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The evolution of regional air transport connectivity in Europe: a comparison between remote and central areas

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Abstract

In this paper, we analyse the evolution of air transport connectivity in Europe for the period 2009-2016 and make a comparison between central and remote regions. We collect data regarding the intra-European air routes to create a dataset containing connections between pair of regions. Then we compute a connectivity measure for each region in the dataset. Finally, we study how connectivity has evolved in the period analysed, trying to identify, through an econometric approach considering time and spatial effects, factors affecting its evolution and controlling whether these factors have different influences in core regions compared to remote ones. The results show significant differences between remote and core regions. More specifically, we find evidence that higher GDP and population's density leads to a better connectivity. We find evidence that LCCs activity is a negative determinant of connectivity, especially in remote regions.

Keywords: Connectivity; Remoteness; Air Transport Networks

1. Introduction

The air transportation sector is growing sharply during the last years, as a sign of the worldwide population's increasing demand for mobility. The International Civil Aviation Organization (henceforth ICAO) reports that a new record of 4.1 billion passengers were carried by the aviation industry in 2017, a +7.6% over 2016.[1]

Forecasts by Airbus and Boeing show that this rapid growth tend to occur also in the future. Airbus estimates a +2.9% compounded annual growth rate (CAGR) for the period 2019-2036, while Boeing for the same period estimates a +3.2% CAGR.[2] Several contributions (Alderighi & Gaggero, 2017; Allroggen & Malina, 2014; Bilotkach, 2015;

[1] See ICAO at the webpage www.icao.int/Newsroom/Pages/Continued-passenger-traffic-growth-and-robust-air-cargo-demand-in-2017.aspx
[2] See at Airbus website the Airbus Global Market Forecast 2017-2036, and at Boeing website the Current Market Outlook 2017

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Blonigen & Cristea, 2015; Brueckner, 2003; Brugnoli et al., 2018; Percoco, 2010) have also shown that the aviation industry is an essential input for local economic growth.[3]

This growing importance of air transportation for both the population life standard and for local economic growth points out the issue of granting equitable connectivity to air services to all people and territories within a country or a community of countries (e.g., the European Union – EU). When considering how people and firms are served by air transportation, an important issue to evaluate is the different access levels provided to core and remote regions. As stated by Fageda et al. (2016), there is a growing awareness that air transportation is a crucial factor in supporting mobility in peripheral or remote locations. Remoteness might be caused by being an island, a landlocked region or a region that has a low stock of infrastructure, areas which are characterised by connectivity problems that may be an obstacle for mobility and therefore their growth. On the contrary, core regions' success is due among other factors to their agglomerative capability and thus they act as an attractor for the aviation network.

In remote regions, on top of aviation being the only mode of transportation granting connection to mainland and to the worldwide network in a reasonable amount of time, there is very frequently the problem of low demand, so that airlines do not find convenient to offer regular flight services (Bitzan & Junkwood, 2006). Fageda et al. (2016) highlight that, by regarding mobility as a public good - so that everybody should have equal access, similarly to education or health care - in many countries populations from remote regions enjoy subsidies for using aviation from the national or local government. These subsidies, such as discounts and public service obligation (PSO), are particularly relevant on islands where surface transportation to mainland is not available, and maritime transportation is an option only for short trips. For instance, Calzada & Fageda (2017) argue that the EU allows member states to impose PSO for scheduled air service on thin routes connecting with an important airport, to stimulate local economic and social development.

While previous contributions have mainly focused on the competitive effects of subsidies and PSO (see Fageda et al., 2018 for a comprehensive review), there are no attempts available, to the best of our knowledge, regarding measures of different connectivity to the air services between remote and core regions, and, above all, on the factors that may explain different access levels and different variations of access levels over time. This is the goal of this paper, that studies the determinants of connectivity to aviation in Europe, with a focus on remote and core regions, and on the possible different contribution to equal access provided by full service carriers (FSC) and low cost carriers (LCC).

The different airline typical network organizations may be an argument for considering the different impact of FSCs and of LCCs on connectivity, especially in remote regions. FSCs have routes mainly organized as a hub-and-spoke (H&S) network, while LCCs operate point-to-point (PTP) connections. In many remote regions demand is low, making the possible route a "thin" connection. In this case, it is unlikely that a LCC may provide a PTP flight, given the low demand. It is possible to think a PTP flight on a thin route between a remote region and the mainland only with very low frequency, which makes the access to aviation very low. However, as pointed out by Fageda et al. (2016), the H&S network of FSCs may help in providing good access to remote regions: even if the route is thin, FSCs may operate small size aircraft connecting the remote region to their hub. In this case the demand coming from the remote region can feed the long-haul or medium-haul flights departing from the hub. If this argument is proved empirically, FSCs should be a positive determinant of equal connectivity to aviation between remote and core regions.

[3] Alderighi & Gaggero (2017) show that air transport is a positive determinant of Italian export of manufacturing goods; Allroggen & Malina (2014) find that airports with good air services for business travellers are a determinant for local economic growth in Germany, while Bilotkach (2015) provides evidence that aviation contributes to employment and number of business establishments in US. Blonigen & Cristea (2015) exploit a natural experiment related to the air service liberalization in the US to show that aviation has a positive impact on local US GDP. A positive effect of aviation on local US employment is found also by Brueckner (2003), while Brugnoli et al. (2018) exploits a natural experiment in Italy (the de-hubbing of Alitalia from Milan Malpensa International airport) to identify that aviation has a positive impact on trade, particularly in high-tech industries. Percoco (2008) finds that air services have a positive effects on Italian local employment with spillover effects in regions close to that where the airport is located.

However, LCCs may have an incentive to connect remote regions if they are touristic destinations: by taking into account for possible seasonality effects, LCCs may provide good PTP connections to remote regions. After controlling for possible tourist flows, it is therefore interesting to evaluate empirically whether LCCs are a positive determinant of access to aviation in remote regions, and if they contribute to reducing over time the difference between remote and core regions.

We analyse these issues by building a new data set that combines aviation activity and socio-economic variables at the NUTS 2 level in Europe, for the period 2008-2015. We investigate this data set by designing a panel data econometric model that identifies the determinants of the NUTS 2 level EU regions connectivity to the aviation network and of the time variations of the NUTS 2 level connectivity.

2. Related Work

Most of the previous contributions have investigated the impact of civil aviation on economic activity, not on connectivity with focus on remote and core regions. The link between air transportation and regional economic growth is well established in the literature. Many papers have studied the impact of civil aviation on local employment (Benell & Prentice, 1993; Button et al., 1999; Button & Taylor, 2000; Brueckner, 2003; Green, 2007; Percoco, 2010; Neal, 2012; Mukkala & Tervo, 2013), on income (Button et al., 2009; Sellner & Nagl, 2010; Mukkala & Tervo; Button & Yuan, 2013; Allroggen & Malina, 2014; Baker et al., 2015; Baltaci et al., 2015; Blonigen & Cristea, 2015; Fernandes & Pacheco, 2015; Hu et al., 2015), population growth (Green, 2007; Blonigen & Cristea, 2015) and on wages (Bilotkach, 2015). Brugnoli et al. (2017) use a dataset for Italy between 2004-2014 to find that civil aviation had a positive impact on international trade, with elasticity ranging from +0.003% to 0.13% in the different econometric specifications, and that this effect is stronger in high-tech and medium-tech manufacturing sectors.

In the early 1990s, the OECD developed a three-way classification of the regions' typology (predominantly urban; intermediate; predominantly rural) based on the population density of districts (LAU2). In 2009, the OECD extended its classification to include the remoteness dimension, along the lines proposed in Dijkstra and Poelman (2008). However, remote areas might be also represented by those regions that under strict market criteria would not be transport supplied due to lack of commercial profitability. This has led to the development of different public policies to support connectivity in remote regions. According to Fageda et al. (2018) these policies are 1) route-based policies; 2) passenger-based policies; 3) airline-based policies; and 4) airport-based policies.

The paper is organized as follows. Section 2 offers a literature review. Section 3 discusses our methodological approach and presents the econometric model. Section 4 describes the available data sets, the data mining process, and descriptive statistics in the econometric model variables. Section 5 presents our empirical results, while Section 6 concludes the paper and highlights some possible policy implications.

3. Methodological Approach

As mentioned in the Introduction, our main goal is to estimate the signs and the magnitude for the regional factors influencing air transport connectivity inside Europe differentiating between core and remote regions.

As a first step in defining our methodological approach to achieve such goals, we establish our research questions. First, we consider some determinants related to regions' characteristics – such as GDP– that may influence the demand of connectivity, then we focus on some network's specific variables – such as the LCCs share– since LCCs rely more on point-to-point rather than on hub-and-spoke service.

Higher GDP levels may incentive carriers to invest in new routes, hence our first research hypothesis is as follows.

RH1: GDP may be a positive determinant for airline connectivity.

Similarly, higher levels of population's density, may incentive carriers to invest in new routes. This argument is the basis of our second research hypothesis.

RH2: Populations' density may be a positive determinant for airline connectivity.

We also want to measure remote regions' connectivity. Often, in remote regions, aviation is the only mode of transportation granting connection to mainland and to the worldwide network in a reasonable amount of time.

RH3: Airline connectivity might be higher for remote regions.

Aviation sector has been dominated by two business models, PTP and H&S, and connectivity may be related to the business model. Remote regions in order to increase their air connectivity must rely especially on H&S and in Europe H&S is mainly adopted by non LCCs, furthermore FSCs are seen also as a mean to reduce connectivity in remote regions .

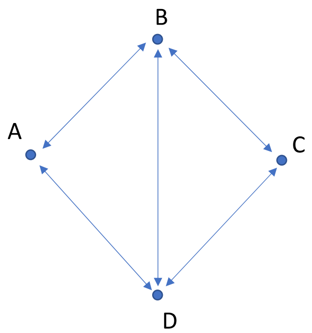
The different airline typical network organizations may be an argument for considering the different impact of FSCs and of LCCs on connectivity, especially in remote regions.

FSCs have routes mainly organized as a hub-and-spoke (H&S) network, while LCCs operate point-to-point (PTP) connections. In many remote regions demand is low, making the possible route a "thin" connection. In this case, it is unlikely that a LCC may provide a PTP flight, given the low demand. In this case the demand coming from the remote region can feed the long-haul or medium-haul flights departing from the hub. If this argument is proved empirically, FSCs should be a positive determinant of equal connectivity to aviation between remote and core regions.

RH4: LCCs' activity may be a negative determinant for airline connectivity in remote regions.

3.1. Measurement of Aviation Connectivity

We considered flights departing and arriving in Europe from 2008 to 2016, aggregated them for the departure and arrival airport's NUTS 2 region, and computed the minimum number of paths to reach each other region.[4] Then we determined the value of Connectivity for each region by calculating the average number of paths required to reach all the other regions. Hence high connectivity levels are expressed with a value close to 1, whereas lower connectivity levels are expressed with a higher value of the variable Connectivity. In order to exclude regional routes, we dropped those connection with less than 208 flights per year (4 flights per week). For a clarifying example see Figure 1.



- $A = \frac{1+1+2}{3} = \frac{4}{3} = 1.\overline{3}$
- $B = \frac{1+1+1}{3} = 1$
- $C = \frac{1+1+2}{3} = \frac{4}{3} = 1.\overline{3}$
- $D = \frac{1+1+1}{3} = 1$

Figure 1: Example of region's connectivity

[4] The NUTS 2 classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU for the purpose of controlling basic regions for the application of regional policies. We used the current NUTS 2016 classification, which is valid from 1 January 2018 and lists 104 regions at NUTS 1, 281 regions at NUTS 2 and 1348 regions at NUTS 3 level.

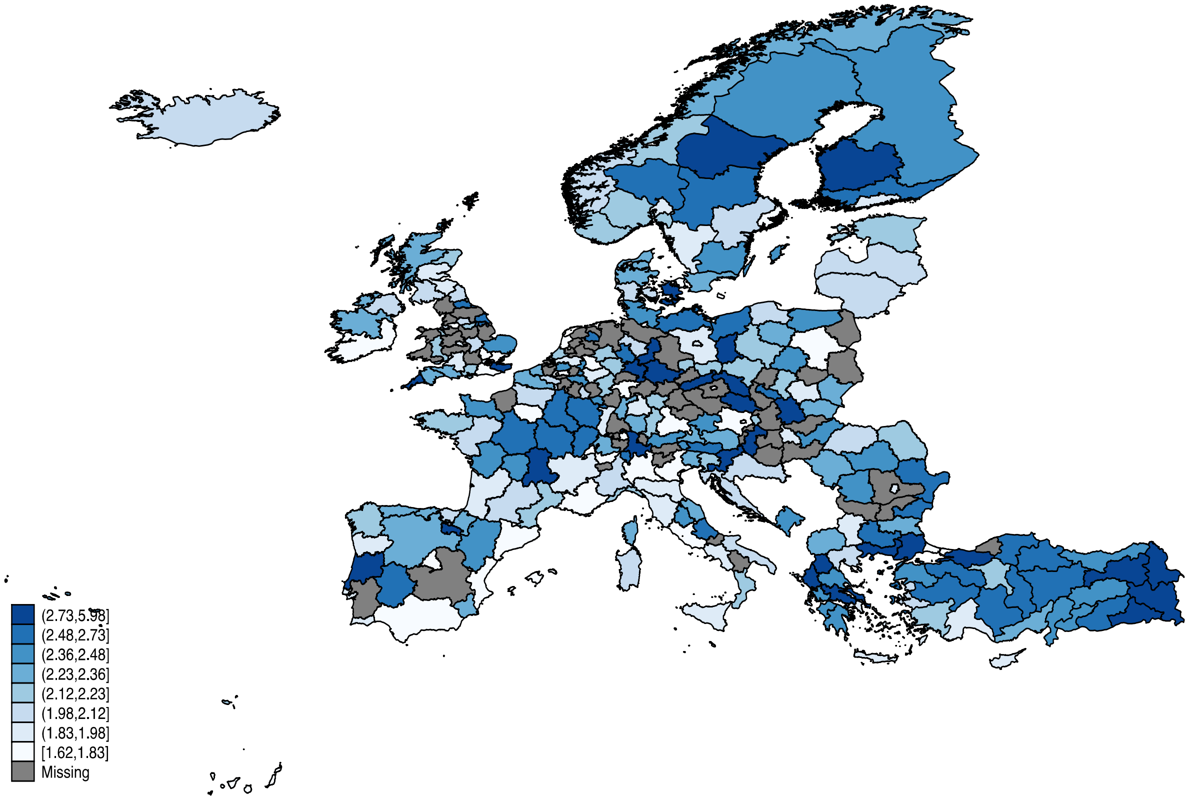


Figure 2: Map of Europe's connectivity in the year 2016

3.2. Identification of remote and core regions

Regional dummy variables were created as control variables in order to identify remote and core regions. As for core regions, we chose the 10 European regions with higher GDP in 2015, listed in Table 1.

Region Code	Nation	Region Name
DE11	Germany	Stuttgart
DE21	Germany	Oberbayern
DE71	Germany	Darmstadt
DEA1	Germany	Düsseldorf
ES30	Spain	Comunidad de Madrid
ES51	Spain	Cataluña
FR10	France	Île de France
FR71	France	Rhône-Alpes
ITC4	Italy	Lombardia
ITI4	Italy	Lazio

Table 1: List of identified core regions

Remote regions were chosen according to the 2009 OECD classification of remoteness. This classification refers to NUTS 3 regions, therefore we had to convert it for the NUTS 2 by computing the average value weighted by population. We followed two steps at NUTS 3 level. First, we include those regions that are defined as predominantly rural and remote by the OECD. More specifically: i) more than 50% of population live in rural areas; ii) less then 25%

of the population live in urban centres with more than 200.000 inhabitants and iii) driving time needed for at least 50% of the population of the region to reach a populated centre (at least 50.000 inhabitants) higher than 60 minutes. Secondly we analysed each island with an area smaller than 25.000km: if the driving/ferry time to the closest European inland city is more than 4 hours, the NUTS 3region is remote. This second step has been necessary because often remote islands were considered non-remote due to the presence of large cities in remote island (e.g. Canary Islands, Crete Cyprus, and Malta). The resulting remoteness has been extended to NUTS 2 level. We consider a NUTS2 remote if more than 50% of the population lives in a remote NUTS3 that belongs to that NUTS2.

Region Code	Nation	Region Name
BG33	Bulgaria	Severoiztochen
CY00	Cipro	Cipro
DK02	Denmark	Sjælland
EL41	Greece	Βόρειο Αιγαίο (Voreio Aigaio)
EL42	Greece	Νότιο Αιγαίο (Notio Aigaio)
EL43	Greece	Creta
EL62	Greece	Ionian Islands
ES42	Spain	Castilla-La Mancha
ES43	Spain	Extremadura
ES53	Spain	Illes Balears
ES63	Spain	Ciudad Autónoma de Ceuta
ES64	Spain	Ciudad Autónoma de Melilla
ES70	Spain	Canarias
FI1D	Finland	Pohjois- ja Itä-Suomi
FI20	Finland	Åland
FR83	France	Corse
HR03	Croatia	Jadranska Hrvatska
HU22	Hungary	Nyugat-Dunántúl (nord ovest)
IE01	Ireland	Border, Midland and Western
ITC2	Italia	Valle d'Aosta/Vallée d'Aoste
ITG2	Italia	Sardegna
MK00	Macedonia	Macedonia
MT00	MT	Malta
NO02	Norway	Hedmark og Oppland
NO03	Norway	Sør-Østlandet
NO05	Norway	Vestlandet
NO07	Norway	Nord-Norge
PL32	Poland	Podkarpackie
PT20	Portugal	Região Autónoma dos Açores
PT30	Portugal	Região Autónoma da Madeira
RO11	Romania	Nord-Ovest
SE21	Sweden	Småland med öarna
SE31	Sweden	Norra Mellansverige
SE32	Sweden	Mellersta Norrland
SE33	Sweden	Estremo nord
UKK3	UK	Cornwall and Isles of Scilly
UKM5	UK	North Eastern Scotland
UKM6	UK	Highlands and Islands
UKN0	UK	Northern Ireland

Table 2: List of identified remote regions

3.3. Econometric Model

Our aim is to identify the determinants of airline connectivity across NUTS 2 regions. Hence, we developed an econometric model to estimate the variation of possible determinants of airline connectivity and to provide empirical evidence of the possible effects of decisions that may indirectly affect connectivity. The model relies on a log-linear formulation in which some determinants are expressed in logarithms and others as dummy variables.

The econometric model that we have estimated assuming panel data random effects is as follows:

$$\log(Connectivity_{jy}) = \alpha + \beta_1 \times \log\ (GDP_{jy}) + \beta_2 \times log(Density_{jy}) + \delta_1 \times Remote_j + \delta_2 \times\ Core_j +$$
$$+\gamma_1 \times \log(tourism_{jy}) + \gamma_2 \times LCCshare_{jy} \times Remote_j + \epsilon_{jy},\ (1)$$

where j is the region, y is the year.

We perform a second panel regression instrumenting the GDP with the share of tertiary educated population in order to overcome an eventual heterogeneous relation between a region's GDP and connectivity.

We also perform a third panel regression that takes into account the spatial effects, to see if the observed variables affect also nearby regions.

The names and description of the variables included in the model are given in Table 1.

TIME	**DESCRIPTION**
$Connectivity_{jy}$	*Average number of paths to reach all the other regions*
GDP	*PPS per inhabitant*
Population	*Number of inhabitants*
Broadband	*% Households with broadband access*
Euro	*Euro area dummy (1 if yes)*
Density	*Population density*
Degree	*% of population holding a tertiary degree*
Hub_j	*Hub airport dummy (1 if yes)*
Base	*Low cost base dummy (1 if yes)*
Seats	*Number of seats offered*
LCCseats	*Number of seats offered by LCCs*
Distance	*Average length of all routes starting in the region*
Frequency	*Number of flights starting in the region*
Remoteness	*The average weighted on the population of the NUTS3*
Remote	*Dummy indicating a remote region*
Core	*Dummy indicating a core*
$HUB1_{jy}$	*Number of seats to hub regions*
$BASE1_{jy}$	*Number of seats to low cost base regions*
$HUB2_{jy}$	*Number of seats from hub regions divided by the region's population*
$BASE2_{jy}$	*Number of seats from base regions divided by the region's population*
$LCCshare_{jy}$	*modal share of LCCs*

Table 3: Description of Variables

3.4. Spatial Effects

In order to perform the analysis, we have to take into account also the fact that the connectivity of a region is influenced by the nearby regions. Therefore we need to implement spatial regression (spatial autoregressive models – SAR)

SAR models extend linear regression by allowing outcomes in one area to be affected by:

- outcomes in nearby areas,

- covariates from nearby areas, and
- errors from nearby areas.

These terms are borrowed from the time-series literature. In time series, an autoregressive AR(1) process is

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \epsilon_t \qquad (2)$$

where $y\_(t-1)$ is called the lag of y. In vector notation, L. is the lag operator, and the above equation could be written as

$$y = \varphi_0 + \varphi_1 L.y + \epsilon \qquad (3)$$

Sometimes, AR(1) models also include autoregressive errors:

$$y = \varphi_0 + \varphi_1 L.y + u \qquad (4)$$

where $u = \rho L.u + \epsilon$ In that case, the equation becomes

$$y = \varphi_0 + \varphi_1 L.y + (I - \rho L.)^{-1}\epsilon \qquad (5)$$

The parameter ρ measures the correlation in the errors and is a parameter to be estimated along with $\varphi0$ and $\varphi1$.

The time-series notation and jargon can be translated to the spatial domain. The lag operator becomes an N x N matrix W. What was L.y becomes Wy, which means matrix W multiplied by vector y. The SAR model corresponding to the above time-series equation is:

$$y = \beta_0 + \beta_1 Wy + \epsilon \qquad (6)$$

The SAR model corresponding to the time-series equation with autoregressive errors is

$$y = \beta_0 + \beta_1 Wy + (I - \rho W)^{-1}\epsilon \qquad (7)$$

W is called a spatial matrix where it is a measure of proximity, therefore we include λWy to allow nearby outcomes to affect outcomes.

4. Data Set

We built a panel data set included all scheduled flights intra Europe from 2008 to 2016. We aggregate this data for each European NUTS 2 region as to compute each region's connectivity level. The source of these data is the Official Airline Guide (OAG) database. The flights have different destination (NUTS 2), distances, carriers (aggregated in full service carriers and LCCs), frequencies, and available seats. Regional connectivity level is then estimated as the average number of paths to reach all the other regions in the given year. We collected also Eurostat regional data for the 284 NUTS 2 regions, out of a total of 1,710 where there has been at least one schedule flight in the analysed timeframe. We also dropped those regions with not available GDP (Switzerland, Turkey, Montenegro, Iceland). Our observations correspond to panel data set of 284 NUTS 2 regions (j = 1, 2, …., 284) and 9 years (y = 2008, 2009, …, 2016). However, not all airports in those regions operated every year.

We collected 2,556 observations and some descriptive statistics for the observed regions and their connectivity are shown in Table 2. The average number of steps to reach every European NUTS 2 region is 2.5.

VARIABLE	OBS.	MEAN	ST. DEV.	MIN	MAX
Connectivity	2,556	2.515	0.86	1.629167	6.97166
GDP	2,556	25,983	12,245	6,700	178,200
Population	2,556	1,804,622	1,509,814	27,153	12,100,000
Density	2,556	449	1,188	2.8	11,290
Degree	2,556	27.5	9.53	6.8	75
Euro	2,556	0.61	0.49	0	1
Tourism	2,556	1,158,482	1,999,757	11,895	17,200,000
Hub	2,556	0.02	0.14	0	1
Base	2,556	0.03	0.17	0	1
Seats	2,556	2,470,148	5,002,502	0.1	36,400,000
LCCseats	2,556	1,609,156	3,791,821	0.1	30,500,000
Distance	2,556	843	626	0.1	3,142
Frequency	2,556	18,594	35,471	0.1	257,289
Remote	2,556	0.12	0.32	0	1
Core	2,556	0.04	0.19	0	1
SeatsHUB	2,556	445,982	961,947	0.1	6,316,443
SeatsBASE	2,556	320,985	688,185	0.1	5,194,133

Table 4: Descriptive Statistics of Observed Regions

Connectivity measurement has been discussed in section 3.1, Gross Domestic Product is expressed in purchasing power standard (PPS) per inhabitant, density id the population over the region's surface in squared kilometres. The variable Degree represents the percentage of population that graduated in a tertiary degree. The dummy Euro indicates whether the country is in the Euro area in a given year, if the country has adopted the European currency we picked 0 if the adoption was within the first 6 months of the year, 1 otherwise. LCCshare represents the percentage of seats offered from a LCC over the total amount of seats.

5. Results

In this section, we present empirical evidence regarding the three previous research hypotheses . We show the estimated coefficients regarding the model for the variation of connectivity in remote and core regions (Eq. 1). The first variable captures the impact on connectivity of the region's GDP. The second captures the impact of population's density and the latter captures the impact on connectivity of LCCs in Europe which have; given that this type of carriers rely more on a point to point model, rather than hub and spoke.

The regressions outcome is shown in Table 5, 6, 7, 8. The dependent variable is region's connectivity. The three columns represent the three different regression performed. The GDP affects negatively our connectivity index, hence affects positively the connectivity.[5] As mentioned in the Hypothesis #3, not only core regions are better connected, but also remote regions. This confirms that remote regions rely more on airline activity because of their inaccessibility that is mainly driven by geographical reasons. We controlled also for PSOs to see if they play a role, but in the analyses that we run we saw no significance.

The share of LCCs is not significant, but when the variable interacts with remote regions the result is significant and shows how LCCs activities worsen connectivity in remote regions. In figure 3 we show the levels of connectivity for each share of LCCs in remote and non-remote regions. We controlled this result also for touristic inflows and the results don't change.

[5] Higher connectivity index indicates lower level of connectivity.

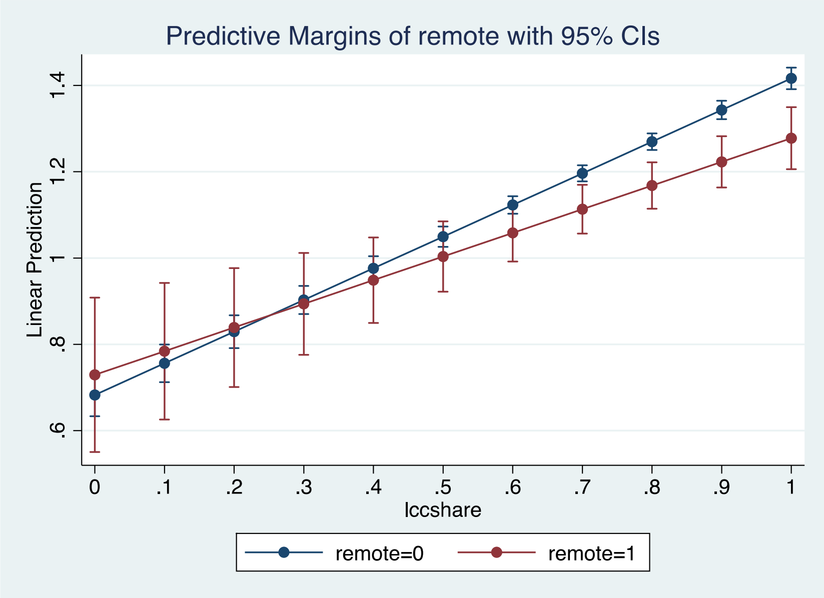


Figure 3: Levels of connectivity for each share of LCCs in remote and non-remote regions.

	Dependent variable: lconn208					
	non IV			IV		
Variables	Estimated coefficient	S.E.	P-value	Estimated coefficient	S.E.	P-value
lgdp	0.0272	(0.0299)	0.363	-0.289***	(0.0625)	0.000
ldensity	0.00986	(0.00854)	0.249	0.0340***	(0.00965)	0.000
remote	-0.376***	(0.100)	0.000	-0.447***	(0.103)	0.000
core10	-0.113**	(0.0546)	0.039	-0.0419	(0.0570)	0.462
ltour	-0.188***	(0.00870)	0.000	-0.152***	(0.0108)	0.000
lccrem	0.396***	(0.122)	0.001	0.487***	(0.125)	0.000
Constant	3.315***	(0.268)	0.000	5.905***	(0.523)	0.000
Observations	2,556			2,556		
R2	0.219			0.184		
Robust standard errors in parentheses						
Legend: *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.10						

Table 5: OLS regression results not considering spatial effects

	Dependent variable: lconn208					
	GDP non IV			GDP IV		
Variables	Estimated coefficient	S.E.	P-value	Estimated coefficient	S.E.	P-value
lgdp	-0.186**	(0.0893)	0.037	-0.144	(0.127)	0.257
ldensity	-0.0654**	(0.0272)	0.016	-0.0676**	(0.0274)	0.014
remote	-0.443	(0.342)	0.195	-0.441	(0.342)	0.197
core10	-0.0303	(0.158)	0.848	-0.0399	(0.160)	0.803
ltour	-0.156***	(0.0259)	0.000	-0.162***	(0.0281)	0.000
lccrem	0.821**	(0.389)	0.035	0.811**	(0.390)	0.038
Spatial Effect on Dep	0.590***	(0.0973)	0.000	0.582***	(0.102)	0.000
Constant	4.799***	(0.774)	0.000	4.467***	(1.056)	0.000
Observations	284			284		
Robust standard errors in parentheses						
Legend: *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.10						

Table 6: OLS Regression results considering spatial effects

	Dependent variable: lconn208					
	GDP non IV			GDP IV		
Variables	Estimated coefficient	S.E.	P-value	Estimated coefficient	S.E.	P-value
lgdp	-0.0391	(0.0581)	0.501	-0.289***	(0.0626)	0.000
ldensity	0.00614	(0.0234)	0.793	0.0340***	(0.00968)	0.000
remote	-0.487***	(0.127)	0.000	-0.447***	(0.103)	0.000
core10	-0.161	(0.152)	0.291	-0.0419	(0.0571)	0.463
ltour	-0.148***	(0.0198)	0.000	-0.152***	(0.0109)	0.000
lccrem	0.531***	(0.114)	0.000	0.487***	(0.125)	0.000
Constant	3.481***	(0.560)	0.000	5.905***	(0.525)	0.000
Observations	2,556			2,556		
Number of _ID	284			284		
Robust standard errors in parentheses						
Legend: *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.10						

Table 7: Panel regression results not considering spatial effects

	Dependent variable: lconn208					
Variables	Estimated coefficient	S.E.	P-value	Estimated coefficient	S.E.	P-value
lgdp	-0.107*	(0.0575)	0.063			
ldegree				-0.103**	(0.0467)	0.027
ldensity	-0.0477**	(0.0238)	0.045	-0.0473**	(0.0237)	0.046
remote	-0.341***	(0.125)	0.006	-0.324***	(0.125)	0.009
core10	-0.104	(0.144)	0.469	-0.129	(0.143)	0.365
ltour	-0.148***	(0.0191)	0.000	-0.154***	(0.0185)	0
lccrem	0.535***	(0.113)	0.000	0.497***	(0.112)	0
Spatial Effect on Dep	0.428***	(0.0687)	0.000	0.409***	(0.0677)	0
Constant	3.990***	(0.547)	0.000	3.330***	(0.273)	0
sigma_u	0.434***	(0.0187)		0.433***	(0.0187)	
sigma_e	0.189***	(0.00281)		0.189***	(0.00281)	
Observations	2,556			2,556		
Number of _ID	284			284		
Robust standard errors in parentheses						
Legend: *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.10						

Table 8: Panel regression results considering spatial effects

6. Conclusion

This preliminary study is an attempt to fill a gap in the existing literature regarding the possible determinants of connectivity in the commercial air transportation sector for remote and core regions. Previous contribution (e.g. Dijkstra and Poelman, 2008) define a region as remote if at least half of its population lives at more than 45 minutes by road from any city of at least 50,000 inhabitants. Fageda et al. (2018), analyzing the policies to support policies in remote regions, related remoteness to the consequent market failure to establish a new route.

In order to identify the determinants of connectivity we designed an econometric model for panel data and applied it to a data set concerning all the flights departing and landing in NUTS 2 regions in Europe over the period 2008-2016. The connectivity of each NUTS 2 was calculated based on the average number of paths required to reach all other regions.

Our main results are as follows. As we expected, connectivity is higher not only for core regions, but also for remote regions. Annual results that show also that connectivity has decreased in the year 2008. GDP and population’s density are both a positive determinant of connectivity. Second, LCCs activity doesn’t play a role in regions’ connectivity, but if we consider it only for remote regions it plays a role and worsen regions’ connectivity. LCCs are therefore a factor that reduces the connectivity differential between core and remote regions, which might provide an argument against subsidising LCCs service to remote regions. On the other hand this could be an argument against subsidising FSCs. Indeed, although the demand is low, it can feed the long-haul or medium-haul flights departing from the hub. FSCs are a positive determinant of equal connectivity to aviation between remote and core regions. This confirms one of the public policies to support connectivity in remote regions in Fageda et al. (2018), airline-based public policies to support connectivity in remote regions.

This is a preliminary draft, we acknowledge that so far it presents some limitations, for instance connectivity is measured using the average number of paths to reach other regions. In research we should consider other connectivity measures (e.g. betweeness centrality, eigenvector centrality, average number of paths to reach all the other destinations in the network, ...).

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