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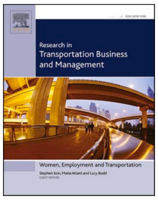

Getting closer to your destination: The role of available surface connections on the supply of low-cost carriers in secondary European tourist airports

Daniel Albalate[a,b,*], Xavier Fageda[a,b]

[a] Observatori d'anàlisi i avaluació de les polítiques Públiques, Universitat de Barcelona, Spain
[b] Universitat de Barcelona & GIM-IREA, Spain

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ABSTRACT

Secondary airports have played a key role in the development of both low-cost carriers and the tourism industry in recent decades. Although they are usually further from tourists' main destination/origin, low-cost carriers take advantage of lower fares to exploit tourists' lower time valuation. Nonetheless, efficient surface commuting is a key attribute of airport accessibility and a source of relative attractiveness in multi-airport systems. Low-cost airlines have recently changed their strategic behavior by opting to spread their presence at primary airports, which represents a challenge for secondary airports that have both declining traffic and high dependency on low-cost carriers. In this paper we evaluate the role of private and public transportation commuting time efficiency in the quarterly market share of secondary airports for a sample of European multi-airport systems between 2018 and 2021. Our results show that relative commuting efficiency– whether public or private –is a determinant of traffic distribution in multi-airport systems. Public authorities might be interested in improving secondary airports' accessibility when other airport policies are constrained, either to reverse their current adverse trend or to efficiently utilize existing capacity in systems with highly congested primary airports.

1. Introduction

Secondary and regional airports – many in multi-airport systems – have helped boost the rapid development of air transport in recent decades and the rise and splendor of Low-Cost Carriers (LCCs) in the early XXI century. LCCs and such airports are closely intertwined - as they also are with tourism - and, therefore, LCCs' business models cannot be understood or separated from the development of these airports (Graham, 2013; Zhang et al., 2008). In LCCs' search for dense point-to-point routes, lower fees, and local and regional government complicity, secondary and regional airports – where LCCs can also usually exert bargaining power (Huderek-Glapska and Nowak, 2016) - become an indispensable part of their competitive advantage that adds to their inherent operational efficiency (Gillen and Lall, 2004). On the other hand, secondary and regional airports often have a unique reason to attract LCCs, which has encouraged their spread and growth (Jimenez et al., 2017) and, with it, boosted tourism.

Therefore, LCCs' management and strategic decisions cannot be analyzed without considering the airports they use to participate in the air transport market. Neither can "low-cost airports" – in Tavalaei and Santalo's (2019) terms- be studied or evaluated without examining the strategic behavior of LCCs and the policy-making that affects airports' attributes and the structural relationship between airport managers and airlines.

In seeking to exchange major airports for distant alternatives, LCCs were initially searching for lower fees and greater bargaining power. This strategy has also meant that LCCs do not aggravate the negative externalities usually linked to major airports such as traffic congestion, pollution, and noise in densely urbanized areas. However, air transportation is an intermediate service, because the real goal of passengers is to get to their specific destination. As a result, commuting from airports to their principal destinations emerges as a need, and the mode of transportation used may also exert negative externalities. Hence, the mode choice and the efficiency of commuting will shape the scale of the social costs. Although this is a concern for policy makers, for LCCs, the distant feature of airports is simply a consequence of their private interest; namely the search for lower fees and better conditions. It is, in fact, an inconvenience, given that commuting costs impose a dis-utility for travelers. Nonetheless, LCCs take advantage of the fact that tourists are willing to spend more time commuting in exchange for lower fares.

Recent evidence points to the end of this strategy, however, with LCCs now more focused on spreading their presence in major airports

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* Corresponding author at: Facultat d'Economia i Empresa, Departament d'Econometria Estadística i Economia Aplicada. John-Maynard Keynes 1-11, Spain.
E-mail addresses: albalate@ub.edu (D. Albalate), xfageda@ub.edu (X. Fageda).

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(Dobruszkes et al., 2017; Wong et al., 2019). Although cost, demand and operational efficiency are still the most important criteria in choosing an airport, recent interest in business travelers and better accessibility (catchment areas) seems to have re-awakened their enthusiasm for major airports (Dziedzic and Warnock-Smith, 2016). Jimenez and Suau-Sanchez (2020) also confirm this pivotal moment, describing two phases in the relationship between LCCs and airports. In the first phase (2001–2008), the rise of LCCs fueled the growth of both primary and secondary airports, with clear contributions to the construction of new small and distant airports and/or the rehabilitation and revitalization of underutilized existing local and regional infrastructures. Because LCCs are oriented towards dense routes and, therefore, to tourist destinations, part of these contributions happened in some of Europe's tourist hotspots and areas surrounding the biggest – and most populated - cities on the continent. On the other hand, the second phase, following the Great Recession, has been characterized by a primary orientation of LCCs to major airports and of a few airports that were keen to support the earliest development of LCCs (See Jimenez and Suau-Sanchez, 2020).

This trend may represent a call for action to concerned public authorities, for three main reasons. First, because the abandonment of secondary airports by LCCs may erode the attractiveness of tourist enclaves served by these airports due to their loss of national and international connectivity. Second, because this trend erodes the efficient utilization of secondary airports' capacity. And third, because when other measures (such as subsidies, taxes, and infrastructure enlargements) are not available in the short/medium term, improving the attractiveness of secondary airports that are under-utilized may contribute to relieving high congestion in primary airports, reducing total social costs.

Because good accessibility - which is determined by the transport services provided- is a fundamental condition of any tourist destination (See Graham et al., 2010), in this paper, we argue that airports' market share in multi-airport systems, particularly that of secondary airports (usually from LCCs), is also determined by how efficient surface transportation is in terms of travel time, as it could be a drawback of further secondary airports and, as a result, of LCCs basing their operations there. Furthermore, by showing the significant role of commuting time, we argue that these journeys seem to be one of many drivers that may explain why LCCs are migrating, wherever possible, to major airports with reduced travel times. Therefore, we suggest that airports with the most inefficient commuting may suffer most from the current trend, leading to traffic leakage that is difficult to reverse (Fu and Kim, 2016). For this reason, improving the surface accessibility of secondary airports may be productive in reversing this trend, and improve the attractiveness of secondary airports.

To study the role of surface transportation efficiency on airports' airline supply, we created a database with all multi-airport cities in Europe and estimate a multivariate econometric model between 2018 and 2021 at airport level to assess the role of commuting time on the share of flights of secondary airports within the multi-airport market.

Our study is clearly related to research that has shown the importance of airport accessibility and catchment areas for their traffic and growth (See Bao et al., 2016; Birolini et al., 2019; Bergantino et al., 2020; Marques and Derudder, 2021; as recent examples, among many others), but it differs in a number of ways. First, many of these papers are based on case studies or use samples from US airports, whereas we have built an international sample of European multi-airport cities to estimate a multivariate econometric model. Second, we focus on the relative market share of the airport, considering the traffic of all airports in the multi-airport system, which is also a novelty in the literature, as far as we are aware. In this regard, this is the first paper that implements an econometric multivariate model to systematically examine the factors that explain the share of secondary airports in multi-airport systems, including demand drivers and proxies for the proportion of leisure travelers. Third, we compare the role of both public and private surface transportation modes, including both road and railway best alternatives in the context of multi-airport systems. As far as we know, no previous study has tested the role of surface transportation modes in explaining the share of secondary airports in multi-airport systems. Fourth, the period considered goes from 2018 to 2021, so that another novelty of our work is that we can assess the effect of the Covid-19 shock on the composition of airport traffic in multi-airport systems.

We are the first to provide econometric evidence that longer commuting times on both public and private transport lead to a lower share of secondary airports. Another novel result is that the share of secondary airports is higher in those cities with higher potential demand for air traffic and with a greater number of leisure travelers. Finally, the huge shock represented by the pandemic seems to have affected secondary airports relatively less than primary airports.

The remainder of the paper is structured as follows. First, we describe the data employed in our analysis and characterize the airports in our sample by providing detailed information. Second, we present the methodology and the variables considered in our empirical strategy. Third, we present and discuss our main results. Finally, we end with some concluding remarks and policy implications.

2. Data source and descriptions of multi-airport systems in Europe

2.1. Data source

Our analysis is based on supply data that have been obtained from RDC aviation (Apex Schedules). RDC provides information on the number of flights per month provided by airlines at route level. The period considered in the econometric analysis goes from 2018 to 2021 with data collapsed at the quarter level to account for the strong seasonal variation that characterizes the aviation market. We use 2019 data at annual level for tables and figures reported for descriptive purposes.

Data on commuting times and distances was collected from direct consultation of Google Maps API (https://www.google.es/maps) during the second week of June 2021. We obtained average commuting times from all airports in a multi-airport system to/from the reference city (downtown), for both private and public transportation (when available). For the latter, the best alternative for public transport was considered when public transport services by both road and railway were available. We created different variables on the relative efficiency of commuting between airports serving downtown areas to evaluate a variety of forms of approaching relative commuting efficiency as a driver of market share. The basic approach was the construction of a Terminal-to-Downtown (and vice versa) time measure (in minutes) for all airports, and we used that to generate variables regarding the relative advantage or disadvantage of those airports in respect to other airports in their multi-airport systems.

We also draw on urban area population data from the United Nations (World Urbanization prospects). These data are publicly available at the following link: https://population.un.org/wup/Download/. Furthermore, we have collected data on income data at country level from the World Bank (World Bank Development Indicators) that can be downloaded from the following link: https://databank.worldbank.org/source/world-development-indicators. We also consider data for the number of bed places in hotels and similar accommodation per inhabitant at regional level (NUTS 2) from Eurostat, which is available at the following link: https://ec.europa.eu/eurostat/databrowser/view/tour_cap_nuts2/default/table?lang=en

Data on the supply of hotels are used to approximate tourism intensity given the lack of information on tourism flows at regional/city level. Data for the number of bed places in hotels and similar accommodation includes the following establishments: Hotels, holiday and other short-stay accommodation, camping grounds, recreational vehicle parks and trailer parks. These data have limitations because they are based on capacity of tourist establishments rather than on occupancy. Eurostat provides data for occupancy measures like arrivals or nights spent at tourist accommodation. However, it does not provide the information for the United Kingdom and Norway that means that these data are not available for London, Oslo, Belfast, and Glasgow, which are relevant cases in our analysis.

Data for income at regional level are available for cities from countries that are members of the European Union. However, these data are only available up to 2019, and therefore the Covid-19 pandemic, which has represented a huge shock in income levels for all countries in 2020 and 2021, is excluded. Hence, we prefer to use income data at the country rather than at the regional level.

Table 1 displays a list of multi-airport cities in Europe. RDC aviation directly provides a variable that groups airports that serve the same city, so we have opted to use the identification of airports and cities that is already available in the database. The sample is based on 24 cities from 12 countries: 16 of these have two airports with commercial flights, two have three airports and the other six have more than three airports. Note that London Heathrow, Paris Charles de Gaulle, Frankfurt, Barcelona, Istanbul Ataturk/New, Moscow Sheremetyevo, Munich and London Gatwick are ranked among the 10 largest airports in Europe. Madrid and Amsterdam are the only cities with airports in the top-10 list of largest airports that are only served by one airport.

The literature on catchment areas and airport competition do support our selection of airports for multi-airport systems. An airport's catchment area is the area surrounding the airport from which it attracts its passengers (Lieshout, 2012). Its size, as well as the airport's market share, are associated with airport choice determinants, such as relative accessibility, fares, frequencies etc. It is usual to consider travel times as the main factor determining the size of a catchment area. For instance, leisure passengers are, in general, willing to tolerate access times of around 2.0 h to reach a chosen airport (Civil Aviation Authority-CAA, 2011; Marcucci and Gatta, 2011). Between 80 and 90% of passengers satisfy this maximum time threshold in more leisure-oriented airports (Starkie, 2008). As is well known, leisure travelers are less sensitive to travel times than business travelers (Pels et al., 2003). In multi-airport systems, catchment areas defined according to travel time do overlap, and since airports cannot price discriminate users according to their locations, this overlap is indicative of potential competition (Starkie, 2008). Indeed, Lieshout (2012) finds that the effective catchment areas become smaller when the same destination is offered by nearby airports.

Table 1
List of Europe's multi-airport cities.

City	Primary airport	Secondary airport(s)
Barcelona	Barcelona (BCN)	Girona (GRO), Reus (REU)
Belfast	Belfast International (BFS)	Belfast city (BHD)
Berlin	Berlin Tegel (TXL)[1]	Berlin Schonefeld (SXF)
Brussels	Brussels -National (BRU)	Antwerp-Brussels North (ANR), Brussels South Charleroi (CRL)
Copenhagen	Copenhagen (CPH)	Copenhagen – Roskilde (RKE)
Dusseldorf	Dusseldorf (DUS)	Dusseldorf – Niederrhein (NRN)
Frankfurt	Frankfurt International (FRA)	Frankfurt – Hahn (HHN)
Glasgow	Glasgow International (GLA)	Glasgow Prestwick (PIK)
Istanbul	Istanbul – New (ISL)[2]	Istanbul – Sabiha Gokcen (SAW)
Kiev	Kiev – Boryspol (IEV)	Kiev – Zhulhany (KBP))
Lyon	Lyon – Saint Exupery (LYS)	Grenoble – Isere (GNB))
London	London -Heathrow (LHR)	London – Gatwick (LGW), London – Luton (LTN), London Southend (SEN), London – Stansted (STN), London City (LCY)
Milan	Milan – Malpensa (MXP)	Milan – Linate (LIN), Milan – Parma (PMF), Milan -Orio al Serio (BGY))
Moscow	Moscow – Sheremetyevo (SVO)	Moscow -Domodevodo (DME), Moscow Vnukovo (VKO)
Munich	Munich – Franz Josef Strauss (MUC)	Memmingen (FMM), Munich – Augsburg – Muehlhausen (AGB)
Oslo	Oslo (OSL)	Oslo (Sandefjord)
Paris	Paris – Charles de Gaulle (CDG)	Paris – Orly (ORY), Paris – Beauvais-Tille (BVA), Paris – Vatry (XCR), Le Bourget (LBG)
Rome	Rome – Fiumicino (FCO)	Rome Ciampino (CIA)
Stockholm	Stockholm – Arlanda (ARN)	Stockholm – Bromma (BMA), Stockholm – Vasteras/Hasslo (VST), Stockholm – Skavsta (NYO)
Tenerife	Tenerife South (TFS)	Tenerife North (TFN)
Turin	Turin – Caselle (TRN)	Cuneo – Levaldigi (CUF)
Verona	Verona (VRN)	Verona – Montichiari (VBS)
Venice	Venice – Marco Polo (VCE)	Venice – Treviso (TSF)
Warsaw	Warsaw – Frederic Chopin (WAW)	Warsaw – Modlin (WMI)

Notes: 1. Berlin Brandenburg (BER) since fourth quarter of 2020. 2. Istanbul Atakurk (IST) until 2018.

2.2. *Descriptions of multi-airport systems in Europe*

Table 2 provides some descriptive statistics that allow us to characterize multi-airport cities in Europe. Data in Table 2 shows the high diversity across cities in our sample in terms of population, income, and hotel supply. Our sample includes huge metropolis like London, Paris, Moscow and Istanbul, with each having populations close to or greater than 10 million inhabitants, large urban areas with a population that ranges between three to five million (Barcelona, Berlin, Milan, Rome) and one to three million inhabitants (Copenhagen, Lyon, Turin, Warsaw, etc.) and mid-size cities with around half-a-million inhabitants (Belfast, Dusseldorf, Venice and so on). Cities' income from countries in the center and north of Europe may be four or five times greater than that in cities from Eastern Europe. Finally, our sample includes cities with a dense supply of hotels per inhabitant such as, for example, Barcelona, London, Tenerife and Venice, and cities with more modest numbers such as, for example Belfast, Dusseldorf and Warsaw.

Figs. 1 and 2 provide information on the share of flights of primary and secondary airports over total flights in city airports. In 11 cities, more than 90% of flights are concentrated in primary airports, including: Barcelona, Copenhagen, Dusseldorf, Frankfurt, Glasgow, Lyon, Munich, Oslo, Turin, Verona and Warsaw. In particular, the role of

Table 2
Descriptive statistics of multi-airport cities (2019).

City	Population (Urban area). 000 inhabitants	Income per capita (country). Euros	Bedplaces in hotels (Region – NUTS 2). Bedplaces per 000 inhabitants	Number of airports
Barcelona	5541	26,430	45.7	3
Belfast	626	37,830	13.2	2
Berlin	3556	41,510	34.4	2
Brussels	2065	41,460	31.8	3
Copenhagen	1333	53,760	27.6	2
Dusseldorf	628	41,510	14	2
Frankfurt	768	41,510	28.7	2
Glasgow	1666	37,830	13.2	2
Istanbul	14,967	8230	12.2	2
Kiev	2973	2076	N.A	2
Lyon	1704	36,140	21.40	2
London	9176	37,830	49.9	6
Milan	3136	29,880	19.6	4
Moscow	12,476	9763	N.A	3
Munich	1521	41,510	40.9	3
Oslo	1026	67,730	33.9	2
Paris	10,958	36,140	25.6	5
Rome	4234	29,980	31.2	2
Stockholm	1608	46,390	31.4	4
Tenerife	364	26,430	117.2	2
Turin	1789	29,980	18.7	2
Verona	625	29,980	44.6	2
Venice	636	29,980	44.6	2
Warsaw	1775	13,900	13	2

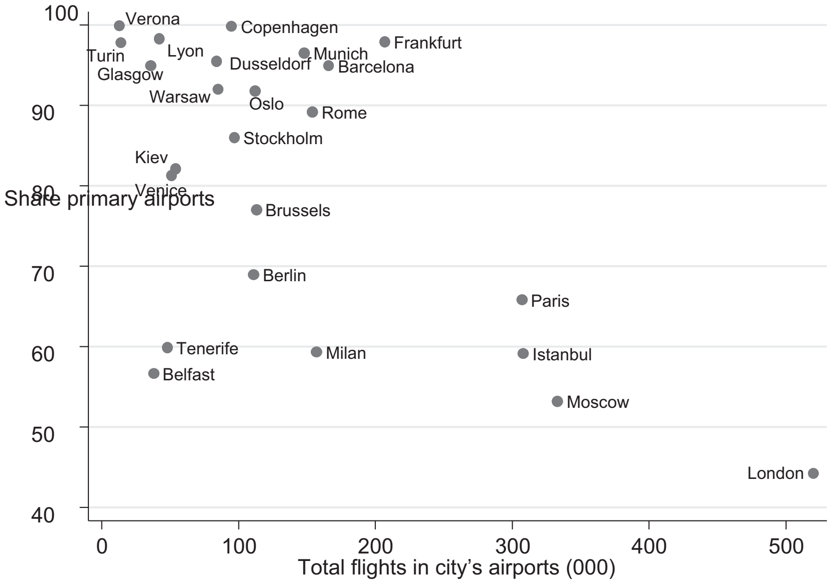

Fig. 1. Share of primary airports over total flights in city airports (2019).

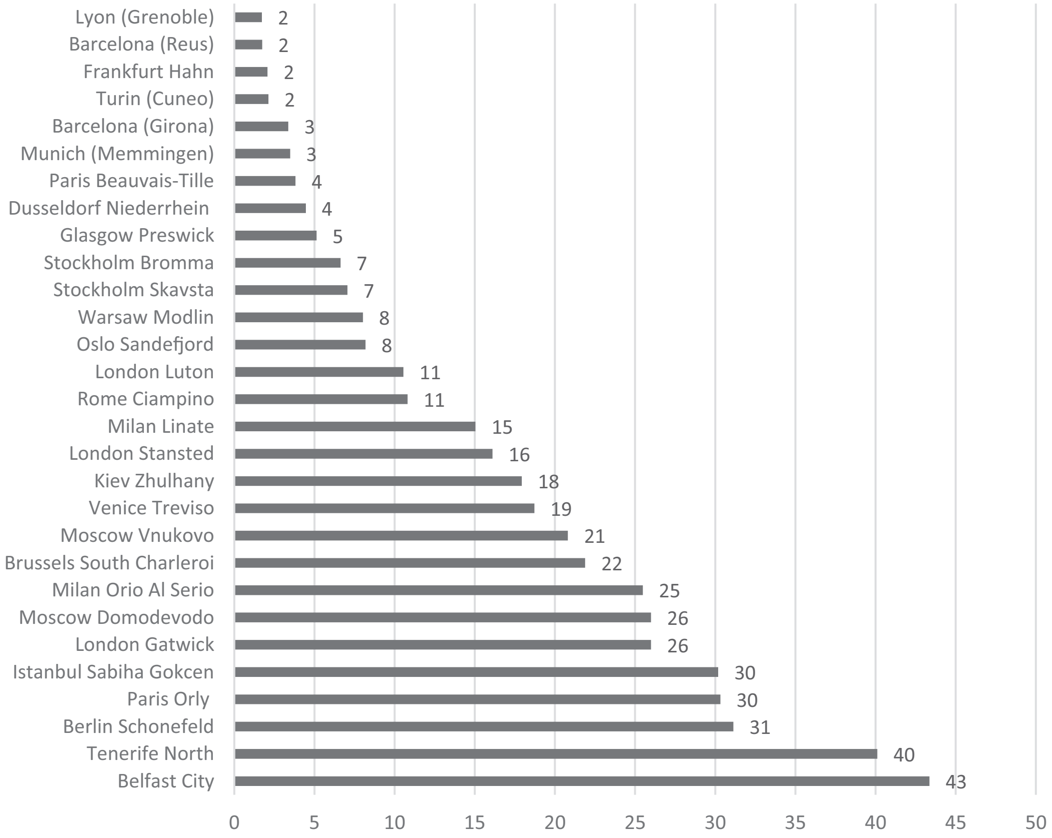

Fig. 2. Share of secondary airports over total flights in city airports (2019).

secondary airports is marginal in Copenhagen and Verona. In five cities, primary airports concentrate between 70% and 90% of total flights: Brussels, Kiev, Rome, Stockholm and Venice. The share of primary airports is below 70% in eight cities. The cities with a more balanced distribution of traffic between primary and secondary airports are the biggest cities in our sample, which are able to generate demand for a high number of flights: London, Paris, Istanbul and Moscow. However, secondary airports also play a very significant role in city traffic in Belfast, Berlin, Milan, and Tenerife.

Figs. 3 and 4 show a scatter plot that relate the share of each airport's flights over total city airport flights with the time spent on commuting in private and public transport options. Data in these figures provide preliminary evidence of a clear negative relationship between shares and time spent on commuting. As might be expected, many airports are well above or well below the mean fitted values of such a relationship; so that other additional factors are driving the share that each airport has over

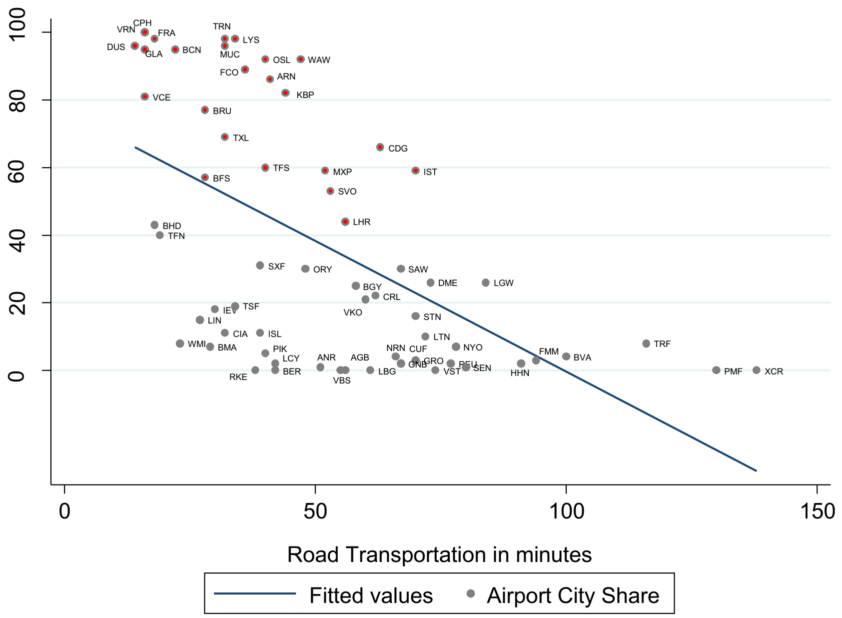

Fig. 3. Scatter plot (Share of airports over total flights in city airports vs commuting time on private transport).
Notes: In red primary airports. Table 1 provides the codes for each airport.

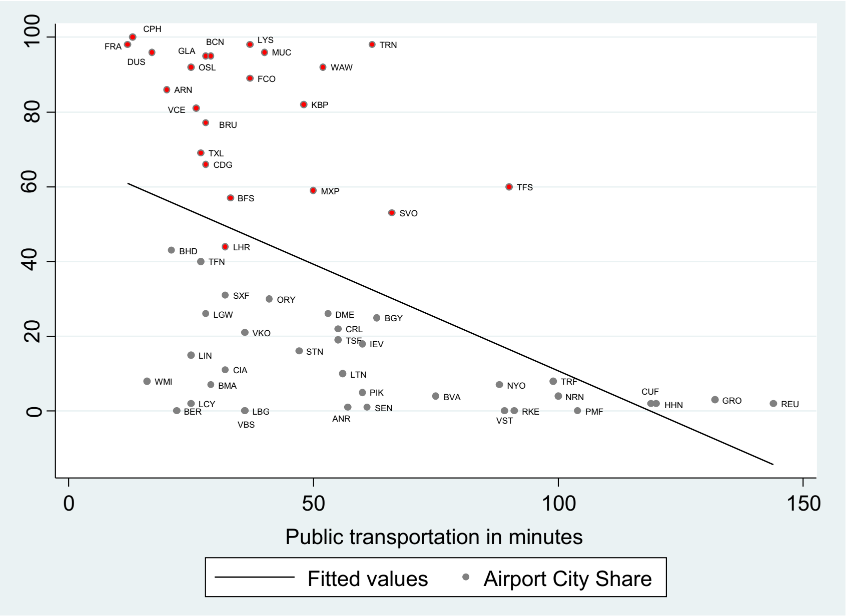

Fig. 4. Scatter plot (Share of airports over total flights in city airports vs commuting time on public transport).
Notes: In red primary airports. Table 1 provides the codes for each airport.

total city airports flights.

Figs. 5 and 6 provide additional information on the airports included in our sample. Data in these figures shows the type of airlines with most presence in each airport. In this regard, the aviation market in Europe is dominated by two different types of airlines. Network airlines, many of them former flag carriers, are airlines integrated into one of the three global alliances (Oneworld, Star, SkyTeam). They operate hub-and-spoke networks and most of their passengers are connecting passengers. In contrast, low-cost airlines operate point-to-point routes and most of their passengers are non-stop travelers. Chapter 5.1 of the Manual on the Regulation of International Air Transport published by the International Civil Aviation Organization (ICAO) defines a low-cost airline as "an air carrier that has a relatively low-cost structure in comparison with other comparable carriers and offers low fares and rates". Based on these criteria, the ICAO provides a list of low-cost airlines that we use here to establish our category of low-cost airlines. Airlines that cannot be considered as either network or low-cost airlines include charter airlines offering scheduled flights, regional carriers operating totally independently of network airlines or airlines with a mixed business model.

Several primary airports in our sample serve as a hub of a network airline. Hub airports with the hubbing airlines in parenthesis are: Brussels National (SN Brussels), Copenhagen, Oslo and Stockholm Arlanda (SAS), Frankfurt International and Munich Franz Josef Strauss (Lufthansa), Istanbul Ataturk/New (Turkish airlines), London Heathrow (British Airways), Moscow Sheremetyevo (Aeroflot), Paris Charles de

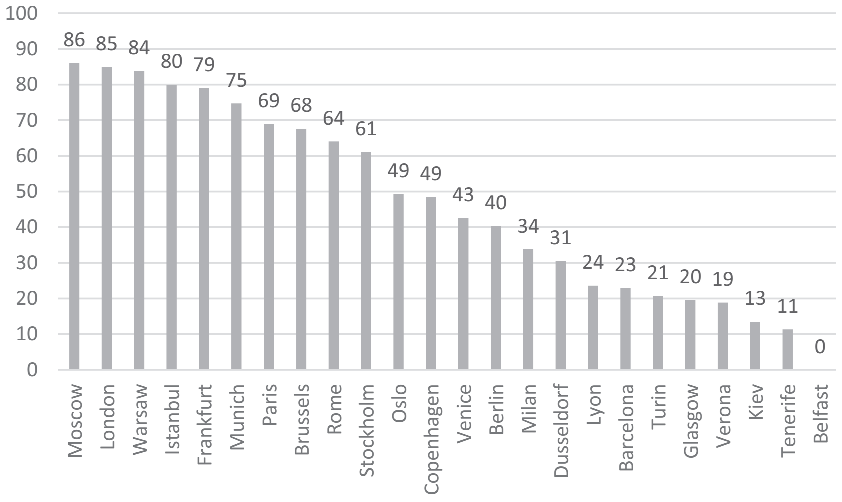

Fig. 5. Share of network airlines over total flights in primary airports.

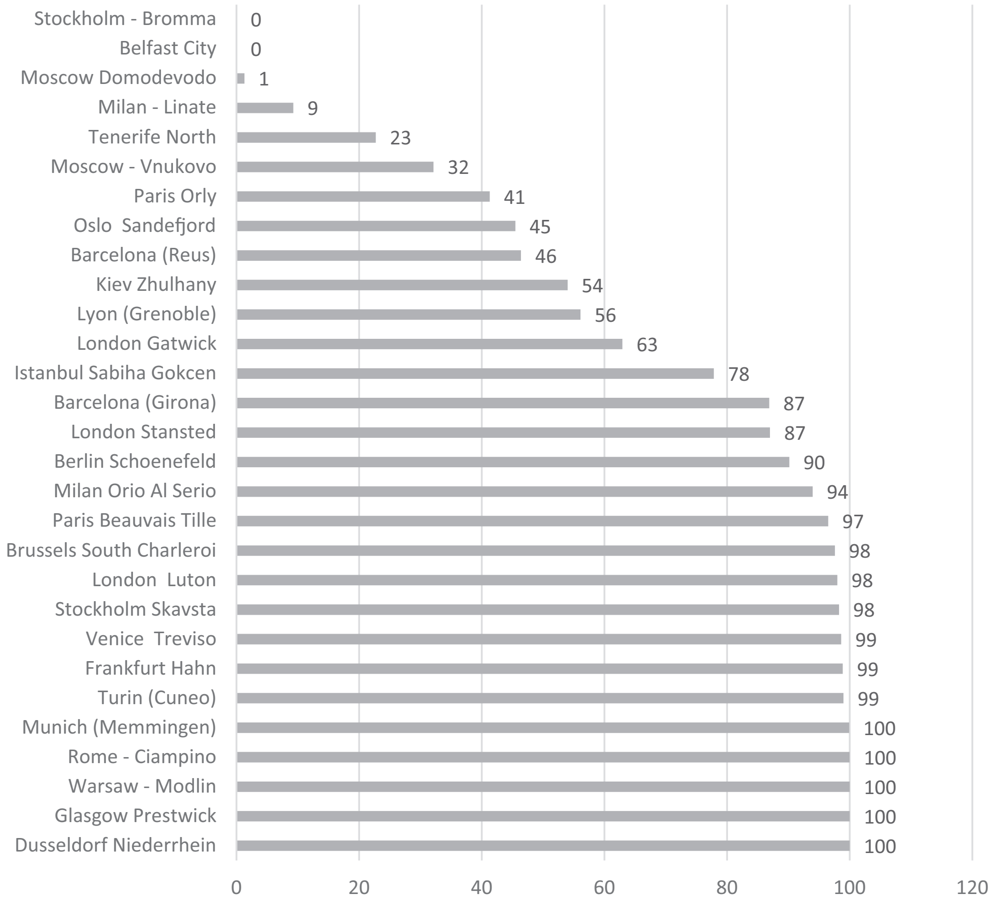

Fig. 6. Share of low-cost airlines over total flights in secondary airports.

Gaulle (Air France), Rome Fiumicino (Alitalia) and Warsaw Chopin (LOT). In all these airports, network airlines concentrate more than 60% of total flights with the exception of Oslo and Copenhagen, which has a share of 49%. In the remaining primary airports, low-cost airlines have higher shares than network airlines.

Low-cost airlines have a high presence (or are dominant) in most of the secondary airports in our sample. Ryanair concentrates more than 70% of flights in Barcelona (Girona, Reus), Brussels South Charleroi, Turin (Cuneo), Paris Beauvais Tille, Dusseldorf Niederrhein, Frankfurt Hahn, Milan Orio Al Serio, Glasgow Prestwick, London Stansted, Rome Ciampino, Warsaw Modlin and Venice Treviso. In addition, it concentrates around half of total flights in Berlin Schonefeld, London Stansted, Munich (Memmingen) and Stockholm Skavsta. Easyjet has a share of between 40 and 50% at several London airports (Gatwick, Luton, Southend), Lyon (Grenoble) and Berlin Schonefeld. These numbers clearly illustrate a different strategic choice of airports between the two leading low-cost airlines in Europe. Despite Ryanair's movement of operation to primary airports in cities like Barcelona, Brussels or Rome, the airline continues to largely determine traffic at secondary airports outside of London.

There are some exceptions to the major role that those low-cost airlines (mainly Ryanair) usually play in secondary airports. Such exceptions are Belfast city, Moscow Vnukovo, Stockholm Bromma and Tenerife North that have a leading position of regional carriers like Flybe, Utair, Braathens or Binter. In addition, Moscow Domodevodo is the only secondary airport that is a hub of a network airline, S7. Finally, network airlines like Alitalia have a significant presence at Milan Linate.

Notes: Low-cost airlines in our sample are: Air Arabia, Air Transat, Atlas Global, Blue Air, Blue Panorama, Condor, Corendon, Easyjet, Germania, Hop!, Level, Meridiana, Niki, Norwegian, Pegasus, Pobeda, Ryanair, SmartWings, SunExpress, TUIFly, Transavia, Volotea, Vueling, WOW, Wizz Air, XL Airways.

3. Econometric analysis

In this section, we estimate a multivariate econometric model to identify the determinants of the share of secondary airports in our sample of cities, with a particular focus on the effect of commuting times on private and public transportation. We use quarterly data from 2018 to 2021, totaling 536 observations. Note that the sample used in the regressions is centered on secondary airports.

Demand in air transportation is usually modelled by applying a gravity model. In this regard, Grosche et al. (2007), Wadud (2013) and Chang (2014) provide detailed reviews of gravity models and list significant factors identified in them. In gravity models, demand depends on socio-economic attributes that can be understood as attraction factors. These factors include mainly population and income, although other variables may also be considered according to the purposes and the context of the study. Considering this, the economic feasibility of air services requires a minimum amount of traffic given that density economies are a relevant characteristic of the airline industry (Berry et al., 2006; Brueckner and Spiller, 1994; Caves et al., 1984). Indeed, airlines may only minimize costs in routes with a sufficiently large volume of traffic so that they may operate with larger aircrafts at higher load factors. It has also been shown that network carriers have a higher proportion of business passengers than low-cost airlines, while low-cost airlines have a higher proportion of leisure passengers (Fageda and Flores-Fillol, 2012a, 2012b). Business passengers are more sensitive to time than leisure travelers, while leisure travelers are more sensitive to prices than business travelers (see Brons et al., 2002).

In multi-airport systems, primary airports have generally relevant advantages in terms of location that make them more attractive for time-sensitive passengers and capacity that allow airlines to better exploit density economies. However, growth in primary airports in cities with high demand may be affected by congestion problems.

Thus, secondary airports may only be able to generate significant flows of traffic in cities with a high demand for air services and in cities that attract many leisure travelers, like tourists. In this context, the quality of the surface connections between the secondary airport and the core city may also have a relevant influence on secondary airports' traffic.

We proxy the air traffic that a city can potentially generate by considering variables of population and income. In addition, we proxy the relevance of leisure travelers by including a measure of tourism intensity and the proportion of traffic channeled by low-cost airlines. Controlling for these variables, the main goal of the econometric analysis is to test the impact of the quality of surface connections.

Taking all this into account, the equation to be estimated for airport *a* in year *t* and quarter *q* is as follows:

$$
\begin{aligned}
Share\_secondary\_airport_{atq} = {} & \beta_0 + \beta_1 Commuting\_private_a \\
& + \beta_2 Commuting\_public_a \\
& + \beta_3 Population\_urban\_area_{at} \\
& + \beta_4 Income\_country_{at} \\
& + \beta_4 Tourism\_per\_capita\_region_{at} \\
& + \beta_5 Share\_low - cost\_airlines_{atq} \\
& + \beta_6 Hub\_primary\_airport_a \\
& + \beta_7 Number\_airports_a + + \delta_i + \lambda_y + \gamma_q + \varepsilon_{ym}
\end{aligned}
\tag{1}
$$

The dependent variable in this model is the share of secondary airports. The main explanatory variables are those that capture the time costs in terms of commuting from the secondary airport to the center of the core city. These variables are named Commuting_private and Commuting_public although we run different specifications of Eq. (1) given that we consider different indicators of commuting costs.

Given that commuting costs impose a dis-utility for travelers, we may expect a lower demand for flights from/to secondary airports that are farthest from the city center, either in terms of distance or travel time. In this regard, we consider different variables to capture the role of commuting costs in explaining the share of secondary airports. First, we use the commuting travel time (in minutes) with public and private transport options. These variables are considered separately because they are highly correlated: so that multicollinearity may prevent us from identifying the specific effect of each variable when considered jointly. We expect a negative sign for both variables. Second, we consider the disadvantage in commuting travel time of secondary airports in relation to primary airports both with public and private transport options. In this regard, we have calculated the commuting travel time from primary and secondary airports to the center of the core city both with public and private transport options. Next, we build a variable that is measured as the rate of the commuting time from the secondary airport in relation to the commuting time from the primary airport. Like previous variables, the disadvantage in commuting travel time variables is also affected by the multicollinearity problem, so they are estimated separately. Again, we expect a negative sign for both variables.

We also use different indicators of the commuting costs to overcome the multicollinearity problem so that we can jointly consider variables for public and private transport options. We run a regression including the commuting travel time with private transport options and a dummy variable for fast public transportation. This dummy variable takes the value one if the travel time in public transport is less than 10 min higher than on private transport. Note that in a few cases public transport may be even faster than private transportation. Results are not altered if we consider different time thresholds (from five to 20 min) for defining our dummy variable. We expect a negative sign for the travel time variable for private transport and a positive sign for the dummy variable for fast public transport. Finally, we consider the road distance from the secondary airport to the city center. This latter variable has the advantage that it is not affected by the variability of the travel time, which is conditioned on the levels of traffic at each specific time.[1] In this specification, we also include a variable for speed on public transport that is defined as the commuting travel time in minutes per kilometer on public transport. We expect a negative sign for both variables.

As mentioned above, we include the population of the urban area and income per capita at country level as drivers of demand. Indeed, demand for air services is expected to be higher in more populated cities and in cities from richer countries. Hence, airlines in secondary airports from high-demand cities may be able to exploit density economies. In

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[1] Teixeira and Derudder (2021) recently showed that actual catchment areas in New York may vary over time during the same day between peak and valley hours, mainly due to variable congestion levels.

addition, primary airports in those cities may be subject to higher levels of congestion both due to high demand and difficulties in expanding facilities in densely populated and richer territories. Thus, we expect a positive sign for these variables.

Another relevant factor that needs to be considered is the proportion of leisure travelers that are more sensitive to fares and less sensitive to time than business travelers. In this regard, we consider tourism per capita proxied through the number of bed places per inhabitant in hotels or similar accommodation. Tourists have a greater willingness to incur commuting costs than business passengers, so that those cities that receive many tourists may have secondary airports with more traffic. In addition, we include a variable that measures the share of low-cost airlines at the secondary airport, considering that a high proportion of travelers channeled by low-cost airlines are leisure travelers. To date, low-cost airlines have been able to reduce the costs of operating short-haul routes by implementing a business model based on the intensive use of aircraft and crews, lower labor costs and a simpler management model, which involves using only one type of plane and a single fare class (Graham, 2009). The low-cost airline with greatest presence in our sample is Ryanair. The leading airline in Europe has also saved costs by operating at secondary airports with low congestion and low airport charges (in some cases airport charges have been in practice negative due to the subsidies received from governments and airport operators). Low-costs translate to lower fares so that low-cost airlines may be able to generate more demand for the secondary airport than other types of airlines. Furthermore, the relative disadvantage of secondary airports in terms of commuting costs may have lesser relevance when the proportion of leisure travelers is higher. Overall, we expect a positive sign for these variables.

We also consider a dummy variable that takes the value one for those secondary airports in cities where the primary airport is a hub of a network airline. Hub airports have much more traffic than is generated by local demand, as a significant percentage of their passengers are connecting passengers. Thus, we expect a negative sign for this variable. An additional control is the number of airports that serve the city. The greater the number of airports serving the same city, the greater the competition between them to capture the traffic generated by that city. Hence, we expect a negative sign for this variable.

We also include quarter dummies to account for the strong seasonality that characterizes the aviation market with higher demand in the spring, and particularly in the summer. Furthermore, we add year dummies to control for yearly effects that are common to all city-pairs. In particular, the dummies for 2020 and 2021 allow us to examine the influence of the Covid-19 pandemic on the distribution of traffic between primary and secondary airports. Standard errors are robust to heteroscedasticity.

Table 4
Descriptive statistics of the variables used in the empirical analysis.

	Mean	Standard deviation	Min. value	Max. value
Share of secondary airports (percentage)	0.126	0.134	0	0.728
Minutes on private transport	63.077	28.345	18	138
Minutes on public transport	66.771	34.064	21	144
Disadvantage secondary/primary on private transport (minutes)	29.848	39.943	−63	116
Disadvantage secondary/primary on public transport (minutes)	23.375	28.168	−25	78
Dummy for fast public transport	0.732	0.443	0	1
Road distance (kms)	62	39.858	7.7	163
Minutes per km on public transport	1.476	1.129	0.4	7.1
Population_urban area (million inhabitants)	4.363	4.287	0.360	15.415
Income_country (thousand dollars)	32.737	13.070	2.609	69.71
Tourism per capita_region (bedplaces in hotels per inhabitant)	33.514	18.921	11.9	117.2
Share Low-cost airlines (percentage)	0.643	0.383	0	1
Hub primary airport	0.630	0.483	0	1
Number of airports	3.328	1.423	2	6

Table 4 shows the descriptive statistics of the variables used in the econometric analysis. The mean share of secondary airports is around 13% although with a high variability, with values ranging from 0% (in some quarters) to 73%. The minutes in commuting on public and private transport are similar with mean values of 63 and 66 min respectively. The variability of the disadvantage variables for commuting on public and private transport is particularly high, with values ranging from negative to positive values. The variability in all control variables is also remarkably high.

Table 5 shows the correlation matrix of the dependent variable and the variables capturing commuting costs. In general, the numbers reported in this table indicate the expected relationships between the variables 'share of secondary airports' and 'commuting time costs', except for the variable minutes per km in public transportation that, in turn, is negatively correlated with distance. As expected, we find a strong correlation between the different variables that measure commuting costs on public and private transport, except for the dummy variable for fast public transportation that is only strongly (negatively) correlated with the variables based on travel time on public transport.

4. Results

Table 6 shows our results. The estimation is made using the generalized linear model with fractional response variables to take into account that the dependent variable is expressed as a share with values between 0 and 1.[2] Fractional models are related to binary response models like probit or logit where the dependent variable is a dichotomous variable that takes the value 0 or 1. However, instead of estimating the probability of being in one category of a dichotomous variable, the fractional model typically deals with variables that take all possible values in the unit interval (from 0 to 1). This is commonly used in models where the dependent variables are proportion rates, indexes from 0 to 1 or a share; as is the case in our context. The standard linear model in these settings is not consistent.

Regarding the controls, we find that the share of secondary airports is higher in more populated cities given that the variable of population is positive and statistically significant in all regressions. Hence, cities with greater demand and likely more congested primary airports have secondary airports with relatively more traffic. Results for the income variable go in the same line, although the variable is only statistically significant in some regressions. In all regressions, the tourism variable is positive and statistically significant, suggesting that cities that receive more tourists have secondary airports with more traffic share. In a similar vein, in most regressions the share of low-cost airlines has a positive and significant impact on the share of secondary airports, so that these airlines may be able to generate more traffic than other airlines at secondary airports. Thus, we find evidence that the share of secondary airports is greater in those cities that have more demand and, in those cities, where the proportion of leisure travelers is higher. Furthermore, as expected, the share of secondary airports is lower in cities with a primary airport that is a hub of a network airline, and in cities with a greater number of airports.

It is also worth mentioning that the dummy variables for 2020 and 2021 take positive values, with the coefficient for 2021 being particularly high. However, these dummy variables are not statistically significant. This means that the mean effect (for 2021) is high but with a considerable dispersion between the cities and airports considered. Thus, we do not find clear evidence that the pandemic has changed the

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[2] See Papke and Wooldridge (1996) for details on this econometric method.

Table 5
Correlation matrix of selected variables.

	Share secondary	Minutes private	Minutes public	Disadvantage private	Disadvantage public	Fast public	Distance	Minutes per km public
Share of secondary airports	1							
Minutes on private transport	−0.404	1						
Minutes on public transport	−0.527	0.615	1					
Disadvantage secondary/primary on private transport	−0.544	0.832	0.800	1				
Disadvantage secondary/primary on public transport	−0.643	0.555	0.908	0.800	1			
Dummy for fast public transport	0.332	0.058	−0.604	−0.281	−0.599	1		
Road distance (kms)	−0.539	0.876	0.817	0.936	0.785	−0.237	1	
Minutes per km on public transport	0.233	−0.562	−0.227	−0.262	−0.561	−0.225	−0.579	1

Table 6
Estimation results (fractional response model).

	Dependent variable: Share of secondary airports					
	(1)	(2)	(3)	(4)	(5)	(6)
Minutes on private transport	−0.031 (0.003) ***	–	–	–	−0.026 (0.002) ***	
Minutes on public transport	–	−0.028 (0.001) ***	–	–	–	
Disadvantage secondary/primary on private transport	–	–	−0.034 (0.002) ***	–	–	
Disadvantage secondary/primary on public transport	–	–	–	−0.029 (0.001) ***	–	
Dummy for fast public transport	–	–	–	–	1.416 (0.190)***	
Road distance (kms)	–	–	–	–	–	−0.027 (0.002) ***
Minutes per km on public transport	–	–	–	–	–	−0.438 (0.140) ***
Population_urban area	0.142 (0.015)***	0.112 (0.014)***	0.090 (0.013)***	0.095 (0.015)***	0.135 (0.014)***	0.083 (0.014)***
Income_country	−0.004 (0.006)	0.010 (0.005)*	0.010 (0.005)*	0.020 (0.005)***	0.002 (0.006)	−0.007 (0.005)
Tourism per capita_region	0.009 (0.002)***	0.007 (0.002)***	0.007 (0.002)***	0.004 (0.001)**	0.007 (0.001)***	0.007 (0.002)***
Share Low-cost airlines	0.231 (0.136)*	0.322 (0.123)***	0.618 (0.138)***	0.611 (0.130)***	0.547 (0.127)***	0.145 (0.177)
Hub primary airport	−0.426 (0.107) ***	−0.628 (0.106) ***	−0.479 (0.104) ***	−0.396 (0.113) ***	−0.758 (0.116) ***	−0.529 (0.102) ***
Number airports	−0.100 (0.049)**	−0.261 (0.043) ***	−0.254 (0.040) ***	−0.224 (0.033) ***	−0.172 (0.048) ***	−0.161 (0.043) ***
Year 2019	−0.068 (0.121)	−0.065 (0.112)	−0.114 (0.117)	−0.112 (0.113)	−0.064 (0.112)	−0.077 (0.115)
Year 2020	0.009 (0.128)	0.016 (0.121)	0.006 (0.123)	0.018 (0.119)	0.043 (0.119)	−0.001 (0.125)
Year 2021	0.156 (0.126)	0.192 (0.118)*	0.164 (0.118)	0.182 (0.115)	0.193 (0.127)	0.192 (0.122)
Intercept	−0.673 (0.252) ***	0.159 (0.225)***	−1.770 (0.232) ***	−1.790 (0.208) ***	−2.084 (0.283) ***	0.045 (0.506)
Log pseudolikelihood	−133.164	−127.379	−128.354	−124.551	−127.809	−129.381
AIC	0.549	0.527	0.533	0.533	0.532	0.542
R2-adjusted	0.359	0.479	0.453	0.523	0.470	0.411
F-test (Joint sign.)	23.31***	41.12***	31.77***	45.32***	32.05***	29.56***
Number obs.	536	536	536	536	536	536

Notes: Standard errors in parentheses (robust to heterocedasticity). All regressions include unreported quarter fixed effects. Statistical significance at 1% (***), 5% (**), 10% (*).

distribution of traffic between primary and secondary airports. However, it seems that the huge shock represented by the pandemic has affected secondary airports relatively less than primary airports. A potential explanation for this is that long-haul travel has been even more affected than short-haul flights for the pandemic, and long-haul traffic is concentrated in primary airports.

Results for the main variables of the analysis work as expected. We find strong evidence that longer commuting times on both public and private transport lead to a lower share for secondary airports. These results hold for all considered variables. The variables of travel time (minutes in absolute values, disadvantage of secondary vs primary airports) and road distance are negative and statistically significant, while the variable that measures the speed of public transportation is also negative and statistically significant, meaning that slower public transport implies less share for secondary airports. In a similar vein, the dummy for fast public transport is positive and statistically significant. The size of the coefficients suggests that a one-minute saving in commuting time or a one-minute reduction in the commuting time gap between the secondary and primary airports leads to a two/three-percentage point increase in the secondary airport share.

Fig. 7 shows the estimated average marginal effects for the commuting variables. Such marginal effects are strong with values close or higher than one for all variables. In addition to the statistical significance reported in the table above, the numbers in this figure show that the magnitude of the impact that commuting time has on the share of secondary airports is very strong.

These results are consistent with previous literature in several aspects. In particular, it is consistent with papers evaluating the cost of time and expense of arrival at airports as determinants of passengers' choices (Harvey, n.d.; Pels et al., 2001; Skinner, 1976).

Table A1 in the appendix shows the results of additional regressions that include a variable for the popularity of Airbnb and Vrbo short-term rentals as covariate. These data are publicly available at this link: https://www.airdna.co/vacation-rental-data/app. This variable is

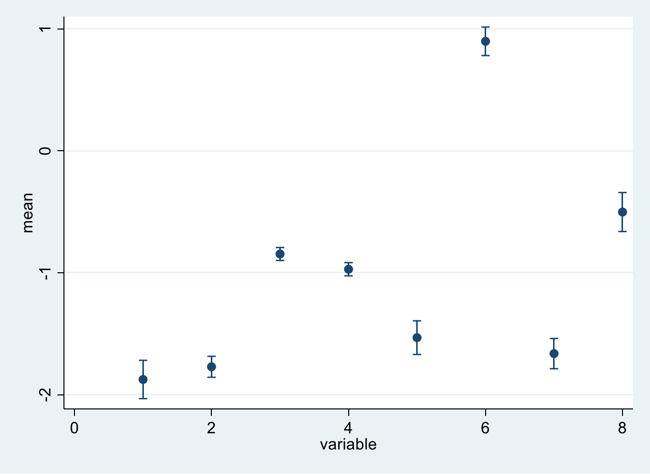

Fig. 7. Estimate of average marginal effects for commuting variables.
Note: 1) Minutes on private transport (regression 1). 2) Minutes on public transport. 3) Disadvantage secondary/primary on private transport. 4) Disadvantage secondary/primary on public transport. 5) Minutes on private transport (regression 5). 6) Dummy for fast public transport. 7) Road distance. 8) Minutes per km on public transport.

strongly correlated with the population variable (correlation is 0.88), so that multicollinearity prevents us from identifying the specific effect of population and Airbnb variables when included in the same regression. Thus, regressions in Table A1 exclude population. The adjustment of the model is slightly worse with smaller R^2 and some unsurprising results as the negative and statistically significant impact of the income variable in some of the regressions. However, results for the different variables that capture commuting times on both public and private transport are like those from previous regressions. Interestingly, the variable of Airbnb and Vrbo popularity is positive and statistically significant in most regressions. Hence, these regressions provide additional evidence that the share of secondary airports is higher in those cities that generate more tourism.

Discussion and conclusions

Although the ties between LLCs and secondary airports remain strong, recent changes in the business strategies of these airlines, with a greater interest in increasing their offer at main airports, are beginning to put some airport managers under pressure. Declines in traffic at regional and secondary airports and their indirect effects on the territories they serve are the obvious consequence of such change in LCCs' airport choice strategies. Our results confirm the importance of the relative efficiency of secondary airport transport connections in multi-airport European systems. We measured access travel time of private and public transportation modes using different variables and found consistent results. Econometric estimates show that all measures of transport accessibility employed are highly statistically significant, which means that they contribute to increasing the market share of secondary airports in European multi-airports systems.

This evidence in the new trend context suggests that regional and secondary airports with relatively inefficient commuting times or worse accessibility might suffer more than other airports that are better or more efficiently connected. As a result, more traffic leakage may occur under this new trend.

These leakages that are explained by airline migration, decreased numbers of routes or frequencies, might be of particular concern for local and regional authorities because they are difficult to reverse and tend to exacerbate over time (Fu and Kim, 2016). Given the economic impact on the regions served by secondary airports, airport managers and governments will be in the spotlight - and traditional recipes and tools to attract airlines, such as co-marketing agreements, direct subsidies, discounts on airport charges and guaranteed-revenue schemes (see Laurino and Beria, 2014) might be intensified with uncertain results.

In the worst cases (highest impact), some airports might stop operations entirely due to abandonment by leading LCCs if they are highly dependent on them, while at others public authorities might engage in desperate interventions to keep them running. This might lead to a disproportionate waste of public resources with the sole aim of maintaining LCCs in response to pressure exerted by economic and political regional lobbies. One example of such desperation is described in Albalate et al. (2018), where the authors detail how the decline of passengers at Girona Airport (from more than five million in 2008 to about two million passengers in 2017) led to proposals about connecting the airport to the high-speed rail network, which would allow more expensive commuting to Barcelona – if large subsidies are not granted -, without offering time savings to the share of passengers traveling to/from Barcelona in respect to current bus services. And this is without counting the investment and time costs for other high-speed rail passengers. Because LCCs face lower entry/exit barriers than network carriers, which can make it easier for them to start or cease operations (Efthymiou et al., 2016), their supply is necessarily more elastic than that of legacy carriers.

In addition to 'rebumping' the contribution of secondary airports to the immediate territory they serve, there are other policy goals that may motivate the interest of public authorities to manage and increase their share within their multi-airport system. For instance, some primary airports are increasingly congested - or are expected to be highly congested - in the coming years, which is expected to bring with it negative externalities and social costs. The role of secondary airports, as alternative channels of tourist demand might be of interest, especially because this might avoid the necessity of investing in airport enlargements.

In this context, there are five different airport policy instruments that can contribute to changing the trends in the distribution of airport traffic that make up a multi-airport city system. However, the implementation of these measures must take into consideration the high complexity of the airlines-airport-destination authority relationships (See Papatheodorou, 2021). In first place, it is possible to grant subsidies (directly or indirectly) to LCCs for operating in secondary airports. Secondly, there is the possibility of investing in expanding the capacity of the main or secondary airport(s). Thirdly, it is to modify airport charges, keeping in mind that the LCCs tend to react more strongly to the changes in charges than the network carriers. In this sense, the main charges are linked to the land fees that relate to the weight of the plane and the fees per passenger that relate to the destination (national, European Union, rest of the world) as well as to the type of passenger – with discounts to connecting passengers-. In fourth place, we highlight the role of incentives for local tourism service providers to improve their destination product offer connected to the use of secondary airports. Finally, a fifth element is the improvement of airports' accessibility or connectivity with the main nodes of demand by decreasing travel times from the secondary airport to the main city, which is the aspect that we have focused on in this research.

Our findings indicate that improving accessibility and surface transportation efficiency may deliver significant market share gains. This is consistent with the results of Koster et al. (2011), who estimated high air travelers' willingness to pay for airport accessibility improvements. This is also true for low-cost airline passengers, as Birolini et al. (2019) found that these passengers are not exclusively cost-driven when confronted with the access mode choice but do place considerable value on access time savings. The required investments may also have local support, as shown by Efthymiou and Papatheodorou (2015), who found that (Greek) domestic passengers are more than willing to engage in cost-sharing to develop intermodal passenger transport improvements.

It also implies that improving the accessibility of more distant secondary airports may improve the efficiency of the multi-airport system strategy (Yang et al., 2016). In this case, public authorities may incorporate on their agenda possible improvements in connections. This might be of particular importance where other instruments are exogenously restricted. For instance, if charges are rigid in nature due to regulation; if subsidies are controversial due to possible violations of competition policy in the EU, or due to opportunity costs; if airports suffer from land and other operational limitations that prevents or hamper further enlargements (i.e. environmental regulations). In sum, improving surface accessibility seems to be a promising measure to utilize existing multi-airport capacity more efficiently at the same time as increasing destination competitiveness.

Finally, we had the opportunity to check whether the Covid-19 crisis has impacted, or not, on the distribution of traffic in multi-airport systems, perhaps by favoring or damaging airports according to their characteristics as primary or secondary airports. Although our findings do not show any statistically significant shock on the composition of traffic affecting market shares, significant shifts can be identified in our data for three cities: primary airports in Moscow and Tenerife have seen their share of traffic considerably reduced following the pandemic, while the primary airport in Venice has seen a substantial increase. However, the short-term impact has been huge for both primary and secondary airports, which may explain why we have not found a significant generalized pandemic impact.

Author statement

Dear Editors and Guest editors of the special issue,

Regarding our manuscript "Getting closer to your destination: The role of available surface connections on the supply of low-cost carriers in secondary European tourist airports", both authors have nor competing interests nor conflicts of interest to declare.

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Appendix A. Appendix

Table A1

Estimation results (fractional response model) including covariates on short-term rentals.

	Dependent variable: Share of secondary airports					
	(1)	(2)	(3)	(4)	(5)	(6)
Minutes on private transport	−0.024 (0.002)***	–	–	–	−0.021 (0.002)***	
Minutes on public transport	–	−0.027 (0.001)***	–	–	–	
Disadvantage secondary/primary on private transport	–	–	−0.034 (0.002)***	–	–	
Disadvantage secondary/primary on public transport	–	–	–	−0.030 (0.001)***	–	
Dummy for fast public transport	–	–	–	–	1.450 (0.181)***	
Road distance (kms)	–	–	–	–	–	−0.027 (0.002)***
Minutes per km on public transport	–	–	–	–	–	−0.438 (0.140)***
Airbnb/Vrbo	0.021 (0.007)***	0.005 (0.007)	0.011 (0.016)*	0.003 (0.006)	0.027 (0.007)***	0.076 (0.010)***
Income_country	−0.030 (0.006)	−0.032 (0.006)***	−0.007 (0.005)	−0.0009 (0.005)	−0.017 (0.006)***	−0.007 (0.005)
Tourism per capita_region	0.005 (0.001)***	0.004 (0.001)***	0.007 (0.001)***	−0.007 (0.001)	0.004 (0.001)***	0.009 (0.002)***
Share Low-cost airlines	−0.025 (0.148)	0.234 (0.144)***	0.532 (0.151)***	0.582 (0.141)***	0.309 (0.137)***	0.437 (0.205)***
Hub primary airport	−0.177 (0.109)*	−0.339 (0.102)***	−0.253 (0.098)***	−0.084 (0.100)	−0.555 (0.115)***	−0.503 (0.095)***
Number airports	−0.028 (0.067)	−0.112 (0.064)*	−0.181 (0.056)***	−0.106 (0.055)**	−0.155 (0.070)***	−0.117 (0.055)***
Year 2019	−0.044 (0.130)	−0.046 (0.118)	−0.089 (0.122)	−0.085 (0.118)	−0.047 (0.120)	−0.085 (0.111)
Year 2020	−0.004 (0.135)	0.004 (0.126)	0.0009 (0.128)	0.014 (0.123)	0.032 (0.125)	−0.014 (0.121)
Year 2021	0.138 (0.131)	0.168 (0.123)	0.149 (0.122)	0.163 (0.120)	0.174 (0.132)	0.183 (0.115)
Intercept	0.153 (0.281)***	0.803 (0.265)***	−1.111 (0.245)***	−1.130 (0.218)***	−1.363 (0.287)***	0.190 (0.532)
Log pseudolikelihood	−135.672	−129.466	−129.436	−125.844	−130.038	−127.356
AIC	0.558	0.535	0.537	0.538	0.541	0.542
R2-adjusted	0.305	0.424	0.424	0.481	0.424	0.467
F-test (Joint sign.)	17.94***	32.15***	26.30***	40.24***	26.32***	35.52***
Number obs.	536	536	536	536	536	536

Notes: Standard errors in parentheses (robust to heterocedasticity). All regressions include unreported quarter fixed. Statistical significance at 1% (***), 5% (**), 10% (*).

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