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Flight availability and international tourism flows☆

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ABSTRACT

This paper analyzes the effect of flight supply on international tourism flows between 20 Italian regions and 24 European countries, observed half-yearly from 1999 to 2010. We find that low-cost carriers have a prominent role in attracting international tourism flows. Our estimates suggest that an additional round-trip flight operated by a low-cost carrier generates about 74 arrivals and 248 overnight stays in hotels or similar facilities; in the case of a full-service carrier these figures decrease to 29 and 97, respectively. These findings are relevant for the current debate on the drivers of tourism development.

Introduction

Italy is acknowledged as one of the most popular tourism destinations due to its cultural, natural, historical, and gastronomic attractions. In 2016 the tourism sector accounted for about 11% of the Italian GDP and employed more than 1.2 million people (WTTC, 2017).[1]

According to UNESCO World Heritage list, in 2016 Italy ranked first with 52 world heritage properties, followed by China (50), Spain (46), France (42) and Germany (41). In the same year, however, Italy hosted only 52.4 million international tourists, whilst China, Spain, France and Germany, respectively, attracted 59.3, 75.6, 82.6, and 35.6 million tourists (UNWTO, 2017). Thus, within this country list, Italy is ranked fourth, only followed by Germany. The explanation for these figures is not trivial, as tourism flows are determined by various factors such as overall tourism facilities, attractions, amenities, climate, proximity to wealthy and populated markets, origin and destination prices, travel costs, and accessibility (Garrod & Fyall, 2000; Russo & van der Borg, 2002; Seetaram, Forsyth, & Dwyer, 2016).

To provide some anecdotal evidence that poor air accessibility can hamper the Italian tourism industry, it is useful to compare

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[1] The tourism sector "relates to the activity of travellers on trips outside their usual environment with a duration of less than one year" (WTTC, 2017, page 11).

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Italy with Spain, its closest tourism alternative, especially during the summer season. According to Eurostat, in 2016 there were 50 percent more the international intra-EU air passengers in Spain than in Italy (132.9 versus 79.4 millions). As shown above, this percentage difference coincides with that reported in international tourism flows between these two countries during the same year (75.6 versus 52.4 millions).

This example indicates that differences in international tourism flows can be explained by differences in air accessibility (Bieger & Wittmer, 2006; Graham, Papatheodorou, & Forsyth, 2010; Hong-bumm, 1998). With this work we aim to investigate this suggested link empirically and quantify the effect of non-stop flights on tourism flows (arrivals and overnight stays). Moreover, our analysis aims to determine the different impact of low-cost carriers (LCCs) and full-service carriers (FSCs), expecting the former to be more effective in expanding tourism flows than the latter (Dobruszkes, 2006), because: (*i*) LCCs tend to generate additional passenger traffic to a greater extent than FSCs, known as the 'Southwest effect' (Garin-Munoz, 2007; Rey, Myro, & Galera, 2011; Vowles, 2001); and (*ii*) price sensitive tourists prefer to fly on LCCs since they offer cheap fares (Barros & Machado, 2010).

We use original and comprehensive data, including information on non-stop flights and tourism flows from 24 European countries to all the 20 Italian regions on a half-yearly basis during the period 1999–2010. The determinants of arrivals and overnight stays are studied by a zero-inflated negative binomial model, which accounts for the fact that discrete dependent variables have a high share of zeros. The selection of the variables is driven by consumer behavior theory and by some predictions based on the gravity theory of international trade.

In consumer behavior theory, individuals are utility maximizing agents and take their consumption decisions on the basis of their preferences, their budgetary constraints, and product and service prices (Stabler, Papatheodorou, & Sinclair, 2010, Chp. 2). Consumers love variety and they have a preference for a mix of products and services, including tourism activities. Since tastes vary among individuals, and because of their love for variety, different destinations are chosen by different tourists or by a single tourist at various points in time (Papatheodorou, 2001).

Tourists' decisions are affected by income and prices (Eugenio-Martin, 2003; Lim, 1997; Seetaram et al., 2016). Most of the empirical studies have found that the income elasticity of tourism demand for a destination is positive and greater than 1, suggesting that international tourism destinations are a superior good (Garin-Munoz, 2007; Song, Kim, & Yang, 2010). Consumer behavior theory suggests that an increase in destination prices reduces their demand and increases the demand for alternatives (Seetaram, 2012). More generally, the choice among destinations includes a comparison of the utility coming from the visit with the overall costs of the stay, i.e. including travel costs. In this respect, the presence of non-stop flights for international destinations reduces the generalized cost of travel and makes the visit to the destination more appealing (Koo, Lim, & Dobruszkes, 2017).

According to the gravity model approach, tourism flows are proportional to the economic size of the origin and destination areas and to trading facilitators (in our case, non-stop flights), while they decay with distance (Khadaroo & Seetanah, 2007; Massidda, Etzo, & Piras, 2015; Morley, Rosselló, & Santana-Gallego, 2014). The negative effect of distance is explained by its positive correlation with the generalized cost of travel, which is softened by the presence of non-stop flights (Francis, Humphreys, Ison, & Aicken, 2006). A larger population in the origin areas of the tourism flows increases the number of prospective tourists, and therefore it shifts the demand upwards; a larger population in the destination area is positively related to better tourism facilities and to a higher number of attractions and amenities (Garin-Munoz, 2007).

The remainder of this paper is structured as follows. The next section reviews the main contributions of the literature. The collection of the data is described in Section 'Data'. The econometric approach and some methodological issues are discussed in Sections 'Econometric model' and 'Methodology', and the results are presented in Section 'Results', together with the robustness checks. Finally, Section 'Conclusions' summarizes and concludes the paper.

Literature review

In this section we link the main predictions of consumer behavior theory and the gravity theory of international trade to the results of the empirical literature on tourism. We start with a general discussion of the main drivers of tourism demand, and then we narrow the analysis down to two relevant determinants of tourism flows: air transport and migration.

Demand for tourism

People go on holiday for various reasons: novel experience; escape; knowledge seeking; fun and excitement; rest and relaxation; family and friends togetherness (Jang & Cai, 2002). One of the key questions that may arise is what drives the choice of a given place from among a large set of available tourism destinations. The attractiveness of the place is a major determinant of tourism flows (Cracolici & Nijkamp, 2009; Tang & Rochananond, 1990). The concept of attractiveness should, however, go beyond the mere natural/cultural beauty of the tourist site, as one place may become more or less attractive simply because of a change in fashion or taste by tourists (Papatheodorou, 1999).

A key role in the choice of the tourism destination is also played by the overall cost of the holiday: the generalized cost of travel and the expenditures for goods and services at the destination (Eugenio-Martin, 2003; Seetaram et al., 2016). The price considered by tourists when they choose their holiday can be reduced to the transportation costs plus the prices of goods and services consumed at the destination.

Low transportation prices can enhance the relative competitiveness of a particular place and make it more desirable amongst a set of destinations (Divisekera, 2003; Prideaux, 2000). In some cases travel costs represent the largest item in the expenses of the holiday, and therefore may be a very relevant driver in the choice of the destination. For example, the overall cost of a holiday to Indonesia for an American or a European tourist is mainly due to the price of the long-haul airline ticket, as the cost of living in Indonesia by Western standards is very low. The cost of travel also affects tourism demand for short-haul destinations: for instance, Garin-Munoz (2007) finds that the cheap fares offered by LCCs have spurred German tourism to Spain.

The cost of living at the tourism destination has been widely documented as another important factor affecting the tourism flows (Garin-Munoz & Montero-Martin, 2007; Garin-Munoz, 2007; Tsui, 2017). The empirical literature uses the real exchange rate, or a weighted version of it, as a measure of the relative price differential between the origin and the destination (Dogru, Sirakaya-Turk, & Crouch, 2017; Massidda et al., 2015). As an alternative to the real exchange rate, a competitiveness index is also found to predict tourism flows (Etzo, Massidda, & Piras, 2014; Seetaram et al., 2016).

A price-related driver of tourism demand is the per-capita income in the place of tourism origin. A higher income enlarges the set of international places to visit, since tourists substitute cheaper domestic destinations with more expensive international ones (Athanasopoulos & Hyndman, 2008). In a detailed review of the empirical works published by the leading tourism journals, Lim (1997) finds that the most used explanatory variable is income (83% of the reviewed papers include the income variable in their empirical specification), followed by relative prices (73%), and transportation costs (55%).

Finally, the habit persistence, also called “repeat visits” or simply “repeats”, represents an important driver of tourism demand, since people tend to choose those destinations with which they are more familiar (Massidda & Etzo, 2012; Garin-Munoz, 2007).

Airlines and tourism

The link between airline supply and international tourism is tied to the travel costs, which are an important component of the destination choice. Since many travelers are price sensitive, the cheap air fares offered by LCCs spur the movement of leisure travelers (Dresner, Lin, & Windle, 1996; Rey et al., 2011; Tsui, 2017).

More specifically, Rey et al. (2011) use a panel data approach covering the EU-15 countries and a selection of six Spain destinations in order to study the impact of airline services on the Spanish tourism sector. They find that LCCs have immediate direct and lagged indirect effects: the short-run elasticity of the LCCs’ passengers to tourism demand (direct effect) is about 0.028 and the long-run elasticity (direct and indirect effects) is almost twice that figure.

Tsui (2017) studies empirically the impact of LCCs on tourism to New Zealand during the period 2009–2015. Similarly to our empirical analysis, he uses data on tourism at the regional level. He finds that the presence of an LCC service, Jetstar, has a positive impact on domestic tourism in New Zealand. In line with the above empirical works, Clavé, Saladié, Cortés-Jiménez, Young, and Young (2015) using an ad hoc survey shows that one of the main reasons influencing the choice of the tourism destination is the availability of an LCC service.

Some authors emphasize the role of LCCs on tourism growth. For instance, Donzelli (2010) studies the link between airlines and tourism in the South of Italy. He finds that those regions which are mainly served by LCCs tend to exhibit a faster growth of tourism activities relative to those regions which are mainly served by FSCs.

Duval and Schiff (2011) investigate whether a direct air link to New Zealand from various countries (Canada, Chile, Indonesia, South Korea and Taiwan) has a positive effect on inbound tourism to New Zealand. Even if their findings vary across countries, they show a positive link between the presence of non-stop flights and international visitors.

Migration and tourism

There are two important related channels by which migration is positively linked to tourism. The first is through labor migration: foreign workers may eventually settle down at the destination and supply their service to the tourism sector (Law, Genç, & Bryant, 2013; Massidda, Etzo, & Piras, 2017; Tadesse & White, 2012; Williams & Hall, 2002). The second channels relates to visiting friends and relatives, which causes inbound and outbound trips (Forsyth, Dwyer, Seetaram, & King, 2012; Prescott, Wilton, Dadayli, & Dickson, 2005; Provenzano & Baggio, 2017; Seetaram, 2012).

This second channel is the one most related to our work. Indeed, it may happen that for leisure or for family celebrations migrants return to their native country, or friends and relatives travel to the migrants’ country of residence. Furthermore, the presence of friends and relatives abroad may save visitors the costs of accommodation and other services, and, thus, it encourages the visit (Massidda & Piras, 2015; Seetaram, 2012). For this reason the nexus migration-tourism does not only pertain to the mere visiting friends and relatives motif, but also concerns other segments of the tourism market, such as holiday and business (Massidda et al., 2015). Etzo et al. (2014) have made a detailed study on the impact of migration on tourism trips. They find that Italians residing in a foreign country have a positive influence on the Italian tourism flows to that country, irrespective of the purpose of the visit. Generalizing, this result bears the important implication that a foreign community abroad can generate both business and tourism.

A similar analysis has been conducted by Seetaram (2012), who investigates the effect of Australians born overseas (proxy for migration) on the tourism arrivals, using data from 1980 to 2008. She finds a positive link between migration and international tourism to Australia; the estimated migration elasticities are 0.028 in the short run, and 0.090 in the long run. Forsyth et al. (2012) apply a different methodology to the Australian data, and find that inbound and outbound migration demand elasticities range between 0.56 and 0.72 in the short term.

Comparing these numbers with the results of other empirical works (the focus is on Italy), the short-run elasticity estimates are 0.038–0.064 for Italian migrants living abroad and 0.049–0.103 for foreign-born immigrants residing in Italy, while the computed long-run elasticities are, respectively, 0.162–0.332 and 0.254–0.438 (Etzo et al., 2014; Massidda et al., 2015).

Data

The data used in this work combines information coming from different statistical sources: the Official Airline Guide (OAG); the Italian National Institute of Statistics (ISTAT); the World Bank; and Eurostat. With the exception of OAG, the regional data were retrieved from ISTAT, while variables at the country level were normally obtained from the World Bank and from Eurostat.

The OAG provides worldwide statistics on airline flights, including: airport of origin and destination; operating carrier; scheduled departure; and arrival date. We retrieved data on bi-directional non-stop weekly frequencies for each airline and each origin-destination linking European countries to the Italian regions from 1999 to 2010 on a half-yearly basis. The airline time schedule is revised twice a year in accordance with the winter schedule (November–March) and the summer schedule (April–October). The data comprise all the 20 Italian regions and the major European countries. Countries which are excluded from the analysis are those not linked regularly to any Italian region by non-stop flights. This is because they are either very small (e.g. Liechtenstein; Principality of Monaco; Vatican City State; etc.) or recently established countries (e.g. Bosnia and Herzegovina; Croatia; etc.) or far from Italy (the Faroe Islands; Iceland; etc.).[2] The analysis on European visitors covers about 72% of the incoming international tourism to Italy (Alivernini, Breda, & Iannario, 2014). Because the main interest of our analysis is on the differential effect of LCCs vs FSCs, we have excluded intercontinental flows, which are the domain of the FSCs.

The classification of an airline as an LCC is based on: (*i*) its membership of the European Low Fares Airline Association; (*ii*) the investigation of some important contributions in the field (Dobruszkes, 2006, 2009, 2013; Francis et al., 2006; Graham & Shaw, 2008); and (*iii*) the analysis of the carrier's mission statement. An airline is classified as an FSC if it has not been classified as an LCC. The FSCs of our sample comprise previous flag carriers (Alitalia, Air France; Lufthansa, British Airways, etc.) and regional carriers (Meridiana, Brit Air, Air Dolomiti, CityJet, etc.). The list of the airlines in our sample with their FSC/LCC classification is reported in Table 1.

The statistics on the number of people (*Arrivals*) and overnight days of stay (*Stays*) in hotels and similar accommodation facilities are obtained from ISTAT on a quarterly basis. This data includes accommodation provided by: hotels and similar establishments (e.g. bed & breakfast), resort hotels, suite/apartment hotels, motels. Data on tourism flows do not account for tourists staying at friends' and relatives' residences or lodging in rented accommodation.[3] The provision of homes and furnished or unfurnished flats or apartments by private people for short stays or for more long-term use (e.g. monthly or longer) are also not considered. However, even if, for this reason, tourism flows may be underestimated, the measurement error of the *Arrivals* and *Stays* variables should be very limited because renting flats or rooms by local people has only gained ground in the recent years due to the expansion of the circular economy: web platforms such as Airbnb or Couchsurfing were not widely used during our sample period.

The temporal structure of the tourism data allows us to establish a correspondence with the time framework of the OAG data, as exemplified in Table 2. Thus, the summer season of the airline time schedule is associated with the second and third quarters of the calendar, while the winter season is associated with the first quarter and the fourth quarter (of the previous year). Quarterly data were then aggregated into semesters for the analysis.

Because we retrieved the bi-directional weekly flight frequency during a semester from OAG, we organize our tourism variables with this weekly framework, so that we can interpret the estimated coefficients more easily in the regression. Thus, we divide the total tourism arrivals and overnight stays in a semester by 26, a figure which represents the number of weeks in a semester.

The time series on the per-capita GDP and population of the Italian regions are provided by ISTAT on a yearly basis, and converted to fit the half-year temporal structure. More precisely, these variables have been evenly split among the four quarters, and then aggregated in a similar fashion to the previous variables. A similar procedure is followed for data on Italian residents abroad and foreign residents in the Italian regions, figures which are still provided by ISTAT on a yearly basis.

From ISTAT we also retrieved the Consumer Price Index (CPI) of each Italian region. This data, which is provided on a monthly basis, is averaged for each semester, complying with the time framework illustrated in Table 2. The CPI of the country of origin and the nominal exchange rate (EXR) were obtained from the World Bank. Both are provided on a yearly basis and then transformed into half-yearly figures in the same way as the per-capita GDP and population of the destination regions. The price indices and the nominal exchange rate were combined to obtain a relative measure of prices, defined as: $Realexchangerate_{crt} = (\mathrm{CPI}_{rt} * \mathrm{EXR}_{crt})/\mathrm{CPI}_{ct}$, where subscripts c and r denote, respectively, the country c of tourism origin and the region r of tourism destination.

Data on country and region railway line development were obtained from ISTAT and World Bank, respectively. More specifically, *Country rail* and *Region rail* variables are defined as the ratio of the total km of railway lines per 100 square kilometers of the country or of the region, respectively.

From Eurostat, we collected quarterly data on the national GDP and population of the European countries in the sample, and the data were aggregated to achieve the same time structure as the other variables. From Googlemaps we retrieved the region-country

[2] The countries of tourism origin included in our sample are: Albania (S), Austria (W), Belgium (W), Bulgaria (E), Czech Republic (E), Denmark (N), Finland (N), France (W), Germany (W), Greece (S), Hungary (E), Ireland (N), Luxembourg (W), the Netherlands (W), Norway (N), Poland (E), Portugal (S), Romania (E), Slovakia (E), Spain (S), Sweden (N), Switzerland (W), Turkey (S), and the United Kingdom (N). The letter in parenthesis defines the macro-area to which the country belongs: North (N), South (S), West (W) and East (E); this categorization comes from the United Nations geoscheme.

[3] (Alivernini et al. (2014), page 14) report that, in our sample period, the percentage of foreign visitors to Italy not staying in a hotel or B&B is in the range 30–42%, which is made up by the following categories: staying with relatives or friends (17–23%); own home (6–10%); and other accommodation, such as motor caravans/campers, cruise ships, youth hostels, residential institutions, clinics (6–9%).

Table 1
Full-service & low-cost carriers in our sample (1999–2010).

Panel A – Full service carriers		
Adria Airways Switzerland	Brussels Airlines	Lufthansa
Aegean Airlines	Bulgaria Air	Luxair
Aer Lingus	Carpatair	MaléV Hungarian Airlines
Aeroflot Russian Airlines	CityJet	Meridiana
Air Berlin	Club Air	Olympic Air
Air Dolomiti	Croatia Airlines	Portugalia Airlines
Air Europa	Crossair/ Swiss	Rossiya Airlines
Air France	Czech Airlines	Scandinavian Airlines
Air Lituanica	Finnair	Swissair
Air Malta	Gandalf Airlines	TAP Portugal
Air One	Hahn Air Lines	Tarom
Alitalia	Helvetic Airways	Turkish Airlines
Austrian Airlines	Iberia	Ukraine International Airlines
Brit Air	KLM	VLM Airlines
British Airways	LOT	
Panel B – Low-cost carriers		
Aer Lingus	FlyMe	Norwegian Air Shuttle
Air Berlin	Flybe	Ryanair
Air Finland	FlyNiki	Sky Europe
Alpi Eagles	Germania	Sterling
Belle Air	Germanwings	Transavia
Blue Air	Go Fly	Virgin Express
Blue Panorama	Hapag-Lloyd Express	Volare Airlines
bmibaby	Intersky	Vueling Airlines
Centralwings	Jet2.com	Wind Jet
dba	Monarch Airlines	Wizz Air
easyJet	My Travel Lite	
Eurowings	Myair	

(a) Aer Lingus appears in both panels of the table as it switched its FSC status to LCC status in 2006.

Table 2
Winter and summer semester spells.

…	Year 2004				Year 2005				…
…	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	…
Winter 2003	Summer 2004		Winter 2004		Summer 2005		Winter 2005		

distance, expressed in thousands of kilometers and defined as the shortest travel path by car between the capitals of each pair.

National and regional GDP are in constant prices with the reference year set at 2005, which represents the middle of the sample period. By combining all the information from the above data sources, we obtained a balanced panel, which comprises all the 20 Italian regions and 24 European countries observed half-yearly during the period 1999–2010, with a total of 11,520 observations. The descriptive statistics and the correlation matrix of the variables used in the analysis are reported in Tables 3 and 4, respectively. Details on how the variables have been built from the retrieved data and a discussion of the instruments (the last four variables of the tables) are presented in the next sections.

Finally, following Tsui (2017), we applied the Im, Pesaran, and Shin (2003) procedure to test for the presence of unit roots on the data. We reject the null hypothesis that all panels contain a unit root at the 1 per cent significance level, and we conclude that all series are stationary, which avoids the problem of spurious regression (Baltagi, 2005, Chp. 12).

Econometric model

The econometric model we estimate can be summarized by the following equation:

$$\begin{aligned} TOUR_{crt} = f\,(&FLY_{crt}, CountryGDP_{ct}, RegionGDP_{rt},\\ &CountryPopulation_{ct}, RegionPopulation_{rt},\\ &Italiansabroad_{ct}, ForeignersinItaly_{rt},\\ &Countryrailway_{ct}, Regionrailway_{rt},\\ &Distance_{cr}, Realexchangerate_{crt}, Unesco_{rt}), \end{aligned} \tag{1}$$

with c identifying the (European) country, r the (Italian) region, and t the semester. We use two different dependent variables measuring tourism activities: the number of incoming people (*Arrivals*) and the number of overnight stays (*Stays*).

Table 3
Descriptive statistics (number of observations 11,520).

Variable	Mean	Std error	Min	Max
Arrivals	590.148	1,858.099	0.000	31,989.040
Stays	2,029.321	7,044.594	0.000	148,930.300
ALL flights	10.200	34.520	0.000	884.000
FSC flights	8.406	29.794	0.000	884.000
LCC flights	1.794	8.359	0.000	197.000
Country GDP	59.125	40.516	2.762	182.353
Region GDP	22.948	5.805	12.463	34.003
Country population	21.127	23.673	0.427	82.537
Region population	2.929	2.335	0.119	9.918
Italians abroad	4.052	13.530	0.000	208.261
Foreigners in Italy	0.984	4.600	0.000	98.205
Country railway	5.481	3.364	1.050	12.978
Region railway	5.316	1.835	1.773	9.385
Distance	1.666	0.634	0.205	3.375
Real exchange rate	101.645	9.553	75.332	159.343
Unesco	1.883	1.829	0.000	7.000
Neighbor FSC flights	38.931	79.607	0.000	1,498.000
Neighbor LCC flights	7.708	21.415	0.000	301.000
Neighbor alliance share	18.341	5.209	0.181	66.667
Internet	12.136	11.643	0.000	42.985

Our set of regressors comprises various variables. *FLY* represents the key variable of our analysis and is expressed either in a single regressor measuring the overall country-region flight frequencies (*All flights*), or in two variables measuring the frequencies of full-service carriers (*FSC flights*) and low-cost carriers (*LCC flights*).

To account for the price differences between country *c* and region *r*, we include two covariates. The first is *Real exchange rate*; because this variable increases when regional prices become higher, we expect a negative sign of the coefficient. The second covariate that controls for the cost of living in the tourism destination is the per-capita GDP of the Italian region (*Region GDP*). This variable can have a twofold effect on tourism. A positive effect is expected because any area with high per-capita GDP usually has superior facilities and infrastructure, which makes the area more attractive to tourists. The second effect points in the opposite direction because rich places are also expensive places and therefore less attractive to tourists. Since the Italian tourism industry is growing in areas which are less developed, we expect the latter effect to prevail, and therefore to observe a negative coefficient of *Region GDP*. We have also included the *Country GDP* variable, which is a measure of the average income in the European country of the origin of the tourism flows; the expected sign of this variable is positive because international tourism is a superior good.

Population of region *r* (*Region population*) and population of country *c* (*Country population*) control, respectively, for the dimension of the hosting region and of the country of tourism origin. Because of a scale effect of origin population and tourism destination attractions, we expect both variables to have a positive impact on tourism flows. *Foreigners in Italy* and *Italians abroad* control for the impact of migrants in expanding tourism. The first variable is the number of people born in country *c* and living in region *r*. The second variable is the number of people born in region *r* living in country *c*. Both variables are expected to have a positive impact on tourism flows: the former since immigration generates visits from friends and relatives, and the latter since immigrants help to promote their region of origin.[4]

Other additional controls include *Country railway*, *Region railway*, *Distance*, and *Unesco*. The railway variables aim to measure the development of the infrastructure in the country of origin and in the region of destination: we expect a better infrastructure to be a facilitator of travel and hence of tourism flows.

Distance is the distance from the capital of country *c* to the capital of region *r*. In line with gravity theory, this variable accounts for the positive role of proximity on tourism flows. Moreover, *Distance* can partially account for the travel cost; however under a panel framework the explanatory power of *Distance* may be limited by the time-invariant feature of the variable, which ignores the changes in market conditions that may occur over time (Seetaram, 2010).

Unesco counts the number of UNESCO World Heritage sites in region *r* and contributes to the debate on the importance of UNESCO in fostering tourism flows (Cellini, 2011; Yang, Lin, & Han, 2010).

Finally, the regressions include a semester time-effect and a macro-regional effect. The latter is measured by a set of dummy variables which split the Italian territory into North-East, North-West, Center, South and Islands.

[4] Note that immigration is a segment of population: that is, *Foreigners in Italy* and *Italians abroad* are, respectively, a small subset of *Country population* and *Region population*. The relatively low correlation among these variables (see Table 4) keeps the multicollinearity concern under control and, by including this entire set of variables, we are able to account for both a scale effect (population) and a migration effect (residents abroad) on tourism.

Table 4
Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 (Arrivals)	1.00																			
2 (Stays)	0.97	1.00																		
3 (ALL flights)	0.66	0.57	1.00																	
4 (FSC flights)	0.62	0.53	0.98	1.00																
5 (LCC flights)	0.51	0.45	0.65	0.47	1.00															
6 (Country GDP)	0.08	0.08	0.05	0.04	0.03	1.00														
7 (Region GDP)	0.14	0.09	0.25	0.25	0.18	0.03	1.00													
8 (Country population)	0.35	0.33	0.32	0.30	0.25	−0.18	0.00	1.00												
9 (Region population)	0.30	0.25	0.43	0.41	0.30	0.00	0.16	0.00	1.00											
10 (Italians abroad)	0.29	0.29	0.19	0.16	0.21	0.14	−0.13	0.30	0.16	1.00										
11 (Foreigners in Italy)	0.03	0.02	0.11	0.08	0.14	−0.21	0.15	0.00	0.18	−0.03	1.00									
12 (Country railway)	0.12	0.14	0.11	0.10	0.09	0.15	0.00	0.04	0.00	0.23	−0.09	1.00								
13 (Region railway)	0.19	0.17	0.19	0.19	0.14	0.00	0.04	0.00	0.48	0.05	0.11	0.00	1.00							
14 (Distance)	−0.11	−0.09	−0.15	−0.16	−0.04	0.13	−0.34	−0.01	−0.03	−0.08	−0.07	−0.46	−0.08	1.00						
15 (Real exchange rate)	−0.05	−0.05	−0.04	−0.05	−0.01	−0.22	−0.11	0.05	−0.01	−0.06	−0.01	−0.07	−0.02	−0.04	1.00					
16 (Unesco)	0.30	0.26	0.27	0.24	0.27	0.01	0.08	0.00	0.75	0.15	0.15	0.00	0.46	−0.01	−0.05	1.00				
17 (Neighbor FSC flights)	0.36	0.33	0.41	0.43	0.18	0.07	0.19	0.51	0.05	0.13	0.01	0.16	0.06	−0.24	−0.09	0.02	1.00			
18 (Neighbor LCC flights)	0.23	0.21	0.25	0.20	0.33	0.04	0.18	0.39	0.02	0.09	0.07	0.14	0.05	−0.08	−0.02	0.05	0.48	1.00		
19 (Neighbor alliance share)	0.03	0.01	0.13	0.17	−0.08	0.07	0.10	0.02	0.05	−0.09	−0.19	0.00	−0.03	−0.08	−0.01	−0.04	0.24	−0.08	1.00	
20 (Internet)	0.08	0.06	0.08	0.03	0.21	0.32	0.33	0.01	0.05	0.09	0.00	0.10	0.04	0.04	−0.27	0.15	0.03	0.32	−0.10	1.00

Methodology

This section covers important methodological issues regarding the choice of: the estimator for Eq. (1); the strategy employed to correct for potential endogeneity; the testing of the validity of the selected instruments; and the way of clustering standard errors.

Estimator

The choice of a suitable estimator for tourism flows is driven by the characteristics of the dependent variables: *Arrivals* and *Stays* variables are countable, and they exhibit a large share of zero values (i.e. about 28% of the sample). According to Cameron and Trivedi (2013), a zero-inflated negative binomial (ZINB) model is to be employed when there is an 'inflation of zeros' and 'over-dispersion'. The first aspect refers to the fact that data can be generated by a particular mixture of two populations: one having only zero counts and another in which the counts are the output of a discrete distribution. In this case, the estimates from a standard count model, such as the Poisson model or the negative binomial model, may suffer from misspecification. The test by Vuong (1989) largely supports the choice of the zero inflated model, beyond the 1% level threshold of significance.

The second aspect refers to the fact that the conditional variance of the dependent variable is larger than its conditional mean. The robustness sub-Section also reports the results of the zero-inflated Poisson (ZIP) model, an alternative estimator for count data, under the equality of conditional mean and variance. However, the presence of over-dispersion means that the assumption of a Poisson distribution for the error process is not satisfied, so that the (zero-inflated) negative binomial, which allows the variance to differ from the mean, is preferred. The choice of ZINB versus ZIP is also supported by a highly significant likelihood ratio alpha test.[5]

The ZINB (ZIP) model has two parts: the logit model, which predicts the probability that the only possible observation is zero; and the negative binomial (Poisson) model that generates counts. As explanatory variables in the logit regression, we use the geometric mean of the population of country *c* and region *r*, together with a time trend. We expect the former variable to have a negative impact on the likelihood of observing a zero value on arrivals or overnight stays because there is a positive correlation both between regional population and accommodation facilities (the attractors of tourism flows) and between country population and people aiming to go on holiday (the generators of tourism flows). Similarly, because tourism has experienced a general expansion over time, we expect the *Time trend* variable to have a negative impact on the likelihood of observing a zero.

Endogeneity

The main source of endogeneity in our analysis is simultaneity. This stems from the circular relation between flight supply and tourism flows: new flights to a destination generate additional tourism flows, which, in turn, induce airlines to schedule more flights (Koo et al., 2017; Tsui, 2017). Thus, the circular effect between these two variables makes it difficult to quantify the impact of flight supply (*ALL flights*, *FSC flights* and *LCC flights*) on tourism (*Arrivals* and *Stays*), as required for the estimation of Eq. (1).

To correct for endogeneity bias in count data models, we follow the two-stage residual inclusion approach implemented in Terza, Basu, and Rathouz (2008). This methodology rests on the use of a control function and is conducted by going through the following steps: (*i*) regress each endogenous variable with ordinary least squares on the exogenous variables, together with the set of additional exogenous regressors (instruments); (*ii*) obtain the residuals from each auxiliary regression; (*iii*) include the residuals as additional explanatory variables in Eq. (1) in order to obtain an unbiased estimate of the model (Wooldridge, 2001).

Instruments

A variable is a valid instrument for an endogenous regressor if it is sufficiently correlated with it (i.e. the instrument is not weak), and it cannot be directly related to the dependent variable (i.e. uncorrelated with the error term). In our analysis we consider four instruments: the geometric mean of the percentage of broadband internet subscribers in the country of origin and in the region of tourism destination (*Internet*); the average market share of the flights from country *c* to the neighboring regions of region *r* that belong to a global airline alliance (*Neighbor alliance share*); and the FSC and LCC frequencies of flights from country *c* to neighboring regions of region *r* (*Neighbor FSC flights* and *Neighbor LCC flights*, respectively).

Statistical tests confirm that these four instruments are valid. First of all, the *F* test reported at the bottom of Table 6 highly rejects the null hypothesis that the instruments are weak: the *F* statistic largely exceeds the often-used threshold of 10 (Staiger & Stock, 1997). Thus, on the basis of this test, we do not have a weak-instrument problem. Moreover, the first-stage estimates show that the coefficients have the expected sign (Table 6 and discussion in Section 'Arrivals'). Second, we have also computed the Sargan-Hansen test of over-identifying restrictions on all the instrumental variable estimates (Tables 5, 7 and 8).[6] The null hypothesis of the test is never rejected at the conventional level of significance, indicating that instruments are not correlated with the error term.

The validity of these instruments can be also confirmed by the following reasoning. *Internet* has been chosen because airlines tend

[5] Previous studies on tourism demand tend to use linear models to analyze tourism flows (Garin-Munoz & Montero-Martin, 2007; Massidda & Etzo, 2012; Massidda et al., 2015; Garin-Munoz, 2007, see, amongst others.) Count data models have only recently been applied. For instance, ZINB is employed to study the impact of immigrants on US tourism arrivals (Tadesse & White, 2012), while ZIP is used to analyze the determinants of the international tourism demand in ASEAN countries (Karimi, Faroughi, & Rahim, 2015).

[6] When not directly provided by the software package, it has been computed using the algorithm suggested by Davidson and MacKinnon (2015).

Table 5
Effect of non-stop flights on arrivals.

	Model 1		Model 2		Model 3		Model 4	
	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error
ALL flights	0.0034***	0.0006			0.0295***	0.0040		
FSC flights			0.0031***	0.0007			0.0271***	0.0037
LCC flights			0.0049***	0.0016			0.0689***	0.0155
Country GDP	0.0115***	0.0012	0.0115***	0.0012	0.0089***	0.0007	0.0085***	0.0007
Region GDP	0.0006	0.0059	0.0004	0.0059	−0.0972***	0.0168	−0.1191***	0.0180
Country population	0.0305***	0.0012	0.0304***	0.0012	0.0189***	0.0017	0.0168***	0.0018
Region population	0.3081***	0.0116	0.3088***	0.0115	0.1612***	0.0238	0.1555***	0.0234
Italians abroad	0.0100***	0.0007	0.0100***	0.0007	0.0079***	0.0012	0.0055***	0.0016
Foreigners in Italy	0.0162***	0.0047	0.0160***	0.0048	0.0094***	0.0037	0.0028	0.0051
Country railway	0.0109	0.0092	0.0105	0.0092	0.0049	0.0053	−0.0024	0.0062
Region railway	0.2712***	0.0095	0.2710***	0.0094	0.2356***	0.0162	0.2290***	0.0178
Distance	−0.4943***	0.0517	−0.4970***	0.0528	−0.3810***	0.0335	−0.4119***	0.0343
Real exchange rate	−0.0208***	0.0050	−0.0209***	0.0050	−0.0171***	0.0021	−0.0193***	0.0022
Unesco	0.0508***	0.0124	0.0497***	0.0122	0.1008***	0.0166	0.0782***	0.0194
ALL First-stage residuals					−0.0273***	0.0039		
FSC first-stage residuals							−0.0255***	0.0036
LCC first-stage residuals							−0.0646***	0.0154
Inflation model (logit)								
Mean population	−0.1258***	0.0078	−0.1258***	0.0078	−0.1240***	0.0065	−0.1239***	0.0065
Time trend	−0.0188**	0.0079	−0.0188**	0.0079	−0.0192***	0.0032	−0.0193***	0.0032
Wald test	64,628***		66,956***		13,179***		11,490***	
Log likelihood	−58,572		−58,571		−58,478		−58,461	
Likelihood-ratio α-test	3,198,875***		3,181,007***		3,083,725***		3,011,196**	
Vuong test	6.575***		6.570***		7.375***		7.474***	
Sargan test					0.3292		0.3292	
Observations	11,520		11,520		11,520		11,520	

(a) Dependent variable: number of arrivals (*Arrivals*); estimator: zero-inflated negative binomial.
(b) Models 3 and 4 are estimated with the control function approach; the exogenous regressors included in the first-stage are: the flight frequencies of FSC flights and LCC flights from country *c* to the neighboring regions of *r*, the airline alliance market share from *c* to the neighboring regions of *r*; the *c*-*r* geometric mean of broadband internet subscribers.
(c) Standard errors clustered by macro-country and semester, bootstrapped in Models 3 and 4; ***, ** and * denote statistical significance at, respectively, the 1%, 5% and 10% level.
(d) Constant, semester-dummies, and macro-region (i.e. Center, Islands, North-East, North-West and South of Italy) dummies included, but not reported.

to schedule flights between denser areas, and broadband access is more likely to be available where there is high density of inhabitants.[7] Some authors point out that the larger the diffusion of the internet, the more likely is the decision to visit a certain destination (Tadesse & White, 2012). First, the choice of tourism destination is based on many sources, such as word-of-mouth, travel agents, published catalogues, and specialized journals. Thus, internet search only partially concerns and affects this choice, especially during the sample period in which the internet and social media were less developed. Second, the correlation between the two dependent variables (*Arrivals* and *Stays*) and *Internet* is quite small, about 8 per cent, and therefore *Internet* is unlikely to be directly related to the dependent variable or correlated with the error term.

The rationale behind the choice of the other three instruments, *Neighbor alliance share*, *Neighbor FSC flights*, and *Neighbor LCC flights*, is twofold. First, a given region and its neighbors share some common characteristics, which induce airlines to schedule their flights with a similar behavior. Second, the developing strategies of an airline are to expand its network based on a geographical criterion. Thus, having a flight in one region increases the likelihood to observe a flight in the neighboring regions. The validity of these three instruments is based on the geographical separation argument: the instrument refers to an area outside the destination region, so that airline activity in that area only marginally affects tourism flows to the region.[8] Finally, we have re-run all the models using the one-semester lagged values of these instruments. This new version of the instruments, in addition to the spatial separation, also shows a temporal separation (Alderighi & Gaggero, 2017). Since summer and winter time schedules are sufficiently different, it is unlikely that the number of flights operated in the neighborhood of a given region during the previous semester can be directly

[7] In Europe, although with some differences, broadband access is provided in two different steps. First, the public sector provides the backbone infrastructure. Second, still uncompleted at present, private companies alone or in partnership with government entities are engaged to provide the last mile. Thus, the diffusion of the broadband starts around larger towns (denser areas) and in the richest part of the respective countries (Moriset, 2003). Since flight supply follows a similar pattern, we expect that there is a positive relationship between *Internet* and the flight variables.

[8] An airport catchment area in Europe is, at most, two hours road travel time to the airport (Lieshout, 2012; Mao, Wu, Huang, & Tatem, 2015). This means that most visitors stay in the region of the destination airport.

Table 6
First-stage estimates – Ordinary Least Squares.

Dependent variable	ALL flights A1		FSC flights A2		LCC flights A3	
	Coeff	Std error	Coeff	Std error	Coeff	Std error
Country GDP	0.0061	0.0067	0.0109**	0.0054	−0.0048**	0.0019
Region GDP	3.5423***	0.2319	2.9016***	0.2001	0.6407***	0.0636
Country population	0.2447***	0.0225	0.1938***	0.0188	0.0509***	0.0065
Region population	6.2034***	0.5236	5.6220***	0.4968	0.5814***	0.0792
Italians abroad	0.1626***	0.0306	0.1010***	0.0229	0.0617***	0.0128
Foreigners in Italy	0.2978***	0.0463	0.1557***	0.0431	0.1421***	0.0172
Country railway	0.1450**	0.0630	0.0717*	0.0409	0.0733**	0.0288
Region railway	1.7944***	0.1711	1.5582***	0.1511	0.2363***	0.0330
Distance	−1.7661***	0.3282	−1.9204***	0.2686	0.1543	0.1381
Real exchange rate	−0.0926***	0.0281	−0.0992***	0.0218	0.0066	0.0091
Unesco	−2.7188***	0.4421	−3.0039***	0.4017	0.2850***	0.0928
Neighbor FSC flights	0.1067***	0.0058	0.1094***	0.0059	−0.0026**	0.0011
Neighbor LCC flights	0.0384**	0.0190	−0.0419**	0.0160	0.0803***	0.0064
Neighbor alliance share	0.2271***	0.0843	0.3096***	0.0752	−0.0824***	0.0201
Internet	0.4771***	0.0741	0.2929***	0.0671	0.1842***	0.0170
R^2	0.426		0.419		0.267	
F-test (weak instr.)	269.551***		156.830***		316.575***	
Observations	11,520		11,520		11,520	

(a) Standard errors clustered by macro-country and semester; ***, ** and * denote statistical significance at, respectively, the 1%, 5% and 10% level.
(b) Constant, semester-dummies, and macro-region (i.e. Center, Islands, North-East, North-West and South of Italy) dummies included, but not reported.

related to stays or arrivals in that region. Also in this case, the results do not substantially change.

Clustered standard errors

Standard errors are clustered by macro-country[9] and semester in order to allow the residuals of the same macro area (to different Italian regions) during the same semester to be correlated. The number of clusters is 96, which is far above the minimum number of clusters indicated as 42 by Angrist and Pischke (2008).

Results

Arrivals

Table 5 reports the results of the estimation of Eq. (1) when the dependent variable is *Arrivals*. The first two models stem from the standard zero-inflated negative binomial estimation, whilst, in the last two models, we correct for the endogeneity bias with the aforementioned control function approach.

The positive and statistically significant sign of the *All flights* variable suggests a direct influence of non-stop flights on arrivals. Interestingly, when we differentiate between the flight frequencies provided by FSCs and by LCCs (Models 2 and 4), we find that the effect of the *LCC flights* variable on tourism flows is stronger than that of the *FSC flights* variable. The estimated coefficients in Model 4 can be employed to compute the marginal impact of flights on tourist arrivals. We find that an additional round-trip flight generates about 74 new arrivals in hotels or in other accommodation facilities of the region when the flight is operated by an LCC, and generates about 29 new arrivals when the flight is operated by an FSC.[10] The difference in the estimated coefficients is statistically significant with a χ^2 equal to 6.90 and a p-value of 0.009.

Our data do not contain information on aircraft seat capacity by route or carrier. Since LCCs may employ larger aircraft than FSCs, the different impact of these two types of carriers on tourism flows can be affected by the different aircraft size. By analyzing the fleet composition of a selection of airlines, we find that there is not such a large difference, so that aircraft size is unlikely to affect our main conclusion.[11] Moreover, under the presumption that some LCC passengers usually seek less-conventional accommodation solutions, the overall differential effect on arrivals between the two types of carriers could also be slightly larger than the estimated effect.[12]

[9] See footnote 2 for the classification of the macro-countries.
[10] These numbers come from command `margins` in Stata and have the following 95% confidence intervals: 19.52–38.60 for LCCs, and 44.39–103.47 for FSCs.
[11] For example, excluding a few minor cases, the seat capacity of Air France and Lufthansa aircraft, which is used for short-haul (Airbus A319, A320, A321), ranges, respectively, between 138 and 200 and between 142 and 212, while easyJet seat capacity (Airbus A319, A320) ranges between 156 and 180, and Ryanair seat capacity (Boeing 737) is 189.

Table 7
Effect of non-stop flights on overnight stays.

	Model 5		Model 6		Model 7		Model 8	
	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error
ALL flights	0.0036***	0.0008			0.0271***	0.0038		
FSC flights			0.0032***	0.0009			0.0248***	0.0036
LCC flights			0.0057***	0.0015			0.0635***	0.0148
Country GDP	0.0115***	0.0012	0.0115***	0.0012	0.0091***	0.0007	0.0087***	0.0008
Region GDP	0.0221***	0.0079	0.0217***	0.0079	−0.0651***	0.0165	−0.0848***	0.0176
Country population	0.0277***	0.0013	0.0276***	0.0013	0.0172***	0.0018	0.0153***	0.0018
Region population	0.3046***	0.0147	0.3055***	0.0147	0.1708***	0.0241	0.1663***	0.0238
Italians abroad	0.0128***	0.0010	0.0128***	0.0011	0.0114***	0.0015	0.0092***	0.0018
Foreigners in Italy	0.0217***	0.0065	0.0216***	0.0066	0.0152***	0.0053	0.0089	0.0064
Country railway	0.0523***	0.0130	0.0517***	0.0131	0.0460***	0.0061	0.0395***	0.0069
Region railway	0.3296***	0.0127	0.3296***	0.0127	0.2979***	0.0172	0.2928***	0.0185
Distance	−0.3573***	0.0633	−0.3612***	0.0646	−0.2564***	0.0367	−0.2852***	0.0376
Real exchange rate	−0.0201***	0.0045	−0.0203***	0.0045	−0.0169***	0.0025	−0.0190***	0.0026
Unesco	0.0011	0.0158	−0.0006	0.0156	0.0466***	0.0174	0.0248	0.0194
ALL First-stage residuals					−0.0248***	0.0038		
FSC first-stage residuals							−0.0231***	0.0036
LCC first-stage residuals							−0.0585***	0.0148
Inflation model (logit)								
Mean population	−0.1304***	0.0079	−0.1304***	0.0079	−0.1296***	0.0065	−0.1295***	0.0065
Time trend	−0.0194**	0.0080	−0.0194**	0.0080	−0.0196***	0.0031	−0.0197***	0.0031
Wald test	54734***		54692***		10543***		9281***	
Log likelihood	−69333		−69332		−69267		−69255	
Likelihood-ratio α-test	13606398***		13540813***		13379010***		13191977	
Vuong test	10.730***		10.712***		11.345***		11.418***	
Sargan test					0.2796		0.2796	
Observations	11,520		11,520		11,520		11,520	

(a) Dependent variable: overnight stays (*Stays*); estimator: zero-inflated negative binomial.
(b) Models 7 and 8 are estimated with the control function approach; the exogenous regressors included in the first-stage are: the flight frequencies of FSC flights and LCC flights from country *c* to the neighboring regions of *r*, the airline alliance market share from *c* to the neighboring regions of *r*; and the *c*-*r* geometric mean of broadband internet subscribers.
(c) Standard errors clustered by macro-country and semester, bootstrapped in Models 7 and 8; ***, ** and * denote statistical significance at, respectively, the 1%, 5% and 10% level.
(d) Constant, semester-dummies, and macro-region (i.e. Center, Islands, North-East, North-West and South of Italy) dummies included, but not reported.

A far as the other regressors are concerned, we find that the sign of the estimated coefficients is generally in line with the expectations. The positive sign of the *Country GDP* variable suggests that Italian destinations are normal or superior goods: the richer the foreign country, the larger the tourism flows to Italy. The negative, albeit not always statistically significant, sign of the *Region GDP* variable may lend support to the presumption that richer tourism destinations are associated with higher costs of living, i.e. higher prices for visitors.

The population of the country of origin, described by the *Country population* variable, positively affects the arrivals. The sign of *Region population* variable is also in line with the expectations, as larger regions usually have a higher number of hotel facilities, and therefore more tourists can be attracted and hosted. The *Italians abroad* variable has a positive and statistically significant impact on arrivals. This result suggests that Italians living abroad generate additional visits by recommending their native places to foreign friends or acquaintances (Balli, Balli, & Louis, 2016). By a symmetric line of reasoning, the *Foreigners in Italy* variable shows a positive effect of immigrants on tourism arrivals to the region where they live. These findings confirm the tourism-migration nexus already documented in the literature (Etzo et al., 2014; Massidda et al., 2015; Seetaram, 2012), and have important managerial implications for the airlines which, in order to increase their sales, can offer a better air service on those country-region pairs where there is a large community of migrants.

As far as the quality of infrastructure in the hosting region is concerned, we find a positive and statistically significant effect of the *Region railway* variable, which suggests a positive impact of the quality of local infrastructure on tourism flows. This result helps to explains the gap in tourism flows to the South of Italy, where the infrastructure is less developed than in the rest of the country

[12] According to the OAG, there is a positive correlation between destinations where LCCs have a dominant position and Airbnb's top destinations (see:https://www.oag.com/blog/airbnb-and-low-cost-airlines-creating-new-trends, queried on April 2018). Even though we have no evidence on previous LCC travel behavior, we reckon that the habit of staying in flats or rooms not included in the hotel statistics may also occur in the sample period of our analysis.

Table 8
Robustness.

Dependent variable	Arrivals Model 9		Arrivals Model 10		Stays Model 11		Stays Model 12	
	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error
Zero-inflated poisson								
FSC flights	0.0017***	0.0004	0.0161***	0.0028	0.0018***	0.0003	0.0126***	0.0023
LCC flights	0.0048***	0.0009	0.0586***	0.0105	0.0050***	0.0010	0.0469***	0.0103
Wald test	96,699***		7,839***		114,942***		8,092***	
Log likelihood	−1,649,074		−1,564,059		−6,839,739		−6,665,243	
Sargan test			0.3294				0.2796	
Tobit								
FSC flights	29.1573***	4.9916	44.2758***	9.8307	92.1129***	16.7673	147.2395***	35.7848
LCC flights	50.4126***	10.2195	58.7556**	25.3673	178.2416***	40.5656	202.6563**	100.1604
Log likelihood	−74,278		−164,788		−86,113		−176,630	
Wald test exogeneity			28.617***				27.399***	
Sargan test			0.2221				0.2324	
Heckman selection								
FSC flights	26.1499***	3.1312	51.8323***	6.6841	81.3506***	10.8913	168.9895***	27.3494
LCC flights	46.2382***	7.1029	58.8274***	17.0086	163.0355***	28.1376	204.6087***	72.3898
R^2	0.5986		0.4882		0.4878		0.3994	
Kleibergen-Paap test			79.221***				79.221***	
Hansen test			0.0450				2.2473	

(a) Models 10 and 12 stem from a two-stage regression. The exogenous regressors included in the first-stage are: the flight frequencies of FSC flights and LCC flights from country *c* to the neighboring regions of *r*, the airline alliance market share from *c* to the neighboring regions of *r*; the *c*-*r* geometric mean of broadband internet subscribers.
(b) Standard errors clustered by macro-country and semester, bootstrapped in Models 10 and 12; ***, ** and * denote statistical significance at, respectively, the 1%, 5% and 10% level.
(c) All the regressors of Tables 5 and 7 are included, but not reported.
(d) Observations 11,520 with the exception of 8345 in 'Heckman selection'.

(Severgnini, 2014). The coefficient of the *Country railway* variable, albeit positive in most estimates, is not statistically significant.

The last three covariates have the expected sign. The higher the prices in region *r* relative to the prices in country *c* (larger value of *Real Exchange rate* variable), the lower the tourism flows from country *c* to region *r*. This result confirms the widely accepted importance of the price competitiveness of a tourism destination (Etzo et al., 2014; Seetaram et al., 2016). The negative sign of the *Distance* variable indicates that the farther the European country is from the Italian region, the lower the flow on the route of the country-region pair. This result is in line with the idea that visitors tend to come from neighboring areas (McKercher, Chan, & Lam, 2008; Ryan, 2002). The coefficient of the *Unesco* variable is positive and highly statistically significant across all the models, confirming the presumption that a region with a higher number of UNESCO heritage sites attracts more tourists (Yang et al., 2010). More specifically, we find that, if a region is awarded an additional UNESCO World Heritage site, about 8,400 additional people will visit the region in a year.

From an overall look at Table 5, we find that most of the variables have the same sign and similar levels of significance across models; and, more importantly, when we control for the endogeneity of the flight variables (the last two models), the flight supply variables maintain their correct positive sign and level of statistical significance.

The higher coefficient on the flight variables in the last two models points towards a downward bias of the estimates. This finding is interpreted by the reverse negative effect that tourism might have on airline supply. Stakeholders of a region with little tourism flows will try to persuade airlines to increase their service to the region in order to expand the number of incoming tourists. On the contrary, when a region already has a large volume of arrivals, the incentive to increase the flight connections in order to attract more tourists becomes weaker.

Moreover, in the inflation model, the *Mean population* variable (the geometric mean of the population of country *c* and region *r*) has a negative sign across all models, reflecting that the larger the population in *c* or *r*, the lower the probability of observing zero tourism flow. The negative sign on the *Time trend* variable shows that the probability of observing no tourism flow from country *c* to region *r* reduces as time goes by. This result reflects the worldwide growth trend of the tourism industry (UNWTO, 2017).

Finally, Table 6 reports the first-stage estimates, and shows how exogenous regressors and the selected instruments contribute to explain the three endogenous flight variables. In general, airlines tend to schedule more non-stop flights where: origin and destination markets are larger (positive signs of the *Region population* and *Country population* variables); infrastructure is more developed (the *Regional railway* and *Country railway* variables); the number of migrants is higher (positive signs of the *Italians abroad* and *Foreigners in Italy* variables); the broadband access is larger, i.e. markets are denser (positive sign of the *Internet* variable); and the destination is closer to the origin (negative sign of the *Distance* variable).

With respect to FSCs, LCCs have a different network design strategy: LCCs tend to avoid areas which are more suitable to FSCs or airlines in alliance (negative signs of the *Neighbor FSC flights* and *Neighbor alliance share* variables); they tend to fly where LCCs are well established (positive sign of the *Neighbor LCC flights* variable); they are more present where consumers are more price sensitive (negative sign of the *Country GDP* variable); they fly to tourism destinations (positive sign of the *Unesco* variable). FSCs, however, are less interested in the LCCs' areas of interest or in tourism destinations (negative signs of the *Neighbor LCC flights* and *Unesco* variables); they fly to destinations served by FSCs and by airlines in alliance or characterized by less elastic consumers (positive signs of the *Neighbor FSC flights*, *Neighbor alliance share* and *Country GDP* variables).

Stays

Table 7 replicates the structure of Table 5 but changes the dependent variable from *Arrivals* to *Stays*. The first two models are basic zero-inflated negative binomial estimates, the last two models tackle endogeneity with a control function approach.

The results are very similar to the ones reported in Table 5, also in terms of the magnitude of the coefficients, thereby indicating that no great differences are observed between the number of incoming tourists (*Arrivals*) and the duration of their holiday (*Stays*). This finding is largely expected due to the high correlation between *Arrivals* and *Stays* (see Table 4).

The variables of interest show the exact path of the previous table: there is a positive effect of non-stop flights on the tourism flows to the region, and LCCs are the main driver of this effect. The estimated coefficients can be employed to compute the marginal impact of an additional round-trip flight on overnight stays. In particular, an additional round-trip flight generates about 248 overnight days of stay in hotels or other similar accommodation facilities of the region when the flight is operated by an LCC and 97 overnight stays when the flight is operated by an FSC. The difference in the estimated coefficients is highly statistically significant, with a χ^2 equal to 6.45 and a corresponding p-value of 0.011.

Robustness

This sub-section presents some robustness checks. Its objective is twofold. First, it verifies whether the variables of interest maintain the same sign and significance under the three alternative estimators. Second, it aims to provide further support to our identification strategy and, in particular, to the choice of instruments.

Because the focus of the above analysis is on the differential impact of FSCs and LCCs on tourism flows, we restrict the estimate of Eq. (1) to those cases that consider only the *FSC flights* and *LCC flights* variables. Moreover, for space reasons, Table 8 only reports the estimates of these two variables, while the other regressors and instruments, which are unchanged from the previous analysis are not reported but available upon request. Four different models are considered in order to account for the two different dependent variables (*Arrivals* and *Stays*) and different estimation approaches (instrumented or not). Thus, Models 9 and 10 of Table 8 correspond to Models 2 and 4 of Table 5, while Models 11 and 12 correspond to Models 6 and 8 of Table 7.

Our robustness checks depend on three different estimators: ZIP, Tobit, and Heckman selection. The ZIP estimator shares most of the properties of the ZINB estimator, apart from a more restrictive assumption on the variance. The Tobit and Heckman selection estimators are in principle more distant from the ZINB, because they model the behavior of a continuous dependent variable and treat the presence of the zeros in the dependent variable differently from the ZINB or the ZIP. The Tobit estimator considers zero as the bound for left-censured values. The Heckman selection is a two-step approach: first, it models the probability of observing a zero using the entire sample from which it obtains the inverse Mill's ratio (the correction term for sample selection), then, on the sub-sample of strictly positive values of tourism flows, it estimates Eq. (1) inclusive of the correction term for sample selection (Heckman, 1979). The probability of observing a zero on the dependent variable with the ZIP and Heckman selection depends on the same set of regressors employed for the ZINB.

The coefficients of the variables of interest (*LCC flights* and *FSC flights*) are positive and statistically significant across all the models and estimators of Table 8, confirming the findings presented in Tables 5 and 7. Moreover, and more importantly, the coefficient of the *LCC flights* variable is always larger in magnitude than the coefficient of the *FSC flights* variable. The difference between the two coefficients is large and highly significant in the ZIP model, while it is more limited in the other two models, especially in the instrumented estimates when the dependent variable is *Arrivals*.

Taking the two-stage Tobit estimates (Models 10 and 12 of Table 8) as the reference, we find that an additional flight brings on average 59 people if the flight service is provided by an LCC, and 44 people if the flight service is provided by an FSC; the total number of overnight stays that a new flight generates is 203 in the case of LCCs, and 147 in the case of FSCs.[13]

It should be mentioned that the estimated coefficients on the *FSC flights* and *LCC flights* variables coming from the Heckman selection are quite similar in magnitude to the estimates originating from Tobit, which, besides being based on different estimation techniques, employs a different number of observations.

As far as the endogeneity is concerned, the highly significant Wald test of exogeneity with the Tobit estimation rejects the null hypothesis of no endogeneity. The direction of the bias is the same as observed in Tables 5 and 7 and points towards a downward bias of the estimates. The diagnostics on the instruments are all sound. The Kleibergen-Paap *F* statistics (underidentification test) in the Heckman selection model is highly statistically significant, confirming that our instruments are relevant. The test of overidentifying restrictions (Hasen/Sargan test) does not reject at the conventional level of significance the joint null hypothesis that the instruments are valid instruments, i.e. they are uncorrelated with the error term, and that the excluded instruments are correctly excluded from

[13] In the Tobit and Heckman selection, the estimated coefficients directly provide the marginal effect.

the estimated equation.

Conclusions

In this paper we have studied the effect of non-stop flights on international tourism flows, distinguishing between flights provided by FSCs and LCCs. We have used an original data set paring 20 Italian regions with 24 European countries of tourism origin. Our period of analysis spans from 1999 to 2010; the observations are collected on a half-yearly basis. Our findings highlight the importance of airline connectivity to sustain the tourism sector. Although this result is expected, the use of econometric techniques allows us to quantify the average impact of an additional flight operated by either an FSC or an LCC. A supplementary round-trip flight operated by an LCC generates about 74 arrivals and 248 overnight stays in hotels or similar facilities; but in the case of an FSC these figures decrease to 29 and 97, respectively.

In the light of the current reform of the Italian air transport system, our results provide some guidance to local authorities, especially of those regions with a high vocation for tourism. LCCs may contribute to boost the economic growth of the region (Brueckner, 2003). Indeed, airlines, and LCCs in particular, have a primary role in the attraction of tourism flows; travel savings due to cheaper fares are partially transferred to higher expenditures at destinations (Eugenio-Martin & Inchausti-Sintes, 2016). Therefore, future policy interventions aimed at favoring the expansion of flight frequencies and/or the opening of new routes of LCCs are recommended. Although state aid legislation may reduce the field of action of policy intervention (e.g. it is not possible to apply different landing fees to different categories of carriers), airports designed to meet the specific needs of LCCs could be useful to reach this objective. In countries such as Italy, where regional governments control and manage most of the airport infrastructure, this policy might be easier to implement.

Other works have emphasized a more prominent role of FSCs to spur the manufacturing sector in Italy (Alderighi & Gaggero, 2012, 2017), thus local authorities may care to attract the right mix of carriers in order to match the different characteristics of the territory (Papatheodorou, 2002). The importance of LCCs could be greater in the South of Italy, which has great potential to attract international tourism flows (Donzelli, 2010). Indeed, most of the Southern Italian regions can only be easily reached by air.

The attraction of LCCs may, however, have some drawbacks: LCCs may reduce the air accessibility of a destination due to the possible high seasonality of their services; LCCs may have a negative impact on local tour operators, thus damaging some tourism activities (Pulina & Cortés-Jiménez, 2010); LCCs may have detrimental effects on environmental sustainability because of the possible reduction of the tourists' length of stay, causing local congestion.

There are five potential limitations of this study. First, carriers have been classified in only two categories. The FSC category includes both mainline and regional carriers, thereby discarding the different effect that each type of carrier may have on tourism. Second, the sample period ends in 2010. In more recent years, we observe a convergence of airline business models (Daft & Albers, 2013), thus, the differential impact of LCCs and FSCs may not be so large as we find in our sample. Third, our data do not include charter traffic, which mainly channels leisure travelers. Fourth, our analysis only focuses on intra-Europe flows, and therefore our conclusions do not apply to long-distance tourism flows. Finally, our data do not include information on the aircraft size, and thus the differential impact of LCCs and FSCs may be partially due to the issue of seat capacity. However, an investigation of the fleet of the main carriers of our sample indicates that this is a minor concern.

Future work could extend the present analysis to other European countries such as Greece or Spain. This would enable us to investigate whether our conclusions also apply to countries in which the tourism industry represents an important driver of the local economy. More recent data on Italy could be also employed to validate our conclusions. Moreover, additional analysis is required to study the impact of airline supply on the duration of the stay, for instance, to test Ferrer-Rosell, Martínez-Garcia, and Coenders (2014) findings that tourists traveling with LCCs stay slightly longer than tourists traveling with FSCs. Finally, it would be worthwhile to study the impact of flight supply on local economic development by simultaneously considering the short- and long-term growth of different sectors.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.annals.2018.11.009.

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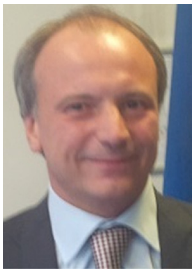

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