



HAL
open science

Enhancing airline multimarket competition analysis with a pairwise competitive intensity index based on weighted Jaccard index

Qian Liu

► **To cite this version:**

Qian Liu. Enhancing airline multimarket competition analysis with a pairwise competitive intensity index based on weighted Jaccard index. *Journal of Air Transport Management*, 2026, <10.1016/j.jairtraman.2025.102931>. <hal-05370342>

HAL Id: hal-05370342

<https://hal.science/hal-05370342v1>

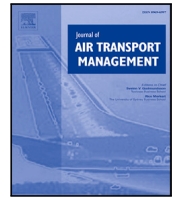
Submitted on 18 Nov 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.


L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY 4.0 - Attribution - International License



Enhancing airline multimarket competition analysis with a pairwise competitive intensity index based on weighted Jaccard index

Qian Liu 

Fédération ENAC ISAE-SUPAERO ONERA, Université de Toulouse, France

ARTICLE INFO

Keywords:

Market competition measurement
Pairwise index
Multimarket contact
Competition asymmetry
European airlines
Single European Sky

ABSTRACT

We advance the measurement of multimarket contact (MMC) in the airline competition literature by introducing a flight frequency weighted Jaccard index. Unlike conventional MMC measures that rely on binary market presence, our proposed index captures both market overlap and supply strategic similarity through flight frequency. Current airline competition research can be divided into market-based metrics (e.g., HHI, CR), which overlook relationships among firms, and airline-based metrics, of which MMC is the most prominent but only considers market overlap. Our index bridges this gap and describes the pairwise competitive intensity among airlines within a specific geographic region. We interpret the use of the index through three applications: unsupervised clustering of airline business models, detection of market shocks, and tracking changes in competitive relationships during disruptions. Our work will allow researchers to refine previous MMC related studies. This work provides policymakers with tools to monitor real-time market competition and may better inform competition regulation design. For airlines, they can leverage the index to identify rivals with the same or different business models, measure their competitive intensity, and choose their competition strategy accordingly.

1. Introduction

Understanding airline competition is vital not only for the economics and operations of individual carriers, but also for shaping the strategic direction of the industry. Beginning with the US Airline Deregulation Act in 1978, extended by the European Single Sky in 1992, and by the ASEAN (Association of Southeast Asian Nations) Single Sky in 2023, the intensity of competition in the air transport market has been increasing in deregulated markets (Goetz, 2002; Wang et al., 2016; Lieshout et al., 2016). On the one hand, airlines must continuously adapt their strategies to maintain profitability and performance in this highly competitive and dynamic environment. Airlines compete in various dimensions, as discussed by Sun et al. (2024), including service quality (Mazzeo, 2003; Greenfield, 2014; Prince and Simon, 2015), price competition (Gerardi and Shapiro, 2009; Liu et al., 2021), route and network competition (Goolsbee and Syverson, 2008; Ciliberto and Tamer, 2009), business models (Mason and Morrison, 2008; Daft and Albers, 2015), and others. While some airline strategies, such as alliances, mergers, and code-sharing agreements, often aim to reduce direct competition by coordinating supply and consolidating market power, others, such as pricing innovations or business model convergence, may intensify competition by targeting similar market segments. On the other hand, understanding airline competition is crucial for regulators and policymakers. It allows them to assess market

dynamics, ensure fair practices, and create regulations that promote safety, efficiency, sustainability, and consumer welfare. By analyzing competition levels, regulators can identify potential anti-competitive behaviors, such as price-fixing or monopolistic practices, and intervene when necessary (Azar et al., 2018; Kim and Sohn, 2022). Additionally, understanding competition can help policymakers make informed decisions about airport infrastructure investments, slot allocations, and market policies to foster a competitive and sustainable industry.

Although a large number of studies have been conducted on airline competition, limited attention has been given to measuring the intensity of competition. On the one hand, airline competition is typically discussed in the context of individual markets, such as specific routes. Existing literature mainly focuses on modeling competition in route markets, including topics as frequency allocation, route entry or exit, and network structure. Existing research methods mainly include game theory models (Oum et al., 1995; Adler, 2005; Vaze and Barnhart, 2012; Ciliberto et al., 2021; Wang et al., 2022) which focus on the strategic interactions among rational decision-makers; econometric and quantitative economic models (Lieshout et al., 2016; Gaggero and Piazza, 2021; Charles et al., 2004) which apply statistical and mathematical techniques to analyze economic data; and microeconomic models (Lijesen and Behrens, 2017; Flores-Fillol, 2009) which analytically explain how to allocate resources under constraints, using

E-mail address: qian.liu@enac.fr.

<https://doi.org/10.1016/j.jairtraman.2025.102931>

Received 24 March 2025; Received in revised form 1 October 2025; Accepted 11 November 2025

0969-6997/© 2025 The Author. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Table 1
Summary of airline competition literature.

Approach	Focus	References
Market-based	Concentration measures	Lijesen et al. (2002), Lieshout et al. (2016)
Airline-based		
Static:	MMC measures	Baum and Korn (1999), Gimeno and Woo (1999), Gimeno (1999), Zou et al. (2011, 2012)
Dynamic (Models):	Game theory	Oum et al. (1995), Adler (2005), Vaze and Barnhart (2012), Ciliberto et al. (2021), Wang et al. (2022)
	Econometrics	Charles et al. (2004), Lieshout et al. (2016), Gaggero and Piazza (2021)
	Microeconomics	Flores-Fillol (2009), Lijesen and Behrens (2017)

optimization models. Market competition measurements (OECD, 2021), notably market concentration measures (Lijesen et al., 2002), including the Herfindahl–Hirschman Index (HHI) (Rhoades, 1993) and Concentration Ratio (CR, e.g., C4, C8 indices), are used as decision variables in these models. Although these approaches provide valuable insights into market structure and the competition dynamics among airlines, they are computationally complex (game theory and microeconomic models) or require comprehensive data (econometric models), making them difficult to be applied to a large number of airlines. On the other hand, competition authorities may focus on broader geographic markets, such as competition within a region, country, or continent. In this context, the concept of MMC (Gimeno and Woo, 1996) becomes more relevant for describing competition among airlines.

Existing airline competition research can be divided into two approaches: market-based and airline-based (Table 1). On the one hand, traditional market-based competition measurements, such as the HHI and CR applied in route markets, fail to account for the multimarket competition among airlines, which is crucial for understanding their true competitive relationship across routes in a specific region. For example, if one is interested in the competition in France, market-based indices only provide a global measure of the whole french passenger flight market, lacking information on the intensity of competition which indicates how strong the rivalry is between two specific airlines. This gap underscores the potential for new methodologies to complement traditional competition metrics. On the other hand, airline-based competition research mainly measures the level of multimarket contact (MMC). Studies examine how MMC impacts airline performance, particularly in pricing or capacity decisions (Baum and Korn, 1999; Gimeno and Woo, 1999). Especially, mutual forbearance, including mutual deterrence and tacit cooperation, represents a key focus within MMC literature (Gayle and Brown, 2014; Yu and Cannella, 2013; Bilotkach, 2011; Bernheim and Whinston, 1990). For example, airlines operating in overlapping markets must survive from intense competitive pressure, which may result in fare wars, capacity shifts, or route adjustments. Consequently, when facing high levels of MMC, airlines may be incentivized to reduce competitive pressure through cooperative arrangements, such as code-sharing, joint ventures, or alliances.

Given that competitive intensity affects the strategic behaviors of airlines, the research question we address is “How to measure the competitive intensity between two airlines?” We answer the question and fill the gap in the literature using the Jaccard index (Jaccard, 1908; da F. Costa, 2021), a statistic well-known for quantifying the similarity between two sample sets. Although in air transport research, the basic Jaccard index is usually used to study network overlap (Milazzo et al., 2022; Sun et al., 2017; Li et al., 2023), its potential for assessing airline competition remains underexplored. In other fields,

such as ecology and microbiology, researchers use pairwise metrics such as Euclidean distance, Cosine similarity, Pearson correlation, or Jaccard index to infer similarities between cells based on features (e.g., peaks, genes) (Faust and Raes, 2012; Yin and Yasuda, 2005). Similarly, in social network research, pairwise distance metrics such as cosine similarity and the Jaccard index are used to assess the overlap of common attributes between users (Chunaev, 2020; Ayub et al., 2018). These methods are also widely used in document collection, where pairwise comparison of words and phrases helps to assess document similarity (Thada and Jaglan, 2013; Deng et al., 2012). The versatility of Jaccard-based indices in capturing similarity patterns is therefore demonstrated in different research domains.

Moreover, competitor identification is a multifaceted topic. For example, Bergen and Peteraf (2002) address this issue through a broad managerial approach, while (Yu et al., 2016) argue that perceived environmental uncertainty influences firms’ perceptions of their competitors. Although competitor identification remains complex, airline competition is more suitable for the Cournot competition (Brander and Zhang, 1990), which has homogeneous products and competes for flight capacity. When choosing flight capacity, airlines should first decide which routes to serve and then decide at what frequency to fly and which aircraft to use. As in Europe, most (> 80%) scheduled flights are operated with large narrow-body (160–199 seats) aircraft, the capacity difference caused by aircraft type can therefore be ignored. Moreover, Givoni and Rietveld (2009) support the fact that airlines mainly compete on frequency. Flight frequency competition reflects underlying market demand and other strategic factors, such as pricing, capacity constraints, and airline differentiation. Therefore, the frequency arises as a Nash equilibrium outcome after accounting for demand shifts, cost structures, and competitive pressure. Therefore, we argue that two airlines with the largest supply overlap (common routes with high flight frequency) can be considered the closest and most direct competitors, as they exhibit similar supply strategies on overlapping routes. We believe that a similarity measure based on the weighted Jaccard index is suitable to quantify airline supply competition intensity.

Our study makes three main contributions to the airline competition literature. First, we measure the intensity of airline pairwise competition by considering both MMC and supply strategic similarity of airlines. Traditional MMC measures share a similar approach with the Jaccard Index, which assesses market overlap using set theory and Venn diagrams (Gimeno and Woo, 1999). However, this study advances the literature by introducing a weighted Jaccard Index that incorporates flight frequency, which is a critical but previously overlooked dimension. Measuring MMC with flight frequency, rather than using binary notation for market presence, better reflects competitive intensity by considering the strategic similarity between airlines in terms of supply, while also differentiating the importance of each flight route. It offers a more empirically nuanced analysis compared to classical approaches. This improvement extends the definition of MMC in the literature, and contributes to studies including reciprocal or non-reciprocal MMC (Gimeno, 1999), MMC between airlines with similar or different costs (Zou et al., 2011), and MMC between airlines within the same alliance or across different alliances (Zou et al., 2012).

Secondly, we propose that the weighted Jaccard index measure is suitable for measuring the intensity of airline pairwise competition. It has the advantages of being highly interpretable and easy to compute. The index, based on flight frequency, captures the outcomes of frequency-based competition, aligning with Cournot competition. It reflects strategic outcomes rather than how the underlying competitive decisions are made. Moreover, the index does not require knowledge of airline types for comparison, allowing the assessment of the intensity of competition between full-service carriers (FSCs), low-cost carriers (LCCs), or hybrid carriers. We also demonstrate two applications of this index in the air transport market: inferring airline business models and monitoring changes in competitive relationships following a market shock.

Thirdly, the asymmetric index captures real-world market asymmetries and offers deeper insight into airline competition dynamics. Indeed, [Chen and Hambrick \(1995\)](#) state that the intensity of competition exhibits an asymmetry, differing between smaller and larger companies. This concept is further developed and substantiated by [Chen \(1996\)](#), who measures and illustrates competitive asymmetry based on market commonality and resource similarity. In addition, our proposed asymmetric index aligns with the concept mentioned by [Baum and Korn \(1996\)](#), which proposes how to measure the MMC level for a focal airline.

Starting from the symmetric case, assuming equal competitive pressure on both airlines, we apply a weighted Jaccard index using the normalized flight frequencies. The choice of normalization is to emphasize that we are interested in “how” airlines compete, regardless of the size of the company. The symmetric Jaccard index is then calculated for individual airlines, to explore airline competitive relationships and seasonal variations. In addition, an asymmetric index, complementary to the symmetric one, is proposed. It aims to better capture the disparity of competition between airlines. Instead of normalizing the flight frequencies of each airline, the asymmetric index takes into account the size of the company. This indicates that small companies are always in a weaker competitive position against large ones, while the symmetric measure reduces this disparity caused by size. Overall, we find that these metrics, symmetric or asymmetric, are effective in measuring airline pairwise competition intensity, and provide a perspective for airlines to identify key competitors. We then show some applications of these metrics. First, they enable unsupervised inference about airline clusters based on business models in a given region. The clustering results are highly consistent with the actual airline business model classification proposed by [Magdalena and Bouzaima \(2021\)](#). Second, they can be used to detect market shocks that manifest as disruptions in the airline operating environment. Last but not least, they can be used to analyze how pairwise competitive relationships of airlines change after a shock. Overall, our work will allow researchers to refine previous MMC related studies. This work provides policymakers with tools to monitor real-time market competition and may better inform competition regulation design. For airlines, they can leverage the index to identify rivals with the same or different business models, measure their competitive intensity, and choose their competition strategy accordingly.

The rest of the paper is structured as follows. In Section 2, we present the definition of the proposed symmetric and asymmetric weighted Jaccard based indices. In Section 3, we present the data used and interpret the index values calculated for 16 FSCs and LCCs, as well as some competitive characteristics that can be observed using the two indices. In Section 4, we show that these indices can be used to infer airline business model clusters. The inferred clusters are consistent with the actual airline classification. Section 5 presents a second application: an analysis of the European passenger aviation market under the impact of COVID-19. Finally, Section 6 concludes the paper and provides suggestions for future work.

2. Metrics definition

In this section, we give the definitions of symmetric and asymmetric competitive intensity indices based on the Jaccard index.

2.1. Symmetric index

To start with, since the similarity between sets is usually measured using distance, and distance is non-directional, we introduce a symmetric measure of competition between airlines. Symmetry means that the intensity of competition is considered equally strong for company a as it is for b .

The Jaccard index ([Jaccard, 1908](#)), also referred to as the Jaccard similarity coefficient, is a statistic used to assess the similarity between

finite sample sets. For X and Y two finite sample sets, the classic Jaccard index is defined as the size of the set intersection divided by the size of the union in (1). It is worth noting that in the literature on air transport networks, the Jaccard index can be used to measure changes in airport networks over two time periods ([Bringmann et al., 2018](#); [Li et al., 2023](#)), or to assess airport brand perception by measuring social network cluster similarity of airports ([Gitto and Mancuso, 2019](#)).

$$J(X, Y) = \frac{|X \cap Y|}{|X \cup Y|} = \frac{|X \cap Y|}{|X| + |Y| - |X \cap Y|}. \quad (1)$$

An index of competitive intensity for airlines can naturally be constructed using the concept of the Jaccard index, as

$$J(a, b) = \frac{N(a \cap b)}{N(a \cup b)} \quad (2)$$

with $N(a \cap b)$ denoting the number of common routes between the two airlines, and $N(a \cup b)$ representing the total number of routes covered by at least one of the two airlines. However, the index $J(a, b)$ solely measures the network overlap between airlines a and b , without accounting for the frequency of flights on shared routes. For instance, if both airlines operate the same set of routes, the index remains unchanged, even though variations in flight frequency can significantly alter the intensity of competition.

Moreover, to balance the effect of airline size on the symmetric measure of competitive intensity, the index should not be affected by airline size (total flight frequency), but only by the distribution of flights within its network. In this way, if two large airlines adopt the same flight allocation strategy on overlapping routes, their competitive intensity index may be the same as that of a large airline and a small airline. For example, for airlines X, Y, Z , both the pairs (X, Y) and (X, Z) have the three common routes A, B, C . If they all allocate $1/3$ of their total capacity on each route, then the two pairs have the same intensity of competition, regardless of the airline size.

Consider the flight frequency distributions for airlines a and b

$$p^a(r_i) = \frac{f^a(r_i)}{f^a(R)}, \quad p^b(r_i) = \frac{f^b(r_i)}{f^b(R)} \quad (3)$$

where $\sum_{i=1}^n p^a(r_i) = 1$, $\sum_{i=1}^n p^b(r_i) = 1$ with $n = |R|$ the total number of routes within a geographic region. Let p^a and p^b denote the normalized flight frequencies of airlines a or b on each route, where normalization is performed with respect to the total frequency of the corresponding airline. The resulting distribution p^a (or p^b) reflects the supply strategy of airline a (or b), indicating how flights are allocated across routes r_i . Normalizing flight frequencies as probability distributions ensures comparability among airlines of varying sizes.

The pairwise competitive intensity can therefore be measured by considering the weighted Jaccard index ([da F. Costa, 2021](#)) between two airline strategies p^a, p^b defined in (4). The index $I_{\text{Sym}}(a, b)$ lies in $[0, 1]$, and equals zero when there is no common route between the two airlines.

$$I_{\text{Sym}}(a, b) = \frac{\sum_{i=1}^n \min(p^a(r_i), p^b(r_i))}{\sum_{i=1}^n \max(p^a(r_i), p^b(r_i))} \quad (4)$$

2.2. Asymmetric index

It is crucial to acknowledge that competition between two airlines can also be seen as asymmetric, especially when considering airline size. The same situation may be more critical for a small airline than for a large one. This argument is evidenced by [Chen and Hambrick \(1995\)](#). In reality, using a symmetric index, a large airline would always have a small index value when compared with a small airline due to their low route overlap. However, this value does not capture the differences in competition intensity faced by airlines a and b given their distinct competitive positions. An asymmetric index can address this. For instance, a smaller airline a with only 20 routes does not face the same level of competition as a competitor b operating on 200 routes and sharing common routes. Therefore, the competitive intensity caused by

a to b is typically low, as a small airline poses little threat to a large airline. Conversely, the competitive intensity of b applied to a is much larger, given its stronger market power.

To account for the potentially unbalanced intensity of competition between two airlines, the unweighted Jaccard index can naturally be adapted to an asymmetric version (5).

$$J(a|b) = \frac{N(a \cap b)}{N(b)}. \quad (5)$$

This index measures the proportion of routes operated by airline a where airline b is present. Consistent with the competition paradigm, high values of the index indicate that airline a tends to focus on routes on which airline b operates. Since this indicator only accounts for the overlapping routes between the two airlines and not on the frequencies on these routes, we propose the weighted version of the asymmetric Jaccard index, defined by (6). In this form, we can also interpret it as a conditional probability, representing the likelihood that airline a operates on a route, given that airline b is already present on that route. The asymmetric index measures and reflects disproportionate pressure on smaller airlines (e.g., a small carrier operating 20 routes experiences stronger competitive pressure from a large rival with 200 routes, compared to the reverse scenario).

$$I_{\text{Asym}}(a|b) = \frac{\sum_{i=1}^n \min(f^a(r_i), f^b(r_i))}{\sum_{i=1}^n f^b(r_i)}. \quad (6)$$

2.3. Link with classical MMC measurements

The literature proposes various measures of multimarket contact (MMC), yet no single approach has gained universal acceptance. Route-specific measures are particularly common in airline industry studies, which count the number of routes on which rivals operate (Gimeno, 1999; Bilotkach, 2011), sometimes with weights (Ma et al., 2020). However, this approach overlooks firm size asymmetries by focusing solely on the number of overlaps. For instance, one shared route between a small and a large carrier may not represent the same competitive intensity as one shared route between two similarly sized carriers. To address this limitation, an alternative is to normalize the overlap by the total number of routes served by both rivals, as adopted by Zou et al. (2012), which is closely related to the idea of the Jaccard index (defined in (2)).

Furthermore, we emphasize that the indices in (4) and (6), derived from the weighted Jaccard index, provide a complementary perspective to traditional MMC measures. Our indices do not replace conventional MMC measures but instead add nuance by capturing competitive intensity differently. Consider the following illustrative scenarios:

- **Case 1:** Airlines A and B compete in three markets. Airline A allocates flights as $1/2, 1/4, 1/4$, while Airline B allocates $1/4, 1/2, 1/4$. The weighted Jaccard index I_{Sym} (4) equals $3/5$.
- **Case 2:** Airlines A and B overlap in two markets. Airline A distributes flights as $1/2, 1/4, 1/4$, while Airline B distributes $1/2, 1/2, 0$. The I_{Sym} equals $3/5$.
- **Case 3:** Airlines A and B overlap in two markets. Airline A distributes flights as $1/2, 1/4, 1/4$, while Airline B distributes $0, 1/2, 1/2$. The I_{Sym} equals $1/3$.

Two conclusions follow. First, although Cases 1 and 2 yield the same value of I_{Sym} , they differ under traditional MMC measures. This suggests that firms may experience comparable intensity in multimarket competition across three routes as they do across two routes. Second, although Cases 2 and 3 yield the same traditional MMC measure (two overlapping routes), our index differentiates between them, reflecting distinct competitive intensities. This illustrates that the weighted Jaccard indices complement traditional MMC measures by capturing competitive intensity with greater precision, depending on how airlines allocate their supply across markets.

3. Results and findings: Identify the main competitors

In this section, we first present the data used to illustrate and analyze the results of the previously proposed symmetric and asymmetric indices. We then calculate and interpret the index values for the selected airline pairs, which are identified by their airline codes. The indices I_{Sym} and I_{Asym} are calculated on the first and the third quarters of 2023 (Q1 and Q3), defining markets as airport pairs for illustration.

3.1. Data

We analyze data sourced from the Official Airline Guide (OAG). This dataset provides details on global scheduled flights, and includes various route and flight characteristics, such as operating carriers, published carriers, departure and destination airports, route distance in kilometers, flight duration, available seats per flight, flight date, departure and arrival times. We extract one-way, non-stop direct passenger flights in 2023, and use data from the winter, i.e., the first quarter (Q1: January, February, March) and the summer, i.e., the third quarter (Q3: July, August, September) of 2023. Q1 (winter) and Q3 (summer) capture peak seasonal network adjustments, aligning with industry practices (Reynolds-Feighan et al., 2022; Zou et al., 2022). We aggregate round-trip flight frequencies for each quarter to analyze the domestic European market based on airport or city origin–destination (OD) pairs. The choice of whether to study city pairs or airport pairs as ODs in aviation networks has been a topic of debate. Brueckner et al. (2014) proposed a method to group airports into city pairs, but concluded that the substitutability of airports depends on trip characteristics, which cannot always be discerned from existing data. Due to the lack of firm conclusions in the literature, we investigate both cases in Section 4.

We choose to study flights with OD within the 41 Eurocontrol member states without overseas territories (see Table 2). Note that since February 2022, the Ukrainian airspace has remained closed to all civil flights due to geopolitical reasons. This limits our 2023 data to 40 countries. We select these countries because they operate under the Single European Sky (SES) project, which ensures the same freedom to set operations (Debyser, 2024). The SES initiative, established by the European Commission (Regulation EC 549/2004), harmonizes air traffic management across participating states, and eliminates preferential treatment for national carriers in airspace access. This regulatory uniformity is critical for measuring airline competition intensity through flight frequency because: (1) it ensures all carriers face equal operational constraints in routing and scheduling, and (2) it prevents artificial frequency distortions caused by unequal access to airspace slots. Therefore, SES makes the observed flight frequencies a reliable proxy for the competitive strategic behavior of airlines in the European aviation market.

We select 33 airlines (Table 3) which are labeled into 4 business models (full-service carriers (FSCs), Hybrid 1 and 2,¹ and low-cost carriers (LCCs)), based on the definition proposed by Magdalena and Bouzaima (2021) and on our available data. Given that airlines are not always financially or strategically independent, nor are they always viewed as direct competitors. Airlines operating under the same holding company are viewed as in the same group. In cases where multiple airlines in a group share the same business model, we consider that they are not competitors. In this case, we randomly include one representative airline from each group in our analysis. Consequently, the number of airlines included in our study is fewer than those mentioned

¹ Hybrid 1 aligns more closely with the FSC business model while retaining several LCC traits (e.g., lower frequency, minimal code-sharing/alliances, and no complimentary beverages), whereas Hybrid 2 primarily exhibits LCC characteristics but incorporates some FSC features (e.g., hub-and-spoke networks, free baggage, and loyalty programs).

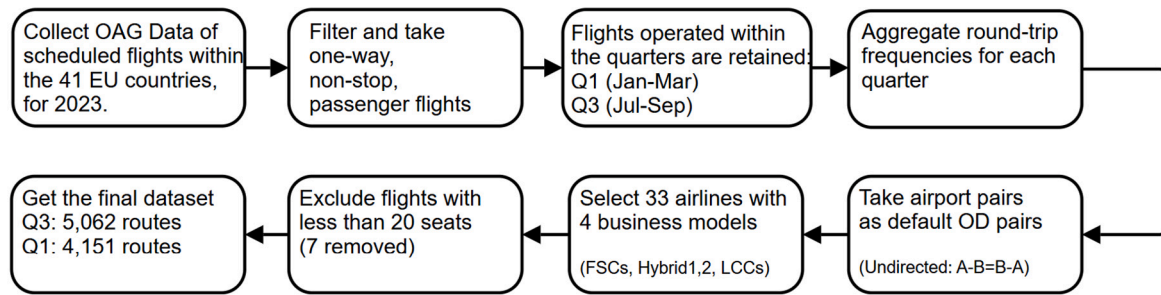


Fig. 1. Data processing flowchart.

Table 2

Definition of Europe as 41 eurocontrol member states.

Albania	Germany	Poland
Armenia	Greece	Portugal
Austria	Hungary	Republic of Moldova
Belgium	Ireland	Romania
Bosnia & Herzegovina	Italy	Serbia
Bulgaria	Latvia	Slovakia
Croatia	Lithuania	Slovenia
Cyprus	Luxembourg	Spain
Czech Republic	Malta	Sweden
Denmark	Monaco	Switzerland
Estonia	Montenegro	Turkey
Finland	Netherlands	Ukraine
France	North Macedonia	United Kingdom
Georgia	Norway	

Source: <https://www.eurocontrol.int/our-member-and-comprehensive-agreement-states>

in the literature. Then we filter out flights with fewer than 20 seats on the aircraft, on which no cabin crew is required (EASA, 2015). This accounts for only 7 flights out of the 1,927,805 scheduled flights. The whole data processing step is illustrated in Fig. 1. After filtering, there are 5062 routes (defined by airport OD pairs) in Q3 and 4151 routes in Q1 for all 33 selected operating airlines. Each route is considered undirected, meaning that the OD pair A–B is equivalent to B–A.

3.2. Competition characteristics

The above indices exhibit two main characteristics: seasonal variation caused by network adjustments of airlines, and asymmetry that reveals disparities among competitors. In this subsection, to illustrate the characteristics of index values, we only consider airport-pair markets and airlines labeled as FSC or LCC.

3.2.1. Seasonality

We focus on the 16 airlines classified as FSC or LCC in Table 3, representing the two most distinct airline business models. First of all, by looking directly into scheduled flight data without calculating the index, we observe that the air transport network is seasonally adjusted: All the 16 FSC and LCC airlines operated a total of 3750 routes in summer, dropping to 3234 in winter.

Then we calculate the symmetric index values (I_{Sym}) and find that seasonality shapes the market competition structure, leading to shifts in the main competitor pairs. Using the symmetric index as the measure of pairwise competitive intensity, Fig. 2 is a scatter plot with winter (Q1) index values on the x-axis and summer (Q3) index values on the y-axis. The points on the diagonal line ($y = x$) represent pairs with the same competitive intensity in summer and winter. Points above the diagonal indicate that these pairs experience more intense competition in summer than in winter, while points below the line indicate greater competition in winter than in summer. For example, we can conclude that the pair BA–U2 exhibits more intense competition in winter. However, in summer, they have less supply overlap, leading to less intense competition.

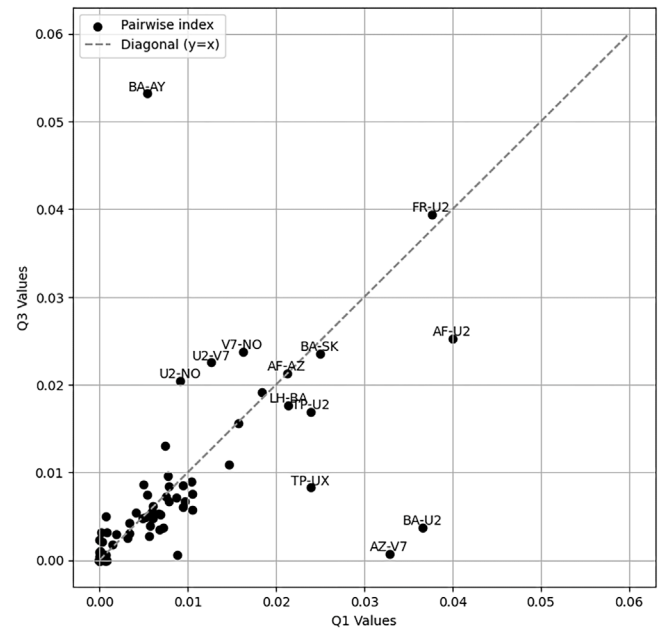


Fig. 2. Competitive intensity between summer (Q3) and winter (Q1) for all pairs of FSCs or LCCs as operating carriers, using symmetric index.

Furthermore, from the perspective of an individual airline, its primary direct competitor varies over time. This variation is, for example, illustrated by the fluctuating competitive index between easyJet and other airlines (Fig. 3). As previously explained, the scatter plot points do not perfectly align with the diagonal line ($y = x$), indicating that competitive relationships change across seasons. For example, we observe that in summer 2023, Ryanair, the largest low-cost airline in Europe by number of passengers,² is the main competitor of easyJet, as can be seen the FR–U2 pair having the largest index value. However, in winter, Air France (AF) becomes the main competitor of easyJet. In fact, we observe that easyJet and Ryanair operate 869 and 1493 routes, respectively, with 124 common routes in Q3 2023, while in Q1 2023, they operate 642 and 1461 routes, respectively, with 117 common routes, which makes the index slightly smaller in Q1. As for easyJet and Air France, in summer they operate respectively 869 and 89 routes, with 35 common routes, while in winter they operate 642 and 62 routes, respectively, with 21 common routes. The expansion of easyJet’s network in the summer has made its competition with Air France less important. This is in line with the findings of Reynolds-Feighan et al. (2022), that FSCs have lower seasonality than LCCs.

² FRACS: Air Transport Data Bulletin — 2024.

Table 3
Selected operating carriers with labels. Airline codes are IATA or ICAO codes.

No	FSC	LCC	Hybrid 1	Hybrid 2
1	LH (Lufthansa)	FR (Ryanair)	DE (Condor)	DY (Norwegian Air Shuttle)
2	BA (British Airways)	U2 (easyJet)	EI (Aer Lingus)	EW (Eurowings)
3	AF (Air France)	W6 (Wizz Air)	JU (Air Serbia)	VY (Vueling)
4	SK (SAS, Scandinavian)	HV (Transavia)	WK (Edelweiss Air)	LS (Jet2.com)
5	AZ (ITA, old Alitalia)	V7 (Volotea)	KM (KM Malta)	A3 (Aegean Airlines)
6	TP (TAP Air Portugal)	NO (Neos Air)		WF (Wideroe)
7	LO (LOT Polish Airlines)			BT (airBaltic)
8	AY (Finnair)			LM (Loganair)
9	UX (Air Europa)			NT (Binter Canarias)
10	RO (TAROM)			LG (Luxair)
11				DX (DAT, Danish Air Transport)
12				OU (Croatia Airlines)

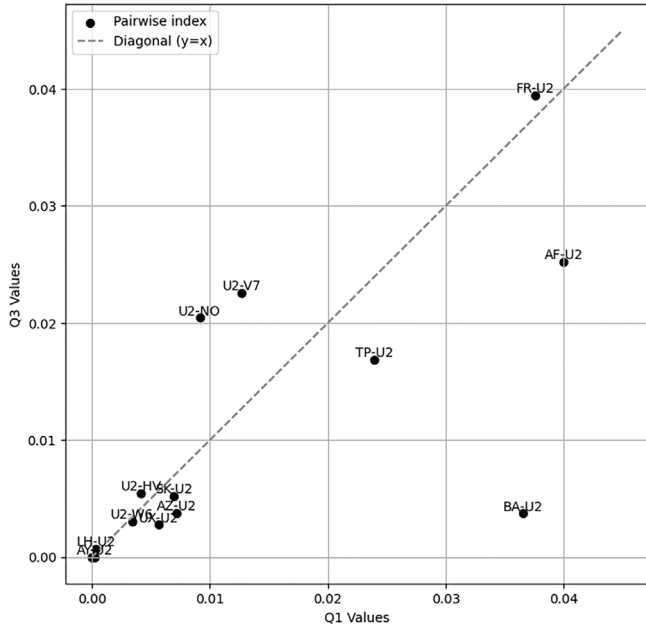


Fig. 3. Competitive intensity between summer (Q3) and winter (Q1) for pairs of competitors solely involving easyJet, using symmetric index.

3.2.2. Competition disparity measured by asymmetric index

Using the proposed asymmetric weighted index I_{Asym} , we calculate the competitive intensity of all FSC or LCC competitors of easyJet for the summer and the winter of 2023. Results are illustrated in Figs. 4 and 5. Specifically, we interpret the results in terms of competition disparity and seasonality. The dot markers represent the competitive pressure exerted by easyJet on its competitors, while the ‘x’ markers represent the competitive pressure that easyJet faces from other carriers.

Competition disparity. For 2023, results are shown in Figs. 4 and 5 with a dumbbell plot, illustrating the differences in index values between airline pairs. We note that the pair easyJet–Neos (U2–NO) exhibits the most significant difference in supply overlap. For example in Q3, when the asymmetric index $I_{Asym}(NO|U2)$ measures 0.003524, it means that only 0.35% of U2’s flights are overlapped by NO. Conversely, the index $I_{Asym}(U2|NO)$ measures 0.248557, indicating that 24.9% of NO’s flight propositions are also offered by U2. Therefore, the competitive pressure from U2 to NO is much more significant than from NO to U2. In other words, in the competition between U2 and NO, NO is in a weaker position compared to U2. Moreover, the plot is ranked from the largest difference to the smallest. Therefore, pairs with small differences but large index values, such as Ryanair–easyJet (FR–U2), tend to have similar flight network sizes. We also observe that Finnair (AY), LOT Polish Airlines (LO), and TAROM (RO) have no direct competition with

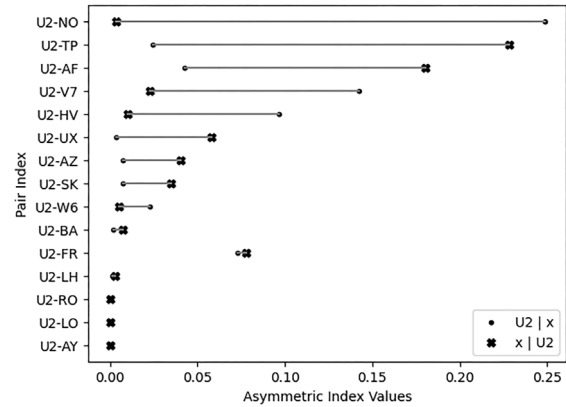


Fig. 4. Q3 Asymmetric competitive intensity index values for airlines competing with easyJet. Dumbbell plot, the line between two points shows the difference between their values.

easyJet, given their null index values. In general, easyJet exerts more competition on LCCs and suffers more pressure from FSCs, as the ‘x’ marker values of LCCs are smaller than the dot markers in the figures.

Seasonality. However, from the dumbbell plots, we notice that the competitive relationship between NO and U2 has changed: the index $I_{Asym}(U2|NO)$ is larger in summer, indicating more intense competition faced by NO from U2. Moreover, seasonality is depicted in Figs. 4 and 5, as the differences in asymmetric index values of airline pairs vary across different seasons. We also remark that the index value difference of easyJet (U2) with Air France (AF) is larger in summer, while the difference with British Airways (BA) is larger in winter. easyJet has less supply overlap with Air France in summer than in winter. The sum of the index values of $x|U2$ in Q3 of 2023 is 0.6714, indicating that these 15 competitors of easyJet have a total supply overlap of 67.14% with easyJet. The results are the same in Q1.

4. Application 1: Airline cluster inference based on business models

We demonstrate that an important application of the indices is to infer airline clusters based on their business models, within the transportation network of a specific geographic region. This enables unsupervised identification of airline types in the region. The approach leverages the seasonality of the indices, as shown previously. A similarity matrix is constructed based on the following assumption: for each pair of airlines, if their Q1 and Q3 indices are similar, they are likely to have comparable route supply strategies and thus similar business models. Conversely, if their Q1 and Q3 indices differ significantly, this suggests that the two airlines operate with different business models. Note that this similarity matrix can be calculated using either a symmetric or an asymmetric index.

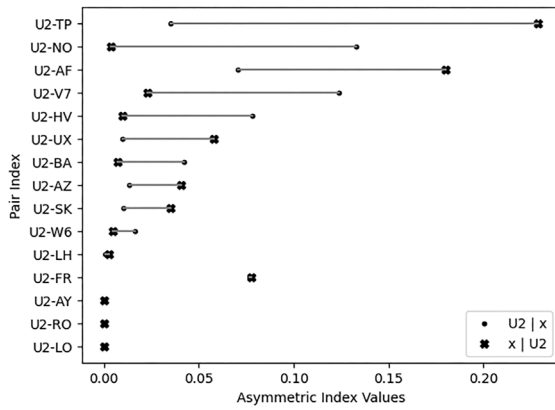


Fig. 5. Q1 Asymmetric competitive intensity index values for airlines competing with easyJet. Dumbbell plot, the line between two points shows the difference between their values.

This hypothesis seems reasonable, as different business models typically exhibit varying degrees of seasonality. For example, LCCs adjust their routes seasonally (e.g., for summer holiday destinations), whereas FSCs maintain a more consistent network across summer and winter (Reynolds-Feighan et al., 2022). This will result in a significant difference between their Q1 and Q3 index values. Based on the hypothesis, let I_{Q_1} and I_{Q_3} denote the index values of Q1 and Q3 of the airline pair, respectively. The index can be either symmetric (I_{Sym}) or asymmetric (I_{Asym}). We then define the similarity $S(i, j)$ between two airlines as in (7). The numerator comes from that $\max(I_{Q_1}, I_{Q_3}) - |I_{Q_1} - I_{Q_3}| = \min(I_{Q_1}, I_{Q_3})$. The idea behind this is that we calculate the seasonal difference (or dissimilarity) of the index and normalize it against the maximum index, under the assumption that the percentage change is more meaningful than the index's value change. Then, we subtract the dissimilarity from 1 to obtain a measure of similarity. A similarity score close to 1 indicates a stable route-sharing pattern across both seasons, while a lower score suggests significant seasonal variations in supply overlap.

$$S(i, j) = \frac{\min(I_{Q_1}, I_{Q_3})}{\max(I_{Q_1}, I_{Q_3})} \quad (7)$$

The entire clustering process is illustrated in Fig. 6. First, we select airlines clearly identified as FSC and LCC in Table 3, based on the work of Magdalina and Bouzaima (2021). Then, for each quarter, we compute $I_{Sym}(a, b)$ and $I_{Asym}(a, b)$ for each airline pair (a, b) . Next, we calculate the similarity for each pair using (7). If the maximum index is zero, it indicates that the two airlines never share common routes in Q3 and Q1, so we assign a similarity of zero to them. After constructing the similarity matrix, we apply SpectralClustering from scikit-learn in Python, specifying two clusters and using the similarity matrix $S(i, j)$ as the precomputed affinity matrix. SpectralClustering applies clustering to a projection of the normalized Laplacian. It is a graph-based method that clusters data by first constructing a similarity graph, then using the eigenvectors of its Laplacian matrix to embed the data into a lower-dimensional space where traditional clustering algorithms like KMeans can be effectively applied. This approach is especially powerful for identifying non-convex or irregular cluster structures that are not well handled by methods relying on Euclidean distances. In other words, using Spectral Clustering over KMeans lies in its ability to leverage the structure of the similarity graph by giving a precomputed affinity matrix, rather than assuming the data lies in a Euclidean space. In addition, we have tested the three embedded strategies for assigning labels ('kmeans', 'discretize', 'cluster_qr'). The final results are the same. Finally, we compare the inferred clusters with the true airline business model labels to assess the relevance of using the Jaccard index. This process is firstly applied to the symmetric index, then to the asymmetric index.

4.1. Airport pairs

Using the European airport network of airlines, Fig. 7 shows the similarity matrix computed using (7) with I_{Sym} , which is crucial in the clustering process. The similarity score $S(i, j)$ measures the percentage change in supply overlap between two airlines across seasons, where higher values indicate stronger similarity in seasonal route supply strategy.

After applying the 2-cluster spectral clustering algorithm on the similarity matrix, we observe that all 6 LCCs are grouped into the same cluster, while 7 out of 10 FSCs are correctly assigned to the same cluster. This model results in an accuracy of 0.8125, with the model's accuracy defined as

$$\text{Accuracy} = \frac{\text{Number of correct assignments}}{\text{Number of all assignments}}$$

Despite this high accuracy, in the results of clustering, three FSCs were misclassified: airlines AZ, TP, and UX. The misclassification of these airlines may result from several factors, including the extensive network coverage of a single airline, geographic overlap in serving the same regional market, or due to some specific high-traffic markets. For example, the large similarity between UX and FR is primarily due to FR's extensive network coverage. Specifically, UX and FR share 15 common routes in Q1, with a total of 33 and 1461 routes for each airline. In Q3, they share other different 16 common routes, with totals of 42 and 1493 routes, respectively. The same reasoning applies to explain the similarity among FR, U2, TP, and AZ. However, the strong similarity between AZ and NO is primarily due to their geographic overlap. ITA Airways (AZ) is the flag carrier of Italy, and Neos Air (NO) is a private Italian airline with its main operating base at Milan Malpensa Airport. They both operate within similar regional markets. Their common routes primarily connect Rome (FCO) with popular vacation destinations in Spain and Greece. Furthermore, while TP (TAP Air Portugal) and HV (Transavia) exhibit a high similarity in this calculation, they operate in distinct markets with different strategic focuses, sharing only one common route: 'AMS-LIS' in Q1 and Q3. This single overlap likely results from strong demand in a high-traffic market rather than a broader operational similarity.

To evaluate the quality of the obtained clusters, we used two additional metrics: Adjusted Rand Index (ARI) (Hubert and Arabie, 1985) and Normalized Mutual Information (NMI) (Estévez et al., 2009). Given U , the clustering inferred from a distance matrix, and V , the ground-truth labels, the ARI is defined as

$$\text{ARI}(U, V) = \frac{\text{RI}(U, V) - E(\text{RI})}{\max(\text{RI}) - E(\text{RI})},$$

where $\text{RI}(U, V)$ is the Rand Index, which quantifies the similarity between the two clustering results by measuring the proportion of sample pairs that are either in the same group or in different groups in both U and V , $E(\text{RI})$ denotes the expected Rand Index between U and a random V , and $\max(\text{RI})$ is the maximum achievable Rand Index between U and any V .

NMI is a function that measures the agreement of the two assignments, ignoring permutations. It is defined as

$$\text{NMI}(U, V) = \frac{2\text{MI}(U, V)}{H(U) + H(V)},$$

where $\text{MI}(U, V)$ is the mutual information between U and V , such that $\text{MI}(U, V) = H(U) - H(U|V)$, with $H(\cdot)$ representing entropy.

Using scikit-learn to compute ARI and NMI, the results are: $\text{ARI} = 0.3500$ and $\text{NMI} = 0.4507$. These values suggest moderate clustering performance: while the results indicate some effectiveness, there is still room for improvement in achieving a better alignment with the ground-truth labels.

Additionally, we computed the clustering results using the asymmetric index I_{Asym} . The asymmetric similarity matrix is shown in Fig. 8. The results of clustering show that all 6 LCCs are grouped into the

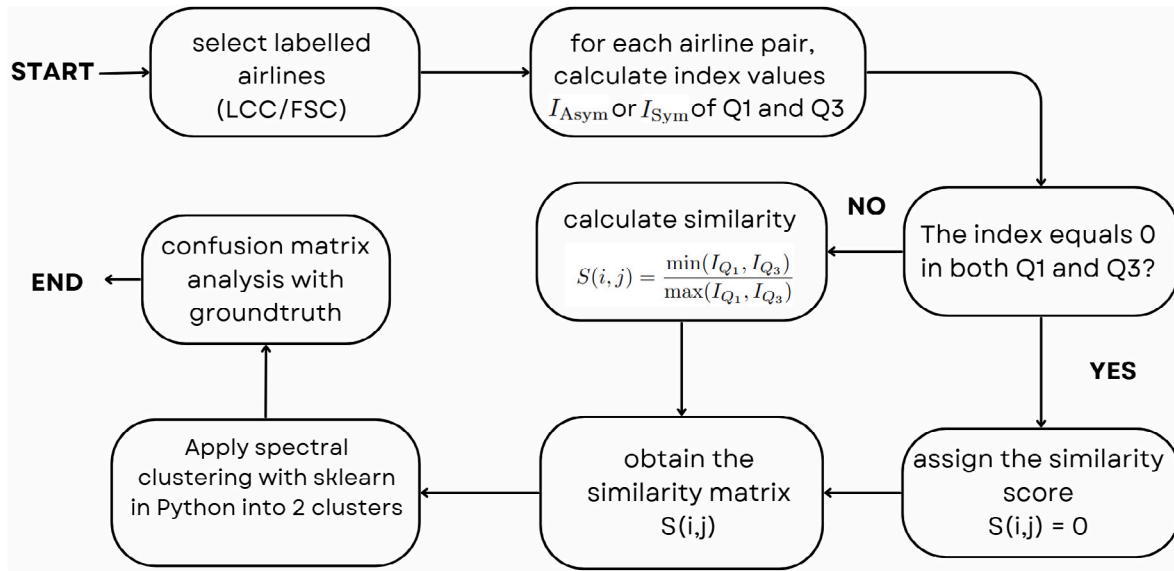


Fig. 6. Airline business model clustering process.

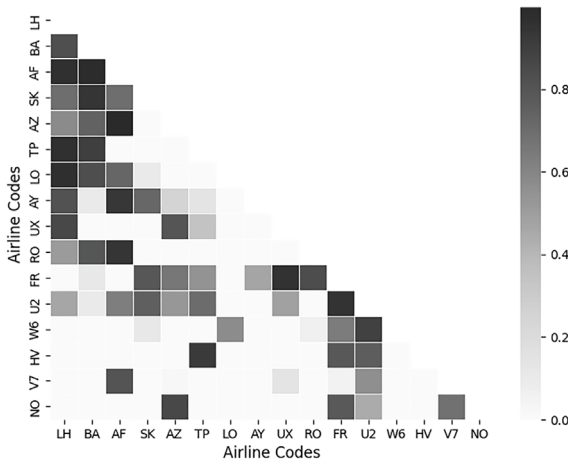


Fig. 7. Similarity matrix using symmetric pairwise index with airport pairs.

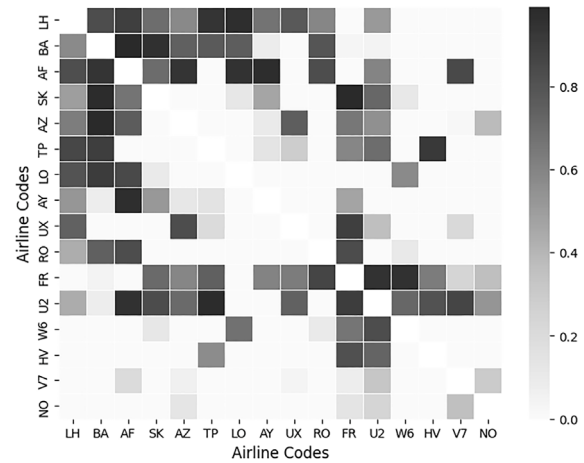


Fig. 8. Similarity matrix using asymmetric pairwise index with airport pairs.

same cluster, while 8 out of 10 FSCs are correctly assigned to the same cluster. The misclassified airlines are TP and UX. It gives the following metrics: ARI = 0.5333, NMI = 0.5616, and accuracy = 0.8750. These values suggest a stronger clustering performance compared to the symmetric index, as all metrics (accuracy, ARI and NMI) become higher. The high accuracy indicates that a significant portion of the data was correctly classified. Therefore, the use of the asymmetric index appears to provide a more accurate and reliable clustering solution of airline business models.

It is also worth mentioning that we attempted to identify clusters encompassing all 4 airline types listed in Table 3, including the 2 hybrid business models. Using the symmetric index, we obtained ARI = 0.0678 and NMI = 0.2596. Using the asymmetric index, we get ARI = 0.0981 and NMI = 0.2556. These values suggest that the model struggles to accurately distinguish between hybrid business models.

4.2. City pairs

We apply the same clustering process to the European city-pair network of airlines, with Fig. 9 representing the similarity matrix using I_{Sym} . Overall, the supply of airport pairs exhibits higher seasonal similarity based on the city-pair network compared to the airport-pair

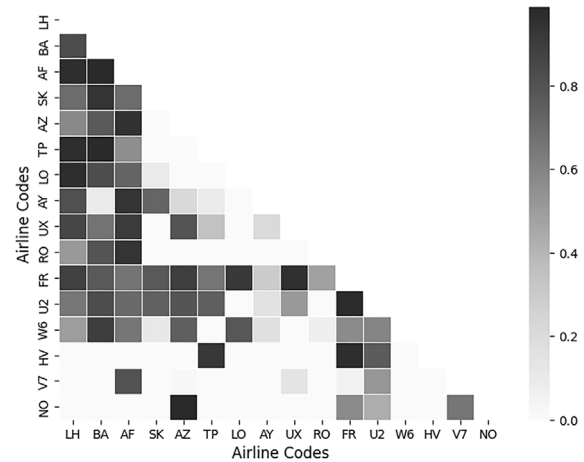


Fig. 9. Similarity matrix using symmetric pairwise index with city pairs.

network. This is because city pairs are fewer than airport pairs, which increases the probability of route overlap between airlines.

Table 4
Overview of previous results.

(Network type; index type)	2 clusters		4 clusters	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Airport pair	ARI 0.3500	ARI 0.5333	ARI 0.0678	ARI 0.0981
	NMI 0.4507	NMI 0.5616	NMI 0.2596	NMI 0.2556
	Accuracy 0.8125	Accuracy 0.8750	–	–
City pair	ARI 0.2000	ARI 0.5333	ARI 0.0396	ARI –0.0174
	NMI 0.2660	NMI 0.5289	NMI 0.1789	NMI 0.1413
	Accuracy 0.7500	Accuracy 0.8750	–	–

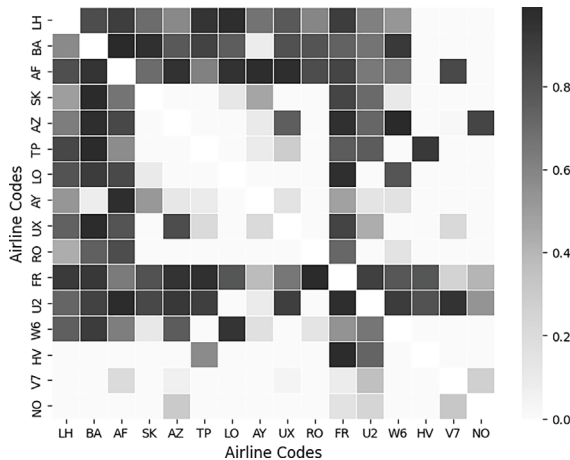


Fig. 10. Similarity matrix using asymmetric pairwise index with city pairs.

Additionally, we observe that FR, U2 and W6 show greater similarity with FSCs when using city pairs than airport pairs. Indeed, while both LCCs and FSCs may target the same city as a destination, LCCs typically operate from secondary airports, whereas FSCs usually serve primary airports, even though this distinction is constantly evolving (Dziedzic and Warnock-Smith, 2016).

After applying the 2-cluster spectral clustering algorithm to the similarity matrix, we observe that all 10 FSCs are correctly grouped into the same cluster. However, only 2 out of 6 LCCs are correctly assigned (V7 and NO), resulting in an overall accuracy of 0.7500. The computed clustering metrics are as follows: ARI = 0.2000, NMI = 0.2660. This indicates low clustering performance. This poor performance is primarily due to the high similarity between U2 and FR with FSCs, which misleads the proper separation of airline types.

We also computed the clustering results using the asymmetric index I_{Asym} . The asymmetric similarity matrix is shown in Fig. 10. The results show that all 10 FSCs are correctly grouped into the same cluster, and 4 out of 6 LCCs are correctly assigned (U2, HV, V7 and NO), resulting in an overall accuracy of 0.8750. The computed clustering metrics are as follows: ARI = 0.5333, NMI = 0.5289. This indicates a stronger clustering performance compared to the symmetric index, as both ARI and NMI are significantly higher. The high accuracy indicates that a significant portion of the data was correctly classified. Therefore, the use of the asymmetric index appears to be more efficient for detecting airline business model clusters.

It is also worth mentioning that we attempted to identify clusters encompassing all 4 airline types listed in Table 3, including 2 hybrid business models. Using the symmetric index, we obtained ARI = 0.0396 and NMI = 0.1789. Using the asymmetric index, we get ARI = –0.0174 and NMI = 0.1413. These low values indicate that the model struggles to effectively differentiate hybrid business models, likely due to overlapping operational characteristics between airline types.

Concluding remarks. Table 4 presents a summary of the previous results. The findings indicate that using airport pairs is more effective in inferring airline business model clusters. Moreover, the presence of hybrid business models complicates the clustering process, making it more challenging to achieve clear distinctions. In the case of 2 clusters, using airport pairs, the clustering based on the symmetric index has an accuracy of 0.8125, and that based on the asymmetric index achieves the highest accuracy of 0.875. Based on these results, we conclude that the weighted Jaccard index, in both symmetric and asymmetric forms, proves to be an effective and valuable tool for inferring airline similarity, and to quantify airline pairwise competitive intensity.

5. Application 2: Analysis of market changes caused by COVID-19

The COVID-19 pandemic significantly reshaped airline networks, altering competitive relationships and market structures. Analyzing market changes before and after COVID-19 using the proposed indices $I_{Sym}(a, b)$ and $I_{Asym}(a|b)$ provides insights into how airlines adapt their supply in response to the pandemic as an exogenous shock to the market. As an illustrative application, we restrict our study to FSCs and LCCs, considering airport-pair markets. By comparing the pre- and post-pandemic index values, we can visualize shifts in airline competition and market positioning, offering a data-driven perspective on market recovery.

5.1. Shock detection

For shock detection, the symmetric index $I_{Sym}(a, b)$ is sufficient, as it captures the overall supply overlap interpreted as the competitive relationship between two airlines. Indices are computed quarterly, with change-point tests applied to detect post-COVID shifts in competitive dynamics.

We detect shocks in the air market using a pairwise approach: we calculate $I_{Sym}(a_{Q_i}, b_{Q_i})$ for each quarter Q_i . The resulting time series provides insight into the evolving interactions between the airline pair. For the 16 airlines classified as FSCs and LCCs, covering 10 years (2015–2025), the change point detection results are as follows (Table 5). The top three periods are 2020-Q2, 2020-Q1, and 2023-Q1. This highlights the temporal extent of the disruption’s impact. Moreover, in our case, as we have a small dataset (42 points in the time series), we need to avoid overfitting (which means do not use complex models). In our case, the Bootstrap Pettitt test (Conte et al., 2019) is especially suitable: it refines the classical Pettitt test (Pettitt, 1979) by applying bootstrap resampling to the data series and deriving empirical distributions from these resamples. The procedure treats the original sample as a pseudo-population from which repeated draws are made. This approach enhances robustness, particularly when working with small samples. We assume there is only one significant change point (which is caused by the COVID-19), and try to find it out through change point detection methods with the calculated index values. For different significance levels (i.e. there is a change point if p -value < 0.05, 0.1, 0.5) of the Bootstrap Pettitt test, we report the following results:

- **count:** The total number of detected change points over all dates.
- **top:** The most frequent (modal) change point time.

Table 5
Change point detection results.

Pairwise approach (time series type; significance level)	5%	10%	50%
(count)	68/120	75/120	88/120
(top)	2020-Q2	2020-Q2	2020-Q2
(freq)	11/68	11/75	11/88
(unique)	23	24	27

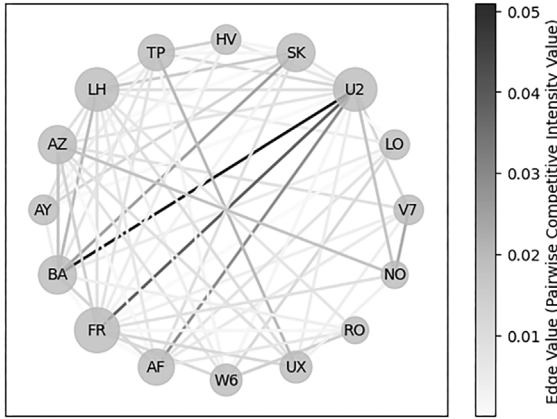


Fig. 11. Q3 2018 airline competition network using symmetric index.

- **freq**: The occurrence count of the modal change point over the total number of detected points.
- **unique**: The number of distinct change point times.

We conclude the following. First, the symmetric index effectively identifies the COVID-19 disruption, with the modal change point occurring in Q2 2020 for airline competitors. Second, we deduce that there are other factors influencing airline competitive relationships. As the significance level for the p -value increases, the number of distinct change point times becomes large and also rises. This suggests the potential presence of other market shocks beyond COVID-19, warranting further investigation.

5.2. Competitive relationship changes

The relationships among airlines within a specific period can be graphically represented by drawing an airline competition network, which is illustrated in Figs. 11 and 12, using the symmetric pairwise index values $I_{Sym}(a, b)$ as edge weights, where darker edges indicate more intense competition.

Its advantages include providing a comprehensive visualization of airline relationships across the European passenger market, and identifying key competitors for a focal airline by determining the airline with the highest index value. For instance, significant changes occurred between Q3 2018 and Q3 2024. The first is the reduction in supply overlap of the pair easyJet (U2) and British Airways ('BA'). This decline was primarily driven by the impact of Brexit, which took effect at the end of January 2020. Second, we note the increase in supply overlap for the pair ('LO', 'W6'). Wizz Air (W6) significantly reduced its network from 511 routes (total frequency: 51,211) in Q3 2018 to 316 routes (total frequency: 35,401) in Q3 2024, leading to greater supply overlap with LOT Polish Airlines (LO). Last, the reduction in supply overlap for ('TP', 'UX'). Air Europa (UX) downsized its network and substantially reduced frequencies on routes shared with TAP Air Portugal (TP) after the COVID period, leading to decreased index values.

For a more detailed analysis of each airline pair, the asymmetric index $I_{Asym}(a|b)$ can be used to capture the directional competition.

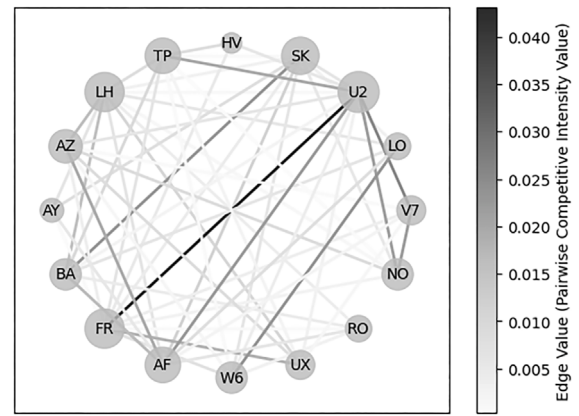


Fig. 12. Q3 2024 airline competition network using symmetric index.

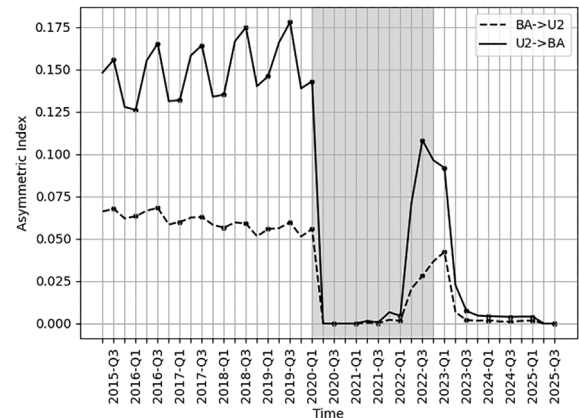


Fig. 13. Asymmetric index variation between easyJet (U2) and British Airways (BA).

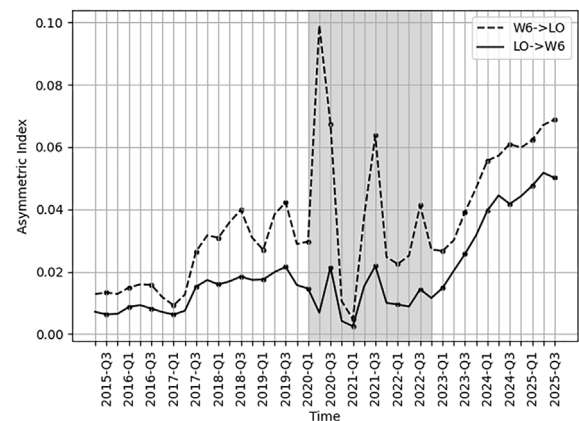


Fig. 14. Asymmetric index variation between Wizz Air (W6) and LOT Polish Airlines (LO).

Figs. 13, 14, 15, and 16 illustrate the 10 year temporal evolution of the asymmetric index for four airline pairs. The COVID period is highlighted in shadow. A direct conclusion from the definition is that the difference between the indices of the two airlines is due to the total frequency difference between them. The larger the total frequency, the smaller the asymmetric index value. For instance, the total frequency offered by TAP Air Portugal (TP) and Air Europa (UX) is comparable (Fig. 15), while easyJet (U2) and Air France (AF) have very different total frequency sizes (Fig. 16). Fig. 13 shows that, following

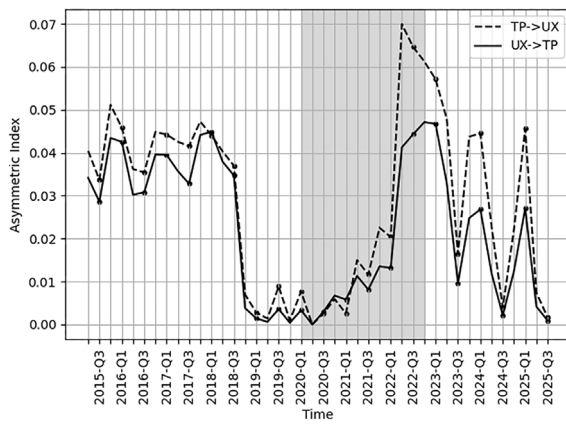


Fig. 15. Asymmetric index variation between TAP Air Portugal (TP) and Air Europa (UX).

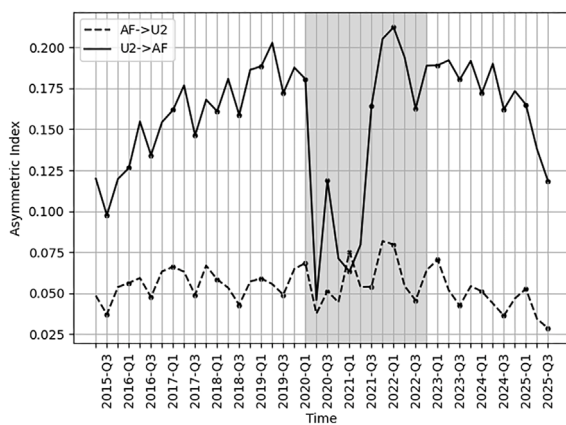


Fig. 16. Asymmetric index variation between easyJet (U2) and Air France (AF).

the Brexit decision, the supply overlap between easyJet and British Airways sharply declined after Q1 2020. After the COVID period, this trend appears to persist at nearly zero in the future. Fig. 14 indicates that the competitive relationship between Wizz Air and LOT Polish Airlines changed after COVID, with their supply overlap increasing, consistent with the previously discussed results using the symmetric index. The relationship between TAP Air Portugal and Air Europa (Fig. 15) also shifted, with reduced frequencies on their common routes and increased frequency fluctuations. Although they only had one common route in both Q3 2018 and Q3 2024, this resulted in index variation, implying that the index is sensitive to frequency. In contrast, Fig. 16 demonstrates that the competitive relationship between easyJet and Air France did not change significantly after COVID, as the asymmetric index follows the same pattern before and after the pandemic. This finding aligns with the visualization of the airline competition networks in Figs. 11 and 12.

6. Concluding remarks

From a novel perspective on market competition measurement, we assess airline pairwise competitive intensity using variations of the Jaccard index weighted by frequency. The proposed indices are easy to calculate and provide immediate insights into airline competition within a specific geographic air transport market. This study makes several theoretical and empirical contributions to the literature on airline competition and multimarket contact (MMC). First, we propose to use the weighted Jaccard index that measures the intensity

of competition between airlines, by incorporating flight frequency as weights and extending the MMC study. Traditional MMC measures generally assess only market overlap, overlooking operational intensity. By embedding flight frequency, the weighted Jaccard index provides a more nuanced assessment of airline competitive intensity. This approach is especially suited to markets with harmonized regulatory and operational environments, such as European domestic flights under the Single European Sky initiative. Second, the index offers a data-driven method to infer airline business models. By capturing supply overlap at the route level, the measure complements existing classification approaches based on cost structure, network configuration, or services (Daft and Albers, 2015; Urban et al., 2018). As highlighted by Gössling and Humpe (2023), achieving net-zero targets may require fundamental shifts in business models in the future. Our method therefore facilitates the rapid identification of business model clusters, supporting both academic research and industry monitoring. Third, we demonstrate the utility of the index in detecting structural changes in airline competition in response to market shocks, such as pandemics. By analyzing index fluctuations around identified change points, we provide a tool for assessing the resilience and recovery of competitive relationships. This aligns with emerging research on post-COVID-19 aviation recovery (Gudmundsson et al., 2021; Su et al., 2023) and supports the temporal competition monitoring during crisis. The policy implication of this index is the following. For airlines, they can leverage the index to identify rivals with the same or different business models, measure their pairwise competitive intensity, and choose their competition strategy accordingly; for regulators, they can monitor real-time market competition, assess recovery of the market after shocks, and be better informed for competition regulatory design.

Our study provides new methods for empirical research and opens up a variety of potential applications. We empirically applied the symmetric and asymmetric Jaccard-based indices using flight frequency data for European domestic direct flights. The results demonstrate seasonality in the indices and reveal competition disparity, particularly for the asymmetric index. Normalized by the airline's total size, the symmetric form allows for the analysis of competition between large and small airlines, which are often not directly comparable. The asymmetry index reveals differences in competitive intensity between airlines, providing a deeper understanding of the competition situation. Through the analysis of index values, we show that both symmetric and asymmetric indices are reliable competitor analysis tools and offer complementary insights. These indices allow for a more detailed analysis of airline competition in specific geographic areas.

Worth mentioning that, we also compared the performance of alternative pairwise metrics, including cosine similarity, total variation distance (TVD), and Pearson correlation. Both cosine similarity and TVD show strong correlation (> 0.9) with the symmetric weighted Jaccard index, indicating that they capture comparable competitive structures. In contrast, Pearson correlation measures similarity from a slightly different perspective, showing a moderate correlation of approximately 0.6 with the weighted Jaccard index. These differences show the importance of selecting an appropriate similarity metric based on the specific objectives.

Our research has several limitations that suggest directions for future work. First, as discussed in Section 2.3, the weighted Jaccard index complements traditional MMC measures by providing additional insights. A promising avenue is to develop a unified measure that integrates flight distribution with the classic MMC metric, thereby offering a single indicator of MMC intensity that could facilitate cross-study comparisons and simplify econometric applications. Future research could also investigate the conditions under which it is preferable to use the weighted Jaccard index together with the traditional MMC measure, or to determine which index is more relevant in specific contexts. Such efforts would contribute to a deeper understanding of airline competition across multiple markets. Second, while the proposed indices can measure the occurrence of shocks, they are not

designed to explain the underlying causes of shocks. The proposed indices quantify competitive intensity from the supply side, represented by flight frequency, without explicitly considering other critical dimensions of airline operations, such as flight distance, aircraft type, schedule timing, and in-flight services. These aspects contribute to product differentiation and also influence competition. Integrating additional explanatory variables will help us understand how other factors influence airline competitive relationships. Future research could explore alternative conceptions to enhance the robustness of the pairwise competitive intensity index, by integrating route distance, hub effects, or other operating characteristics.

Another limitation of our approach is the exclusive focus on direct, non-stop flights, which overlooks competition involving connecting flights. Specifically, our analysis compares the routes of two airlines, and does not account for the network structure of each airline. FSCs often operate hub-and-spoke networks that rely heavily on connecting itineraries, which are not explicitly captured in our dataset. This may lead to an underestimation of the index value, and an overestimation of the competition among LCCs. For example, two airlines may not compete directly on a specific OD pair, yet still target overlapping passenger segments through indirect routes. To address this limitation, future research could incorporate passenger itinerary data or scheduled multi-leg flight information to better capture connecting traffic and examine the extent to which connecting flights influence the measured competitive intensity.

Funding

This research was possible thanks to the financial support of the Région Occitanie/Pyrénées Méditerranée and the École nationale de l'aviation civile (ENAC), under the CHOCTA project.

Acknowledgements

The author thanks Prof Paul Rochet and Prof Chantal Roucolle for their insightful guidance throughout this work. Appreciation is also extended to the journal's Editor-in-Chief, Prof Gianmaria Martini, for his helpful feedback. The author further expresses sincere gratitude to the anonymous reviewers for their valuable evaluations and constructive criticism, which significantly strengthened this paper.

Data availability

The data that has been used is confidential.

References

- Adler, N., 2005. Hub-spoke network choice under competition with an application to Western Europe. *Transp. Sci.* 39 (1), 58–72.
- Ayub, M., Ghazanfar, M.A., Maqsood, M., Saleem, A., 2018. A Jaccard base similarity measure to improve performance of CF based recommender systems. In: 2018 International Conference on Information Networking. ICOIN, IEEE, pp. 1–6.
- Azar, J., Schmalz, M.C., Tecu, I., 2018. Anticompetitive effects of common ownership. *J. Financ.* 73 (4), 1513–1565.
- Baum, J.A.C., Korn, H.J., 1996. Competitive dynamics of interfirm rivalry. *Acad. Manag. J.* 39 (2), 255–291.
- Baum, J.A.C., Korn, H.J., 1999. Dynamics of dyadic competitive interaction. *Strat. Manag. J.* 20 (3), 251–278.
- Bergen, M., Peteraf, M.A., 2002. Competitor identification and competitor analysis: A broad-based managerial approach. *Manag. Decis. Econ.* 23 (4–5), 157–169.
- Bernheim, B.D., Whinston, M.D., 1990. Multimarket contact and collusive behavior. *Rand J. Econ.* 1–26.
- Bilotkach, V., 2011. Multimarket contact and intensity of competition: Evidence from an airline merger. *Rev. Ind. Organ.* 38, 95–115.
- Brander, J.A., Zhang, A., 1990. Market conduct in the airline industry: An empirical investigation. *Rand J. Econ.* 567–583.
- Bringmann, K., De Langhe, K., Kupfer, F., Sys, C., Van de Voorde, E., Vanelander, T., 2018. Cooperation between airports: A focus on the financial intertwinement of European airport operators. *J. Air Transp. Manag.* 69, 59–71.
- Brueckner, J.K., Lee, D., Singer, E., 2014. City-pairs versus airport-pairs: A market-definition methodology for the airline industry. *Rev. Ind. Organ.* 44, 1–25.
- Charles, B., Ito, H., Lee, D., 2004. Entry patterns in the southwest airlines route system. *Rev. Ind. Organ.* 1 (25), 317–350.
- Chen, M.-J., 1996. Competitor analysis and interfirm rivalry: Toward a theoretical integration. *Acad. Manag. Rev.* 21 (1), 100–134.
- Chen, M.-J., Hambrick, D.C., 1995. Speed, stealth, and selective attack: How small firms differ from large firms in competitive behavior. *Acad. Manag. J.* 38 (2), 453–482.
- Chunaev, P., 2020. Community detection in node-attributed social networks: A survey. *Comput. Sci. Rev.* 37, 100286.
- Ciliberto, F., Murry, C., Tamer, E., 2021. Market structure and competition in airline markets. *J. Political Econ.* 129 (11), 2995–3038.
- Ciliberto, F., Tamer, E., 2009. Market structure and multiple equilibria in airline markets. *Econometrica* 77 (6), 1791–1828.
- Conte, L.C., Bayer, D.M., Bayer, F.M., 2019. Bootstrap pettitt test for detecting change points in hydroclimatological data: Case study of itaipu hydroelectric plant, Brazil. *Hydrol. Sci. J.* 64 (11), 1312–1326.
- Daft, J., Albers, S., 2015. An empirical analysis of airline business model convergence. *J. Air Transp. Manag.* 46, 3–11.
- Debysier, A., 2024. Air transport: Single European sky. <https://www.europarl.europa.eu/factsheets/en/sheet/133/air-transport-single-european-sky>. [Online].
- Deng, F., Siersdorfer, S., Zerr, S., 2012. Efficient jaccard-based diversity analysis of large document collections. In: Proceedings of the 21st ACM International Conference on Information and Knowledge Management. pp. 1402–1411.
- Dziedzic, M., Warnock-Smith, D., 2016. The role of secondary airports for today's low-cost carrier business models: The European case. *Res. Transp. Bus. Manag.* 21, 19–32.
- EASA, 2015. EASA proposed CM no.: Proposed CM-CS-008 issue 01. URL <https://www.easa.europa.eu/en/downloads/23411/en>.
- Estévez, P.A., Tesmer, M., Perez, C.A., Zurada, J.M., 2009. Normalized mutual information feature selection. *IEEE Trans. Neural Netw.* 20 (2), 189–201.
- da F. Costa, L., 2021. Further generalizations of the Jaccard index. URL <https://arxiv.org/abs/2110.09619>.
- Faust, K., Raes, J., 2012. Microbial interactions: From networks to models. *Nat. Rev. Microbiol.* 10 (8), 538–550.
- Flores-Fillol, R., 2009. Airline competition and network structure. *Transp. Res. Part B: Methodol.* 43 (10), 966–983.
- Gaggero, A.A., Piazza, G., 2021. Multilayer networks and route entry into the airline industry: Evidence from the U.S. domestic market. *Res. Transp. Econ.* 90, 101044. <http://dx.doi.org/10.1016/j.retrec.2021.101044>, URL <https://www.sciencedirect.com/science/article/pii/S0739885921000160>.
- Gayle, P.G., Brown, D., 2014. Airline strategic alliances in overlapping markets: Should policymakers be concerned? *Econ. Transp.* 3 (4), 243–256.
- Gerardi, K.S., Shapiro, A.H., 2009. Does competition reduce price dispersion? New evidence from the airline industry. *J. Political Econ.* 117 (1), 1–37.
- Gimeno, J., 1999. Reciprocal threats in multimarket rivalry: Staking out 'spheres of influence' in the US airline industry. *Strat. Manag. J.* 20 (2), 101–128.
- Gimeno, J., Woo, C.Y., 1996. Hypercompetition in a multimarket environment: The role of strategic similarity and multimarket contact in competitive de-escalation. *Organ. Sci.* 7 (3), 322–341.
- Gimeno, J., Woo, C.Y., 1999. Multimarket contact, economies of scope, and firm performance. *Acad. Manag. J.* 42 (3), 239–259.
- Gitto, S., Mancuso, P., 2019. Brand perceptions of airports using social networks. *J. Air Transp. Manag.* 75, 153–163.
- Givoni, M., Rietveld, P., 2009. Airline's choice of aircraft size—explanations and implications. *Transp. Res. Part A: Policy Pr.* 43 (5), 500–510.
- Goetz, A.R., 2002. Deregulation, competition, and antitrust implications in the US airline industry. *J. Transp. Geogr.* 10 (1), 1–19.
- Goolsbee, A., Syverson, C., 2008. How do incumbents respond to the threat of entry? Evidence from the major airlines. *Q. J. Econ.* 123 (4), 1611–1633.
- Gössling, S., Humpe, A., 2023. Net-zero aviation: Time for a new business model? *J. Air Transp. Manag.* 107, 102353.
- Greenfield, D., 2014. Competition and service quality: New evidence from the airline industry. *Econ. Transp.* 3 (1), 80–89.
- Gudmundsson, S.V., Cattaneo, M., Redondi, R., 2021. Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. *J. Air Transp. Manag.* 91, 102007.
- Hubert, L., Arabie, P., 1985. Comparing partitions. *J. Classification* 2, 193–218.
- Jaccard, P., 1908. Nouvelles recherches sur la distribution florale. *Bull. Soc. Vaud. Sci. Nat.* 44, 223–270.
- Kim, M., Sohn, J., 2022. Passenger, airline, and policy responses to the COVID-19 crisis: The case of South Korea. *J. Air Transp. Manag.* 98, 102144.
- Li, S., Xu, G., Zhou, Y., 2023. How air transport networks respond to long-lasting disruptive events like COVID-19: The first step toward long-term resilience. *Transp. Res. Part A: Policy Pr.* 177, 103836.
- Lieshout, R., Malighetti, P., Redondi, R., Burghouwt, G., 2016. The competitive landscape of air transport in Europe. *J. Transp. Geogr.* 50, 68–82.
- Lijesen, M., Behrens, C., 2017. The spatial scope of airline competition. *Transp. Res. Part E: Logist. Transp. Rev.* 99, 1–13.

- Lijesen, M.G., Nijkamp, P., Rietveld, P., 2002. Measuring competition in civil aviation. *J. Air Transp. Manag.* 8 (3), 189–197.
- Liu, C., He, R.-c., Zhou, W., Li, H., 2021. Dynamic analysis of airline bidding game based on nonlinear cost. *Phys. A* 565, 125547.
- Ma, W., Wang, Q., Yang, H., Zhang, Y., 2020. Is multimarket contact an antitrust concern? A case of China's airline market. *Transp. Res. Part A: Policy Pr.* 132, 515–526.
- Magdalina, A., Bouzaima, M., 2021. An empirical investigation of European airline business models: Classification and hybridisation. *J. Air Transp. Manag.* 93, 102059.
- Mason, K.J., Morrison, W.G., 2008. Towards a means of consistently comparing airline business models with an application to the 'low cost'airline sector. *Res. Transp. Econ.* 24 (1), 75–84.
- Mazzeo, M.J., 2003. Competition and service quality in the US airline industry. *Rev. Ind. Organ.* 22, 275–296.
- Milazzo, M., Musciotto, F., Micciché, S., Mantegna, R.N., 2022. Analysis of the structure and dynamics of European flight networks. *Entropy* 24 (2), URL <https://www.mdpi.com/1099-4300/24/2/248>.
- OECD, 2021. Methodologies to measure market competition. OECD Compét. Comm. Issues Pap. URL <https://oe.cd/mmmc>.
- Oum, T.H., Zhang, A., Zhang, Y., 1995. Airline network rivalry. *Can. J. Econ.* 28 (4a), 836–857, URL <http://www.jstor.org/stable/135934>.
- Pettitt, A.N., 1979. A non-parametric approach to the change-point problem. *J. R. Stat. Soc. Ser. C. Appl. Stat.* 28 (2), 126–135.
- Prince, J.T., Simon, D.H., 2015. Do incumbents improve service quality in response to entry? Evidence from airlines' on-time performance. *Manag. Sci.* 61 (2), 372–390.
- Reynolds-Feighan, A., Zou, L., Yu, C., 2022. Seasonality in European and North American air transport markets: Network structures and implications for airline performance and recovery. *Transp. J.* 61 (3), 284–304.
- Rhoades, S.A., 1993. The Herfindahl–Hirschman index. *Fed. Res. Bull.* 79, 188.
- Su, J., Wu, H., Tsui, K.W.H., Fu, X., Lei, Z., 2023. Aviation resilience during the COVID-19 pandemic: A case study of the European aviation market. *Transp. Res. Part A: Policy Pr.* 177, 103835.
- Sun, X., Wandelt, S., Hansen, M., Li, A., 2017. Multiple airport regions based on inter-airport temporal distances. *Transp. Res. Part E: Logist. Transp. Rev.* 101, 84–98. <http://dx.doi.org/10.1016/j.tre.2017.03.002>, URL <https://www.sciencedirect.com/science/article/pii/S1366554516308109>.
- Sun, X., Zheng, C., Wandelt, S., Zhang, A., 2024. Airline competition: A comprehensive review of recent research. *J. Air Transp. Res. Soc.* 100013.
- Thada, V., Jaglan, V., 2013. Comparison of jaccard, dice, cosine similarity coefficient to find best fitness value for web retrieved documents using genetic algorithm. *Int. J. Innov. Eng. Technol.* 2 (4), 202–205.
- Urban, M., Klemm, M., Ploetner, K.O., Hornung, M., 2018. Airline categorisation by applying the business model canvas and clustering algorithms. *J. Air Transp. Manag.* 71, 175–192.
- Vaze, V., Barnhart, C., 2012. Modeling airline frequency competition for airport congestion mitigation. *Transp. Sci.* 46 (4), 512–535.
- Wang, J., Bonilla, D., Banister, D., 2016. Air deregulation in China and its impact on airline competition 1994–2012. *J. Transp. Geogr.* 50, 12–23.
- Wang, C.-H., Zhang, W., Dai, Y., Lee, Y.-C., 2022. Frequency competition among airlines on coordinated airports network. *European J. Oper. Res.* 297 (2), 484–495. <http://dx.doi.org/10.1016/j.ejor.2021.04.037>, URL <https://www.sciencedirect.com/science/article/pii/S0377221721003696>.
- Yin, Y., Yasuda, K., 2005. Similarity coefficient methods applied to the cell formation problem: A comparative investigation. *Comput. Ind. Eng.* 48 (3), 471–489.
- Yu, T., Cannella, Jr., A.A., 2013. A comprehensive review of multimarket competition research. *J. Manag.* 39 (1), 76–109.
- Yu, C.-L., Wang, F., Brouters, K.D., 2016. Competitor identification, perceived environmental uncertainty, and firm performance. *Can. J. Adm. Sci.* 33 (1), 21–35.
- Zou, L., Dresner, M., Windle, R., 2011. Many fields of battle how cost structure affects competition across multiple markets. *J. Transp. Econ. Policy* 45 (1), 21–40.
- Zou, L., Reynolds-Feighan, A., Yu, C., 2022. Airline seasonality: An explorative analysis of major low-cost carriers in Europe and the United States. *J. Air Transp. Manag.* 105, 102272. <http://dx.doi.org/10.1016/j.jairtraman.2022.102272>, URL <https://www.sciencedirect.com/science/article/pii/S0969699722000928>.
- Zou, L., Yu, C., Dresner, M., 2012. Multimarket contact, alliance membership, and prices in international airline markets. *Transp. Res. Part E: Logist. Transp. Rev.* 48 (2), 555–565.