Transportation Research Part E 70 (2014) 177–189

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

What hurts the dominant airlines at hub airports?

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ARTICLE INFO

Article history:
Received 13 February 2014
Received in revised form 30 June 2014
Accepted 5 July 2014

Keywords:
Hub airports
Competition
Network airlines
Low-cost airlines

ABSTRACT

This paper estimates a frequency equation to explain the determinants of network airline service levels at their hub airports. Drawing on European data for 2002–2013, we find that network airlines reduce frequencies when the share of low-cost airlines increases both on the route and at the hub airport. On the contrary, frequency choices of network airlines are not affected by competition from low-cost airlines operating in nearby secondary airports. We also find some evidence that mergers in Europe may result in a re-organization of the route structure in favor of the hubs of the larger airline.

0. Introduction

Network airlines have increasingly concentrated their flights in a small number of airports that they dominate and from which they operate their hub-and-spoke routes. By adopting this strategy they are able to reduce their costs, through the exploitation of density economies, and they can offer higher flight frequencies, which are highly valued by business and connecting passengers.[1] While competition between network airlines operating at different hubs to attract connecting passengers may be intense, at their own hub airports the airlines have typically benefited from a rather weak competition with low-cost airlines.

However, in Europe, network airlines are increasingly concerned by the expansion of the operations of low-cost carriers at their operating bases. For example, the current financial distress being faced by Iberia and Alitalia is, in part, attributable to competition from low-cost airlines operating in Madrid and Rome-FCO airports, respectively. KLM has been forced to operate with a low-cost subsidiary on many routes out of Amsterdam, while the bankruptcy of Malev can be explained in part by the success of low-cost airlines operating from Budapest. More generally, in the period 2002–2013, the network airlines' share has fallen in 17 of 22 large European airports that have traditionally been dominated by former flag carriers (see details in Table 1).

A loss in the competitiveness of the dominant network airlines may have a markedly negative impact on their respective hub airports. The dominance of the network airlines has benefitted the airports and their corresponding urban areas in a number of ways. The traffic is higher than that generated solely by local demand because a large proportion of passengers in hub airports are connecting passengers.[2] Furthermore, the geographical scope of non-stop destinations is especially high at

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[1] It is generally accepted that the route operations of airlines are subject to density economies (Brueckner and Spiller, 1994), and that airlines can attract more connecting passengers in a hub-and-spoke structure by increasing service frequency than by increasing aircraft size (Wei and Hansen, 2006).

[2] Systematic data for the proportion of connecting passengers at Europe's large airports are not readily available. However, Urban Audit data for 2007 (Urban Audit, 2008) provide the following figures for major hubs: London-LHR: 35%; Frankfurt-FRA: 54%; Amsterdam-AMS: 42%; Paris-CDG: 32%.

http://dx.doi.org/10.1016/j.tre.2014.07.002
1366-5545/

Table 1
List of low-cost airlines offering air services in routes of our sample.

Air Arabia Maroc, Air Finland, Air One, Air Transat, Air Berlin, Alpi Eagles, Blue Air, bmi baby, Cai Second, Centralwings, Condor, Corsairlfy, dba, easyjet, Fly Me, FlyNordic, Germanwings, Hapagfly, Jet2, Jet4you, LTU, Monarch, MyAir, MyTravelLite, NIKI, Norwegian, OLT, Ryanair, SkyEurope, Smart Wings, Sterling, Thomson, Transavia, TUIFly, Virgin Express, Volare, Vueling, Wind Jet, Wizzair, Zoom Air

hub airports.[3] In this regard, several studies have shown that air traffic services have a strong influence on firms' location choices (Brueckner, 2003; Green, 2007; Bel and Fageda, 2008; Bilotkach, 2013).

However, airport dominance and high route concentration may lead to higher average air fares, as has been well documented in the literature. Without intending to be exhaustive, this is a conclusion reported in Borenstein (1989), Brander and Zhang (1990), Brueckner et al. (1992); Evans and Kessides (1993); Oum et al. (1993), Marín (1995), Berry et al. (1996), Fisher and Kamerschen (2003), Fageda (2006), Goldsbee and Syverson, (2008) and Bilotkach and Lakew (2014). Equally well documented is the downward pricing pressure that low-cost airlines exert on the routes they operate. Studies that deal with the impact of low-cost airlines on price competition include Dresner et al. (1996), Windle and Dresner (1999), Morrison (2001), Hofer et al. (2008) and Oliveira and Huse (2009).

Overall, an airport may be dominated by airlines operating hub-and-spoke or point-to-point networks and this may have advantages and disadvantages from a social point of view. Within this context, the objective of this paper is not to examine the welfare implications of the entry of low-cost airlines in hub airports. Our aim is to determine which dimensions of competition might undermine the competitive position of dominant airlines at hub airports. In particular, we want to examine whether network airlines must reduce frequencies at their hubs when they are competing with low-cost airlines.

We estimate an equation in which the dependent variable is the frequencies offered by European network airlines on routes departing from their hub airports, using data for the period 2002–2013. Specifically, we seek to address the question of whether competition takes place at the route, airport and/or city-pair levels. We identify the competitive position of each airline by the flight frequencies they are able to provide on a given route. Flight frequency is typically considered the main attribute of air service quality as it determines the schedule delay cost, i.e., the difference between the desired and actual time of departure.

Our contribution is set in the context of the literature on airline frequency competition at the route level. Previous studies examining the determinants of airline frequencies have focused primarily on route competition (Schipper et al., 2002; Richard, 2003; Pai, 2010; Bilotkach et al., 2010, 2013; Brueckner and Luo, 2013). Indeed, these studies use as indicators of competition the route concentration index, the presence of low-cost airlines on the route and whether the airport is a hub or not. We add to this literature by examining the impact on frequencies of competition at the airport level using as additional indicators of competition the airport concentration index and the share of low-cost carriers in the airport. Furthermore, we also consider the impact of competition at the city-pair level by including as explanatory variable of frequencies the number of flights offered by low-cost airlines from secondary airports in the same city-pair market. Finally, we also provide evidence about the effect of mergers on frequencies offered by the smaller of the two merging airlines in Europe.

Additionally, some studies have analyzed the impact of low-cost airlines on price and capacity competition but less evidence has been found regarding their impact on service levels in hub-and-spoke structures. An important difference with previous studies on airline competition is that we put exclusively the attention on choices of network airlines at their hub airports.

In this regard, Goldsbee and Syverson (2008) examine the responses of incumbent US airlines to the threat of entry of Southwest using a sample of routes between 59 airports that Southwest ever flies any flights in 1993–2004. They define the threat of entry on a route in those cases where Southwest is offering flights in both endpoint airports of the route but not on the route. They find that incumbents reduce prices when Southwest threatens a route but these fare cuts are not accompanied by an increase in frequencies or seats. Goldsbee and Syverson (2008) also examine passenger traffic when Southwest threatens entry to a metropolitan area's secondary airport and they did not find significant results. While the study of Goldsbee and Syverson (2008) examined whether the mere presence of Southwest in both endpoints (or in a nearby airport) of the route influence the behavior of the incumbent airline in the route, we examine the impact of a higher share of low-cost airlines in the origin (hub) airports and the influence of the amount of flights offered by low-cost airlines from secondary airports.

Another study that is closely related with this paper is to Bettini and Oliveira (2008). They analyze the determinants of major carrier's capacity in routes connecting the 30 biggest Brazilian airports, including as explanatory variables a dummy for those routes in which Gol is offering flights and a dummy for those routes that have as endpoint a city with two commercial airports. They found positive effects of low-cost entry and negative effects of the variable for adjacent airports on major carrier's capacity. While the focus of the study of Bettini and Oliveira (2008) is about the effects of a low-cost airline offering flights in the route or not and whether the city is served by two commercial airports, we provide evidence on the effects of a higher share of low-cost airlines in both the route and the origin airport and of the amount of flights offered by low-cost airlines from secondary airports.

[3] In Europe, only hub airports offer a significant number of non-stop flights to intercontinental destinations, and it is unlikely that low-cost airlines can replicate their business model in the long-haul sector (Francis et al., 2007).

It should be stressed that most empirical studies of airline competition have been conducted for the US market, for which data availability is much better. In this paper, however, we provide evidence of competition between network and low-cost airlines for a large sample of European airports. To this point, we also provide evidence about the impact of mergers on the hubs of the smaller merging airline in Europe. In this regard, Bilotkach et al. (2013) show that the merger of Delta and Northwest led to a re-organization of the route structure in favor of the hubs of the larger airline.

The rest of this paper is organized as follows. In the next section, we explain the data used in the empirical analysis and the criteria applied in building the sample and variables. Then, we specify the empirical model and state our expectations for each explanatory variable. The following section deals with various econometric issues and reports the regression results. The last section contains our concluding remarks.

1. Data

The empirical analysis draws on route-level data from large airports in the European Union (as well as Norway and Switzerland) and covers a period that extends from 2002 through 2013. We include the large European airports at which the same airline was dominant throughout the period of study and at which that dominant airline was not a low-cost carrier. Following these criteria, our sample is based on the following airline-airport pairs: Air France (Paris-CDG, Paris-Orly), Air Lingus (Dublin), Alitalia (Rome-FCO), Austrian Airlines (Vienna), British Airways (London-LHR, London-LGW), Czech Airlines (Prague), Iberia (Madrid), Finnair (Helsinki), KLM (Amsterdam), LOT (Warsaw), Lufthansa (Frankfurt, Munich, Dusseldorf), SAS (Stockholm-ARN, Copenhagen, Oslo-OSL), SN Brussels (Brussels), Swiss (Zurich), TAP (Lisbon) and Tarom (Bucharest). Observations from Air France in Paris (CDG and Orly) and British Airways in London (LHR and LGW) are treated as single observations because Air France and British Airways could make coordinated decisions regarding frequencies from the two airports within the same urban area they serve.

A number of large European airports are not included in the analysis because we were unable to identify one dominant airline operating out of them for the whole period. For example, the bankruptcy of Malev in 2011 prevents us from including Budapest, while the de-hubbing of Alitalia from Milan-MXP has meant that Alitalia has operated very few flights at this airport since 2011.[4] Likewise, it has proved impossible to determine whether Olympic Airlines or Aegean was the dominant airline in Athens, while Manchester has had a highly diversified pool of airlines offering flights with no single company accounting for a share of more than 10 per cent, and various airlines have been dominant in the period in Barcelona (Iberia, Clickair and Vueling).[5] Other airports, such as Palma de Mallorca, Berlin-TXL and London (LTN, STN), are not included because they are dominated by low-cost carriers.

However, it should be pointed out that not all the airports included in our sample can be unequivocally classified as hub airports throughout the whole period.[6] Specifically, British Airways has been progressively reducing its traffic at London-LGW, but it continues to account for around 18 per cent of the total flights at this airport. According to data from the UK Civil Aviation Authority, the share of connecting passengers at LGW is still higher than 10 per cent.

The exclusion of important European airports from our sample is a limitation but the aim of the analysis we conduct is to determine the influence of different attributes of competition on the hub operations of network airlines. In this regard, our restricted sample covers a very high proportion of all hub operations undertaken by network airlines at Europe's airports.

We have been able to collect complete data for 936 routes on which the airlines under consideration provided an air service in all the years of the period studied (2002–2013). As such, the analysis excludes information for thin routes. Overall, our sample contains 11,232 observations, although regressions are based on 10,296 observations because we use a one-year lag of some of the explanatory variables.

Our data include intra-European routes as well as links to non-European destinations. However, the collection of population and per capita GDP data is more homogeneous in the case of the intra-European routes. For EU destinations, population and per capita GDP data refer to the NUTS 3 regions (the statistical unit used by Eurostat) and have been provided by Cambridge Econometrics (European Regional Database publication). For non-EU destinations, population data refer to metropolitan areas and the information has been drawn from various sources: the OECD, United Nations (World Urbanization Prospects), World Bank and national statistics agencies. To construct the per capita GDP variable for these non-European destinations, we use the country classification by income groups developed by the World Bank. Thus, we construct an index in which we distinguish between low income, lower middle income, upper middle income and high income countries. As such, the regressions that consider all routes use the country index for the per capita GDP variable, while the regressions that consider solely the intra-European routes use the continuous variable at the NUTS 3 level. Note that population and per capita GDP data (the latter when considered at the EU regional level) are only available up to 2011 so that the numbers for regional population and GDP per capita in 2012 and 2013 are the same as in 2011.

Airline frequency data at the route and airport level have been obtained from RDC aviation (Capstats statistics), while route distance data are taken from the Official Airline Guide (OAG). We have aggregated supply data that contains

[4] Redondi et al. (2012) provide an aggregate analysis of the impact of the de-hubbing of European airports.

[5] Castillo-Manzano et al. (2012a,b) report that competition with low-cost airlines has had a substantial impact on the traffic moved by network airlines at Spain's large airports.

[6] By definition, hub airports are those airports in which a dominant network carrier exploits the transfer traffic through coordinated banks of arrivals and departures.

information on the frequencies provided by the airline on the route (from airport i to airport j). This is a major limitation of our data because we are not able to make the distinction between passengers that fly to the hub airport as final destination and connecting passengers. To this point, we would like to remark that the contribution of this paper is set in the context of the literature of airline frequency competition at the route level. This being said, results of our analysis should be complemented with studies that use origin and destination data of passengers.

Note we use explanatory variables that consider the share of low-cost airlines in the origin airport and in the route. Table 1 provides a list of low-cost airlines that offer services in routes of our sample in at least one of the years of the considered period.

We also consider whether the dominant airline has been involved in a merger with a larger company. In our sample, the airlines involved in such mergers are KLM (since 2005), Iberia (since 2012), Austrian Airlines (since 2010) and Swiss (since 2006). SN has signed a strategic partnership deal with Lufthansa but the latter does not have a majority stake.

Finally, we include a variable that examines the influence of low-cost airlines operating from a nearby secondary airport. Hence, we include a variable that identifies the number of flights offered by low-cost airlines from an airport that is less than 100 km from the city center of the airport of origin in our sample. We compute the frequencies offered by low-cost airlines in the same city-pair market as that of the dominant airline in the airports in our sample. For example, SN Brussels offers flights on the Brussels–Manchester route and Ryanair also provides a service to Manchester from Brussels–Charleroi. The secondary airports that are relevant in our context are Baneasa (Bucharest), Charleroi (Brussels), Skavasta (Stockholm), Beauvais (Paris), Stansted and Luton (London), Ciampino (Rome), Weeze (Dusseldorf), Bratislava (Vienna) and Moss (Oslo). The dominant airline in the primary airport is not offering flights at any of these secondary airports and they are dominated by low-cost airlines. Ryanair has currently a leading position in most of them except in Baneasa and Luton where the leading airlines are Wizzair and Easyjet, respectively.

Table 2 reports data about the airline structure for the sample airports. The mean traffic share of the dominant airline is in all circumstances higher than 30 per cent and in some cases as high as 60 per cent. Here, the dominance of the leading airlines at some airports has been strengthened while in other it has weakened. In particular, the share of the dominant airline has been reduced in 14 of the 22 airports making up our sample. The share of network airlines (i.e; former flag carriers and/or airlines integrated in alliances) is generally well above 50 per cent, with the exceptions of Dublin, Oslo, London-LGW and Bucharest where low-cost airlines, such as Ryanair, Norwegian, Easyjet and Wizzair, have a sizeable presence. This being said, the network airlines' share has fallen in most of the airports in the period of study – in fact, in 17 of the 22 airports.

Table 3 shows supply data for the sample airports. In the period 2002–2013, the evolution in total traffic is quite diverse with some airports recording substantial growth (for example, Helsinki, Lisbon, Oslo and Bucharest), and others recording losses (for example, Stockholm, Brussels and Madrid). Focusing on routes of our sample, the evolution of frequencies offered by the dominant airline is also quite diverse. Some dominant airlines have substantially reduced the mean number of flights offered in routes from their hub airports (airlines at Stockholm, Copenhagen, London-Gatwick, Madrid or Oslo) while others have increased frequencies from their hubs (for example, airlines at Amsterdam, Helsinki, Lisbon, Bucharest or Prague). Regarding the total number of destinations offered from hub airports, only two of the largest hubs (London-Heathrow and Frankfurt) and Zurich record some loses while dominant airlines in 8 of the 22 airports have reduced the number of non-stop destinations from their hub airports.

Overall, the airports considered here present great variation in the evolution of their traffic and in the respective shares attributed to the different airlines operating out of them. Yet, what seems clear is the trend towards an increase in the presence of airlines not integrated in an alliance in many airports that were previously controlled by former flag carriers. This is quite remarkable if we consider that our sample of airports excludes those that are the home base of a low-cost airline.[7] While it is not clear the aggregated effect of the increasing presence of low-cost airlines at European hub airports, they may have weakened the dominance of the former flag carriers. In the following sections, we focus the attention on competition between network and low-cost airlines operating from hub airports.

2. Empirical model

In this section, we implement a multivariate analysis to identify the determinants of the flight frequencies offered by the dominant airlines at Europe's large airports. We use similar control variables to those employed in other empirical studies that estimate the determinants of frequencies on air routes (see, for example, Schipper et al., 2002; Richard, 2003; Pai, 2010; Bilotkach et al., 2010; Brueckner and Luo, 2013).[8] Our specific contribution is to analyze the impact of several variables of competition at the route, airport and city-pair levels. To this end, we estimate the following equation using data for a large number of routes departing from our sample of European airports:

[7] Ryanair has recently announced plans to expand its operations in Brussels-BRU and Rome-FCO, so this trend seems set to be reinforced in forthcoming years.

[8] Other empirical studies of competition in frequencies include Borenstein and Netz (1999) and Salvanes et al. (2005).

Table 2
Airline data for sample airports in 2002–2013.

Airport	Share dominant airline		Concentration index (HHI)		Share Network airlines	
	Mean (%)	Variation (%)	Mean	Variation (%)	Mean (%)	Variation (%)
Amsterdam (AMS)	52.7	18.9	0.288	39.1	77.6	3.7
Stockholm (ARN)	40.9	−8.2	0.205	−13.9	62.0	−7.9
Brussels (BRU)	35.3	34.4	0.147	47.1	74.5	5.8
Paris (CDG)	58.0	−0.4	0.344	−1.0	83.9	−7.8
Copenhagen (CPH)	47.0	−7.1	0.241	−9.0	64.6	−4.2
Dublin (DUB)	35.5	37.6	0.251	62.5	51.0	7.6
Dusseldorf (DUS)	40.9	−4.4	0.213	20.4	65.7	−23.4
Rome (FCO)	45.2	−6.5	0.223	−13.6	68.0	−4.7
Frankfurt (FRA)	62.2	11.6	0.391	23.4	87.7	−0.6
Helsinki (HEL)	54.1	14.7	0.328	25.8	71.0	−5.9
London (LGW)	33.0	−68.8	0.213	−29.5	41.8	−71.1
London (LHR)	42.6	34.5	0.201	61.5	75.9	13.4
Lisbon (LIS)	56.3	53.9	0.350	83.4	74.1	21.1
Madrid (MAD)	52.1	−14.1	0.297	−22.7	85.6	−14.2
Munich (MUC)	62.7	14.2	0.402	27.8	80.2	5.5
Oslo (OSL)	45.6	−30.5	0.276	−22.5	45.6	−30.5
Paris (ORY)	57.1	−17.5	0.344	−33.6	68.2	−18.2
Bucharest (OTP)	52.6	−36.9	0.301	−53.6	52.6	−36.9
Prague (PRG)	51.5	−41.8	0.285	−61.6	80.3	−22.6
Vienna (VIE)	57.2	−18.3	0.341	−30.9	80.4	−20.1
Warsaw (WAW)	63.8	−17.0	0.418	−29.8	88.4	−15.4
Zurich (ZRH)	56.2	−9.1	0.328	−17.4	83.7	−9.7

Table 3
Supply data for sample airports in 2002–2013.

Airport	Total frequencies from the airport		Total frequencies of the dominant airline in the routes of the sample		Total destinations from the airport		Total destinations of the dominant airline from the airport	
	Mean	Variation (%)	Mean	Variation (%)	Mean	Variation (%)	Mean	Variation (%)
Amsterdam (AMS)	189,822	15.4	1078	14.75	222	14.51	126	29.70
Stockholm (ARN)	100,056	−11.9	1293	−24.74	106	13.00	46	46.15
Brussels (BRU)	97,324	−12.3	892	6.03	140	7.94	58	1.85
Paris (CDG)	239,592	−8.0	1198	−6.66	228	3.76	152	−2.70
Copenhagen (CPH)	118,790	−2.3	1219	−14.38	118	8.04	61	17.24
Dublin (DUB)	79,930	7.1	916	9.08	124	101.47	58	155.56
Dusseldorf (DUS)	96,167	19.7	1185	−0.18	120	22.64	48	63.64
Rome (FCO)	151,038	11.1	1387	−1.6	159	22.96	68	40.68
Frankfurt (FRA)	225,961	2.9	1080	9.59	250	−4.86	159	14.08
Helsinki (HEL)	69,132	110.9	801	27.91	75	144.74	59	94.29
London (LGW)	110,484	22.9	1006	−38.34	163	19.44	66	−48.86
London (LHR)	245,117	−4.4	1195	12.23	183	−16.33	119	5.04
Lisbon (LIS)	63,518	40.1	931	60.22	61	65.57	58	100.00
Madrid (MAD)	200,263	−11.4	1365	−24.36	158	24.22	100	3.37
Munich (MUC)	182,979	15.2	1519	13.89	173	20.55	104	63.89
Oslo (OSL)	94,181	69.5	2220	−18.41	52	92.31	35	131.58
Paris (ORY)	110,926	18.2	2205	−4.94	117	16.33	42	−6.25
Bucharest (OTP)	30,214	84.6	421	35.05	52	40.00	37	−29.17
Prague (PRG)	60,225	26.6	716	19.89	102	24.32	64	−28.33
Vienna (VIE)	112,920	22.2	852	6.18	135	11.40	104	−13.59
Warsaw (WAW)	55,436	27.3	754	8.80	80	55.74	56	−3.51
Zurich (ZRH)	112,232	−5.7	1011	2.06	130	−7.91	76	−37.38

$$\begin{aligned} \mathit{Frequencies}_{kt}^{\mathit{dominant\_airline}} = {} & \alpha + \beta_1 \mathit{Population}_{kt}^{\mathit{destination}} + \beta_2 \mathit{Income}_{kt}^{\mathit{destination}} + \beta_3 \mathit{Distance}_k + \beta_4 \mathrm{D}_k^{\mathrm{EU}} + \beta_5 \mathrm{D}_{kt}^{\mathrm{US\_openskies}} \\ & + \beta_6 \mathrm{D}_{kt}^{\mathrm{interhub\_same\_alliance}} + \beta_7 \mathrm{Hub\_competition}_{kt} + \beta_8 \mathrm{D}_k^{\mathrm{routes\_with\_multiple\ origin\_airports}} \\ & + \beta_9 \mathrm{D}_{kt}^{\mathrm{merger}} + \beta_{10} \mathrm{HHI}_{kt}^{\mathrm{route}} + \beta_{11} \mathrm{Share\_low-cost}_{kt}^{\mathrm{route}} + \beta_{12} \mathrm{HHI}_{kt}^{\mathrm{origin\_airport}} \\ & + \beta_{13} \mathrm{Share\_low\text{-}cost}_{kt}^{\mathrm{origin\_airport}} + \beta_{14} \mathrm{Frequencies}_{kt}^{\mathrm{secondary\_airport}} + \alpha' \mathrm{D}_k^{\mathrm{origin\_airport}} + \mu' \mathrm{D}_t^{\mathrm{year}} + \varepsilon_{kt} \qquad (1) \end{aligned}$$

In this equation, the dependent variable is the total number of annual flights offered by the dominant airline on route k in year t. As explanatory variables, we include variables that measure the population and per capita income of the destination in order to control for demand. We expect airlines to offer higher frequencies on routes that link richer and more populous cities.

We also take into account the influence of the route's distance, calculated as the number of kilometers flown to link the route's endpoints. Airlines may prefer to use smaller planes at higher frequencies on short-haul routes. Thus, we would expect a negative relationship between distance and frequency as it has been found in Pai (2010) or Bilotkach et al. (2010).

Additionally, we include dummies for intra-European routes and routes to the United States for the period after the EU–US open skies agreement was signed. Controlling for other factors, demand on intra-European routes might be higher as a result of the greater degree of integration of EU members and the fact that the EU market is a liberalized market. By contrast, former European flag carriers may encounter more competition in the EU–US market following the open skies agreement, while the supply of flights may have diversified with the introduction of new airlines and airports. Thus, we expect a positive sign for the coefficient associated with the intra-EU route variable and a negative sign for the variable capturing US destinations after the introduction of the open skies agreement.

Unfortunately, our data only provide information of the airline that is effectively operating the flight so that we do not know whether other airlines are involved in the route through code-share agreements. Taking this into account, we include a variable that may work as a proxy for the effects of code-share agreements. Indeed, we include a dummy that takes the value one for those routes that connects two hubs of airlines integrated in the same alliance.[9]

While code-share agreements may be set between airlines in different scenarios, one of the main areas of coordination of airlines integrated in an alliance has to do with the code-share agreements. Hence, it is sensible to argue that the likelihood that the dominant airline has code-share agreements with other airlines at its hubs is higher in those routes that that have the hub of another airline in the same alliance as destination. We expect a negative sign for the coefficient associated with this variable because additional flights in the route may be offered by code-share partners of the dominant airline.

As we mention above, a limitation of our data is that we just have aggregated supply information on the frequencies provided by the airline on the route. Taking into account the limitations of our data, we include a variable that may capture part of the effect of inter-hub competition on the frequencies offered by the dominant airline in the corresponding route. This variable is constructed as the number of airports in the sample that have direct flights to the route's destination in the considered year. It is not clear the expected sign for the coefficient associated with this variable. One the one hand, more airports serving the destination of the route may have a negative effect on frequencies of the dominant airline in its hub due to stronger competition coming from network airlines in other hubs. On the other hand, more airports serving the destination could be indicating higher demand of flights to such destination which is not captured by the other explanatory variables.

We also consider a dummy variable that takes a value of one for routes and periods in which air services are offered simultaneously by the dominant airline from two origin airports (i.e; London-LHR and London-LGW, Paris-CDG and Paris-ORY). Demand in those routes could be higher than predicted by the other explanatory variables of our model.

Furthermore, we consider a dummy variable that takes a value of one for routes and periods in which the dominant airline at the airport was acquired by another larger airline. Following the merger, a reorganization of the route network might have been implemented in favor of the airports of the larger airline (Bilotkach et al., 2013). Hence, we expect a negative sign for the coefficient associated with this variable.

The main focus of our analysis is on the competition variables. An important difference with previous studies on airline competition is that we put exclusively the attention on choices of network airlines at their hub airports. Under hub-and-spoke structures, the service levels of airlines in the route will depend on the amount of traffic related with direct and connecting passengers. Taking this into account, we include the following variables as indicators of competition at the route, airport and city-pair level.

We include two variables that seek to capture competition at the route level. First, we consider the route concentration, measured using the Herfindahl–Hirschman index, in terms of flight frequencies. In addition to route concentration, we consider a variable that identifies the share of low-cost airlines on the route. The expected sign of the coefficient associated with route concentration is positive, while the expected sign of the coefficient associated with the share of low-cost competitors is negative.

A possible strategy of an incumbent airline against the entry of rivals in a route is to cut fares and add flights to boost demand. However, this could only be considered a short-term strategy of the incumbent airline. The entry of low-cost carriers in our context should have negative effects on frequencies of network airlines in a route. While a network airline operate under a hub-and-spoke structure, low-cost airlines operate under a point-to-point structure. Hence, network airlines are likely competing with low-cost airlines with different cost structures and different quality standards so that they could have to set higher prices. Thus, the entry of a low-cost airline in a route may imply less demand coming from direct passengers and a possible reaction of the incumbent airline to lower direct traffic is to reduce frequencies.

We include two additional variables as explanatory factors: the Herfindahl–Hirschman index in terms of airline frequencies at the airport level, and the share that low-cost airlines have at the airport. The expected sign of the coefficient associated with the airport concentration variable is positive, while the expected sign of the coefficient associated with the airport share of low-cost competitors is negative.

[9] We do not compute the value one in those routes that connect hubs of the same airline. For example, the dominant airline in both endpoints of the route Stockholm-Copenhagen is SAS so that here the code-share agreements should not be relevant.

As we have explained above, network airlines at their hubs can react by decreasing frequencies when route competition is more intense. The decrease in frequencies offered by the hubbing airline in one route may affect negatively other routes departing from the same hub airport because the change in waiting times in the connecting flights may affect demand of connecting passengers. Hence, competition at the airport level may have a negative effect on route frequency choices of the dominant airline. Frequencies of the dominant airline may be especially affected by competing airlines that operate point-to-point routes, because these airlines are more likely to be disputing the passengers with final destination at the airport under consideration by means of aggressive offers.

Furthermore, we include a variable that identifies the number of flights offered by low-cost airlines in the same city-pair market from a nearby secondary airport. The expected sign of the coefficient associated with this variable is not *a priori* clear. Indeed, demand of the dominant airline at the large airport could be negatively affected by competition from low-cost airlines operating at the nearby airport. However, it might be the case that city-pair markets that are connected via different airports are particularly dense corridors whose demand is not fully controlled by our explanatory variables.

Finally, we include dummies for the airports of origin and year and ε_{kt} is a mean-zero random error term. The airport dummies control for time-invariant airport-specific omitted variables, while the year dummies control for the common trend on all routes in the dataset. Specifically, airport and time fixed effects may help to control for relevant factors for which, unfortunately, we have no available data. Indeed, one potential omitted variable in our empirical model is airport congestion. This being said, the use of airport dummies may help in controlling its effect because some airports are systematically more congested than others, and the use of year dummies may also be helpful because the relevance of congestion is higher in boom periods. However, we must recognize that a potential limitation of our analysis is that we are not able to control explicitly for airport congestion.

Another potential explanatory factor that cannot be controlled in our model is fares given the lack of data. In this regard, airline behavior can be viewed as a multistage process (Marín, 1995; Schipper et al., 2002). In the first stage, airlines choose whether they enter in the market or not; in a second stage, once they have entered in the market, they decide the routes to be operated and the aircraft technology to be used. In the third stage, airlines should make decisions on the flight schedule, and finally, they should set prices that are the most flexible variable. Usually, studies about the determinants of airline frequencies (e.g., Schipper et al., 2002; Pai, 2010; Bilotkach et al., 2010; Brueckner and Luo, 2013) focus on the third stage so that prices are not included as explanatory factor. Other studies that examine the impact of low-cost airlines on capacity or traffic (Bettini and Oliveira, 2008; Goldsbee and Syverson, 2008) neither use fares as explanatory factor. Note also that studies that use reduced form equations to examine the determinants of route prices include similar explanatory variables as those studies that use reduced form equations to analyze route frequencies. In particular, demand shifters, route distance and competition variables are always used as key explanatory factors in both price and frequency equations. Hence, the impact of pricing strategic decisions of airlines can be indirectly considered in our frequency equation through competition variables.

3. Estimation and results

In this section, we deal with a number of econometric issues and discuss the results of the regressions. The estimates may present non-stationarity and temporal autocorrelation problems. We apply the Wooldridge test for autocorrelation in panel data. Under the null hypothesis of no first-order autocorrelation, the residuals from the regression of the first-differenced variables should have an autocorrelation of -0.5. This implies that the coefficient on the lagged residuals in a regression of the lagged residuals on the current residuals should be -0.5 (see Wooldridge, 2002 for further details). The Wooldridge test shows that we may have a problem of serial autocorrelation, which must be addressed. We also apply the panel unit root test developed by Levin et al. (2002), which can be regarded as an augmented Dickey–Fuller (ADF) test when lags are included with the null hypothesis of nonstationarity I(1) behavior. This test with one lag indicates that there is no non-stationarity problem with our dependent variable.

We perform the estimation using two different techniques that take advantage of the panel nature of our data: the route fixed and random effects models. The use of any of the two models allows us to consider unobserved route heterogeneity.

An advantage of the fixed effects model is that it allows us to control for any omitted variables that correlate with the variables of interest and which do not change over time. As such, the fixed effects model is more reliable than other estimation techniques. A shortcoming of the fixed effects model is that it may be less informative than other techniques because the effect of time-invariant variables cannot be identified. Indeed, the random effects model has the advantage that it may capture both the between and the within variation of the data while the fixed effect model only captures the within variation of the data. However, a disadvantage of the random effects model is related with the potential bias derived from the correlation between the explanatory variables and the random effects.

The Hausman test shows the existence of substantial differences between the random and the fixed effects. An important reason why the two estimators could be different is the existence of correlation between the explanatory variables and the random effects, although other sorts of misspecification may also lead to rejection (Verbeek, 2000). For example, the fixed effects estimator may be particularly imprecise when several explanatory variables are rarely changing or not changing at all. In this regard, some studies have applied Monte Carlo simulations to show that the Hausman test may be misleading when the variables used in the empirical analysis have a low within variation (Clark and Linzer, 2012; Troeger, 2008).

Table 4
Mean values of the variables used in the empirical analysis.

Variable	All routes	Intra-EU routes	Intra-EU routes <900 km	Intra-EU routes >900 km
$Frequencies^{dominant\_airline}$ (annual)	1143.78	1411.42	1722.90	940.78
$Frequencies^{route}$ (annual)	1753.01	2106.60	2487.97	1564.40
$Frequencies^{airport}$ (annual)	184227.7	170,259	176138.8	161,667
$Population^{destination}$ (thousands)	4287.73	2041.02	1601.43	2705.26
$Income^{destination}$ (index)	3.78	3.96	3.98	3.93
Distance (km)	2272.61	874.89	527.54	1399
D^{EU} (dummy)	0.717	–	–	–
$D^{US\_openskies}$ (dummy)	0.034	–	–	–
$D^{interhub\_same\_alliance}$	0.13	0.11	0.09	0.15
Hub_competition	10.84	12.24	10.79	14.43
D^{merger} (dummy)	0.12	0.12	0.12	0.11
$Frequencies^{secondary\_airport}$ (annual)	76.61	106.79	92.17	128.88
HHI^{route}	0.67	0.68	0.72	0.62
$Share\_low\text{-}cost^{route}$	0.05	0.06	0.07	0.06
$HHI^{origin\_airport}$	0.30	0.30	0.30	0.30
$Share\_low\text{-}cost^{origin\_airport}$	0.12	0.13	0.13	0.13

In our model, many explanatory variables are either time-invariant or have a low within-variation. However, the results of the Hausman test do not allow us to be totally confident with the random effects model. Hence, what we have opted to do is to present the results using both the random and fixed effects models assuming an AR(1) process in the error term and standard errors robust to heteroscedasticity.

Airlines do not change flight frequency very frequently and therefore current shocks in capacity allocation could be expected to be passed to the future observations. Hence, we could consider including the lagged dependent variable as a regressor. To this point, note that several previous studies like the one of Bettini and Oliveira (2008) uses quarterly data, while we use annual data. This may help to overcome the potential inertia in frequency data. In our context, the use of a dynamic model would require us to first differentiate all variables due to the presence of autocorrelation in the residuals and the fact that we have a large number of cross-sections in relation to the time periods. We have experimented with dynamic regressions and almost all explanatory variables are not statistically significant. This may be a consequence of the low within-variation (or not variation at all) of many explanatory variables.

An additional issue that must be addressed is the potential endogeneity of the concentration variables. To deal with this, we include a one-year lag of the concentration variables as explanatory variables. It is difficult to make a case for the correlation between lagged concentration and current unobserved shocks. We also experimented with additional lags of these variables and the results are not affected. In order to simplify the presentation of our results, we only report the results of regressions with a one-year lag of the concentration variables.[10]

We make the estimation using all the observations and for the different subsamples. Specifically, we distinguish between intra-EU routes and routes that link the airports of origin in our sample with non-EU destinations. Population and per capita income data are richer in the case of the intra-European routes and we may find a high variability in the regulatory regimes of routes with non-EU destinations.

Note also that in Europe the dominant network carrier is only offering flights in more than one airport within the same urban area in London and Paris. Apart from the cities where are the hubs of the sample, other European cities with more than one airport are Belfast, Berlin, Milan, Glasgow and Goteborg. Potential competition from airports in the same city may be relevant in few observations of our sample of European routes and this potential competition is already captured by our secondary airports variable. Recall that this variable identifies the number of flights offered by low-cost airlines in the same city-pair market from a nearby secondary airport. For example, Alitalia is offering flights from Rome-FCO to Brussels-BRU while Ryanair is offering flights from Rome-CIA to Brussels-CRL. Thus, the secondary airport variable considers the impact of frequencies of Ryanair in the link CIA-CRL on the frequencies offered by Alitalia in the link FCO-BRU.

In non-EU routes, competition from airports in the same urban area is more complicated to identify (particularly in routes that have large US cities as destination). The difficulty in capturing potential competition from different airports in the same urban area is an additional argument to justify that our preferred regressions are those based on the EU sample.

In the case of intra-EU routes, we report results of an additional regression in which we exclude those routes with presence of low-cost subsidiaries of the dominant airline. The presence of low-cost subsidiaries in a route may distort our competition analysis. Several low-cost subsidiaries of network carriers have their main base in airports away from the main hubs of the dominant airline as it is the case of Germanwings (Lufthansa) with the main base in Cologne, Vueling/Clickair (Iberia) with the main base in Barcelona or Air One (Alitalia) which is mainly placed in tourist Italian destinations. However, some observations are affected by the presence of low-cost subsidiaries of the dominant airline, particularly several routes from

[10] All variables of competition could be exposed to an endogeneity bias in case that we were not able to capture appropriately the intensity of competition that low-cost airlines exert from secondary airports. In this regard, the variable of number of flights offered by low-cost airlines from secondary airports should help in mitigating such potential bias in our regressions.

Table 5
Correlation matrix of the main variables used in the empirical analysis.

	Freq	Pop	Inc.	Dist	D^{mer}	$D^{interhub}$	Hub_comp	$Freq^{secondary}$	HHI^{ro}	$Share^{ro}$	HHI^{ap}	$Share^{ap}$
Freq.	1											
Pop.	−0.22	1										
Income	0.27	−0.39	1									
Dist.	−0.41	0.65	−0.32	1								
D^{merger}	−0.04	0.03	−0.02	0.009	1							
$D^{interhub}$	−0.06	0.17	0.23	−0.30	0.01	1						
Hub_comp.	0.20	−0.04	0.23	−0.30	0.01	0.18	1					
$Freq^{secondary}$	0.15	−0.06	0.07	−0.10	−0.07	−0.05	0.11	1				
HHI^{route}	−0.03	−0.12	−0.01	0.03	0.04	−0.15	−0.31	−0.08	1			
$ShareLCC^{route}$	−0.01	−0.07	0.05	−0.10	−0.02	−0.05	0.03	0.06	−0.12	1		
HHI^{airp}	0.002	0.02	0.04	−0.14	−0.06	0.06	−0.05	−0.23	0.12	−0.14	1	
$ShareLCC^{airp}$	0.06	−0.05	0.11	−0.13	−0.06	0.005	0.13	0.02	−0.06	0.21	−0.49	1

Table 6
Results of estimates (random effects – GLS regression with an AR 1 disturbance).

Explanatory variables	Dependent variable: Frequencies of dominant airline				
	All routes (1)	Intra-EU routes (2)[1]	Intra-EU routes (3)[2]	Intra-EU routes <900 km (4)	Intra-EU routes >900 km (5)
$Population^{destination}$	0.028 (0.005)***	0.10 (0.01)***	0.09 (0.01)***	0.12 (0.02)***	0.10 (0.008)***
$Income^{destination}$	239.82 (60.52)***	7.09 (1.76)***	7.25 (1.61)***	11.55 (2.89)***	6.94 (1.21)***
Distance	−0.14 (0.017)***	−0.89 (0.06)***	−0.88 (0.06)***	−1.03 (0.26)***	−0.47 (0.05)***
D^{EU}	376.54 (113.13)***	–	–	–	–
$D^{US\_openskies}$	−1.68 (19.84)	–	–	–	–
$D^{interhub\_same\_alliance}$	−24.05 (18.46)	−15.53 (28.59)	−21.21 (25.73)	−32.79 (60.32)	−0.07 (22.17)
Hub_competition	4.18 (1.76)**	5.27 (2.39)**	5.40 (2.18)***	5.27 (3.80)	9.07 (2.24)***
$D^{routes\_with\_multiple\ origin\_airports}$	3462.99 (223.28)***	3451.57 (246.04)***	3451.67 (223.59)***	3766.04 (305.92)***	1049.10 (329.82)***
D^{merger}	−19.77 (10.70)*	−29.28 (15.28)**	−14.61 (14.45)	−32.53 (23.35)	−20.85 (15.96)
HHI^{route}	18.14 (17.25)	15.32 (23.95)	20.10 (21.67)	−14.94 (37.57)	48.10 (23.81)**
$Share\_low\text{-}cost^{route}$	−162.33 (29.63)***	−196.19 (39.45)***	−204.87 (36.04)***	−313.15 (61.16)***	−36.39 (39.79)
$HHI^{origin\_airport}$	294.48 (72.97)***	422.95 (100.98)***	446.10 (91.69)***	492.96 (160.17)***	297.39 (99.94)***
$Share\_low\text{-}cost^{origin\_airport}$	−206.36 (84.49)***	−205.47 (105.0)**	−229.79 (104.08)**	−533.54 (181.61)***	145.49 (115.24)
$Frequencies^{secondary\_airport}$	0.04 (0.02)	0.03 (0.02)	0.03 (0.02)	0.13 (0.04)***	−0.04 (0.02)
Intercept	−2.20 (235.83)	1442.1 (160.36)***	1377.77 (156.97)***	1143.40 (269.66)***	1155.89 (125.59)***
Airport dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
R^2	0.44	0.46	0.51	0.45	0.60
Joint significance test	1120.24***	891.87***	1018.32***	582.64***	648.31***
ADF test – nonstationarity	−75.72***	−60.49***	−62.52***	−39.27***	−40.72***
Wooldridge test – autocorrelation	306.03***	256.56***	237.33***	169.87***	173.83***
Hausman test	15.43*	23.84***	18.93**	55.60***	15.61*
Number observations	10,296	6985	6765	4114	2871

Note 1: Sample with all intra-EU routes.
Note 2: Sample with Intra-EU routes excluding those routes with flights of low-cost subsidiaries of the dominant airline.
Note 3: Standard errors in parenthesis (robust to heterocedasticity).
Note 4: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 5: We use one lag of concentration variables (HHI_route, HHI_airport).

Amsterdam, Madrid and Munich with presence of Transavia (KLM), Vueling and Germanwings, respectively. Note here that the variables that compute the share of low-cost airlines at the route and airport level are constructed as the sum of the shares of independent low-cost airlines, excluding the low-cost subsidiaries of the dominant airline.

We also distinguish between short-haul and long-haul routes in the European sample. Thus, we estimate our equation for routes shorter and longer than the mean distance for intra-EU routes, which is about 900 km.

In short, we make the estimation using these samples: (1) all routes, (2) all intra-EU routes, (3) intra-EU routes excluding routes with presence of low-cost subsidiaries of the dominant airline, (4) intra-EU routes of less than 900 km, (5) intra-EU routes of more than 900 km.

Table 4 shows the descriptive statistics of the variables used in the empirical analysis, while Table 5 presents the correlation matrix of these variables. Note that HHI variables have been constructed as the sum of the squares of the shares of airlines in terms of flight frequencies. The shares of airlines have been computed over one. It can be seen that all the variables present sufficient variability, as the standard deviation is high in relation to the mean values. In the case of the correlation

Table 7
Results of estimates (fixed effects – within regression with an AR 1 disturbance).

Explanatory variables	Dependent variable: Frequencies of dominant airline				
	All routes (1)	Intra-EU routes (2)[1]	Intra-EU routes (3)[2]	Intra-EU routes <900 km (4)	Intra-EU routes >900 km (5)
Population^{destination}	0.019 (0.012)	0.28 (0.17)*	0.24 (0.16)	0.17 (0.34)	0.05 (0.14)
Income^{destination}	–	3.32 (3.66)	3.11 (3.29)	2.84 (5.61)	3.89 (3.79)
Distance	–	–	–	–	–
D^{EU}	–	–	–	–	–
D^{US_openskies}	1.68 (21.62)	–	–	–	–
D^{interhub_same_alliance}	−16.93 (20.77)	−19.76 (32.11)	−25.98 (28.66)	20.45 (68.21)	−35.61 (25.45)
Hub_competition	1.16 (1.93)	−0.43 (2.63)	0.58 (2.38)	−2.02 (4.24)	1.01 (2.56)
D$^{routes_with_multiple\ origin_airports}$	–	–	–	–	–
D^{merger}	−33.41 (11.48)***	−47.28 (16.32)***	−28.51 (15.33)*	−58.95 (24.99)***	−28.03 (16.82)*
HHI^{route}	−7.79 (18.21)	−12.63 (25.21)	−7.65 (22.67)	−60.17 (39.50)	44.55 (25.18)*
Share_low-cost^{route}	−176.20 (31.34)***	−224.04 (41.76)***	−228.84 (37.95)***	−369.50 (64.32)***	−18.40 (42.71)
HHI^{origin_airport}	144.41 (91.73)	247.32 (127.34)**	312.84 (114.41)***	387.87 (202.32)**	86.89 (124.74)
Share_low-cost^{origin_airport}	−379.62 (91.62)***	−407.75 (125.29)***	−454.55 (112.89)***	−762.28 (197.70)***	1.22 (123.91)
Frequencies^{secondary_airport}	0.006 (0.02)	−0.008 (0.03)	−0.006 (0.02)	0.05 (0.06)	−0.03 (0.03)
Intercept	983.24 (21.23)***	576.88 (116.51)***	638.70 (104.08)***	1289.42 (182.89)***	517.39 (128.64)***
Airport dummies	NO	NO	NO	NO	NO
Year dummies	YES	YES	YES	YES	YES
R^2	0.04	0.04	0.06	0.07	0.04
Joint significance test	18.31***	15.50***	16.80***	12.61***	5.78***
ADF test – nonstationarity	−75.72***	−60.49***	−62.52***	−39.27***	−40.72***
Wooldridge test – autocorrelation	306.03***	256.56***	237.33***	169.87***	173.83***
Hausman test	15.43*	23.84***	18.93**	55.60***	15.61*
Number observations	10,296	6985	6765	4114	2871

Note 1: Sample with all intra-EU routes.
Note 2: Sample with Intra-EU routes excluding those routes with flights of low-cost subsidiaries of the dominant airline.
Note 3: Standard errors in parenthesis (robust to heterocedasticity).
Note 4: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 5: We use one lag of concentration variables (HHI_route, HHI_airport).

matrix, it is notable that the correlation between the concentration variables and those that reflect the presence of low-cost competitors is sufficiently low for us to be able to identify the specific effects of each variable.

Tables 6 and 7 show the results of the estimates when using the random and fixed effects model, respectively. As explained above, the fixed effects model is not able to capture the effect of time-invariant variables and the within-variation of several explanatory variables is low. This explains why the overall explanatory power of the model is considerably higher in the regressions that use random effects and why more explanatory variables are statistically significant with the use of random effects.

In the regressions that use the random effects model, the control variables, in general, work as expected. The frequencies of the dominant airline are higher when the route links more populous and richer endpoints. The fixed effects model does not seem to capture the impact of these control variables as it concentrates on the within-variation of data. Furthermore, we find a negative relationship between frequencies and distance in the regressions that can be identified.

The coefficient associated with the dummy variable for intra-EU routes is positive and statistically significant in the regressions that can be identified. As expected, frequencies on intra-EU routes are higher due to greater demand in a geographical area characterized by no regulatory restrictions and strong economic integration. Interestingly, it is not clear from our results that former European flag-carriers have been exposed to more intense competition in the EU–US market after the open skies agreement came into force.

The coefficient associated with the dummy variable for routes that connect two hubs of airlines integrated in the same alliance is negative in almost all regressions but it is generally not statistically significant. Thus, we found no clear differences between routes more or less likely to be affected by code-share agreements. The coefficient associated with the variable for hub competition is positive and statistically significant in the random effects regressions but not statistically significant and with different sign in the fixed effects regressions. Hence, we cannot reach definitive conclusions regarding this variable. Otherwise, the coefficient associated with the variable for routes in which air services are offered simultaneously by the dominant airline from two origin airports is positive and statistically significant in the regressions that can be identified.

We also find that the frequencies of dominant airlines are lower in the period following their merger with a larger airline. The coefficient associated with this variable is always negative (although it is more clearly significant in the regressions that use the fixed effects model). Overall, we find some evidence for Europe that mergers may imply a re-organization of the route structure in favor of the hubs of the larger airline (see Bilotkach et al., 2013, for an analysis with similar results for the US airline market).

At the route level, the coefficient of the route concentration variable is not statistically significant except in the regression that uses the sample of EU routes of more than 900 km. On the contrary, the coefficient associated with the variable for share of low-cost competitors is negative and statistically significant in all the regressions except in the random effects regression that uses the sample of EU routes of more than 900 km. This is in contrast with the results in Bilotkach et al. (2010, 2013) that find a negative relationship between frequencies and route concentration and they also differ with results of Bettini and Oliveira (2008) that found a positive effect on incumbent's capacity of entry of a low-cost airline in a route. Recall that an important difference with previous studies is that we put exclusively the attention on choices of network airlines at their hub airports.

At the airport level, the coefficient of the variable of airport concentration is positive in all the regressions. It is statistically significant in the regressions that use random effects and it is generally statistically in the regressions that use the fixed effects model. Notably, the coefficient associated with the variable of the share of low-cost airlines at European airports is negative and statistically significant in all the regressions except in those that uses the sample of EU routes of more than 900 km.

Overall, the picture is quite clear and the outcomes are similar in the random and fixed effects regressions. Dominant airlines reduce frequencies in routes departing from their hubs when the share of low-cost airlines in those routes is higher. In our sample, network airlines at their hubs do not seem to follow the strategy of cutting fares and increase frequencies against the entry of low-cost airlines. The reduction in frequencies by dominant airlines may be a consequence of lower demand coming from direct passengers.

Furthermore, dominant airlines reduce frequencies in routes departing from their hubs when the share of low-cost airlines in those hubs is higher. Results for the variable of share of low-cost carriers in the route suggest that the dominant airline may receive less demand from direct passengers on those routes that suffer the rivalry of low-cost airlines, which may reduce the flight frequency offered. Lower frequencies by the dominant airline on some routes may have indirect effects on other routes because the demand from connecting passengers may be lower as a result of less competitive connections; the coordination of banks of arrivals and departures could be poorer with increased connecting times when the dominant airline reduces frequencies in some routes.

Looking at results in Tables 6 and 7, it seems that the impact of the share of low-cost carriers in the airport is higher than the impact of their share in the route. However, this result may be qualified when we make the analysis in terms of elasticities. The random effect regressions should render more plausible elasticities than the fixed effects regressions because the random effects regressions may capture the effect of important time-invariant variables. When we examine the elasticities in the random effects regressions that do not distinguish between route distance, we find that a 10 percent increase in the share of low-cost airlines in the airport implies about a 2 percent decrease in frequencies of the dominant carrier, while a 10 percent increase in the share of low-cost airlines in the route implies about a 1 percent decrease in frequencies. From the descriptive statistics that are shown in Table 3 for the whole sample, we can derive that an airline needs to provide 18,422 annual flights in the airport (355 weekly flights) to achieve a 10 percent increase in that airport while an airline needs to provide 175 annual flights in the route (3 weekly flights) to achieve such increase in the route. Hence, results of our analysis do not imply that the impact of the share of low-cost carriers is higher at the airport than at the route level.

To this point, recall that a major limitation of our data is that we are not able to make the distinction between passengers that fly to the hub airport as final destination and connecting passengers. While we consider that results that we find for the variable of share of low-cost airlines in the hub airports has to do with demand of connecting passengers, our analysis should be complemented with empirical exercises using origin and destination data of passengers.

We do not find evidence that competition from low-cost airlines operating out of secondary airports has a clear impact on frequencies of dominant airlines considered here.[11] The coefficient associated with the variable of frequencies of low-cost airlines in nearby secondary airports is generally positive in the regressions that use the random effects model and generally negative in the regressions that use the fixed effects model. This being said, it is not statistically significant in all the regressions that use fixed effects and it is only statistically significant in the regressions that use random effects for EU routes with less than 900 km. Hence, results of our analysis for the variable of secondary airports are similar to those obtained by Goldsbee and Syverson (2008) while they differ from results obtained by Bettini and Oliveira (2008).

Note that Ryanair is the airline that typically operates in secondary nearby facilities of hub airports. It could be that Ryanair and former flag carriers attract different types of passenger, so that the leading low-cost airline in Europe is in fact fighting for more price-sensitive passengers. Another possible explanation of results for this variable is that frequencies offered at secondary airports are too small to impact the dominant carrier. It appears from the descriptive statistics that low-cost carriers in secondary airports provide an average frequency of two flights per week compared to the dominant carrier frequency of 4 flights per day in the primary airport. If flights are offered at inconvenient times it may be that the low-cost carrier is not a viable competitor. This does not mean that if the low-cost carrier provided meaningful service out of the secondary airport that it would not impact the dominant carrier.

Overall, our empirical analysis indicates that dominant airlines may be worried by the increased presence of low-cost airlines at their hub airports. Critically, the negative effects suffered by dominant airlines as a result of the stronger presence of

[11] In a similar vein, Pels et al. (2009) find low cross-price elasticities in an analysis that examines competition between low-cost and network airlines in the multi-airport area of London.

low-cost airlines at their operating bases are not only felt on the routes on which they compete directly with each other, but also on other routes that may suffer a reduction in demand from connecting passengers. In contrast, dominant airlines seem to be less affected by operations of low-cost airlines in secondary nearby airports. However, results of the secondary airport variable must be assessed in the context of our data.

4. Concluding remarks

The main contribution of this paper has been to show that network airlines at their hubs reduce frequencies when the share of low-cost airlines increases both on the route and at the hub airport. On the contrary, frequency choices of network airlines at their hubs do not seem to be affected by competition from low-cost airlines operating in nearby secondary airports. We also find some evidence that mergers in Europe may result in a re-organization of the route structure in favor of the hubs of the larger airline.

A major limitation of our data is that we are not able to make the distinction between passengers that fly to the hub airport as final destination and connecting passengers. Hence, our analysis should be complemented with empirical studies using origin and destination data of passengers. Another potential limitation of our analysis is that we are not able to control explicitly for airport congestion. Further research could investigate the implications of flight delays in the competition between network and low-cost airlines.

From our analysis, it seems clear that the increasing presence of low-cost airlines in European hub airports has negative consequences for the network airlines that have traditionally dominated those hubs. However, this does not mean that the levels of service at the hub airport are worse when the share of low-cost airlines increases. In fact, it may be that there is only sufficient traffic to support a certain number of hub airports and network carriers. The US market has seen a reduction in the number of hubs and the number of network carriers over the last years. Europe has a large number of hubs and network carriers in a relatively limited geographic area, and this may not be a viable equilibrium in a more competitive environment.

This being said, results of our analysis may have implications for airport management. Capacity expansions at large airports are usually conditioned by financial, technical and environmental restrictions. Hence, a reasonable objective of airport managers should be achieving the best possible use of the current capacity by airlines operating in hubs. For example, an increase of airport charges may have a differential impact on network and low-cost airlines. Furthermore, the introduction of market-based mechanisms in the allocation of slots could ensure that they go to the airlines able to make the best use of them.

Acknowledgements

I would like to thank Martin Dresner, Jiuh-Biing Sheu and two anonymous reviewers for their helpful comments made on an earlier version of this paper. I would also like to thank the Spanish Government (ECO2012-38004) and the Government of Catalonia (SGR2009-1066) for their financial support.

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