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Business model hybridization but heterogeneous economic performance: Insights from low-cost and legacy carriers in Europe

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ABSTRACT

Over the last decade, low-cost and legacy carriers have evolved their respective business models, leading to business model "hybridization". However, the economic performance impacts of such convergence remain underinvestigated. We therefore evaluate whether airline business model hybridization has led to homogeneous economic performance in Europe. Using 2019 data for 25 European airlines, we implement hierarchical clustering based on principal components. We show that regardless of the analysis level (i.e., the number of clusters into which we group airlines), low-cost and legacy carriers remain distinct groups with specific economic performance characteristics (e.g., volume, revenue, cost and profitability). That is, despite increasing hybridization, the economic performance of airline business models is not homogeneous; overall, low-cost carriers remain more profitable (with lower costs and more affordable fares) than legacy carriers.

1. Introduction

In recent decades, low-cost carriers (LCCs) have become key players in the air transport industry, especially in Europe, where they account for more than 40% of total intra-European traffic (OAG, 2019). The term LCCs refers to those airlines that have common characteristics (e.g., point-to-point flights, lower flight frequencies from secondary airports, single-model aircraft with densified monoclass cabins, unbundled fare policies, and direct online distributions through airline websites) yet present some significant differences with "legacy carriers" in terms of their operations, network structures or commercial policies (Fageda et al., 2015; Koklic et al., 2017). The term legacy carriers usually refers to those airlines that often existed before the liberalization of air transport and the arrival of LCCs.

Some of these differences have decreased over time as the result of a "hybridization process" (Tomova and Materna, 2017) that has been ongoing since the early 2000s, with some LCCs serving major airports, being distributed in global distribution systems (GDS) and offering frequent flyer programs. Thus, low-cost airlines have progressively adopted some elements of legacy carriers' business models to compete with them in markets or for customers who they did not previously serve (corporate passengers, lower-density routes, etc.). Conversely, amid ever-growing competition with LCCs, traditional airlines have borrowed elements from LCCs' business models, blurring the boundaries between airline categories (Klophaus et al., 2012; Lohmann and Koo, 2013; Magdalina and Bouzaima, 2021; Aghaie et al., 2022). While focusing on airlines' business model components (product, marketing, network or operational airline characteristics), some scholars have therefore underlined a hybridization process between the business models of legacy carriers and LCCs in both the American and European markets (Daft and Albers, 2012, 2015; Jean and Lohmann, 2016). Nevertheless, the economic performance implications of such hybridization remain undefined. Some studies, based primarily on cost indicators such as cost per available seat mile (CASM), show contrasting results in the US, highlighting either divergences, convergences or similar distances among US carriers in terms of economic performance (Borenstein, 2011; Hüschelrath and Müller, 2012; Corbo, 2017; Moir and Lohmann, 2018; Azadian and Vasigh, 2019).

Thus, given the lack of consensus and absence of European market analyses, we aim to investigate whether airline business model hybridization in Europe implies a homogeneity of their economic performances. Thus, our objective is to examine whether low-cost and legacy carriers have the same levels of economic performance today, following this process of the hybridization of models that began in Europe in the

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early 2000s. Accordingly, we do not investigate the convergence of economic performance (i.e., the process) but, rather, focus our attention on the consequences of the hybridization of airline business models (i.e., the outcome). This choice is justified by our willingness to address the economic performance of airlines through a multidimensional perspective building on 7 variables across 4 dimensions to simultaneously analyze the volume/size effect, cost competitiveness, revenues and profitability. Having access to such a broad number of variables (especially regarding revenues and fares) has limited the number of years for which data are available for a sufficient number of European airlines. We thus focus our attention on the "end result" of this hybridization process, with a focus on 2019, which is considered the last "normal year" in the pre-coronavirus disease 2019 (COVID-19) era.

To investigate the impacts of hybridization on airline economic performance, we use hierarchical clustering on principal components (Argüelles et al., 2014). This approach consists of combining (1) a principal component analysis (PCA) of our dataset to obtain two or three principal components that reduce its dimensionality (i.e., number of initial variables) and (2) a hierarchical cluster analysis (HCA) on the principal components obtained in the PCA to create clusters of observations that are close to one another. We apply this method to a sample of 25 European carriers who offered more than 5 million seats for intra-European flights in 2019. This sample accounts for more than 80% of the total air traffic in Europe for that year. For both legacy carriers and LCCs, the geographical scope investigated covers only the intra-European market to allow for a comparison of economic performance across airlines.

Our findings reveal that regardless of the level of analysis (i.e., the number of clusters into which we gather airlines), LCCs and legacy carriers remain separate groups with distinct characteristics of economic performance (i.e., volume, revenue, cost or profitability). In other words, our analysis underlines that in Europe, airline business model hybridization has not led to the homogeneous economic performance of airlines. Overall, we show that LCCs remain more profitable (with lower costs and more affordable fares) than legacy carriers.

Accordingly, this research makes three theoretical contributions to the literature. First, it expands the knowledge on airline business model hybridization by clearly distinguishing between business model hybridization and the convergence of economic performance, as the two factors are not directly related. Second, this study discusses the implication of this absence of homogeneous economic performance for European airlines. More precisely, this work raises the question of whether or not these airlines have actually seen their business models converge (as we would expect economic performance to follow such convergence). Finally, this study contributes to the literature on airline economic performance by underlining the importance of investigating in other geographical contexts and by offering a broader depiction of economic performance than do traditional studies that focus only on cost competitiveness.

The remainder of this paper is structured into 4 parts. While the first part provides an overview of the literature about airline business models and how they converge, the second part elaborates on the method used in this research. In the third part, we present the results of hierarchical clustering on the PCs. Finally, the fourth part discusses our findings and underlines our contributions with respect to the literature.

2. Theoretical background

2.1. Defining the main characteristics of LCCs

Developed in the US in the 1970s with Southwest Airlines, LCCs have experienced strong growth in Europe since the 2000s; just before the COVID-19 pandemic, these airlines comprised more than 40% of total intra-European air traffic (Brechemier and Combe, 2020). LCCs have quickly attracted the attention of researchers, aiming to define the boundaries of the low-cost carrier business model and differentiate it from that of full-service carriers (FSCs) by focusing on short- and medium-haul routes.[1] Thus, many low-cost airline features have been identified (Mason and Morrison, 2008; Chiambaretto and Fernandez, 2014; Delaplace; Dobuszkes, 2015; Vatankhah et al., 2019): LCCs operate point-to-point flights, whereas FSCs rely on dense networks of routes organized around a hub. Flight frequency is lower for LCCs than for FSCs. Moreover, LCCs use a single-aircraft model and renew their fleets more frequently, operate with a densified cabin and do not offer business class on short- or medium-haul flights. LCCs also use (per day and per year) their aircraft more intensely and adopt unbundled fare policies, pricing each service separately. Additionally, LCCs rarely provide frequent flyer programs or programs dedicated to corporate customers and do not code-share often, entailing limited presence in global alliances. Furthermore, ancillary revenues account for a large part of LCC revenues and margins; these carriers outsource a significant portion of their activities that involve higher labor productivity (Koklic et al., 2017). Finally, some authors have highlighted LCCs' specific work organization—the outsourcing of noncore activities, high employee functional flexibility and multitasking, lower trade union presence (Hunter 2006), limited use of wide-body aircraft (Magdalina and Bouzaima, 2021), more intensive use of secondary airports (Pels et al., 2009), direct rather than intermediated sales (through GDS; Escobar-Rodriguez & Carvajal-Trujillo, 2014), and dynamic pricing strategies—all of which are in contrast with those of FSCs (Bachis and Piga, 2011; Morlotti et al., 2017; De Oliveira et al., 2021). In summary, LCCs have focused their attention on simplifying the customer experience to change their business model while reducing costs, allowing them to offer lower fares in the end (Keiningham et al., 2020; Nguyen et al., 2022).

2.2. LCCs: A homogenous category?

After the identification of the main characteristics of the low-cost model, several studies sought to highlight clear heterogeneities among low-cost airlines, particularly in the European market, aiming to classify low-cost airlines according to different criteria and, ultimately, to establish a typology.

One of the first attempts was the work of Mason and Morrison (2008), which compares six European airlines identified as LCCs through 11 variables that combine product characteristics with airline organizational structure and economic performance. Economic performance is measured by three variables: the profitability of a company (measured by a profitability index score), cost levels (cost driver index score) and revenues (revenue index). The above authors highlight strong differences among low-cost European airlines regarding specific variables, such as "comfort" or airport attractiveness.

Mason et al. (2013) extend this seminal work by analyzing a sample of 20 European airlines using 37 variables grouped into 11 categories (e.g., markets, products and economic performance) and conclude that low-cost airlines can be divided into "ultra-low-cost" and "middle-cost" carriers. On the one hand, ultra-LCCs, such as Ryanair, are characterized by the combination of a low level of service, a low unit cost and a low level of unit revenue. On the other hand, middle-cost carriers, such as EasyJet, have higher unit costs but manage to obtain higher unit revenues and offer a wide range of services. Mason and colleagues show the internal coherence of these two low-cost models: there is a strong positive correlation among revenue, cost and service levels. However, the above authors do not draw any conclusions about the relative

[1] A similar approach has been undertaken more recently in long-haul segments. For instance, Francis et al. (2007) and Zuidberg and de Wit (2020) investigated whether low-cost characteristics could be transferred to long-haul operations, while Soyk et al. (2018, 2021) highlighted the differences in dynamic-pricing strategies, connections, ancillary revenues, load factors and cabin densifications between LCCs and legacy carriers on long-haul routes and their implications in terms of airfares for both LCCs and their competitors.

performance of these two models.

More recently, the study by Fageda et al. (2015) has investigated the positioning of low-cost airlines based on two main criteria: connecting flights and ticket fare structures. The above authors create a typology of three groups of LCCs: the "archetypal" LCC, which does not offer connecting flights and, instead, offers a single type of ticket; the "*adapted low-cost carrier offering connecting flights and fare bundling*"; and the "*adapted low-cost carrier offering fare bundling but not connecting flights*". Accordingly, this study demonstrates that the three low-cost models have different positions regarding their routes, the competitiveness of these routes, their presence in hubs, the distances between the airports they use and city centers, and their shares of tourist clients. However, this approach does not provide any information on the comparative economic performance of these three different models.

2.3. LCCs and legacy carriers: increasing business model hybridization

In addition to classifying LCCs into different groups, several scholars focus on how LCCs have evolved by incorporating aspects of legacy carriers, a phenomenon known as a "hybridization process" (Tomova and Materna, 2017). Such evolution, which consists mainly of incorporating typical legacy carrier characteristics into a low-cost model, occurs when an LCC reaches a limit in terms of its extensive growth; the number of routes in Europe is not infinitely expandable. De Wit and Zuidberg (2012) estimate that LCCs therefore have no choice but to expand into lower-density routes or into those routes where legacy carriers are already present. To compete with legacy carriers, LCCs have had to reconsider their business models, converging slightly toward the legacy model by adopting some of its characteristics and targeting some of its traditional customers (Huse and Evangelho, 2007; Bettini et al., 2018; Klophaus et al., 2021; Aghaie et al., 2022). Accordingly, some LCCs in Europe (Norwegian and Ryanair) have added connecting flights, established themselves in major airports (e.g., EasyJet in Paris and Ryanair in Rome), entered the GDS (Volotea), code shared with other airlines (EasyJet), enriched their fare offerings, and even introduced long-haul flights (Norwegian).

In parallel, legacy airlines have reacted to LCC threats by not only adapting their pricing policies to newly competitive environments (Windle and Dresner, 1999; Kangis and O'Reilly, 2003; Varella et al., 2017) but also implementing structural reforms aimed at increasing productivity to reduce competitiveness gaps with low-cost airlines. Such reforms imply outsourcing certain tasks to transfer activities to a low-cost subsidiary, simplifying fare structures and offerings, developing direct sales, increasing ancillary revenues, etc. (Dennis, 2007; Azadian and Vasigh 2019; Chiambaretto, 2021; Magdalina and Bouzaima, 2021).

This hybridization process can be studied first by identifying a particular variable. For example, Tomová and Ramajová (2014) study loyalty program introductions and find growing but differentiated adoptions of these loyalty programs according to airline type. Similarly, de Wit and Zuidberg (2016) and Dobruszkes et al. (2017) evaluate the types of airports in which low-cost airlines operate and show that in Europe, there has been a general shift toward large hubs, which also indicates a trend among low-cost airlines toward hybridization.

Hybridization can also be investigated in a broader sense that accounts for a larger number of variables and/or airlines. For example, Klophaus et al. (2012) analyze a sample of 20 European airlines based on 13 variables focusing on product, aircraft fleet and network structure, without explicit reference to performance measures, and confirm the dichotomy between "pure LCCs" and "middle-cost carriers" identified by Mason et al. (2013). The above authors also highlight a distinction between "full-service airlines", such as Air Baltic, and "hybrid carriers with dominating full-service airline services", such as Germanwings. Thus, the above authors classify airlines into four groups and, notably, do not draw any conclusions regarding the economic performance of these four categories. In a more recent study, Magdalina and Bouzaima (2021) establish clusters of airlines based on 20 variables that are mainly organizational and commercial. From a sample of 49 European airlines, the above authors refine 4 main clusters that are rather similar to those of Klophaus et al. (2012): FSCs, pure low-cost airlines (such as Ryanair and EasyJet) and two hybrid models (each hybrid model borrows more or fewer elements from the FSC or LCC business model).

Instead of developing carrier typologies, Lohmann and Koo (2013) move beyond the cluster approach to establish a continuum of companies, analyzing 9 US airlines, both low-cost and non-low-cost, through 6 indices using the methodology developed by Mason and Morrison (2008). The studied airlines are classified according to the following criteria: revenue, connectivity, comfort, type of aircraft, labor cost and convenience. The above authors establish a spectrum of airlines ranging from pure LCCs to FSCs, without establishing true clusters. The research by Jean and Lohmann (2016) extends and updates the study of Lohmann and Koo (2013). Focusing on the American market, the above authors show how three US companies that did not merge after the 2009 crisis have evolved toward a pure low-cost model. Conversely, the 5 airlines that participated in the merger and acquisition (M&A) movement have evolved toward a traditional airline model.

2.4. Hybridization consequences: A growing convergence between FSCs and LCCs?

The hybridization process described in the previous sections compels researchers to investigate whether it has led to convergences between low-cost and traditional airlines. Such convergences, defined as reductions in the number of differences between LCCs and FSCs, could result from a dual phenomenon—LCC expansion and FSC contraction.

One strategy to measuring LCC and FSC convergence is to use a multicriteria approach based on the main organizational characteristics of airlines and their products. Thus, an initial study by Daft and Albers (2012) measures the evolution of the positioning of 5 German airlines during 2003–2010 by using a large number of variables, which are mainly organizational and product related. The above authors show that there is a collective convergence of LCCs toward the FSC model. In a second and broader study, Daft and Albers (2015) conduct a longitudinal analysis using more variables and based on a larger sample of 26 European companies between 2004 and 2012. The authors thus calculate a similarity index (Gower index) that measures the distance between any 2 companies, concluding that FSCs and LCCs are converging. This trend essentially highlights how low-cost airlines have moved closer to the legacy model. However, Ryanair has not converged to the mean and, thus, appears to be a special case.

While providing valuable insights, the two studies of Daft and Albers (2012, 2015) focus on the operational or marketing characteristics of airlines, without empirically investigating economic performance criteria such as profitability, revenue or cost. Several studies have taken a step in this direction by measuring performance through an economic indicator: CASM, defined as airline operating cost per available seat mile (ASM) produced.[2] These studies, however, provide mixed results, which can be explained by the differences in their samples of companies and selected periods.

On the one hand, Tsoukalas et al. (2008) show a statistical trend toward a convergence of CASM among both legacy carriers and LCCs in the US market during 1995–2006. This convergence is driven largely by changes in the labor cost component: legacy carriers have cut labor unit costs by 30%, while LCC labor unit costs continue to increase due to their employees becoming more senior and their slowing growth. Moreover, Bitzan and Peoples (2016) confirm a convergence of costs among US

[2] Because most of these studies investigate the US market, their cost criterion is estimated through CASM. However, when focusing on European airlines, studies prefer to use CASK, which measures the cost per available seat kilometer (ASK) (instead of per mile).

FSCs and LCCs across a wider period of time (from 1993 to 2014) using a sample of 61 airlines, but this evolution is not linear.

These mixed results can effectively explain why Borenstein (2011) does not find any convergence in CASM between FSCs and LCCs. The unit costs of FSCs are shown to be between 30 and 60% higher than those of LCCs and, on average, 40% higher between 2001 and 2011 (with no signs of convergence). Similarly, Hüschelrath and Müller (2012) find that LCCs either maintained or increased their cost advantage during 1995–2009 and show that revenue, measured by revenue per ASM (RASM), increased for both FSCs and LCCs. More recently, Azadian and Vasigh (2019) perform an econometric analysis of convergence on a sample of 8 US legacy carriers and 7 US LCCs (including Southwest Airlines) during 2000–2016, with CASM as the only variable. The above authors do not detect any general convergence of unit costs between these two types of companies when Southwest is excluded from the low-cost sample. In contrast, when the above authors analyze the specific case of Southwest Airlines, they show a continuous convergence of this airline with 8 traditional companies after 2001. This convergence stems mainly from Southwest Airline's increasing CASM rather than from a reduction in the costs of legacy carriers. Furthermore, the authors find no evidence of convergence between Southwest Airlines and other US LCCs.

2.5. Has the hybridization of airline business models led to homogeneous economic performance?

From a theoretical perspective, it would be interesting to investigate the possible relationship between airline business model hybridization and airline economic performance homogenization based on key indicators such as unit cost, revenue and volume. Currently, this relationship is undefined since two opposing forces may be at work.

On the one hand, as Gillen and Gados (2008) argue, the hybridization of models should lead to the homogenization of economic performance: the productivity of low-cost airlines decreases due to increases in their costs, while FSCs improve their operational efficiency and thus increase their profitability. Accordingly, Alamdari and Fagan (2005) find an inverse relationship between operating margin and the degree of adherence to the low-cost model. Similarly, Mason and Morrison (2008) observe an inverse relationship between an airline's "comfort" index and its unit production cost. More recently, Budd et al. (2014) rank 43 LCCs according to their degrees of adherence to the low-cost model, demonstrating that bankruptcy rates are lower among "pure" LCCs than among other types of LCCs.

On the other hand, when LCCs incorporate elements of the FSC model, they do not always degrade their economic performance, especially if such hybridization also leads to higher revenues. Thus, Klophaus and Fichert (2019) show that Ryanair has developed a hybrid form of connecting, i.e., a mesh network, without negatively impacting its cost competitiveness. Furthermore, additional connecting flights facilitate increases in both load factors and revenues.

Thus, the relationship between hybridization and economic performance convergence is *a priori* indeterminate. Corbo's (2017) empirical study supports this view by comparing the performance of two airlines that have become hybrids: Air Berlin and JetBlue. The above author shows that on the one hand, Air Berlin's service upgrades have been accompanied by deteriorations in its economic performance and that on the other hand, JetBlue has successfully become a hybrid airline without affecting its profitability.

An important factor that explains the differences in the economic performance of these two "hybrid" airlines is consistency between cost and revenue structures. Moir and Lohmann (2018) construct indexes of competitive advantage in terms of costs and revenues to derive an overall index of airline competitiveness. The above authors thus show that the higher its overall index is, the better a company's economic performance. Conversely, two airlines with the same cost index display differences in terms of economic performance if they do not have the same capacity to generate revenues: this situation is true for Southwest Airlines, which has managed to generate more revenue than that of Hawaii Airlines.

In summary, several recent articles have made valuable contributions by highlighting hybridization processes among airline business models in Europe, underlining this hybridization by focusing on products, marketing practices, networks or operational airline characteristics. Nevertheless, the performance implications of such hybridization remain ambiguous: US studies based primarily on CASMs offer mixed results. Accordingly, we aim to investigate whether airline business model hybridization in Europe implies economic performance homogeneity by using a more systematic measure of economic performance, which is not limited to CASM. We therefore focus only on economic performance, disregarding all organizational or product variables. However, we do not investigate the convergence of airlines' economic performance (because longitudinal data are lacking) but only the potential homogeneity of their economic performance as an outcome of this hybridization or business model convergence.

3. Methods

3.1. Research design

To investigate the impacts of hybridization on the homogeneity of airline economic performance, we rely on what Argüelles et al. (2014) call "hierarchical clustering on principal components". This approach consists of two steps. First, we apply principal component analysis (PCA) to our dataset to obtain two or three principal components that reduce its dimensionality (i.e., its number of initial variables). Second, we implement a hierarchical clustering analysis (HCA) based on those principal components obtained in the first step to create clusters of observations that are close to one another.

A PCA is suitable for this study because we investigate a large number of European airlines (more than 20) and a significant number of variables (more than 5) to address the multidimensionality of the economic performance of an airline. PCA is "*a technique for reducing the dimensionality of datasets, increasing interpretability but at the same time minimizing information loss*" (Jolliffe and Cadima, 2016). PCA is thus highly relevant when the number of variables investigated is larger than 3, as it transforms variables into a limited number of dimensions (called "Principal components") to facilitate graphical representations of observations initially involving more than 3 dimensions. The usefulness and relevance of this statistical technique to reduce the dimensionality of datasets have made it pervasive in the transportation and tourism literature. For instance, PCA has been used to investigate port competitiveness (Tongzon and Heng, 2005), railway stations (Brons et al., 2009), transport-related lifestyles (Thogersen, 2018) and even electric vehicles (Onat et al., 2019). Regarding the air transport industry, scholars have used PCA to study airline networks (Adler and Golany, 2001; Roucolle et al., 2020), route performance (Chiou and Chen, 2006), air cargo business (Hong et al., 2018), air passenger characteristics (Lu, 2017), airline service quality (Gursoy et al., 2005) and even airline business models in long-haul markets (Soyk et al., 2017).

In addition to using PCA, we seek to cluster the airlines in our sample based on economic performance. Thus, we use Hierarchical Clustering Analysis (HCA). As explained by Cabral and Ramos (2014), in HCA, "*Each observation initially is placed in its own cluster, and the clusters are successively joined together in order of their closeness. The closeness of any two clusters is determined by a dissimilarity matrix and can be based on a variety of agglomeration methods (Ward's, complete, single or average). This method allows us to build a hierarchy of clusters (groups) whose results can be presented in a dendrogram that easily allows us to see which [airline] belongs to each group*". Contrary to other clustering methods such as K-means clustering, HCA is particularly useful when one does not know in advance the number of clusters in which observations need to be gathered (Malik and Tuckfield, 2019). Considering our research question, which specifically addresses the question of the homogeneity or heterogeneity of economic performances, the use of K-means clustering would have forced us to twist the results in a specific direction, while HCA allows us to adopt a more exploratory approach. Because of its relevance for gathering cluster observations into clusters according to their closeness, HCA is also extensively used in the transportation and tourism literature. Researchers use HCA to investigate greenhouse gas emissions (Arbolino et al., 2017), port competitiveness (Cabral and Ramos, 2014), alternatives to fuel vehicles (Campbell et al., 2012), high-speed train stations (Tapiador et al., 2009), road safety policies (Nikolaou and Dimitriou, 2018) and even tourist pictures (Zhang et al., 2019). Naturally, HCA is also used to study air transport-related topics such as airport performance (Sarkis and Talluri, 2004; Richardson et al., 2014), competitive airline positions (Wen and Chen, 2011), European Union Emissions Trading System (EU-ETS) in the aviation sector (Nava et al., 2018) and airline business models (Soyk et al., 2017).

3.2. Sample composition, variable selection and data collection

We first have to establish our sample of European airlines. Considering the significant impacts of the COVID-19 pandemic and the fact that airlines have not yet reached their annual precrisis levels, we focused on 2019 data.[3] Accordingly, we first selected all carriers who offered more than 5 million seats in 2019 within Europe, which yielded 40 airlines. Of these 40 airlines, 2 were non-European carriers (Pegasus and Turkish Airlines) and were thus not related to our research question. Among the 38 remaining airlines, 8 were charter airlines (TUI Airways, Thomas Cook Airlines, Sunexpress, etc.) and were thus outside the scope of our investigation (as they are neither LCCs nor legacy carriers). Using the RDC Aviation Apex database, we sought to collect additional information regarding the economic performance of these 30 airlines for the construction of our variables (Fares, Load factor, CASK, etc.). For 5 of the airlines (LOT Polish Airlines, Olympic Air, Laudamotion, Ukraine International Airlines, and Air Europa), we had incomplete information (for instance, information regarding fares or operating profit per passenger) that could not be collected manually. Ultimately, the 25 remaining airlines accounted for 94.7% of the seats offered by the 30 airlines that ideally would have been in our sample.

In our sample, some LCCs (e.g., Ryanair or EasyJet) were independent, while others were subsidiaries (created or acquired) of larger airlines (e.g., Vueling being a subsidiary of International Airlines Group (IAG) or Transavia being a subsidiary of Air France-KLM). Because all the airlines in our sample had their own autonomous business model, leading to a specific strategy and yielding a specific economic performance, we considered that being a subsidiary of a larger airline/group did not have any impact on the comparability of their economic performance in our analysis.

Regarding all the variables detailed below, the information was found in the RDC Aviation Apex database. The use of a unique database allowed us to guarantee not only homogeneous quality for the different airlines but also, above all, consistency in the data for the different variables. This database has been extensively used by scholars regarding various economic variables (charges, revenues, etc.) of airlines and airports (Jones et al., 2013; Wasiuk et al., 2015; Lee et al., 2017; Fuellhart et al., 2021; Calzada et al., 2022). This database allows for route-, country- or continent-level analyses for the most important airlines worldwide. More precisely, the database provides specific data on the revenues and costs on all of the routes served by a given airline based not only on the overall cost structure of the airline (derived from financial reports) but also on the type of aircraft used, distance flown and airports served. Regarding revenues (for instance, fares), RDC Aviation has collected data on the fares of many airlines over the years at the route level and with different time lags (i.e., number of days or weeks between the booking and the flight). Using scrapping tools, RDC Aviation directly collects airfares from airlines' websites at different intervals (between the day of booking and the day of the flight) for all the routes an airline serves at a given period of time. Collecting airfares directly through airlines' websites allows having data for all the airlines whether they use GDS or not. This route-level data provided by RDC Apex allowed us to focus on the economics of the specific route, independent of the presence or absence of connecting passengers. As we focused on both legacy carriers and LCCs, the geographical scope (for the variables used) covered only the intra-European market to allow for a comparison of the economic performance between LCCs and legacy carriers. In addition, even when they belonged to the same group (e.g., Air France–KLM or IAG), the RDC Aviation database provided financial data at the airline/carrier level.

To investigate the economic performance of these 25 European carriers, we adopted a multidimensional perspective of economic performance. In contrast to Tsoukalas et al. (2008), Bitzan and Peoples (2016) and Azadian and Vasigh (2019), who focus on costs as their main indicator, we integrated two other performance variables: volume (or size dimension) and revenue. Indeed, from an economic point of view, firm profit combines (i.e., multiplies) a margin (i.e., a difference between unit revenue and unit cost) and a quantity. It is thus important to combine a different set of variables and dimensions to benefit from a global perspective of the economic performance of airlines.

The volume or size dimension attempts to measure whether an airline has become a large and significant player in the European air transport industry. To measure this dimension, we used three indicators: number of *Available Seat Kilometers* (ASKs) in 2019 (for flights that were both departing from and arriving in Europe), number of *Flights* in 2019 (for intra-European flights) and number of *Passengers Carried* in 2019 by an airline (in the same geographical scope).

The cost competitiveness dimension addresses whether an airline is able to maintain low operating costs. To assess this dimension, we used the variable *Adjusted Cost* per *Available Seat Kilometer* in 2019 (only for intra-European flights). Because the cost per ASK (CASK) is dependent on the average trip length of an airline, we adjusted the CASK of each company to the average length of all companies in the sample, i.e., 1350 km. The formula used to adjust the length, which comes from the International Air Transport Association (IATA) and McKinsey, is as follows:

$$Adjusted\ CASK = Unadjusted\ CASK \times \left(\frac{Airline's\ stage\ length}{Average\ stage\ length\ in\ the\ sample}\right)^{\frac{1}{2}}$$

The revenue dimension assesses the ability of an airline to sell its seats in a profitable manner. To structure this, we built on two variables. The first, *Fare Per Kilometer,* measures the ability to offer attractive and affordable plane tickets. Priced in euros, this variable was measured during only one month (in June 2019 for all the flights on all the routes taking place in July 2019) to prevent any bias in terms of seasonality. Indeed, LCCs tend to present a higher seasonality in the seats and routes offered than do legacy carriers, with a significant reduction during the winter season. To avoid any bias due to this situation, we focused our attention on a single month, during the summer, when all of the airlines are at their full capacity. For a given airline, the *Fare Per Kilometer* variable is constructed as the average (for all the departure days of the "target month" and on all the intra-European routes operated by the airline) of the "1-month fare" (i.e., booked one month before the flight) of a given route divided by the number of kilometers of this route. Using these average values allows avoiding potential biases due to outliers or random fares that may be due to pricing errors. The second factor, *Load Factor* on European routes in 2019, measures an airline's ability to sell

[3] A similar analysis was conducted for 2018 (the only other year for which we had data for all the variables investigated), yielding the same conclusions as those for 2019. To provide the latest analysis before the COVID-19 crisis, we thus kept the analysis and conclusions for 2019 only.

seats optimally.

Finally, as a result of these three dimensions, *Profit* per *Passenger* for European routes in 2019 addresses whether seats were profitably sold. This variable measures the operating profit divided by the number of airline passengers specifically for European routes.

For each of the 25 European airlines in our sample, we collected data for these 7 variables, allowing us to first implement PCA and then perform HCA. Table 1 summarizes the 4 dimensions of economic performance used and their respective indicators.

4. Findings

4.1. Step 1: principal component analysis (PCA)

Given the number of airlines in our sample (25), we integrated 7 variables (that have been normalized) in our analysis: (1) *Available Seat Kilometers* in 2019 (ASK in the following figures and tables); (2) number of *Flights* in 2019 (NbOfFlights); (3) number of *Passengers Carried* in 2019 (Passengers); (4) *Adjusted Cost* per *Available Seat Kilometer* in 2019 (CASKadj); (5) *Fare Per Kilometer* in August 2019 (FarePerKM); (6) average *Load Factor* (LoadFactor); and, finally, (7) *Profit* per *Passenger* carried in 2019 (ProfitPerPax).

Before implementing PCA, it was necessary to measure whether PCA is useful or adapted to these variables. In our case, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is equal to 0.7 and larger than 0.6, which is the traditional threshold for testing the adequacy of PCA (Kaiser and Rice, 1974). Moreover, Bartlett's test of sphericity (approximate chi-square = 190.737; df = 21; sig. = 0.000) confirms that PCA is adapted to our dataset.

The analysis of the eigenvalues (Table 2) reveals that two principal components, with eigenvalues larger than 1, account for 79.22% of total variance. Thus, by projecting our observations onto these two principal components (instead of the 7 initial variables), we still retained more than 79% of the information in our initial dataset.

The factor scores of the different variables can be found in Table 3. Fig. 1 represents the loadings of principal components 1 (PC1) and 2 (PC2) with the 7 variables. Both Table 3 and Fig. 1 therefore allow us to interpret the two principal components.

PC1 is positively loaded with ASK, Passengers and NbOfFlights, meaning that airlines with positive PC1 values tend to be large with a high number of flights and offer seats that carry many passengers. Accordingly, airlines with negative PC1 values tend to be small with a limited number of flights and offer seats that carry fewer passengers.

PC2 is positively loaded with ProfitPerPax and LoadFactor and negatively loaded with CASKadj and FarePerKM, meaning that airlines with positive PC2 values have a high load factor and a high profit per passenger due to reduced costs and inexpensive fares. Hence, airlines that have negative PC2 values are less profitable with a reduced load factor, high costs and expensive fares.

Thus, in Fig. 2, we plot airline scores according to PC1 and PC2. Initially, we observe different groups or clusters of airlines.

Table 1
Dimensions of economic performance and their indicators and variables.

Key dimensions of economic performance	Indicators	Name of the variable (in the following tables and figures)
Volume/size	Available Seat Kilometers	ASK
	Number of Flights	NbOfFlights
	Passengers Carried	Passengers
Cost competitiveness	Adjusted Cost per Available Seat Kilometer	CASKadj
Revenue	Load Factor	LoadFactor
	Fare per Kilometer	FarePerKM
Profitability	Profit per Passenger	ProfitPerPax

Ryanair and, to a lesser extent, EasyJet appear to be clearly distinct from the rest of the European carriers. Regarding PC1 and PC2, these two airlines can be described as large airlines (both in terms of seats offered and passengers carried) that are profitable with a high load factor and limited costs and fares. A second distinguishable group encompasses Air France and Lufthansa. Both airlines remain larger than most of their European counterparts but are characterized by low profits per passenger and reduced load factors due to their high fares and significant costs. Finally, we observe a broader group comprising the 21 remaining carriers in our sample; nevertheless, it is difficult to characterize this group and to differentiate the airlines within it. Accordingly, HCA facilitates a closer evaluation or categorization of all the airlines in our sample.

4.2. Step 2: Hierarchical cluster analysis (HCA)

As we explain above, HCA entails locating airlines in clusters and then merging these clusters according to their closeness. Thus, using a dendrogram and depending on the number of clusters we want to obtain, we can group airlines and observe whether these groups can be decomposed into subgroups. To create a dendrogram that presents these different clusters, we use Ward's method, which creates balanced (in terms of the number of observations) clusters (Ward, 1963). The closeness between observations is assessed through squared Euclidian distance. The resulting dendrogram is displayed in Fig. 3.

This dendrogram allows us to identify different clusters based on the level of aggregation we want to reach. At the lowest level of aggregation (i.e., on the left side of Fig. 3), each airline is in its own cluster (because there is no distance between observations). In contrast, at the highest level of aggregation (i.e., the right side of Fig. 3), all the airlines belong to the same cluster because we accept a higher level of distance between observations that belong to the same cluster.

Following the logic of hierarchical clustering on principal components, we also plot the principal component factor scores for the airlines, with different clusters generated for various levels of distance. In other words, we return to Fig. 2 to identify clusters of airlines within this figure by using the clusters shown in the dendrogram (Fig. 3). Thus, Fig. 4 depicts the principal component factor scores with the clusters identified in the dendrogram for various distance levels. Fig. 4a is based on a reduced distance between airlines and allows us to identify 5 clusters of airlines, and Fig. 4b illustrates a larger distance between members of the same cluster and yields only two final clusters.

Similarly, Table 4 lists the European airlines belonging to different clusters according to the number of clusters we favor. The larger the number of clusters is, the more similar the cluster members appear; however, at the same time, this situation limits the number of conclusions that we can draw (as our analysis is fragmented). In contrast, the lower the number of clusters is, the less cluster members resemble each other, allowing us to draw more general conclusions regarding the entire sample.

By adopting a fine-grained approach (with 5 clusters), we observe different profiles of airlines within the European market (Fig. 4a). These profiles can be described through the two principal components that we have identified. Focusing on the configuration with 5 clusters, we first identify cluster 5a, which is mostly composed of legacy carriers (such as Finnair, Flybe, and Aer Lingus) that are smaller than average (carrying approximately 33.8 million passengers) and unprofitable (−17.2 euros per passenger on average) because of their intermediate costs and fares. The only surprise in cluster 5a is the presence of Eurowings, a subsidiary of Lufthansa that is usually categorized as an LCC.[4] Cluster 5 b comprises only two legacy carriers, Air France and Lufthansa, which can be

[4] This result is not truly surprising, as this Lufthansa subsidiary has reached a low-cost structure and has posted recurring losses since its merger with Germanwings in 2015.

Table 2
Total variance explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.569	50.986	50.986	3.569	50.986	50.986	2.934
2	1.976	28.229	79.215	1.976	28.229	79.215	2.611
3	.698	9.970	89.185				
4	.437	6.250	95.435				
5	.293	4.179	99.614				
6	.017	.248	99.862				
7	.010	.138	100.000				

Table 3
Rotated factor loadings of PCA.

Variables	Component	
	1	2
NbOfFlights	.987	−.056
ASK	.956	.271
FarePerKM	−.097	−.726
Passengers	.974	.206
LoadFactor	.238	.785
CASKadj	−.170	−.871
ProfitPerPax	−.038	.769

described as both large (83.3 million passengers on average) and unprofitable (−41.4 euros per passenger on average) because of their high costs and expensive fares. In contrast, Cluster 5c includes two LCCs, Ryanair and EasyJet, which are not only large but also profitable (+7.2 euros per passenger) because of their limited costs and inexpensive fares. Cluster 5 d gathers smaller airlines (34.5 million passengers on average), which are mostly LCCs that are profitable (+9.9 euros per passenger), such as Volotea, Vueling or Air Baltic. Nevertheless, the presence of Swiss and Aegean Airlines, which are traditionally considered legacy carriers, highlights the rather effective economic performance of these actors. Finally, Cluster 5e encompasses LCCs (such as Transavia, Jet2 or Wizz Air) that are smaller (32.7 million passengers) than the average European airline yet remain profitable (+9.6 euros per passenger) because of their low costs and inexpensive fares. Notably, Transavia, a low-cost subsidiary of Air France, is categorized in a cluster with other low-cost airlines, whereas its larger German counterpart, Germanwings, belongs to Cluster 5a, which is composed mainly of legacy carriers. Overall, despite the cases of Eurowings, Swiss and Aegean Airlines, we note that most of the 5 clusters include airlines that are similar, putting LCCs with LCCs and legacy carriers with legacy carriers.

From a broader perspective, as shown in Fig. 4b, only two clusters quite clearly separate LCCs from legacy carriers (except for the above-mentioned Eurowings, Swiss and Aegean Airlines). The first cluster, Cluster 2a, encompasses all the carriers that were previously in Clusters 5a and 5 b and, thus, all European legacy carriers. In contrast, the second cluster, Cluster 2 b, comprises all those airlines that were in Clusters 5c, 5 d and 5e. Thus, Cluster 2 b collects all European LCCs. As shown in Table 4, while offering a rather similar number of average flights (199,000 for Cluster 2a vs. 193,000 for Cluster 2 b), these two clusters present different specificities. The airlines in Cluster 2a (mostly legacy carriers) present a higher average level of adjusted CASK than do those in Cluster 2 b (mostly LCCs) (9.3 cents vs. 6.1 cents, respectively), a smaller average load factor (77.9% vs. 88.3%, respectively) and a lower profit per passenger (−20.9 euros vs. 9.3 euros, respectively).

In addition to the 5- and 2-cluster approaches, the 3- and 4-cluster approaches are also rich in information. The 3-cluster approach (Fig. 4c) is useful for distinguishing within the LCCs two groups in terms of size (Clusters 3 b and 3c; Cluster 3a gathers mostly legacy carriers). First, we find, in Cluster 3 b, the two LCC giants in Europe, Ryanair and EasyJet, which are characterized by the number of flights (680,000 for Cluster 3 b vs. 95,600 for Cluster 3c) and passengers transported (239 million vs. 33.8 million), which is 7 times higher than that of the companies in Cluster 3c. In contrast, Cluster 3c is composed of LCCs that are smaller than the average airlines in the sample. In this cluster, we find two low-cost subsidiaries of incumbent operators (Transavia France and Vueling) but also the low-cost operator Wizzair. Companies in Cluster 3c perform well in terms of profitability compared to those in Cluster 3 b (9.7 euros vs. 7.2 euros, respectively), but this result is largely due to the outperformance of Wizzair.

The 4-cluster approach allows us to carry out an exercise similar to the previous one but on legacy carriers (Fig. 4d). Within the group of incumbent airlines, we can clearly distinguish two subgroups according

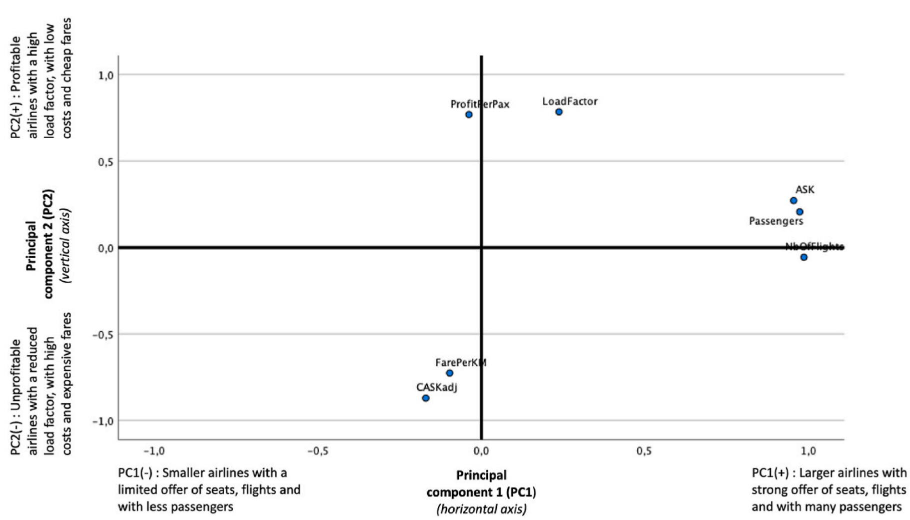

Fig. 1. Factor loadings of the principal components.

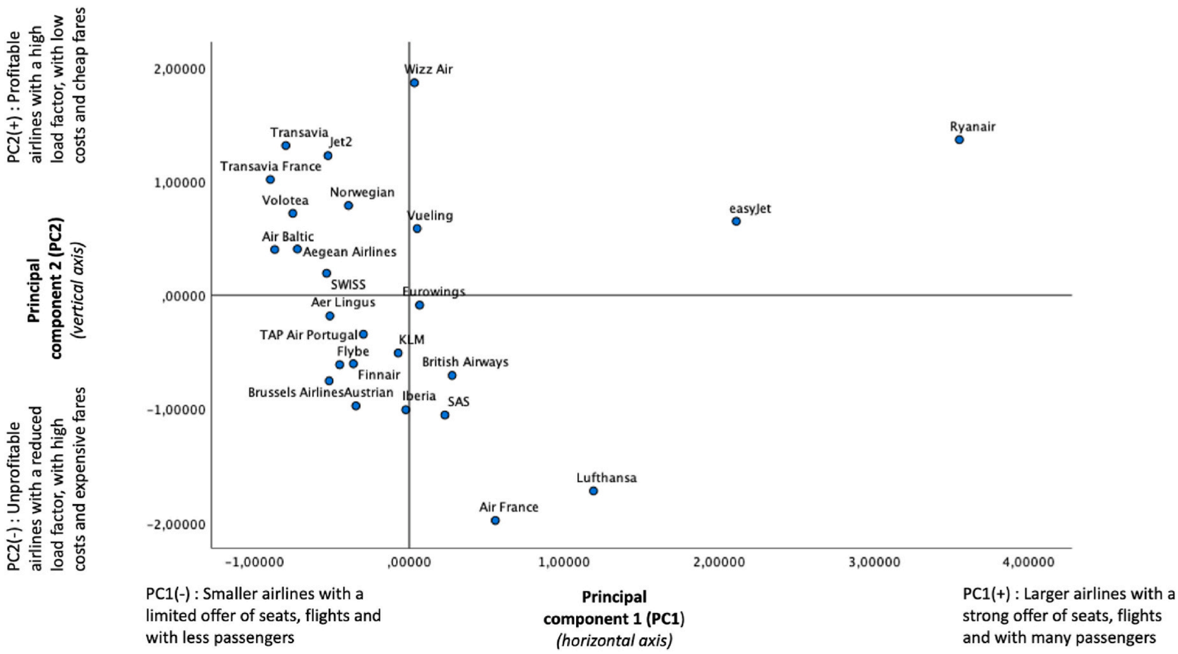

Fig. 2. Principal component factor scores for the airlines in the sample.

to their profitability. First, Cluster 4 b includes Air France and Lufthansa, whose losses are 2.5 times higher per passenger than are those of the rest of the incumbent airlines found in Cluster 4a (−41.4 euros per passenger vs. −17.2, respectively). This underperformance of Air France and Lufthansa in terms of profitability per passenger is reinforced by a size effect: the two incumbent airlines are 2.5 times greater in size than the other incumbent airlines in terms of number of passengers carried (83.3 vs. 33.8 million) and 2.2 times greater in terms of number of flights (368,100 vs. 168,800). Cluster 4 b is in some ways the mirror image of Cluster 4c, in which Ryanair and EasyJet combine both performance and size.

In summary, regardless of the level of analysis, our HCA on principal components reveals that in terms of economic performance (assessed through volume, revenue and cost), LCCs and legacy carriers remain two distinct groups with different characteristics. Accordingly, despite growing airline business model hybridization in Europe, airline carriers have not achieved homogeneous economic performance. Overall, LCCs remain more profitable (with lower costs and more affordable fares) than do legacy carriers.

5. Discussion and concluding remarks

5.1. Interpretation of the findings

Our empirical study on European airlines confirms that when an economic performance approach is adopted, maintaining the distinction (made both in the academic literature and in the specialized press) between LCCs and legacy carriers is relevant. Indeed, when we group 25 European airlines into two clusters, the partition of our sample almost perfectly reproduces the distinction between the two types of business models, with the exception of Eurowings (classified as a traditional airline and not an LCC) and Swiss and Aegean Airlines (classified as LCCs, although traditionally categorized as legacy carriers). Notably, therefore, any hybridization between low-cost business models and those of incumbent companies has not eliminated the low-cost/legacy distinction with respect to economic performance. Several factors may explain the maintenance of this difference in economic performance.

First, contrary to the many US carriers that took advantage of the 9/11 and 2008 crises to restructure their core businesses and become more competitive (Jean and Lohmann, 2016), European legacy carriers did not benefit from a specific legal framework (such as Chapter 11 for bankruptcies) to restructure their activities and reduce the gap between themselves and the most competitive airlines in the European market. Second, since they were unable to restructure in depth, legacy carriers in Europe sought economic performance on short- and medium-haul routes mostly through the creation of low-cost subsidiaries (Gilen and Gados, 2008; Pearson and Merkert, 2014). Our analysis underlines important differences in economic performance between the legacy and low-cost subsidiaries of large groups such as Air France–KLM or IAG, revealing how these groups' low-cost subsidiaries are the means by which they compete with independent LCCs. Third, because the European market is growing in the leisure segment and because most of this growth is being captured by low-cost airlines, large orders are being placed, resulting in the better amortization of the fixed costs of low-cost companies and decreasing aircraft purchase costs. Accordingly, the strong growth of LCCs allows them to maintain a gap in terms of economic performance, making it difficult for traditional airlines to catch up. Finally, European LCCs, such as Ryanair and EasyJet, have a management style based on the charisma of their founders, who focus almost exclusively on keeping costs low and maintaining their competitive advantage (Wilson and Lohmann, 2019). Both theory in strategic management research and empirical research into the psychology of entrepreneurship argue that chief executive officer (CEO) characteristics are important determinants of firm performance (Certo et al., 2006).

A second important lesson from our empirical study is the ambivalent role played by airline size. Regarding EasyJet and Ryanair, for instance, there is a positive relationship between airline size and profitability. However, a more fine-grained approach reveals that the economic performance of similarly sized airlines can be different. For instance, a small LCC, such as Wizzair, shows much higher profitability than that of airlines such as Vueling or Germanwings, even though they are all similar in size. Moreover, among the legacy carriers, Air France has lower economic performance than that of British Airways despite being approximately the same size. Being a large airline is therefore neither necessary nor sufficient for good economic performance.

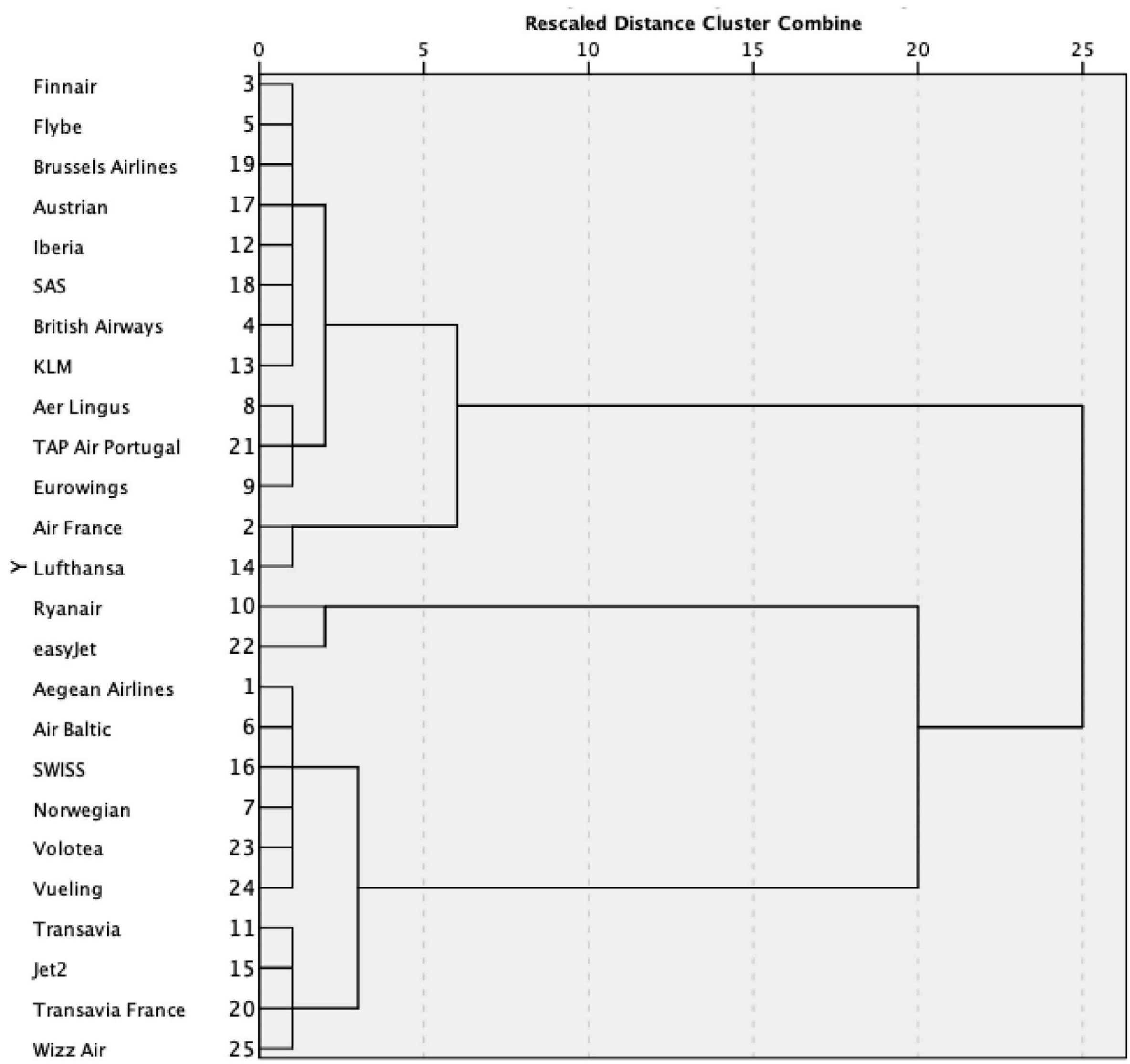

Fig. 3. Dendrogram resulting from cluster analysis using Ward linkage.

5.2. Contributions to the literature

Our study makes several contributions to the growing literature that compares LCCs and legacy carriers.

First, our findings clearly distinguish between two different subjects: the hybridization of business models and the convergence of their economic performance. Indeed, our analysis reveals that business model hybridization does not necessarily imply a homogeneity of economic performance among LCCs and legacy carriers. While many studies have shown convergence among the business models of these airlines (Klophaus et al., 2012; Lohmann and Koo, 2013; Tomova; Ramajova, 2014; Daft and Albers, 2015; Jean and Lohmann, 2016; de Wit and Zuidberg, 2016; Dobruszkes et al., 2017; Magdalina and Bouzaima, 2021), our analysis shows that from an economic performance perspective, LCCs and legacy carriers remain two distinct groups. In other words, the convergence or hybridization of airline business models in Europe has not led to homogeneous economic performance.

Second, this absence of homogeneous economic performance for airlines that are supposed to have converging business models raises the question of whether or not these airlines have actually seen their business models converge. Following contributions on business model evolution or innovation, such as those of Demil and Lecocq (2010), Chesbrough (2010), Amit and Zott (2012) and Foss and Saebi (2017), one can argue that a long-lasting business model evolution or innovation takes place when (1) at least one of the dimensions of the business model has evolved and (2) this evolution also results in a change in firm profitability (as the value proposition, organization and margin are interrelated). In the case of the European airlines investigated, previous researchers have indeed shown a change or convergence in some of the business model dimensions (presence of the first condition), but our findings reveal that these evolutions do not result in changes in the economic performance of the firms (absence of the second condition). This finding forces us to question whether European airlines have actually converged or if the convergence process is still ongoing. Our findings lead us to conclude that the convergence process is still underway and that the convergence of business models will be reached only when economic performance is homogeneous among airlines.

Third, this study adds to the growing literature on airline economic performance by investigating these issues in a European context and by using new performance variables. While extant studies are based on US data (Tsoukalas et al., 2008; Borenstein, 2011; Hüschelrath and Müller, 2012; Bitzan and Peoples, 2016; Moir and Lohmann, 2018; Azadian and Vasigh, 2019), we use a European dataset to investigate the economic performance of European carriers. Our findings in this European context yield similar conclusions to those obtained by Borenstein (2011), Hüschelrath and Müller (2012) and Azadian and Vasigh (2019), namely,

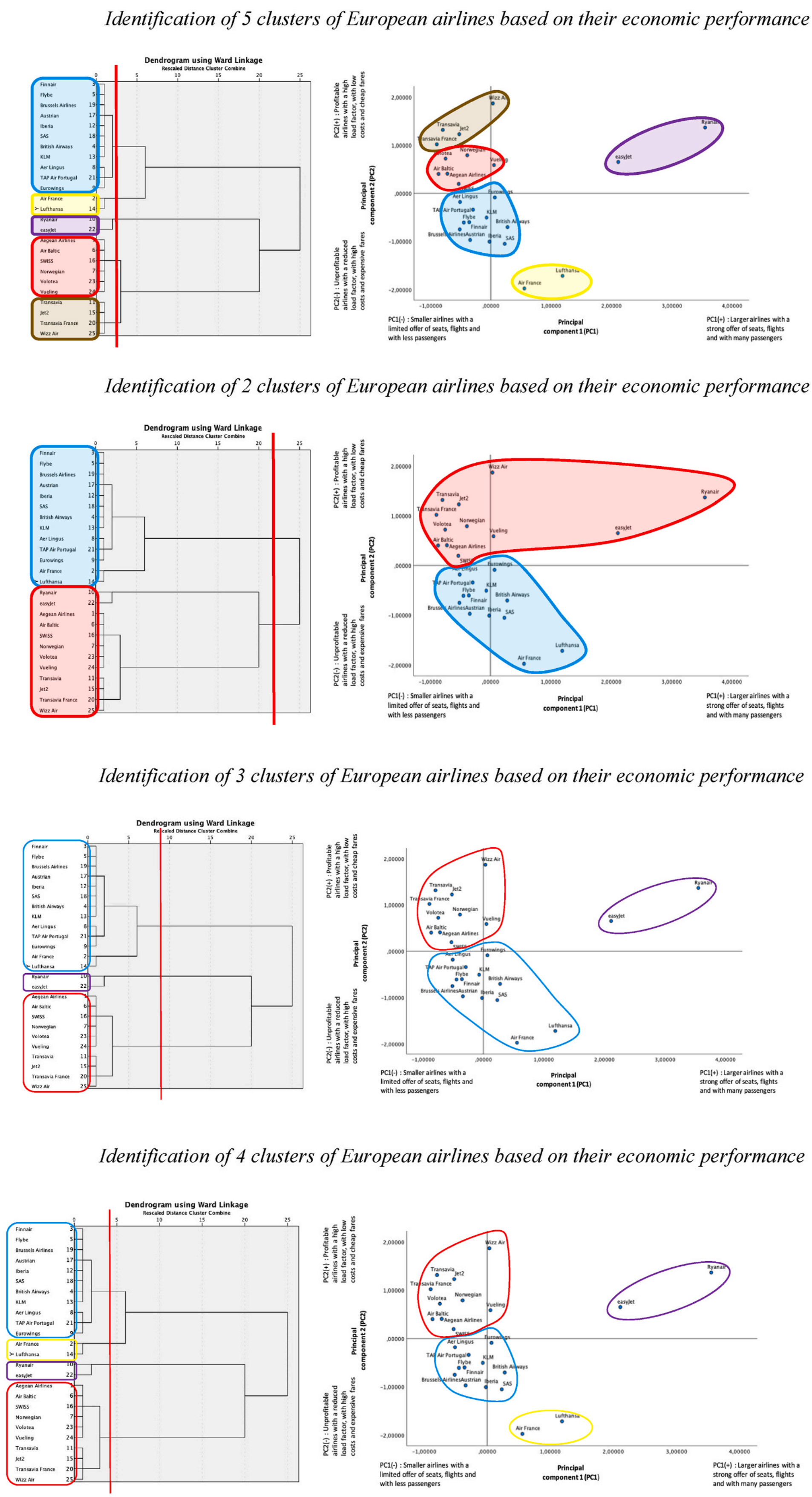

Fig. 4. Principal component factor scores with the clusters identified in the dendrogram for various distance levels
Fig. 4a. Identification of 5 clusters of European airlines based on their economic performance
Fig. 4b. Identification of 2 clusters of European airlines based on their economic performance
Fig. 4c. Identification of 3 clusters of European airlines based on their economic performance
Fig. 4d. Identification of 4 clusters of European airlines based on their economic performance.

Table 4
(part 1). Average values associated with airlines belonging to various clusters.

Number of clusters	7							5				
Name of cluster	7a.	7 b.	7c.	7 d.	7e.	7f.	7 g.	5a.	5 b.	5c.	5 d.	5e.
Airlines	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM	Aer Lingus, TAP Air Portugal, Eurowings	Air France, Lufthansa	Ryanair	EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling	Transavia, Jet2, Transavia France, Wizz Air	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings	Air France, Lufthansa	Ryanair, EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling	Transavia, Jet2, Transavia France, Wizz Air
Average Number of Flights (thousands)	177.0	147.1	368.1	766.2	594.9	101.3	86.9	168.8	368.1	680.5	101.3	86.9
Average ASK (million)	21,591.8	23,874.9	42,606.5	191,000.0	115,000.0	17,053.7	28,609.8	22,214.5	42,606.5	153,000.0	17,053.7	28,609.8
Average Passengers (million)	33.8	33.8	83.3	289.9	188.3	34.5	32.7	33.8	83.3	239.1	34.5	32.7
Average Adjusted CASK (euro cents)	9.5	8.0	10.5	4.0	6.0	6.5	6.0	9.1	10.5	5.0	6.5	6.0
Average Load Factor (%)	77.2	80.4	77.2	96.6	91.4	83.7	92.3	78.1	77.2	94.0	83.7	92.3
Average Fare per Kilometer (euro cents)	13.1	10.7	17.0	7.0	11.0	12.0	8.0	12.5	17.0	9.0	12.0	8.0
Average Profit per Passenger (euros)	−16.8	−18.4	−41.4	8.2	6.2	9.9	9.6	−17.2	−41.4	7.2	9.9	9.6

(part 2). Average values associated with airlines belonging to various clusters

Number of clusters	4				3			2	
Name of cluster	4a.	4 b.	4c.	4 d.	3a.	3 b.	3c.	2a.	2 b.
Airlines	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings	Air France, Lufthansa	Ryanair, EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings, Air France, Lufthansa	Ryanair, EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings, Air France, Lufthansa	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air, Ryanair, EasyJet
Average Number of Flights (thousands)	168.8	368.1	680.5	95.6	199.5	680.5	95.6	199.5	193.1
Average ASK (million)	22,214.5	42,606.5	153,000.0	21,676.1	25,351.7	153,000.0	21,676.1	25,351.7	43,563.4

(*continued on next page*)

Table 4 (*continued*)

(part 2). Average values associated with airlines belonging to various clusters

Number of clusters	4				3			2	
Name of cluster	4a.	4 b.	4c.	4 d.	3a.	3 b.	3c.	2a.	2 b.
Airlines	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings	Air France, Lufthansa	Ryanair, EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings, Air France, Lufthansa	Ryanair, EasyJet	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air	Finnair, Flybe, Brussels Airlines, Austrian, Iberia, SAS, British Airways, KLM, Aer Lingus, TAP Air Portugal, Eurowings, Air France, Lufthansa	Aegean Airlines, Air Baltic, Swiss, Norwegian, Volotea, Vueling, Transavia, Jet2, Transavia France, Wizz Air, Ryanair, EasyJet
Average Passengers (million)	33.8	83.3	239.1	33.8	41.4	239.1	33.8	41.4	68.0
Average Adjusted CASK (euro cents)	9.1	10.5	5.0	6.3	9.3	5.0	6.3	9.3	6.1
Average Load Factor (%)	78.1	77.2	94.0	87.1	77.9	94.0	87.1	77.9	88.3
Average Fare per Kilometer (euros cents)	12.5	17.0	9.0	10.4	13.2	9.0	10.4	13.2	10.2
Average Profit per Passenger (euros)	−17.2	−41.4	7.2	9.7	−20.9	7.2	9.7	−20.9	9.3

a lack of economic performance convergence between LCCs and legacy carriers (with the notable exception being Southwest Airlines in Azasian and Vasigh's (2019) study). This lack of economic performance convergence in both US and European markets invites us to adopt a more nuanced view of the so-called convergence of business models (as economic performance is one of the dimensions). In addition to broadening the geographic scope of the literature, we adopt a more comprehensive and multidimensional approach regarding the variables used to assess economic performance. Indeed, whether the classical business model canvas conceptualized by Osterwalder and Pigneur (2010) or more academic articles (Teece, 2010; DaSilva and Trkman, 2014) are considered, business models require taking into account the revenues and costs associated with the business model implemented simultaneously. In that line, while we account for CASK, we argue that economic performance depends not only on unit cost but also on a company's ability to earn unit revenue above the unit cost or to be sufficient in size. For instance, an important factor that explains the differences in economic performance between two "hybrid" airlines is consistency between cost and revenue structures, as highlighted in the study by Moir and Lohmann (2018) using US data. This result is why we argue that adopting a more multidimensional approach to economic performance is important to better understand the evolution of airline business models.

5.3. Limitations and directions for future research

Our empirical study has several limitations that call for future and complementary research.

First, we show that the hybridization of airline business models, which has been underway since the 2010s in Europe, did not translate into homogeneous airline economic performance in 2019. Such a result, however, does not mean that economic performance cannot converge over the long term. In this respect, the case of Southwest Airlines in the US is interesting. Azadian and Vasigh (2019) show that the convergence between Southwest and legacy carriers occurred quite late, after 2001 (i.e., 30 years after the creation of low-cost airlines), and resulted from both external and internal factors. In the European case, we cannot exclude, for example, that such a convergence may happen in the long term and that ultra-low-cost airlines, such as Ryanair or Wizzair, might experience an external shock in terms of flight crew compensation in the context of pilot shortages and the harmonization of rules in Europe on posted workers. In addition, because data for all the economic performance variables are not available for the previous years, it would therefore be useful to reproduce the same study with the same sample of airlines and the same measurement indicators after several years have elapsed to detect possible evolutions in economic performance (in the directions of convergence, stability or divergence). A more dynamic approach based on time series would probably yield interesting results.

Second, while we assess economic performance with 7 variables to analyze 4 different dimensions, other potential measurement indicators of performance could be used. For instance, several studies have investigated the impacts of LCC and legacy carrier interactions on stock markets (Detzen et al., 2012; Yang and Baasandorj, 2017) and have underlined the relevance of such measures of economic performance. Accordingly, future contributions could investigate the consequences of this hybridization on financial performance, with indicators such as the cash level, the differentiated evolutions of stock prices and market capitalizations in Europe of incumbent and low-cost airlines. In that vein, future researchers may study whether the hybridization of airlines' business models has led to a convergence of stock prices or market capitalizations (for airlines that are similar in size). For instance, in March 2023, Ryanair's market capitalization was 50% larger than that of Lufthansa and more than 5 times as large as that of Air France-KLM, despite these three airlines being approximately the same size. In that case, the hypothesis of homogeneous financial performance seems difficult to embrace. In contrast, EasyJet's market capitalization is almost equivalent to that of Air France-KLM's, such that one could argue in favor of this homogeneous financial performance. We thus invite future researchers to consider other measurements of performance to test the robustness of our conclusions with other types of measures.

Third, our study focuses on a given geographical area, namely, Europe, which brings into question the external validity of our findings. Is the heterogeneity of economic performance also observable on other continents, particularly in Southeast Asia, where LCCs have undergone a strong expansion since the 2010s (Zhang et al., 2014; Fu et al., 2015; Bowen, 2019), and, more recently, in Latin America (Almeida Pereira et al., 2015)? Such a geographical extension either would allow us to confirm or generalize the significance of our main results and those observed by Azadian and Vasigh (2019) in the US (excluding Southwest Airlines) or could moderate our results based on the maturity level of these air transport markets.

Finally, we find that the low-cost subsidiaries of IAG, Air France–KLM, and Lufthansa, all incumbent carriers, differ in their economic performance. Specifically, Vueling (IAG's subsidiary) and Transavia (Air France–KLM's subsidiary) are much more profitable than and yet are approximately the same size as Eurowings (a Lufthansa subsidiary). Thus, they do not belong to the same cluster as Eurowings, regardless of the number of clusters selected. Therefore, it would be useful, through a comparative qualitative analysis (based on interviews and case studies), to explain these differences by mobilizing the literature on the conditions of success for an "airline within an airline" (Graf, 2005; Gilen; Gados, 2008; Lin, 2012; Pearson and Merkert, 2014).

Nevertheless, we remain confident regarding the scope of our contributions to the literature on airline business models and their economic performance, and this topic provides a promising pathway for future research.

Credit author statement

Paul Chiambaretto: Conceptualization, Methodology, Data Analysis, Writing – original draft, review editing, Supervision and funding. Emmanuel Combe, Conceptualization, Data analysis, Visualization, Writing – original draft, review and editing.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

Adler, N., Golany, B., 2001. Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. Eur. J. Oper. Res. 132 (2), 260–273. https://doi.org/10.1016/S0377-2217(00)00150-8.

Aghaie, S., Javadinia, A., Mirahmad, H., Janani, S., 2022. How incumbents' response strategy impacts rivals' market exit timing? J. Bus. Res. 146, 251–263. https://doi.org/10.1016/j.jbusres.2022.03.043.

Alamdari, F., Fagan, S., 2005. Impact of the adherence to the original low-cost model on the profitability of low-cost airlines. Transport Rev. 25 (3), 377–392. https://doi.org/10.1080/01441640500038748.

Amit, R., Zott, C., 2012. Creating value through business model innovation. MIT Sloan Manag. Rev. 53 (3), 41–49.

Arbolino, R., Carlucci, F., Cirà, A., Ioppolo, G., Yigitcanlar, T., 2017. Efficiency of the EU regulation on greenhouse gas emissions in Italy: the hierarchical cluster analysis approach. Ecol. Indicat. 81, 115–123. https://doi.org/10.1016/j.ecolind.2017.05.053.

Argüelles, M., Benavides, C., Fernández, I., 2014. A new approach to the identification of regional clusters: hierarchical clustering on principal components. Appl. Econ. 46 (21), 2511–2519. https://doi.org/10.1080/00036846.2014.904491.

Azadian, F., Vasigh, B., 2019. The blurring lines between full-service network carriers and low-cost carriers: a financial perspective on business model convergence. Transport Pol. 75, 19–26. https://doi.org/10.1016/j.tranpol.2018.12.012.

Bachis, E., Piga, C.A., 2011. Low-cost airlines and online price dispersion. Int. J. Ind. Organ. 29 (6), 655–667. https://doi.org/10.1016/j.ijindorg.2011.02.006.

Bettini, H.F.A.J., Silveira, J.M.F.J., Oliveira, A.V.M., 2018. Estimating strategic responses to the march of a low cost carrier to primary airports. Transport. Res. E Logist. Transport. Rev. 109, 190–204. https://doi.org/10.1016/j.tre.2017.11.004.

Bitzan, J., Peoples, J., 2016. A comparative analysis of cost change for low-cost, full-service, and other carriers in the US airline industry. Res. Transport. Econ. 56, 25–41. https://doi.org/10.1016/j.retrec.2016.07.003.

Borenstein, S., 2011. Why can't US airlines make money? Am. Econ. Rev. 101 (3), 233–237. https://doi.org/10.1257/aer.101.3.233.

Bowen, J., 2019. Low-Cost Carriers in Emerging Countries. Elsevier.

Brechemier, D., Combe, E., 2020. *After Covid-19, Air Transportation in Europe: The Time for Decision-Making* (Fondapol).

Brons, M., Givoni, M., Rietveld, P., 2009. Access to railway stations and its potential in increasing rail use. Transport. Res. Pol. Pract. 43 (2), 136–149. https://doi.org/10.1016/j.tra.2008.08.002.

Budd, L., Francis, G., Humphreys, I., Ison, S., 2014. Grounded: characterising the market exit of European low cost airlines. J. Air Transport. Manag. 34, 78–85. https://doi.org/10.1016/j.jairtraman.2013.08.002.

Cabral, A.M.R., Ramos, F. de S., 2014. Cluster analysis of the competitiveness of container ports in Brazil. Transport. Res. Pol. Pract. 69, 423–431. https://doi.org/10.1016/j.tra.2014.09.005.

Calzada, J., Fageda, X., Safronov, R., 2022. How do global airline alliances affect flight frequency? Evidence from Russia. J. Air Transport. Manag. 98, 102156 https://doi.org/10.1016/j.jairtraman.2021.102156.

Campbell, A.R., Ryley, T., Thring, R., 2012. Identifying the early adopters of alternative fuel vehicles: a case study of Birmingham, United Kingdom. Transport. Res. Pol. Pract. 46 (8), 1318–1327. https://doi.org/10.1016/j.tra.2012.05.004.

Certo, S.T., Lester, R.H., Dalton, C.M., Dalton, D.R., 2006. Top management teams, strategy and financial performance: a meta-analytic examination. J. Manag. Stud. 43 (4), 813–839. https://doi.org/10.1111/j.1467-6486.2006.00612.x.

Chesbrough, H., 2010. Business model innovation: opportunities and barriers. Long. Range Plan. 43 (2), 354–363. https://doi.org/10.1016/j.lrp.2009.07.010.

Chiambaretto, P., 2021. Air passengers' willingness to pay for ancillary services on long-haul flights. Transport. Res. E Logist. Transport. Rev. 147, 102234 https://doi.org/10.1016/j.tre.2021.102234.

Chiambaretto, P., Fernandez, A.-S., 2014. Transferring low-cost marketing practices from air to rail services: the Ouigo case. Research in Transportation Business & Management 10, 40–44. https://doi.org/10.1016/j.rtbm.2014.05.003.

Chiou, Y.-C., Chen, Y.-H., 2006. Route-based performance evaluation of Taiwanese domestic airlines using data envelopment analysis. Transport. Res. E Logist. Transport. Rev. 42 (2), 116–127. https://doi.org/10.1016/j.tre.2005.09.005.

Corbo, L., 2017. In search of business model configurations that work: lessons from the hybridization of Air Berlin and JetBlue. J. Air Transport. Manag. 64, 139–150. https://doi.org/10.1016/j.jairtraman.2016.09.010.

DaSilva, C.M., Trkman, P., 2014. Business model: what it is and what it is not. Long. Range Plan. 47 (6), 379–389. https://doi.org/10.1016/j.lrp.2013.08.004.

Daft, J., Albers, S., 2012. A profitability analysis of low-cost long-haul flight operations. J. Air Transport. Manag. 19, 49–54. https://doi.org/10.1016/j.jairtraman.2012.01.010.

Daft, J., Albers, S., 2015. An empirical analysis of airline business model convergence. J. Air Transport. Manag. 46, 3–11. https://doi.org/10.1016/j.jairtraman.2015.03.008.

de Oliveira, R.P., Oliveira, A.V.M., Lohmann, G., 2021. A network-design analysis of airline business model adaptation in the face of competition and consolidation. Transport. Sci. 55 (2), 532–548. https://doi.org/10.1287/trsc.2020.1025.

de Wit, J.G., Zuidberg, J., 2012. The growth limits of the low cost carrier model. J. Air Transport. Manag. 21, 17–23. https://doi.org/10.1016/j.jairtraman.2011.12.013.

de Wit, J.G., Zuidberg, J., 2016. Route churn: an analysis of low-cost carrier route continuity in Europe. J. Transport Geogr. 50, 57–67. https://doi.org/10.1016/j.jtrangeo.2015.04.003.

Delaplace, M., Dobruszkes, F., 2015. From low-cost airlines to low-cost high-speed rail? The French case. Transport Pol. 38, 73–85. https://doi.org/10.1016/j.tranpol.2014.12.006.

Demil, B., Lecocq, X., 2010. Business model evolution: in search of dynamic consistency. Long. Range Plan. 43 (2), 227–246. https://doi.org/10.1016/j.lrp.2010.02.004.

Dennis, N., 2007. Stimulation or saturation?: perspectives on European low-cost airline market and prospects for growth. Transport. Res. Rec. 2007 (1), 52–59. https://doi.org/10.3141/2007-07.

Detzen, D., Jain, P.K., Likitapiwat, T., Rubin, R.M., 2012. The impact of low cost airline entry on competition, network expansion, and stock valuations. J. Air Transport. Manag. 18 (1), 59–63. https://doi.org/10.1016/j.jairtraman.2011.09.004.

Dobruszkes, F., Givoni, M., Vowles, T., 2017. Hello major airports, goodbye regional airports? Recent changes in European and US low-cost airline airport choice. J. Air Transport. Manag. 59, 50–62. https://doi.org/10.1016/j.jairtraman.2016.11.005.

Escobar-Rodríguez, T., Carvajal-Trujillo, E., 2014. Online purchasing tickets for low cost carriers: an application of the unified theory of acceptance and use of technology

(UTAUT) model. Tourism Manag. 43, 70–88. https://doi.org/10.1016/j.tourman.2014.01.017.
Fageda, X., Suau-Sanchez, P., Mason, K.J., 2015. The evolving low-cost business model: network implications of fare bundling and connecting flights in Europe. J. Air Transport. Manag. 42, 289–296. https://doi.org/10.1016/j.jairtraman.2014.12.002.
Foss, N.J., Saebi, T., 2017. Fifteen years of research on business model innovation: how far have we come, and where should we go? J. Manag. 43 (1), 200–227. https://doi.org/10.1177/0149206316675927.
Francis, G., Dennis, N., Ison, S., Humphreys, I., 2007. The transferability of the low-cost model to long-haul airline operations. Tourism Manag. 28 (2), 391–398. https://doi.org/10.1016/j.tourman.2006.04.014.
Fu, X., Lei, Z., Wang, K., Yan, J., 2015. Low cost carrier competition and route entry in an emerging but regulated aviation market – the case of China. Transport. Res. Pol. Pract. 79, 3–16. https://doi.org/10.1016/j.tra.2015.03.020.
Fuellhart, K., Dai, L., Grubesic, T., Derudder, B., 2021. The U.S. Essential air service program and SARS C0V-2, 2019–2020. J. Transport Geogr. 96, 103169 https://doi.org/10.1016/j.jtrangeo.2021.103169.
Gillen, D., Gados, A., 2008. Airlines within airlines: assessing the vulnerabilities of mixing business models. Res. Transport. Econ. 24 (1), 25–35. https://doi.org/10.1016/j.retrec.2009.01.002.
Graf, L., 2005. Incompatibilities of the low-cost and network carrier business models within the same airline grouping. J. Air Transport. Manag. 11 (5), 313–327. https://doi.org/10.1016/j.jairtraman.2005.07.003.
Gursoy, D., Chen, M.-H., Kim, H.J., 2005. The US airlines relative positioning based on attributes of service quality. Tourism Manag. 26 (1), 57–67. https://doi.org/10.1016/j.tourman.2003.08.019.
Hong, S.-J., Randall, W., Han, K., Malhan, A.S., 2018. Estimation viability of dedicated freighter aircraft of combination carriers: a data envelopment and principal component analysis. Int. J. Prod. Econ. 202, 12–20. https://doi.org/10.1016/j.ijpe.2018.05.012.
Hunter, L., 2006. Low cost airlines: business model and employment relations. Eur. Manag. J. 24 (5), 315–321. https://doi.org/10.1016/j.emj.2006.08.001.
Huse, C., Evangelho, F., 2007. Investigating heterogeneity: low-cost vs full-service airline users? Transport. Res. E Logist. Transport. Rev. 43 (3), 259–268. https://doi.org/10.1016/j.tre.2006.10.005.
Hüschelrath, K., Müller, K., 2012. Low cost carriers and the evolution of the domestic U. S. Airline industry. Compet. Regul. Netw. Ind. 13 (2), 133–159. https://doi.org/10.1177/178359171201300202.
Jean, D.A., Lohmann, G., 2016. Revisiting the airline business model spectrum: the influence of post global financial crisis and airline mergers in the US (2011−2013). Research in Transportation Business & Management 21, 76–83. https://doi.org/10.1016/j.rtbm.2016.06.002.
Jolliffe, I.T., Cadima, J., 2016. Principal component analysis: a review and recent developments. Phil. Trans. Math. Phys. Eng. Sci. 374 (2065), 20150202 https://doi.org/10.1098/rsta.2015.0202.
Jones, O.C., Budd, L.C.S., Pitfield, D.E., 2013. Aeronautical charging policy incentive schemes for airlines at European airports. J. Air Transport. Manag. 33, 43–59. https://doi.org/10.1016/j.jairtraman.2013.06.009.
Kaiser, H.F, Rice, J, 1974. Educational and Psychological Measurement. American Psychological Association.
Kangis, P., O'Reilly, M.D., 2003. Strategies in a dynamic marketplace: a case study in the airline industry. J. Bus. Res. 56 (2), 105–111. https://doi.org/10.1016/S0148-2963(01)00282-X.
Keiningham, T., Aksoy, L., Bruce, H.L., Cadet, F., Clennell, N., Hodgkinson, I.R., Kearney, T., 2020. Customer experience driven business model innovation. J. Bus. Res. 116, 431–440. https://doi.org/10.1016/j.jbusres.2019.08.003.
Klophaus, R., Conrady, R., Fichert, F., 2012. Low cost carriers going hybrid: evidence from Europe. J. Air Transport. Manag. 23, 54–58. https://doi.org/10.1016/j.jairtraman.2012.01.015.
Klophaus, R., Fichert, F., 2019. From low-cost carriers to network carriers without legacy? Evolving airline business models in Europe. In: Airline Economics in Europe, vol. 8. Emerald Publishing Limited, pp. 57–75. https://doi.org/10.1108/S2212-160920190000008003.
Klophaus, R., Merkert, R., Lordan, O., 2021. Mesh network as a competitive advantage for European LCCs: an alternative topology to hub-and-spoke for selling online connections. Transport Pol. 106, 196–204. https://doi.org/10.1016/j.tranpol.2021.04.012.
Koklic, M.K., Kukar-Kinney, M., Vegelj, S., 2017. An investigation of customer satisfaction with low-cost and full-service airline companies. J. Bus. Res. 80, 188–196. https://doi.org/10.1016/j.jbusres.2017.05.015.
Lee, B.L., Wilson, C., Pasurka, C.A., Fujii, H., Managi, S., 2017. Sources of airline productivity from carbon emissions: an analysis of operational performance under good and bad outputs. J. Prod. Anal. 47 (3), 223–246. https://doi.org/10.1007/s11123-016-0480-4.
Lin, M.H., 2012. Airlines-within-airlines strategies and existence of low-cost carriers. Transport. Res. E Logist. Transport. Rev. 48 (3), 637–651. https://doi.org/10.1016/j.tre.2011.11.004.
Lohmann, G., Koo, T.T.R., 2013. The airline business model spectrum. J. Air Transport. Manag. 31, 7–9. https://doi.org/10.1016/j.jairtraman.2012.10.005.
Lu, J.-L., 2017. Segmentation of passengers using full-service and low-cost carriers – evidence from Taiwan. J. Air Transport. Manag. 62, 204–216. https://doi.org/10.1016/j.jairtraman.2017.05.002.
Magdalina, A., Bouzaima, M., 2021. An empirical investigation of European airline business models: classification and. of Air Transport Management 93, 102059. https://doi.org/10.1016/j.jairtraman.2021.102059.
Malik, A., Tuckfield, B., 2019. Applied Unsupervised Learning with R: Uncover Hidden Relationships and Patterns with K-Means Clustering, Hierarchical Clustering, and PCA. Packt Publishing Ltd.
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. Transport. Econ. 24 (1), 75–84. https://doi.org/10.1016/j.retrec.2009.01.006.
Mason, K., Morrison, W.G., Stockman, I., 2013. Liberalization of Air Transport in Europe and the Evolution of Low Cost Airlines. Working Paper.
Moir, L., Lohmann, G., 2018. A quantitative means of comparing competitive advantage among airlines with heterogeneous business models: analysis of U.S. airlines. J. Air Transport. Manag. 69, 72–82. https://doi.org/10.1016/j.jairtraman.2018.01.003.
Morlotti, C., Cattaneo, M., Malighetti, P., Redondi, R., 2017. Multi-dimensional price elasticity for leisure and business destinations in the low-cost air transport market: evidence from. Tourism Manag. 61, 23–34. https://doi.org/10.1016/j.tourman.2017.01.009.
Nava, C.R., Meleo, L., Cassetta, E., Morelli, G., 2018. The impact of the EU-ETS on the aviation sector: competitive effects of abatement efforts by airlines. Transport. Res. Pol. Pract. 113, 20–34. https://doi.org/10.1016/j.tra.2018.03.032.
Nguyen, M.-A.T., Yu, M.-M., Lirn, T.-C., 2022. Revenue efficiency across airline business models: a bootstrap non-convex meta-frontier approach. Transport Pol. 117, 108–117. https://doi.org/10.1016/j.tranpol.2022.01.007.
Nikolaou, P., Dimitriou, L., 2018. Evaluation of road safety policies performance across Europe: results from benchmark analysis for a decade. Transport. Res. Pol. Pract. 116, 232–246. https://doi.org/10.1016/j.tra.2018.06.026.
Oag, 2019. Decade Delights: Ten Years of Aviation Development. https://www.oag.com/blog//decade-delights-ten-years-of-aviation-development.
Onat, N.C., Kucukvar, M., Afshar, S., 2019. Eco-efficiency of electric vehicles in the United States: a life cycle assessment based principal component analysis. J. Clean. Prod. 212, 515–526. https://doi.org/10.1016/j.jclepro.2018.12.058.
Osterwalder, A., Pigneur, Y., 2010. Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers. John Wiley & Sons.
Pearson, J., Merkert, R., 2014. Airlines-within-airlines: a business model moving East. J. Air Transport. Manag. 38, 21–26. https://doi.org/10.1016/j.jairtraman.2013.12.014.
Pels, E., Njegovan, N., Behrens, C., 2009. Low-cost airlines and airport competition. Transport. Res. E Logist. Transport. Rev. 45 (2), 335–344. https://doi.org/10.1016/j.tre.2008.09.005.
Richardson, C., Budd, L., Pitfield, D., 2014. A hierarchical cluster analysis of the financial performance of US hub airports in relation to lease agreement types. J. Airpt. Manag. 8 (1), 42–56.
Roucolle, C., Seregina, T., Urdanoz, M., 2020. Measuring the development of airline networks: comprehensive indicators. Transport. Res. Pol. Pract. 133, 303–324. https://doi.org/10.1016/j.tra.2019.12.010.
Sarkis, J., Talluri, S., 2004. Performance based clustering for benchmarking of US airports. Transport. Res. Pol. Pract. 38 (5), 329–346. https://doi.org/10.1016/j.tra.2003.11.001.
Soyk, C., Ringbeck, J., Spinler, S., 2017. Long-haul low cost airlines: characteristics of the business model and sustainability of its cost advantages. Transport. Res. Pol. Pract. 106, 215–234. https://doi.org/10.1016/j.tra.2017.09.023.
Soyk, C., Ringbeck, J., Spinler, S., 2018. Revenue characteristics of long-haul low cost carriers (LCCs) and differences to full-service network carriers (FSNCs). Transport. Res. E Logist. Transport. Rev. 112, 47–65. https://doi.org/10.1016/j.tre.2018.02.002.
Soyk, C., Ringbeck, J., Spinler, S., 2021. Effect of long-haul low-cost carriers on North Atlantic air fares. Transport. Res. E Logist. Transport. Rev. 152, 102415 https://doi.org/10.1016/j.tre.2021.102415.
Tapiador, F.J., Burckhart, K., Martí-Henneberg, J., 2009. Characterizing European high speed train stations using intermodal time and entropy metrics. Transport. Res. Pol. Pract. 43 (2), 197–208. https://doi.org/10.1016/j.tra.2008.10.001.
Teece, D.J., 2010. Business models, business strategy and innovation. Long. Range Plan. 43 (2), 172–194. https://doi.org/10.1016/j.lrp.2009.07.003.
Thøgersen, J., 2018. Transport-related lifestyle and environmentally-friendly travel mode choices: a multi-level approach. Transport. Res. Pol. Pract. 107, 166–186. https://doi.org/10.1016/j.tra.2017.11.015.
Tomová, A., Materna, M., 2017. The directions of on-going air carriers' hybridization: towards peerless business models? Procedia Eng. 192, 569–573. https://doi.org/10.1016/j.proeng.2017.06.098.
Tomová, A., Ramajová, L., 2014. Frequent flyer programs and low-cost airlines: ongoing hybridization? Procedia Social and Behavioral Sciences 110, 787–795. https://doi.org/10.1016/j.sbspro.2013.12.923.
Tongzon, J., Heng, W., 2005. Port privatization, efficiency and competitiveness: some empirical evidence from container ports (terminals). Transport. Res. Pol. Pract. 39 (5), 405–424. https://doi.org/10.1016/j.tra.2005.02.001.
Tsoukalas, G., Belobaba, P., Swelbar, W., 2008. Cost convergence in the US airline industry: an analysis of unit costs 1995–2006. J. Air Transport. Manag. 14 (4), 179–187. https://doi.org/10.1016/j.jairtraman.2008.04.005.
Varella, R.R., Frazão, J., Oliveira, A.V.M., 2017. Dynamic pricing and market segmentation responses to low-cost carrier entry. Transport. Res. E Logist. Transport. Rev. 98, 151–170. https://doi.org/10.1016/j.tre.2016.12.010.
Vatankhah, S., Zarra-Nezhad, M., Amirnejad, G., 2019. Tackling the fuzziness of business model concept: a study in the airline industry. Tourism Manag. 74, 134–143. https://doi.org/10.1016/j.tourman.2019.01.022.
Ward, J.H., 1963. Hierarchical grouping to optimize an objective function. J. Am. Stat. Assoc. 58 (301), 236–244. https://doi.org/10.1080/01621459.1963.10500845.
Wasiuk, D.K., Lowenberg, M.H., Shallcross, D.E., 2015. An aircraft performance model implementation for the estimation of global and regional commercial aviation fuel

burn and emissions. Transport. Res. Transport Environ. 35, 142–159. https://doi.org/10.1016/j.trd.2014.11.022.
Wen, C.-H., Chen, W.-Y., 2011. Using multiple correspondence cluster analysis to map the competitive position of airlines. J. Air Transport. Manag. 17 (5), 302–304. https://doi.org/10.1016/j.jairtraman.2011.03.006.
Wilson, R., Lohmann, G., 2019. Airline CEOs: who are they, and what background and skill set are most commonly chosen to run the world's largest airlines? Transp. Res. Interdiscip. Perspect. 2, 100054 https://doi.org/10.1016/j.trip.2019.100054.
Windle, R., Dresner, M., 1999. Competitive responses to low cost carrier entry. Transport. Res. E Logist. Transport. Rev. 35 (1), 59–75. https://doi.org/10.1016/S1366-5545(98)00025-8.
Yang, A.S., Baasandorj, S., 2017. Exploring CSR and financial performance of full-service and low-cost air carriers. Finance Res. Lett. 23, 291–299. https://doi.org/10.1016/j.frl.2017.05.005.
Zhang, A., Hanaoka, S., Inamura, H., Ishikura, T., 2014. Low-cost carriers in Asia: deregulation, regional liberalization and secondary airports. In: Low Cost Carriers. Routledge.
Zhang, K., Chen, Y., Li, C., 2019. Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: the case of Beijing. Tourism Manag. 75, 595–608. https://doi.org/10.1016/j.tourman.2019.07.002.
Zuidberg, J., de Wit, J.G., 2020. The development of long-haul low-cost networks in the North Atlantic airline market: an exploratory data approach. Transport Pol. 95, 103–113. https://doi.org/10.1016/j.tranpol.2020.05.020.