entered Seasonal Airports in Year t+2

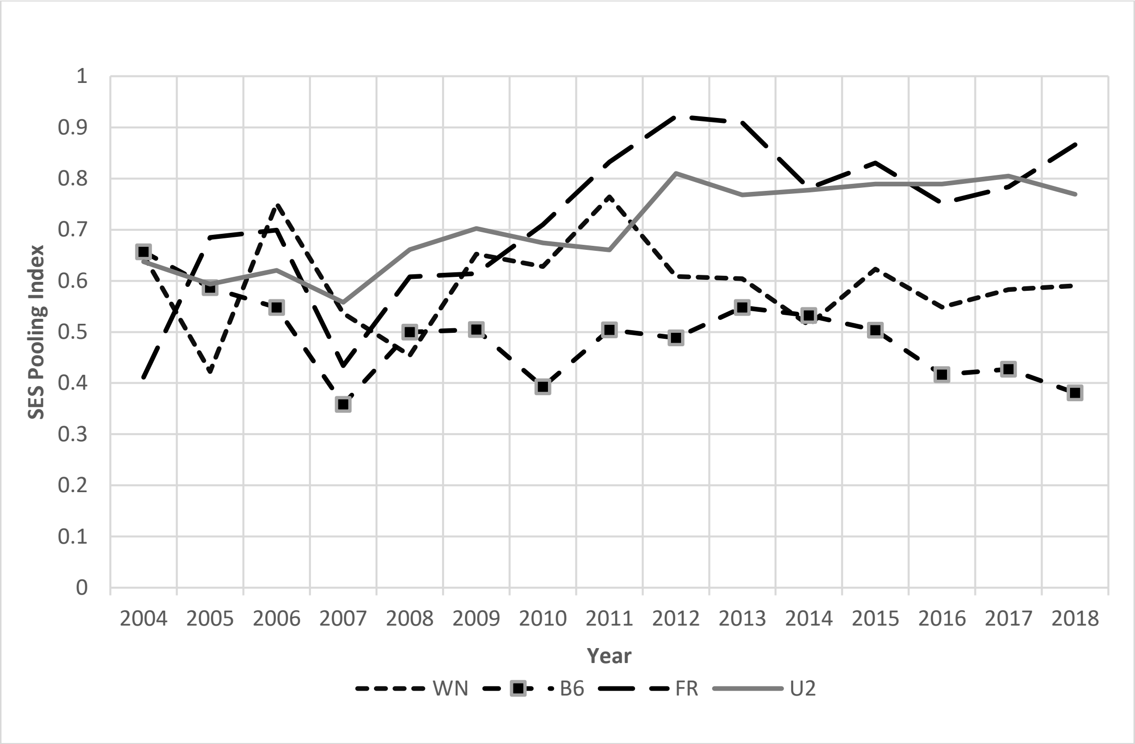

Figure 7. The SES Pooling Index for Selected Airlines

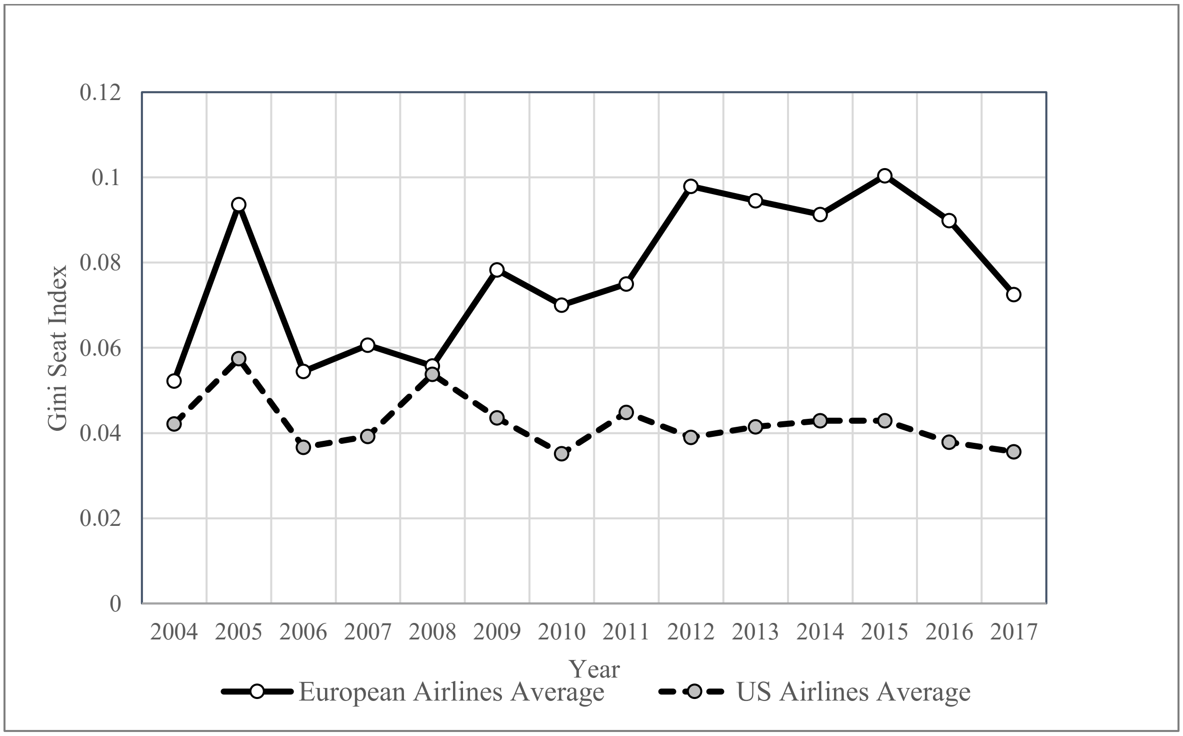

Figure 8. Comparison of Gini Seats Index between US and European LCCs

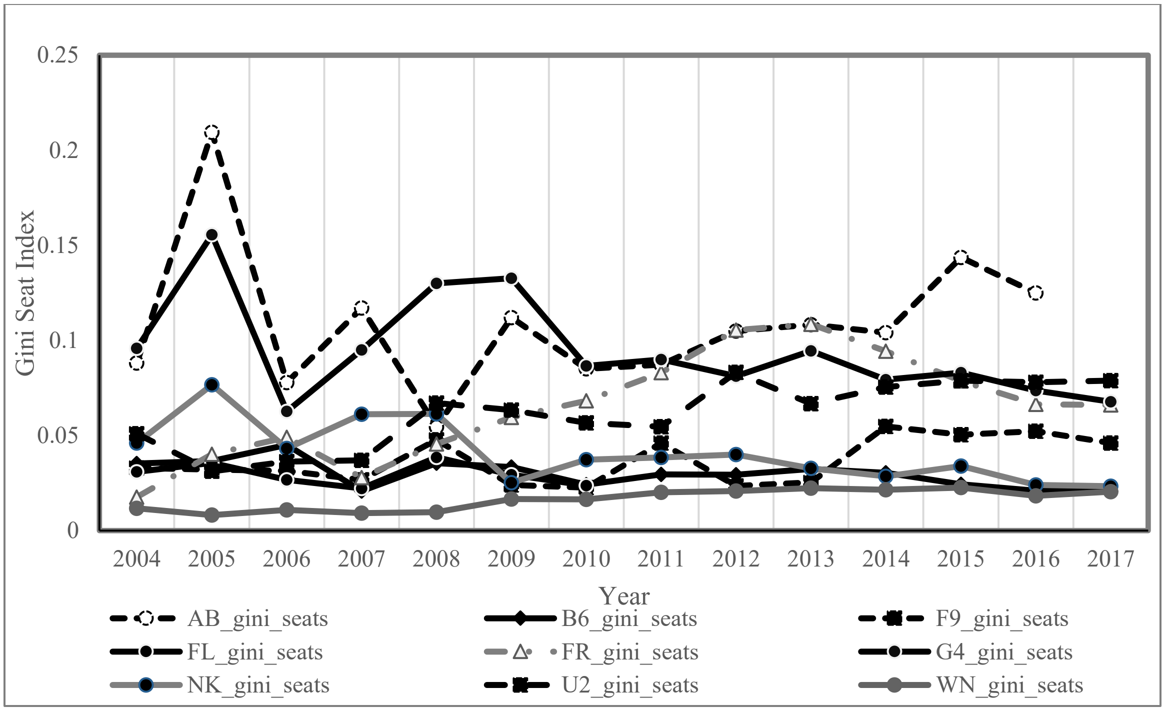

Figure 9. Comparison of Gini Seats Index among Selected Airlines over time

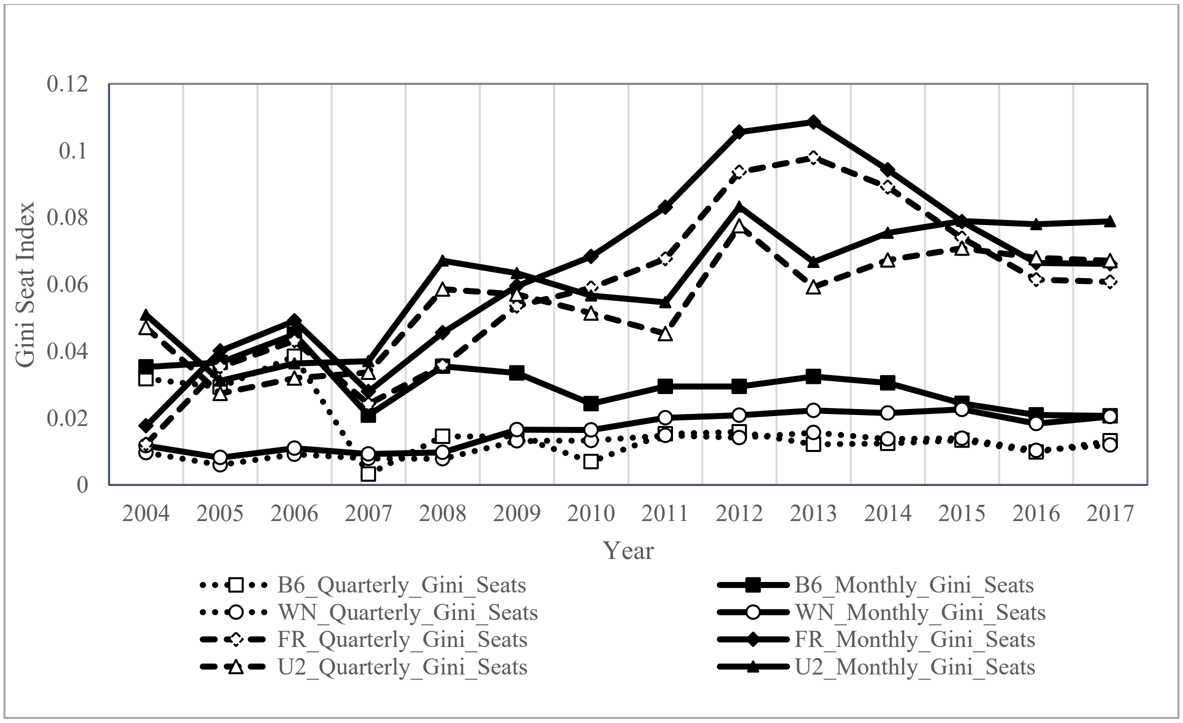

Figure 10. Comparison between Quarterly Gini and Monthly Gini Indices

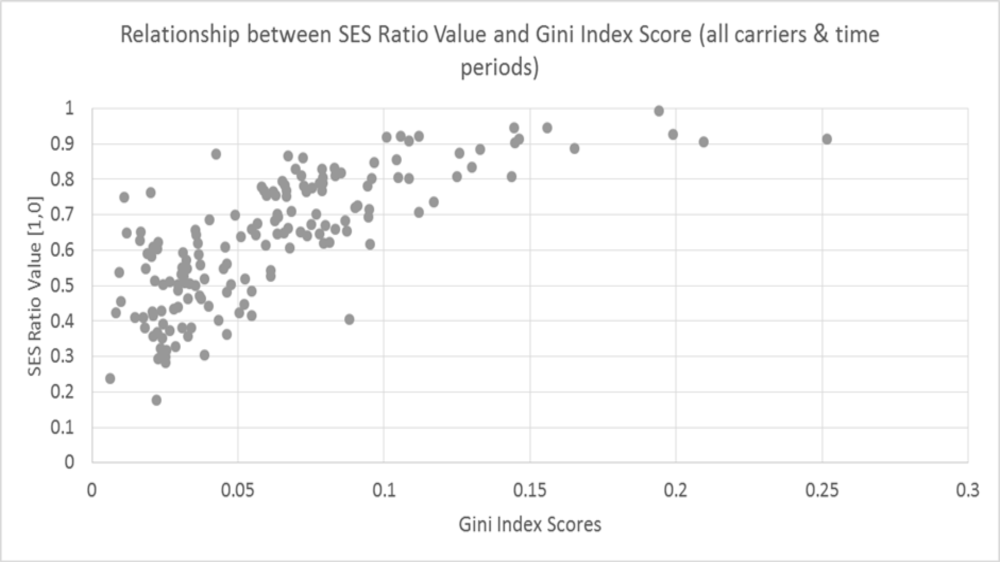

Figure 11. Gini and SES Pooling Index

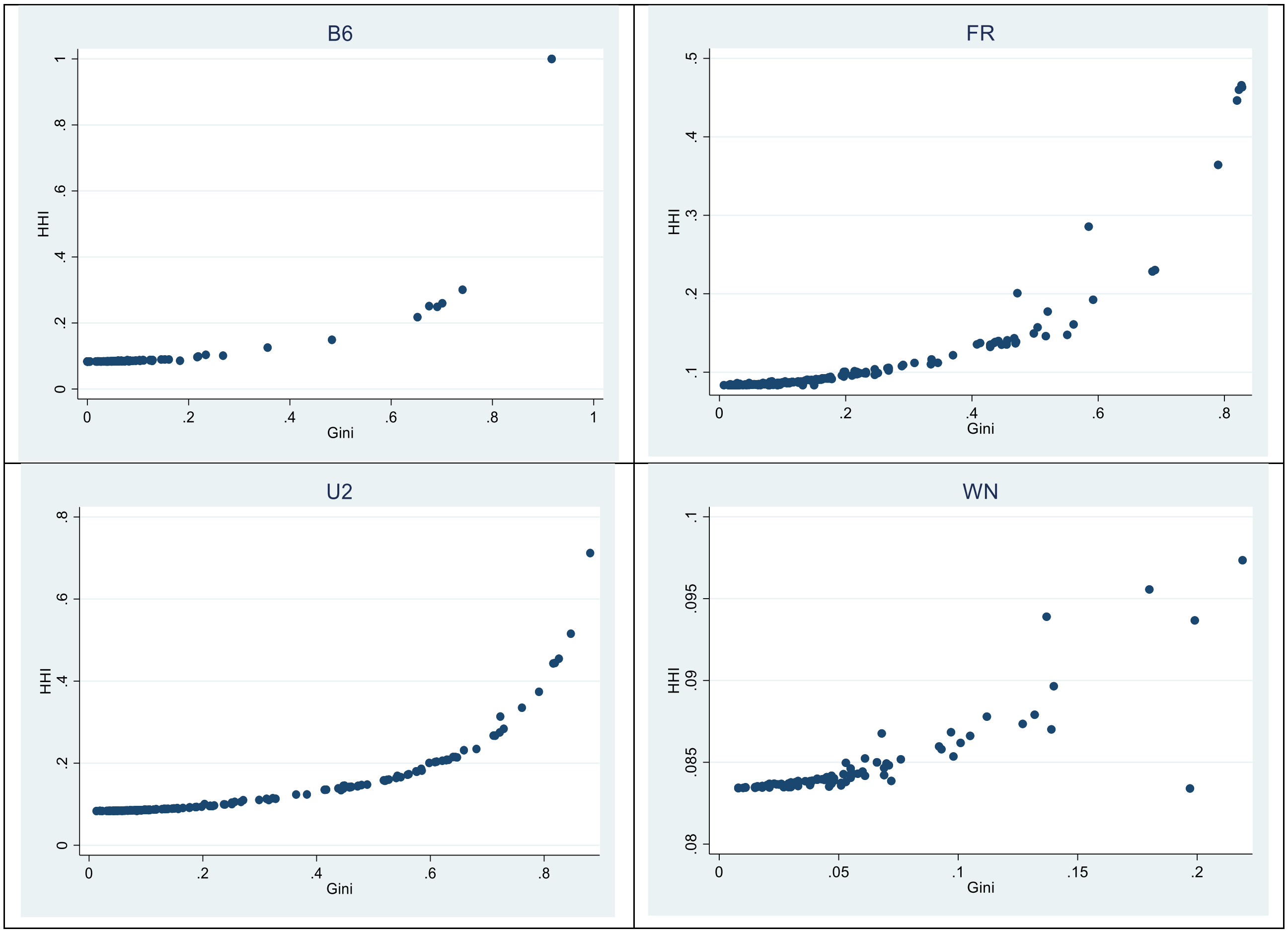

Figure 12. Gini Index and Monthly Seat Concentration Index