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Highlights

- Analyzes the effects of LCCs subsidies on tourism, a common policy in many countries
- Predict changes in regional tourist flows from exogenous shocks in the aviation market through
- Compares different subsidy policies: centralized uniform, decentralized (sub national) and optimal subsidy allocation
- Counterfactual analyses show that centralized subsidy policy dominates a sub national decentralized regime

The Effects of LCC Subsidies on the Tourism Industry*

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Abstract

This paper studies the relationship between aviation, tourist flows, and subsidies to Low–Cost Carriers (LCCs), a policy tool used by many national and local governments to stimulate tourist arrivals. To evaluate this policy's impact, we estimate a two–stage empirical model. In the first stage, we estimate a structural model applied to air transport; in the second stage, we estimate the link between passenger flows and regional tourism flows. In this way, we use exogenous aviation shocks (subsidies to LCCs) to analyze the causal effect on tourist arrivals. This model is estimated using data on aviation and tourist flows from European to Italian regions during 2016–2018. Counterfactual analyses consider different regimes for implementing the policy, i.e., a subsidy adopted by a benevolent central planner and/or by subnational institutions. Our simulations show that subsidies to LCCs are effective in stimulating tourism and that a centralized regime is more effective than a decentralized one. In fact, the latter generates externalities in regions that do not implement the subsidy, making the decentralized policy economically suboptimal.

JEL classification: R41, R48, O18
Keywords: Air transportation and tourism, structural model

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1 Introduction

It is well known that good accessibility by air is a crucial factor for tourism (Brueckner, 2003; Green, 2007; Bel and Fageda, 2008; Seetaram et al., 2016). For example, Koo et al. (2017) report that the aviation sector supports approximately 58 million jobs in the global economy, and 35 million of these jobs are in the tourism sector. Recent data show that, in the U.S., the travel and tourism industry was worth \$1.6 trillion in 2017, of which \$270 million came from air travel (Forbes and Kosová, 2023). Globally, the travel and tourism sectors generated 10.4% of the global GDP in 2019, and these industries have been a major source of job creation, accounting for one in four net new jobs in the 2014–2019 period (WTTC, 2020). Empirical evidence confirms the existence of a positive relationship between air transport and tourism (see Forbes and Kosová, 2023; Tsui, 2017; Alderighi and Gaggero, 2019; Chow et al., 2021; Tang et al., 2023), usually through reduced form models.

In parallel, the development of Low Cost Carriers (LCCs) in Europe has been a transformative force in the aviation industry during the last 20 years, following the 1998 market liberalization. As a result, the LCC market share in Europe grew from around 5% in 1996 to over 40% in 2019, reshaping travel patterns and accessibility. Indeed, the low fare policy of LCCs stimulates the typically price–sensitive tourist segment of air travel; their point–to–point network model allows for direct connections between origin and destination cities. Finally, LCCs' use of secondary airports allows access to regions with high seasonal tourist attractiveness, but few full–service airline connections. This expansion has not only made air travel more affordable for consumers, but has also stimulated economic growth in regional areas, including the tourism sector. Bilotkach et al. (2019) examine the relationship between the presence of LCCs and international passengers in Asia and find a positive effect. Alderighi and Gaggero (2019) show that LCCs had a beneficial impact on tourist flows in Italy over the 1999–2010 period (see also Papatheodorou and Lei, 2006; Donzelli, 2010; Castillo-Manzano et al., 2011; Rey et al., 2011; Massidda and Etzo, 2012).

Based on this empirical evidence, national and regional governments in many European countries have adopted policies to subsidize LCCs in order to stimulate tourist arrivals. These policies are not specific to Europe. In the Greater Bay Area[1] in China, a megacity the size of Great Britain, there is a heated debate about greater coordination among various governments to implement air transportation policies as a stimulus for the tourism sector.[2] Fageda et al. (2018) stated that Spain spent 250 million euros on subsidies between 2007 and 2011, underlying the

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[1] The Guangdong–Hong Kong–Macao Greater Bay Area is commonly referred to as the Greater Bay Area (GBA). It is the largest and most populated urban area in the world. Source Wikipedia.

[2] See the news in South China Morning Post, https://www.scmp.com/news/hong-kong/hong-kong-economy/article/3261639/hong-kong-government-can-boost-tourism-better-coordination-alignment-bay-area-plans-industry-leaders.

different types of subsidies granted to LCCs, including co–marketing agreements, direct subsidies, and discounts on landing and terminal charges. In Italy, LCCs received about 391 million euros in subsidies in 2019, of which approximately 260 million went to *Ryanair* and 75 million to *EasyJet*.[3] In the European Union (EU), these subsidies have often been classified as state aids under competition laws. Recently, however, some contributions (Malavolti and Marty, 2017, 2019) have shown that LCC subsidies can actually correct (and not introduce) distortions in airline (and airport) competition. In addition, studies of the relationship between LCC subsidies and their impact on tourism thus far have used a reduced–form approach (e.g., Wu et al. (2020); Salesi et al. (2022)), which implies that quantifying the impact of the subsidies has not been efficiently addressed.

In this paper, we develop a structural model of air transport that we link to the local tourism market to assess the impact of a change in LCC subsidy policy. In our model, potential air travelers living in a European region decide whether to fly to Italy for the summer vacations. If they decide to do so, they then choose among different available options. We model this decision with a standard discrete choice demand model with differentiated products *à la* Berry (1994). In this setting, a product is a direct or connecting flight with a specific airline from the region in the European origin country to the Italian destination airport. At the same time, we model the pricing strategy of the European airlines to attract potential consumers.

The regional flows of Italian tourists from the different European regions are derived from a model in which each region receives international tourist flows arriving by air and other transport modes. Tourists arriving by air might stay where they land or move to a nearby region. Thus, the air transport equilibrium model feeds regional tourist flows directly (passengers stay in the region where they land) and indirectly (nearby regions receive tourists from neighboring airports). We have therefore established a link between the air transport sector and the tourism sector.

We estimate our model using specific data on international tourism,[4] to study tourist flows from European countries to Italian regions in the 2016–2018 period during the summer semesters (from April to September), when the majority of holiday arrivals are concentrated. The Italian tourism market is an interesting case both in terms of air connections and from a tourism point of view. Most Italian regions are well served by the main European LCCs, while the legacy carriers have connections to the main Italian airports and alliances with *Alitalia–ITA Airways*, the former Italian flag carrier. As a tourism market, Italy ranks fifth in terms of international arrivals, which translates to approximately 27 million visitors in 2020 (WTO, 2023). Its tourism sector is particularly important, contributing over 13% to GDP with international tourists spending

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[3] See the Italian national newspaper *Corriere della Sera*, `https://www.corriere.it` using the keywords *sussidi low cost Italia*.

[4] Based on data availability, our model can be applied to any spatial context.

€45.6 billion, which represents 8.0% of total exports. In addition, tourism policy in Italy is highly decentralized, as the tourism and hotel industry have been supervised by regional governments since the Italian constitutional law of 1948. Finally, there are significant differences in tourism intensity between regions, given that Italy has the highest number of UNESCO World Heritage Sites, which are unevenly distributed across the country,[5] and the northern, central, and southern macro–regions have different characteristics regarding their attractiveness.[6]

After having estimated this model, we are able to quantify the relationship between air transport and tourist flows. In particular, our model can be used to predict changes in the economic environment of the European air transport industry, and, in turn, on predicted variations in regional tourism flows. Here, we consider a change triggered by a subsidy policy for LCCs. This policy generates non–trivial substitution effects in the passenger–choice process, which in turn affect tourist flows across arrival regions. Our model allows us to describe and quantify these effects in detail. Specifically, following the debate in Oates (1993, 1999), this paper aims to analyze whether a centralized–uniform subsidy policy applied across the entire territory of a country is preferable to a decentralized subsidy policy in which individual regional governments implement subsidies for LCCs that land only in their region, a popular policy in many European regions to attract tourists.

Our results show that the central government's uniform subsidy is generally more effective in increasing tourist flows than the decentralized regime. Both regimes increase tourist flows, but the former grants higher increases. In fact, our counterfactual experiments show that when the subsidy is adopted in a decentralized manner by a single regional government, it creates three different effects on tourist flows: (1) an increase in tourists in the region that adopts the subsidy; (2) a decrease in tourists in several other regions due to the new equilibrium created in the air transport sector; and (3) an increase in tourists in some regions, without any monetary investment, due to the movement of some tourists to neighboring regions. The second effect is problematic because it creates competition between regions and is therefore hardly stable. The third effect, on the other hand, highlights that the entire subsidy investment made by the regional government is not internalized, which leads to economic inefficiency. However, the second and third effects do not arise if the subsidy policy is implemented in a uniform manner by the central government.

The rest of the paper is structured as follows. Section 2 describes the literature review. Section 3 details the structural model and how we link air arrivals to tourist flows. Section 4

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[5] See the UNESCO website at `https://whc.unesco.org/en/list`.

[6] The southern regions have many beautiful beaches and plenty of sunny days in the summer. The central regions have important historical cities, such as Rome and Florence. The northern regions, on the other hand, have several ski resorts in the Alps.

displays the data set and provides some descriptive evidence. Section 5 presents and discusses our estimates of the model. Section 6 displays the results of our counterfactual analysis that compares the two subsidy policies, while section 7 draws the main conclusions. In the appendix, we provide further details on our estimation methodology, more detailed information on the construction of some variables, tables on the instrumental variables adopted, and some estimations. In a Supplemental Appendix available online, we display the results for each individual region from the counterfactual analyses under the decentralized policy.

2 Literature Review

Our work contributes to the literature that studies the determinants of tourism (Papatheodorou, 1999; Seetaram et al., 2016) and the relationship between air transport and tourism, and seeks to identify a causal relationship between these two factors. Empirical research on the determinants of tourism demand highlights the importance of income, general transport costs, and destination attractiveness. Regarding the relationship between air transport and tourism, the contributions of Papatheodorou and Lei (2006); Donzelli (2010); Castillo-Manzano et al. (2011); Rey et al. (2011); Massidda and Etzo (2012); Alderighi and Gaggero (2019) examine the impact of air transport activities on tourism in Great Britain, Italy, and Spain, focusing on the impact of LCCs, while Tsui (2017); Koo et al. (2017); Bilotkach et al. (2019); Chow et al. (2021); Law et al. (2022); Kuok et al. (2023); Tang et al. (2023); Shen et al. (2023) analyze this relationship in Australia, Cambodia, China, Laos, Myanmar, New Zealand and Vietnam. Forbes and Kosová (2023) study how airline competition affects hotel performance in the U.S. All of these papers are based on a reduced form and find (with the exception of Kuok et al., 2023) that air transport is a positive determinant of tourism and that LCCs are the main factors characterizing this relationship.

Furthermore, our paper completes the list of the few contributions that have examined the effects of LCC subsidies on various economic outcomes. Surveys of aviation subsidies and their effects have been conducted by Fageda et al. (2018); Wu et al. (2020), while Barbot (2006) presents a model that studies the effect of subsidies to the European LCC *Ryanair* and shows a positive effect on the Irish airline's performance while penalizing its competitors. Fageda et al. (2016) examine the impact of subsidies granted to airlines (and in particular to *Ryanair*) under public service obligation programs implemented in Spain to improve connections to remote regions and islands. They do not find any evidence that the subsidies lower prices while comparing the subsidized to the non–subsidized routes. Chow et al. (2021) investigate the relationship between subsidies, aviation activity, and tourist flows in China and find a positive effect only when airlines serve small– to medium–sized airports. Salesi et al. (2022) provide some evidence that tourism is boosted by aviation subsidies in some South Pacific regions. Our work differs from all of these contributions both in terms of methodology and the quality of the data available. In terms of empirical methodology, we provide more structure to the empirical relationship between aviation, tourism, and the impact of LCC subsidies; we also have data on market transactions related to ticket prices and reservations that allow us to quantify this relationship.

Our model is derived from the literature on the demand for differentiated products used in industrial organization (IO). Some contributions apply it to the airline industry, mostly in the U.S. domestic market. For example, Berry et al. (2006) introduce discrete taste heterogeneity (leisure and business) among passengers and quantify their willingness to pay for different products. In a similar model, Berry and Jia (2010) report the shift in demand preferences towards direct flights between 1999 and 2006. Ciliberto and Williams (2014) study tacit collusion between airlines that repeatedly operate in the same markets. Chen and Gayle (2019) study the post–merger quality of an airline as a function of its past level of competition. Bontemps et al. (2022) propose an ex–post evaluation of the recent merger between American Airlines and US Airways, taking into account product repositioning for both the merged entity and its competitors. Marra (2024) evaluates the implications of the introduction of airport slot auctions in Europe.

Finally, our paper contributes to the literature comparing the effects of policy decentralization implemented by sub–national institutions (e.g., regional governments) with the outcomes achieved by a central regime. Oates (1993, 1999) provide the first studies that show the superiority of decentralized regimes over centralized ones, due to better information on the target population and higher accountability, in a context of heterogeneous preferences across regions. Brueckner (2006) shows that economic growth is higher under decentralization. However, one problem with decentralized regimes is that they induce competition between sub–national governments (see Balia et al., 2018). Specifically, they do not internalize the possible spillover effects of their policies on other regions and therefore determine suboptimal intervention levels. For example, Di Novi et al. (2019) show that decentralization in the Italian health sector has not reduced inequalities between regions.

To the best of our knowledge, our paper is the first to empirically investigate the effect of decentralization in air transport subsidy policy. Our results show that, contrary to what Oates (1993, 1999) claim from a theoretical point of view, a centralized and uniform regime across all regions provides better effects on tourist flows than a decentralized one due to the presence of positive and negative externalities.

3 The Model

In this section, we present our structural model used to analyze the relationship between the European airline sector and the tourism sector in Italy. The model is divided into three parts, which we explain in detail. First, we propose a demand model in which potential air travelers decide whether to fly to Italy for their summer vacations and, conditional on flying to Italy, choose their preferred destination. We model demand using a one–level nested logit model. The upper level is the choice to fly to Italy or not, and the flight to an Italian airport is the lower–level decision. We then model the pricing strategy of airlines competing to carry travelers from each European city–region to Italy origin–destination (O–D hereafter) pair. Finally, we convert passenger flows into tourist flows using a discrete choice model described at the end of the section. The estimation strategy is presented in a final subsection.

3.1 Demand

To simplify the notation, we omit the year index t in this section. In our context, the definition of a market differs slightly from the usual O–D market. A potential air traveler, living in a European region, decides between going on vacation to Italy for the summer season by flying to one of the Italian regions with a specific flight or consuming an "outside option", i.e., going to another country, not going on vacation, or traveling to Italy by other means of transport.

As a result, the market is defined by the traveler's origin region and is labeled m. The choice of market definition differs from the usual one considered in the literature. Traditionally, researchers focus on O–D city or airport pairs, as in Berry and Jia (2010), for example. However, note that these papers usually consider all types of passengers while we focus specifically on those traveling for tourism purposes. When traveling for holidays, tourists choose between products serving different destinations. To corroborate this behavior, we consider in Section 5.3, an alternative model in which consumer choice is specified as a two–level nested model.[7] In this model, the consumer first decides whether to fly to Italy or not, then selects a destination region, and finally, given this destination, chooses a specific flight (product).

This more complex structure allows for different substitution patterns between products serving the same destination and those serving different destination regions.[8] Importantly, this two–level nested model encompasses our original specification, enabling a formal test of the one–level nested structure against the more general alternative. The test does not provide any evidence to reject our specification. Note that competing destinations outside Italy are included in the outside option.

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[7] We would like to thank one of the referees for raising this question.

[8] See Appendix D for more detailed calculations.

In such a market, the list of products proposed to the potential consumer i (in addition to the outside option) is composed by all possibilities to fly to Italy from her European origin region. Therefore, a product is defined as a seat on a flight from an airport in the region of departure[9] to an airport in Italy on a given airline and with or without a connecting flight. For example, in 2018, a consumer living in the Toulouse region (France) can fly from Toulouse/Blagnac airport to Naples with *Air France* with a connecting flight, or directly to Milan with *EasyJet*, among 35 other flight options, most of them with one–stop.

We denote the total number of products offered in market m (excluding the outside option) by J_m, and the products are indexed from 1 to J_m, leaving the subscript 0 for the outside option. The additional product characteristics are price, departure frequency, and the business model of the airline proposing the product (e.g., Full Service Carrier (FSC) *vs* LCC). Our specification captures the competitive dynamics between (Italian) regions, which compete through their "air products" to attract tourists by providing incentives to airlines to serve European destinations to/from their local airports.

We assume that consumers are homogeneous, and we model their consumption choices by the maximization of a utility function defined on the space of product characteristics. Consumption of product j in market m (from 1 to J_m) gives each consumer i an indirect utility, which can be decomposed into:

$$u_{ijm} = X_{jm}^{\top}\beta + \alpha p_{jm} + \gamma f_{jm} + \xi_{jm} + \eta_{ijm}(\sigma), \tag{1}$$

where X_{jm} is a vector of exogenous characteristics of product j, p_{jm} is its price, f_{jm} is the per–semester frequency of departures, and ξ_{jm} is a product–specific characteristic observed by consumers and airlines, but not by the applied economist. More details about the vector of exogenous characteristics are given in the empirical section.

Finally, the random utility term $\eta_{ijm}(\sigma)$ follows the generalized extreme value distribution necessary to derive the usual nested logit formula (see, among others, Galichon, 2022, for further details). This distribution depends on a parameter $\sigma \in [0, 1)$ that controls the degree of correlation of the random term across products of the same nest. If σ is equal to zero, the random terms are independent and we are back to the logit case. When σ tends to 1, the correlation between the random terms of the air products tends to 1 and substitution occurs only within the nest and not with the outside option.

As a result, with the notation $\delta_{jm} = X_{jm}^{\top}\beta + \alpha p_{jm} + \gamma f_{jm} + \xi_{jm}$ and $\lambda = 1 - \sigma$, the model predicts the market share of the outside option in market m, s_{0m}, as well as the market shares s_{jm} of the air products, $j = 1, \ldots, J_m$, (see, for example, Berry, 1994, for further details):

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[9] Some European regions have more than one airport. For example, from Paris, passengers can depart from Orly, Charles de Gaulle, or Beauvais.

$$s_{0m} = \frac{1}{1 + \left(\sum_{k=1}^{J_m} e^{\delta_{km}/\lambda}\right)^{\lambda}}, \tag{2}$$

$$s_{jm} = \frac{e^{\delta_{jm}/\lambda}}{\sum_{k=1}^{J_m} e^{\delta_{km}/\lambda}} \left(1 - s_{0m}\right). \tag{3}$$

3.2 Supply

We assume that airlines in each market m compete *à la* Bertrand with differentiated products, having constant marginal costs. In the following, mc_{km} is the marginal cost of product k proposed in market m.

Let $h = 1, \dots, H$ be the index of airlines and $\mathcal{J}_{h,m}$ be the subset of indices of products offered by airline h in market m (i.e., a subset of $\{1, \dots, J_m\}$). Airlines set their prices independently in each market, taking the strategies of their competitors into account via the market shares defined in Equations (2) and (3). The optimal prices of products $j \in \mathcal{J}_{h,m}$ offered by airline h result from the optimization of its profit in market m defined as:

$$\Pi_{h,m} = \sum_{j \in \mathcal{J}_{h,m}} (p_{jm} - mc_{jm}) \times s_{jm} \times \text{MS}_m, \tag{4}$$

where MS_m is the size of market m.

Therefore, the optimal prices satisfy the first–order condition:

$$S_{h,m} + \frac{\partial S_{h,m}^{\top}}{\partial P_{h,m}} (P_{h,m} - MC_{h,m}) = 0. \tag{5}$$

where $S_{h,m}$, $P_{h,m}$, $MC_{h,m}$ are the vectors stacking $s_{j,m}$, $p_{j,m}$, and mc_{jm}, respectively, for each product $j \in \mathcal{J}_{h,m}$. $\frac{\partial S_{h,m}^{\top}}{\partial P_{h,m}}$ is the matrix collecting the partial derivatives of product shares with respect to prices.

In Equation (5), the airline takes into account the effect of a change in its product prices on the market shares of its other offered products in the same market through the term $\frac{\partial S_{h,m}^{\top}}{\partial P_{h,m}}$, which is known from the demand side. This potential cannibalization effect leads, at the equilibrium, to the same markup for all products offered by the same airline in market m.

3.3 Predicting tourist flows from passenger flows

Our objective is to relate the flow of air passengers to the flow of tourists visiting Italy during the summer. The goal of the final component of our general model is to predict the proportion of passengers landing in a given Italian region, l, who then become tourists in region r. This region may be l itself or any other region.

To achieve this, we propose a model estimated from individual–level data collected through a survey conducted at points of entry/exit to/from Italy for travelers (border crossings, airports, ports).[10] In our dataset, we do not observe the number of tourists visiting Italy by European region of departure, but only by country of origin, c. To estimate the percentage of people who travel by air, land at an Italian airport in region l ($l \in \{1, \ldots, L\}$), and decide to spend their vacation in the same region or move to region r ($r \in \{1, \ldots, R\}$, $R > L$), we use a discrete choice model, here a multinomial logit (MNL) model.

For each individual i landing at an Italian airport, we denote the landing region by L_i, the visited region by Y_i, and the characteristics of this individual by C_i, a vector of size k. Note that our possible choices for C_i are limited, as our prediction model must be consistent with the output of our structural model, which is estimated using aggregate rather than individual–level data. Therefore, we only use information related to the country of origin of the respondent, i.e., a dummy variable for the country or the distance from the country of origin to the visited region. We describe in Section 5.4 the different specifications considered, though they can all be represented as:

$$Prob(Y_i = r | L_i = l, C_i) = \frac{e^{\beta_{rl} + \gamma_{rl}^{\top} C_i}}{\sum_{r=1}^{R} e^{\beta_{rl} + \gamma_{rl}^{\top} C_i}}, \quad r = 1, \ldots, R, \ l = 1, \ldots, L, \tag{6}$$

where the parameters $\beta_{rl}, \gamma_{rl,1}, \ldots, \gamma_{rl,k}$ must be estimated.

Since the parameters are identified only up to a constant, we need a normalization. Here, we choose one region, R, for example, and set the β_{Rl}s and the $\gamma_{Rl,j}$s to zero ($l = 1, \ldots, L, \ j = 1, \ldots, k$). We therefore have a maximum of $(R-1) \times L \times k$ parameters to estimate. Note that this is the general form, and additional restrictions may be imposed on the parameters if necessary, particularly to reduce the number of parameters to be estimated.

3.4 Estimation

We estimate the parameters of the demand and supply parts jointly from our aggregate data using the generalized method of moments (GMM), which is the standard approach. On the demand side, we know that we can invert the system of equations (2) and (3) to recover the values of ξ_{jm} given the observables. Following Berry (1994), we actually have the usual inversion

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[10] See Section 4 for more details.

formula:

$$\xi_{jm} = \log\left(\frac{s_{jm}}{s_{0m}}\right) - \left(X_{jm}^{\top}\beta + \alpha p_{jm} + \gamma f_{jm} + \sigma \log \frac{s_{jm}}{1 - s_{0m}}\right). \tag{7}$$

In the above equation, the product characteristics X_{jm} are exogenous—i.e., $E(\xi_{jm}|X_{jm}) = 0$. However, p_{jm}, f_{jm}, and $\log \frac{s_{jm}}{1-s_{0m}}$ are correlated with the unobserved characteristic ξ_{jm}. Therefore, we need to find additional instruments (at least 3) to consistently estimate the vector of demand parameters, denoted, from now on, θ_d. We describe our instruments in the empirical section. Let Z_{kjm}, $k = 1, \dots, K$ be the K instruments used to estimate the demand, including X_{jm}; our K moments for the demand part are:

$$E\left(\xi_{jm} Z_{kjm}\right) = E\left(Z_{kjm}\left(\log\left(\frac{s_{jm}}{s_{0m}}\right) - X_{jm}^{\top}\beta - \alpha p_{jm} - \gamma f_{jm} - \sigma \log \frac{s_{jm}}{1 - s_{0m}}\right)\right) = 0, \tag{8}$$

for $k = 1, \dots, K$.

On the supply side, we assume that the marginal cost of production depends linearly on various product characteristics summarized in the vector W_{jm},

$$mc_{jm} = W_{jm}^{\top}\psi + \zeta_{jm}. \tag{9}$$

W_{jm} is a $L \times 1$ vector of observed characteristics $w_{l,jm}$, $l = 1, \dots, L$ and ζ_{jm} a marginal cost shock. To estimate parameter ψ, we rely on the L normal equations, in which the marginal cost mc_{jm} is derived from Equation (5) given the demand parameters.

$$E\left(\zeta_{jm} w_{l,jm}\right) = E\left(w_{l,jm}\left(mc_{jm} - W_{jm}^{\top}\psi\right)\right) = 0, \; l = 1, \dots, L. \tag{10}$$

Note that the latter system of moment equations includes both ψ and the demand parameters, θ_d, since the marginal costs are derived from Equation (5), i.e., the airline's optimal strategy that takes demand into account. The system of $K + L$ moment equations above is used for the estimation using the optimal weighting matrix computed from a first–step estimation. More details can be found in Appendix A.

We estimate the probability model — i.e., the probability of a passenger visiting a given region, given that they are landing in a specific region and coming from a specific European country — using Maximum Likelihood applied to detailed data provided by the Bank of Italy as explained in section 4. We also compare models with different sets of fixed effects and select the one with the lowest Akaike Information Criterion (AIC) value.

4 Data and descriptive analysis

4.1 Data sources and sample selection

The data sources are diversified. Data on air transport come from the Official Aviation Guide (OAG) platform.[11] We use two databases from this source: the Schedule Analyzer (SA) and the Traffic Analyzer (TA). SA provides data on all direct commercial O–D flights in the world that airlines regularly schedule. It also provides information on frequency, distance, flight time, and aircraft type for each flight. TA, on the other hand, provides data on prices[12] and quantities for O–D travel with or without connections. This information is broken down by booking class—from first class to discounted economy. Unlike the well–known U.S. Department of Transportation data (DB1B), we do not have individual data. TA information is aggregated monthly for each route used by passengers flying on a particular airline from an origin airport to a destination airport.

With these data, we can build our air transportation dataset, which consists of all the possible flights from the regions[13] of 26 European countries to the 16 Italian regions that have an international airport. The list of countries and regions is given in Appendix B. Figure 1 shows a map of Italy with its regions, and the black dots indicate the airports with commercial air service and their international codes. Three regions (in red in the figure), Basilicata, Trentino–Alto Adige and Valle d'Aosta, have no airports. Tourists traveling by air who visit these regions land at nearby regional airports, as illustrated for Valle d'Aosta in the upper right part of Figure 1.[14]

We have data for three consecutive years (2016 to 2018), and we only retain information for the summer semester (April to September). We focus on the summer period, as it is when the majority of tourist flows from Europe to Italy are most concentrated. In addition, since we are studying the relationship between air transport and tourism, we only consider the economy discount–booking class provided by the TA data. Also, trips with two connections within Europe are very rare. We limit the options to a maximum of one connection and eliminate the rare trips with more than one connection. Also, we aggregate all connecting flights proposed by the same airline on the same O–D irrespective of their connecting airport. We believe this is reasonable, as tourists typically do not place much weight on the specific connection point.

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[11] `https://www.oag.com/`

[12] TA prices do not include airport taxes.

[13] We consider the NUTS 2 regions. The acronym NUTS comes from the French *Nomenclature des Unités territoriales statistiques*. It is a geographical nomenclature that divides the economic territory of the EU into regions at three different levels (NUTS 1, 2 and 3, from larger to smaller territorial units). A NUTS 2 region corresponds to the provinces in the vast majority of European countries.

[14] In this paper, we consider Molise as part of Abruzzo, even though administratively they are two separate regions. There are two reasons for this: on the one hand, Molise is too small to generate meaningful statistical analyses, to the extent that the European regional classification NUTS2 aggregates it with Abruzzo. On the other hand, until 1963 they were also administratively a single region, and this still entails a certain uniformity in infrastructure provision and political decisions, especially in the field of tourism.

Finally, we remove some of the products with extreme characteristics. We drop all observations with less than 10 passengers per week, or with an average fare of less than 10 euros, or with a frequency of less than once a week. The calculation of the frequency of an *O–D* flight with a connection is explained in Appendix B.

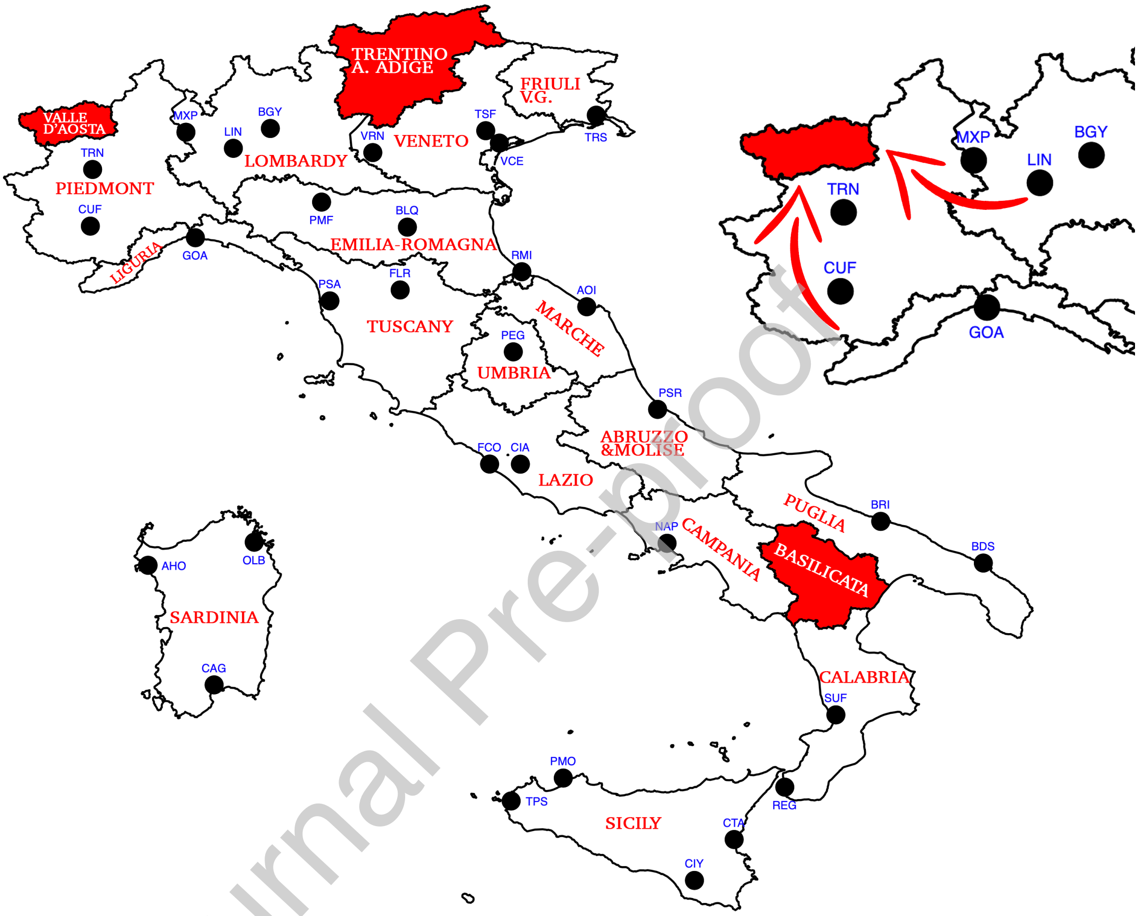

Figure 1: Map of Italian airports and regions with no airports

We also use two databases for considering the tourist flows from the various European regions to the Italian regions. First, we use information from the annual survey on international tourism in Italy published by the Bank of Italy.[15] The survey collects individual–level data on passengers at specific airports and their vacation destinations. We only consider information on tourists

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[15] See the website `https://www.bancaditalia.it/statistiche/tematiche/rapporti-estero/turismo-internazionale/index.html?com.dotmarketing.htmlpage.language=1`. The Italian central bank has been conducting, since 1996, a survey on international tourism based on interviews at the Italian points of entry/exit (border crossings and passport controls in road and rail crossings, international ports, and airports) of resident and non–resident travelers at the Italian borders. To estimate the number of international travelers, the information collected through the survey is integrated with administrative data and, since the end of 2020, also with mobile phone data.

arriving from European countries and traveling to Italian regions by air, which allows us to estimate the probability of a tourist arriving in a given Italian region by air to visit this region or moving on to other Italian regions as their final destination.[16]

Second, we work with data provided by the Italian Institute for Statistics (Istat) reporting, for each European origin region, the monthly number of tourists staying in any Italian region, as recorded in the administrative registers of the tourist offices, and covering all transport modes. Hence, these are official aggregate data and are used in the counterfactual analysis to determine the percentage changes of the number of tourists visiting a given region induced by the different LCC subsidy schemes considered.

Finally, information on some control variables (that is, GDP per capita and the share of people with tertiary education, both at the regional level), used in the demand model, is obtained from Eurostat.[17]

4.2 Airline data summary

Table 1 reports some summary statistics of the variables in our air transportation structural model. The top panel reports summary statistics at the product level, and the bottom one reports at the market level. All statistics are calculated across products regardless of the number of passengers assigned to each product in the first two columns. In the last two columns, these statistics are weighted by the number of passengers. Note the significant amount of heterogeneity across the 6,525 products and 397 markets. The mean number of passengers flying to Italy per semester (pax_{jmt}) is 5,527 with a standard deviation of 9,853, indicating a large variability. The mean price of directional tickets (p_{jmt}) is €101.31, with a standard deviation of €51.15, while weighting by passengers it averages €84.23, with a standard deviation of €37.10. The mean frequency of flights (f_{jmt}) is 457 (i.e., about 18 flights per week), with a standard deviation of 508, indicating a high variance.

Figure 2 shows the dispersion of airline fares. The vertical axis shows the frequency, which is separate for FSCs and LCCs and for direct and connecting flights at a gateway airport. It is evident that the LCC fares are more concentrated on lower price levels than the FSC fares. In addition, connecting flights, products offered by FSCs, have higher prices than direct flights, mainly offered by LCCs.

Because of the specific market definition, we define the market size as the population of the NUTS 2 origin region provided by Eurostat. A common feature of airline data is that the average market share of a product, s_{jmt}, is very small, 0.3% in our case. If we consider only the people

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[16] The survey also includes information on the per capita expenditure during the vacation.

[17] See https://ec.europa.eu/eurostat.

Table 1: Summary statistics of the main variables

Product average				
	Unweighted		Weighted on pax_{jmt}	
Variable	Mean	S.D.	Mean	S.D.
pax_{jmt}	5,527	9,853		
s_{jmt}	0.003	0.006	0.009	0.012
$s_{jmt\|a}$	0.061	0.121	0.099	0.103
p_{jmt} (€)	101.31	51.15	84.23	37.10
f_{jmt} (# flights)	457	508	462	471
$direct\_fsc_{jmt}$	0.19	0.39	0.31	0.46
$direct_{jmt}$	0.53	0.50	0.93	0.26
lcc_{jmt}	0.35	0.48	0.62	0.49
$ryanair_{jmt}$	0.14	0.34	0.28	0.45
$easyjet_{jmt}$	0.07	0.25	0.17	0.37
$other\_non\_allied\_lcc_{jmt}$	0.05	0.21	0.06	0.23
$oneworld_{jmt}$	0.16	0.37	0.18	0.38
$star_{jmt}$	0.35	0.48	0.18	0.38
$skyteam_{jmt}$	0.22	0.42	0.12	0.33
Observations	6,525			
Market Average				
	Mean	S.D.		
No. products	16.44	16.50		
No. carriers	4.51	3.45		
No. direct passengers	84,110	140,568		
No. connecting passengers	6,727	9,860		
No. FSC passengers	34,592	78,359		
No. LCC passengers	56,245	92,281		
s_{0mt}	0.957	0.072		
edu_{mt} (%)	42.32	10.79		
gdp_{mt} (€)	31,242	11,592		
$expenditure_{mt}$ (€)	778	105		
No. of markets	397			
No. of European regions	138			

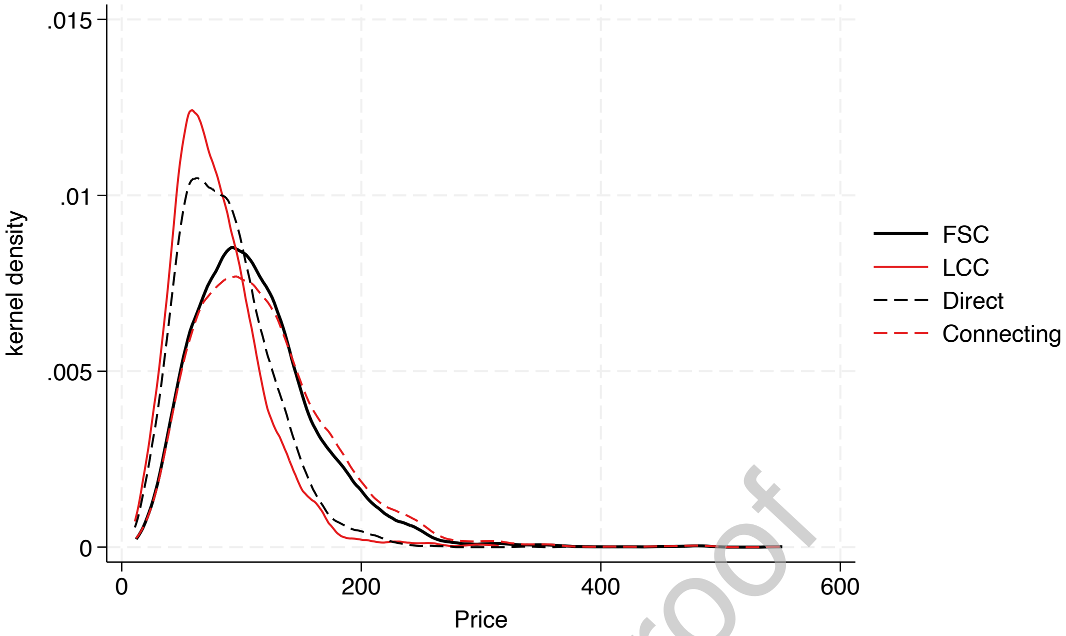

Figure 2: Fare dispersion per type of carriers and flights

that decide to fly Italy, the average share of a product ($s_{jmt|a} = s_{jmt}/(1 - s_{0mt})$) is 6%, with a standard deviation of 0.12.

Concerning the airlines' different travel options from a European region to an Italian airport, the LCCs represent 35% of the products (dummy *lcc*) for 62% of the passengers. Among them, the two main European LCCs, *Ryanair* and *EasyJet*, represent respectively 14% and 7% of the products for 28% and 17% of the passengers transported to Italy by air. The remaining passengers either fly with LCCs that belong to one of the three main alliances (such as *Vueling* or *Eurowings*) or are not members of one of them (like *Wizz Air*). Most of the products offered by LCCs are direct flights (96%); among the 65% of products proposed by the FSCs, the direct ones correspond to 29% of these products, for a total of 19%. The three main alliances *Oneworld*, *Star Alliance* and *Skyteam* represent respectively 16%, 35%, and 22% of the products, and 18%, 18%, and 12% of the passengers. The remaining 2% of products correspond to flights operated by non–allied FSCs (e.g., *Air Baltic*).

The bottom panel of Table 1 reports the summary statistics at the market level. There are 397 markets in our data set.[18] On average, there are approximately 16 possibilities to fly from a European region to Italy.

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[18] Some markets are not always active and are in the data set only for some years, e.g., Tyrol in Austria and Auvergne in France in 2016. We have 397 markets instead of 414 (138 NUTS 2 European regions for 3 years) if the data set had been balanced.

Although the market share of the outside option, s_{0mt}, is, as known in the literature, quite high, [19] it is less important than in the standard O–D market. The average market share of the outside option is equal to 0.96, with a very low standard deviation of 0.07. In the majority of the European regions, most people do not fly to Italy for summer vacation.

As for the control variables, the percentage of the tertiary–educated population aged 30–34 in the NUTS 2 origin region (edu_{mt}) is 42%, with a standard deviation of about 11%. The average GDP per capita in the region of origin, expressed in purchasing power parity (gdp_{mt}), is €31,242, with a standard deviation of €11,592. On average the per capita tourist expenditure ($expenditure_{mt}$) is €778, with a standard deviation of €105.

4.3 Tourism data summary

The tourism sector is the second component of our work, in which we observe the effects of an indirect incentive policy for tourism based on subsidies to LCCs. As mentioned above, we use two databases on tourism originating from a European country and destination to an Italian region. Table 2 shows the Italian region where European tourists land and their final destination for vacation according to the survey conducted by the Bank of Italy. The data refer to 84,225 European tourists in the period 2016–2018 who traveled exclusively by air for vacation. The first column of Table 2 describes the Italian region where tourists arrive by air, defined as the landing region. The other 19 columns to its right show their final destination (Destination region). The last column on the right displays the total number of landing passengers in each region (Total landing). The bottom row reports the total number of European tourists in each region who either land in the same region or reach it as their final destination using other transport modes from the airport where they land.

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[19] For example, Berry and Jia (2010) have a mean value of s_0 close to 99.5%.

Table 2: Regional landings and final destinations of European tourists in Italy–Bank of Italy survey

	Destination region																		
Landing region	Abruzzo	Basilicata	Campania	Emilia	Lazio	Lombardy	Marche	Puglia	Sardinia	Sicily	Tuscany	Trentino	Umbria	Veneto	Calabria	Liguria	Piedmont	Friuli	Aosta	Total landings
Abruzzo–Molise	444	0	1	0	3	0	10	8	14	0	1	0	2	0	0	0	0	0	0	483
Calabria	0	0	31	0	0	0	0	0	0	5	10	0	0	0	151	0	0	0	0	197
Campania	5	18	6,753	1	134	21	2	46	1	30	33	2	3	17	17	11	2	0	0	7,096
Emilia–Romagna	8	4	15	3,262	42	72	184	29	7	15	646	30	40	177	7	31	9	6	0	4,584
Friuli–Venezia Giulia	0	0	0	1	1	3	0	0	0	0	1	1	0	16	0	0	0	238	0	261
Lazio	163	5	576	54	16,965	57	37	70	76	394	440	4	150	203	95	63	13	10	0	19,375
Liguria	0	0	21	3	31	6	0	0	3	20	8	0	0	1	0	395	11	0	0	499
Lombardy	11	3	149	522	188	12,381	18	166	231	291	386	351	9	1,062	126	407	1,055	41	61	17,458
Marche	8	0	0	56	3	4	280	0	0	0	2	0	14	1	0	0	0	0	0	368
Piedmont	0	0	6	4	7	19	0	2	1	3	2	0	0	3	0	26	1,305	0	25	1,403
Puglia	16	133	89	2	8	5	2	2,281	5	8	10	2	2	9	40	0	1	0	0	2,613
Sardinia	0	0	2	0	4	8	0	2	3,237	27	2	0	4	0	0	2	1	0	0	3,289
Sicily	0	0	4	0	12	1	9	0	6	8,758	2	0	0	2	6	0	15	0	0	8,815
Tuscany	1	5	20	48	95	20	8	6	7	6	6,190	23	52	73	6	228	7	1	1	6,797
Veneto	0	0	22	19	31	288	1	0	0	2	20	377	0	10,139	1	12	1	74	0	10,987
Total	656	168	7,689	3,972	17,524	12,885	551	2,610	3,588	9,559	7,753	790	276	11,703	449	1,175	2,420	370	87	84,225

We also construct a second data set, coming from administrative sources, related to the tourism market available from Istat. In this data set, an observation is a tourist flow, during the summer months of one of the years 2016 to 2018, from a European country c to an Italian region r of destination independent of the transportation mode. These flows are unevenly distributed among the Italian regions, as shown in Figure 3, which presents an indicator of tourism intensity—i.e. the total number of European tourists in a region compared to the local population. It can be seen that arrivals are particularly high in Veneto and Tuscany (where Venice and Florence are located), Lombardy (Milan), Lazio (Rome) and Sardinia. In contrast, the Southern regions have lower tourist intensity scores, which may open the field for policies to stimulate international tourist arrivals.

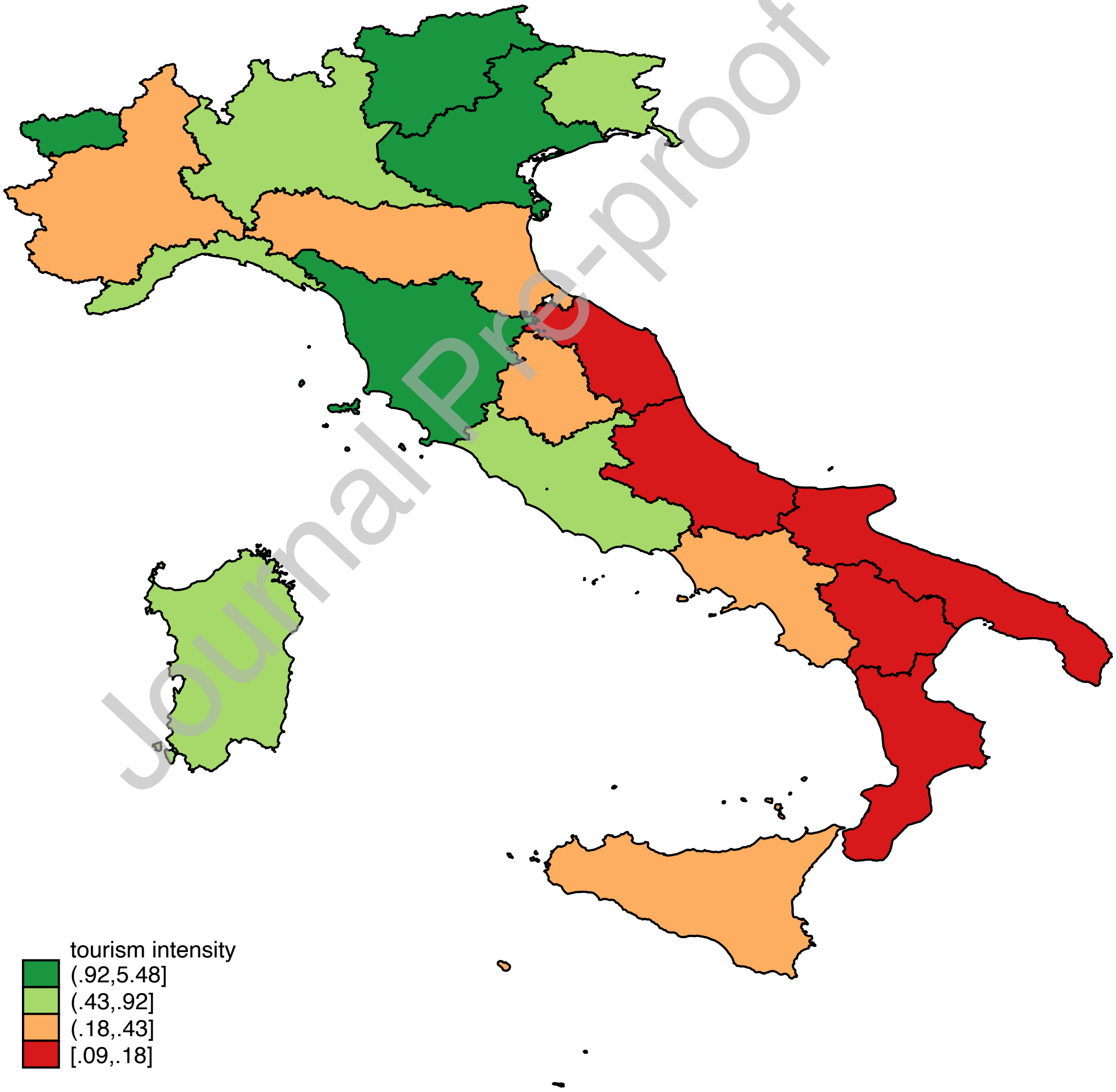

Figure 3: Intensity of European tourism in Italian regions: tourists *vs* population

Table 3 presents the summary statistics of the tourist flows per Italian region from the 138 European regions considered in our model. Veneto, Trentino–Alto Adige, Lombardy, Tuscany, and Lazio have the highest average tourist flows among the 26 European countries. These regions include highly attractive cities, while Trentino–Alto Adige offers summer vacations in the mountains. The Southern Italy regions receive fewer European tourists per country during the summer period in our data: for instance, Sicily 47,745 tourists, Campania 39,953, and Sardinia 45,943.

Table 3 also displays summary statistics of the number of passengers (# *Pax*) traveling by air and landing at Italian airports. Lazio records around 120,000 passengers from each European country during the summer season, similar to Lombardy. The most important airports are located in these two regions: Rome–Fiumicino in Lazio, Milan–Malpensa, Milan–Linate and Bergamo in Lombardy. The number of passengers landing in other regions is much lower and, as previously mentioned, Trentino–Alto Adige, Valle d'Aosta, and Basilicata do not have international airports. In total, around 28 million European tourists arrive in Italy every summer, including approximately 12 million by air.

Table 3: Summary statistics of the tourist flows

	Region	Mean		LCC
		# Tourists	# Pax	
North	Emilia–Romagna[1]	56,958	22,824	70%
	Friuli–Venezia Giulia	34,296	1,199	53%
	Liguria	43,767	2,876	35%
	Lombardy	135,767	119,651	67%
	Piedmont	42,930	6,934	59%
	Trentino–Alto Adige	143,298	-	-
	Valle d'Aosta	8,821	-	-
	Veneto	234,795	57,952	56%
Center	Abruzzo–Molise	4,422	2,120	99%
	Lazio	69,965	120,132	55%
	Marche	8,533	1,423	79%
	Tuscany	117,396	33,687	65%
	Umbria	11,536	921	100%
South	Basilicata	2,241	-	-
	Calabria	7,341	3,237	62%
	Campania	39,953	28,825	65%
	Puglia	21,260	13,974	72%
	Sardinia	45,943	17,663	64%
	Sicily	47,745	28,917	62%

1: each figure is the average per European country, per year. For example, on average, 56,958 people are visiting Emilia–Romagna from a European country each summer period.

The last column of Table 3 shows the share of passengers arriving by LCCs in each region. The figures are fairly scattered, with an average of 62%. In all regions, with the sole exception of Liguria (35%), the share of LCC passengers is higher than 50%. The importance of LCCs in terms of European passengers arriving in different regions of Italy is therefore evident, especially in the regions of Southern and Central Italy, where tourism is an important component of the local economy in terms of regional GDP. This explains the decisions taken by some regional governments to subsidize LCCs to open new regional airport routes to stimulate tourism demand.[20]

5 Results

The parameters' estimates related to demand and supply in the aviation sector are first presented and discussed. We then show the model results for predicting tourist flows from tourist arrivals in the various Italian regions.

5.1 Demand parameter estimates

As mentioned in Section 3, we need at least three instruments to consistently estimate Equation (7) to address the endogeneity of the ticket price (p_{jmt}), the frequency (f_{jmt}), and the product market share given that people decide to travel to Italy by air, $s_{jmt}/(1-s_{0mt})$, denoted $s_{jmt|a}$. These instruments are introduced below.

Instruments

Following the literature, we first consider a cost shifter to instrument for the price, known to be an important factor for nonparametric identification of such a demand model (Berry and Haile, 2024). The cost shifter that we use is an indicator of fuel consumption per seat for each flight. Changes in this indicator account for part of the variation in prices. It is worth mentioning that the capacity of the aircraft, rather than the number of seats occupied, is used to calculate this index. Fleet choice is a medium–term decision that can be considered independent of short–term demand shocks. Moreover, as Marra (2024) also notes when using a similar instrument, the validity of this instrument is related to the assumption that "consumers do not value how fuel–efficient the aircraft is", which is reasonable, as consumers mainly care about the final price.

Fuel consumption is not easy to compute because it is not available in official statistics and depends on several factors such as aircraft and engine models and the specific aircraft used for

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[20] For example, local newspapers report that, in 2017, the Puglia region, in Southern Italy, approved an annual subsidy of around €20 million to LCCs operating at the Bari and Brindisi airports through commercial agreements.

each flight. The exact calculation of this fuel index is explained in detail in Appendix B and is based on three parameters: (1) the age of the fleet, (2) the distance flown and (3) the aircraft's seat capacity. As a result, the mean value of this index per product is equal to €37.8 for a standard deviation across products of €16.8, i.e., around half the mean value, a ratio similar to that observed for price.

Another cost shifter used is the dummy variable labeled *gateway_hub_fsc* and constructed as follows. Recall that we aggregate all the connecting flights offered within the same *O–D* pair and on the same airline. For example, a connecting flight offered by *Air France* from Toulouse to Milan might connect through its main hub (Paris–*Charles de Gaulle* Airport) or, occasionally, through secondary hubs such as Lyon or Nice. For each trip offered by a FSC with a connection, we count the number of options offered by the same airline at the connecting airport. If there are many hub options, we calculate a weighted average (weighted by the number of passengers actually transported by this FSC). Our variable equals 1 if the resulting value is among the top 25% values calculated for all connecting products proposed by all FSCs. Thus, when the variable equals 1, passengers are transported via the main European hubs, and when it equals 0, they are transported via secondary hubs.

Connecting at a major hub has a non–trivial effect on marginal costs. On one hand, pooling passengers with the same origin but with different destinations or passengers with the same destination but different origins, generates denser traffic and reduces marginal costs. On the other hand, connecting requires an extra take–off and landing phase, which is fuel–consuming and requires more coordination at the main hub, especially at the hub–management level. The coefficient of *gateway_hub_fsc* in the marginal cost regression measures the net effect of these opposing forces, and can serve as a demand instrument.[21]

We then consider two so–called "BLP instruments" for the market share within the nest, $s_{jmt|a}$, i.e., specific functions of characteristics of competing products. First, we consider the number of competing airlines offering a direct flight on the same *O–D* route. Such a competing product is indeed a close substitute for the product considered. An increase in the number of competing products corresponds to an increase in the competitive options and decreases the market share of the airline's product. Second, we also consider the number of competing airlines offering a direct flight from the same European region of origin but to adjacent regions of the Italian region of destination. Such a competing product is also a close substitute for the product considered. These two instruments remain valid for the two–level nested model considered below.

The validity of these two instruments hinges on the assumption that the network is exogenous, at least in the short term. This is a reasonable assumption since network decisions are made at

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[21] See Berry and Jia (2010), page 25–26 for a similar discussion.

a longer term. Most papers in the literature use similar instruments.[22]

Finally, as in Berry and Jia (2010), the instrument for the frequency we use is the fitted value of the median regression of the frequency on various exogenous variables, which are detailed in Appendix B.

Table 15 in Appendix C shows the three first stage regressions—one for each endogenous variable. All instruments are statistically significant and have the expected sign. For example, the cost of fuel increases the price, decreases the frequency, and decreases a product's market share. The number of competing products on a direct flight leads to a lower price, higher frequency (to compensate for the longer flight), and lower market share. With respect to diagnostic tests, we observe high F–test statistics, suggesting that we do not face problems related to weak instruments (Stock and Yogo, 2002).

Estimates

In the demand equation (7), we consider the following variables for the exogenous characteristics. First, the dummy variable *direct_fsc* which is equal to one if the flight is direct and the product is provided by a FSC, capturing the willingness to pay for direct flights. Second, the variable *expenditure* (in hundreds of euros) measures the local expenses at the destination, which form part of the total trip expenses.[23] In doing so, we implicitly assume that the consumers have perfect foresight regarding their future expenses when making decisions (i.e., they are aware of hotel prices and have the right expectations regarding their other expenses).

We also add fixed effects for the Italian destination regions. These fixed effects enable us to consider the difference in attractiveness of the various regions alongside the other characteristics, such as the number of attractions, tourist sites, and the quality of the beaches. We also include a set of dummies related to the year, the European country of origin, the airline alliance, *Ryanair*, *EasyJet*, and all other nonallied low–cost carriers.

Finally, the variables *gdp* (GDP per capita in thousands of euros) and *edu* (share of people with tertiary education), both calculated for the European region of origin, are introduced. They are related to the propensity of people living in this region to fly to Italy for summer vacations.

In the left panel of Table 4, we report estimated coefficients of the regressors in the demand equation using the optimal two–step GMM procedure jointly with (right panel of Table 4) the marginal cost equation (9) (see Eqs. (17) and (18) in Appendix A). Standard errors are reported in parentheses, as well as indicators of level of significance.

The estimated coefficients of the demand regression in Table 4 have the expected signs (with

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[22] See Berry and Jia, 2010; Ciliberto and Williams, 2014.

[23] We thank one of the referees for this suggestion.

Table 4: Estimates of coefficients for demand and cost components in air transport

Demand estimates		Marginal cost estimates	
Regressors		Regressors	
$Constant$	-3.2023***	$Constant$	92.9639***
	(0.7069)		(9.7681)
p_{jmt}	-0.0240***	$direct_{jmt}$	-13.7573***
	(0.0039)		(1.8766)
$\log(s_{jmt\|a})$	0.5675***	$fuelcost_{jmt}$	0.1561***
	(0.0546)		(0.0582)
f_{jmt}	-0.0002	$gateway\_hub\_fsc_{jmt}$	10.7180***
	(0.0003)		(1.7618)
$direct\_fsc_{jmt}$	0.5247***		
	(0.0556)		
gdp_{mt}	0.0435***		
	(0.0037)		
edu_{mt}	-0.0328***		
	(0.0034)		
$expenditure_{mt}$	-0.0467*		
	(0.0297)		
No. observations	6,525	No. observations	6,525
Year dummies	✓	Year dummies	✓
Italian region dummies	✓	Italian region dummies	✓
European country dummies	✓	European country dummies	✓
Airline/Alliance dummies	✓	Airline/Alliance dummies	✓

Standard errors in parentheses ***p-value<0.01, **p-value<0.05, *p-value<0.1

the exception of *edu*) and are statistically significant (excluding frequency f). We cannot reject the hypothesis that frequency does not change the level of tourist demand at the first order (the p–value for this test is greater than 10%). Again, a tourist is probably less sensitive to the departure time of her flight than a regular passenger flying for business or pleasure.

The nesting parameter σ, related to the variable $\log(s_{jmt|a})$ in the regression, lies between 0 and 1, indicating substitution exists between the outside option and the nest given by all the possible air products. As expected, we find a preference for direct flights. Since most of the products offered by LCCs are direct flights, the dummy in the regression only concerns the direct FSC flights. On average, a passenger is willing to pay around €21.8 more[24] to fly direct with a FSC, with a 95% confidence interval ranging from €14.4 to €28.2. In other words, given that the mean airfare proposed by a FSC is equal to €112.7, it represents around 21.5%, i.e., more than in Berry and Jia (2010) for the tourist traveler in 2006 (around 12.4%). However, Ciliberto and Williams (2014) estimate the same amount at $98 for leisure travelers for a mean price of $223, that is, around 44% of the mean airfare. Our figure lies between these two ratios.

The variable representing income per capita in the region of origin (gdp_{mt}) has a positive and significant effect on air travel demand, as expected. Finally, the coefficient of *edu* is statistically significant but negative. One possible explanation for this result is that regions with a higher proportion of graduates may have consumers who travel more for business or to destinations beyond Italy, either elsewhere in Europe or further abroad, thereby opting for the outside good.

Price elasticities, marginal costs and markups

The demand estimates allow us to calculate the elasticities of demand with respect to price, which are shown in Table 5. We calculate the elasticities for each market (by averaging across products) and report the average and standard deviation across markets. We find an average own–price elasticity of −5.17 (with a standard deviation of 2.02). Our estimates of price elasticity for air transport products are of the same order of magnitude than those found in previous studies. For example, Berry and Jia (2010) has an estimate for tourist travelers of −5.01 in 1999, −6.55 in 2006, Ciliberto and Williams (2014) estimate price elasticities for the same category around −6.1 for the 2006–2008 period, and both are calculated from nested logit models with two types of travelers. In a model without consumer heterogeneity, Bontemps et al. (2022) estimate an aggregate price elasticity of −4.16 in 2011 and −3.49 in 2016. All these works are derived from U.S. data, and to the best of our knowledge, little evidence exists for European elasticities. Recently, Marra (2024) estimated a price elasticity of tourist–type passengers departing from Paris airports equal to −4.61. This estimate is based on flight–level data.

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[24] Given by the ratio between the coefficient of $direct\_fsc$ and the price coefficient.

Table 5: European air transport: own and cross price elasticities

	Mean	S.D.
Own price elasticity	-5.17	2.02
Cross price elasticity	0.56	0.78

Estimation of each product's marginal cost can be obtained by solving Equation (5) using the demand–parameter estimates. From there we can calculate the markups both for the sample as a whole and for the sub–samples of LCC, FSC, direct, and connecting flights. Table 6 reports the averages of these quantities across all products. The average estimated marginal cost is about €78, with a large difference between LCC (around €54) and FSC (around €92). Marginal costs are much higher for connecting flights (€97) than for direct flights (€62). The average markup is around €23, with LCCs averaging €27 and FSCs €21. The markup is higher for direct flights (€25) than connecting flights (€21).

Table 6: European aviation markups and marginal costs estimates

	Markup		Marginal Cost	
	Mean	S.D.	Mean	S.D.
All flights	23.01	6.98	78.29	52.61
LCC	26.70	8.56	53.65	41.34
FSC	21.02	4.90	91.65	53.23
Direct	25.19	7.80	61.55	41.13
Connecting	20.59	4.90	96.95	57.50

5.2 Estimates of the supply parameters

The right panel of Table 4 shows the estimated coefficients for the different components of the marginal cost. *Stricto sensu*, we do not need to perform this regression for our counterfactual analysis, but it is interesting to analyze some of the marginal cost determinants.

As expected, direct flights generate lower marginal costs: the estimated coefficient of *direct* is equal to about -13.76 and is statistically significant. Fuel cost has a positive effect on marginal costs: the estimated coefficient of $fuelcost$ is about $+0.16$ and significant. As this is an index, the value of the estimate has no direct interpretation.

The estimated coefficient of the variable $gateway\_hub\_fsc_{jmt}$ is positive and significant. Flights connecting at major European hubs have higher marginal costs than those connecting at secondary hubs. Berry and Jia (2010) found a similar pattern for trips of equivalent distance in the U.S. in 2006.

5.3 Estimation of a two–level nested model for the demand

As explained above, one could ask whether the substitution between the different options is different between products serving the same region and products serving different regions. To check the validity of our demand model, we consider in this section the estimation of a two–level nested model for the demand.

In such an extended model, conditional on having decided to fly to Italy, it is assumed that travelers first select their Italian destination region. Then, conditional on selecting this destination region, the traveler subsequently chooses the specific product (i.e., flight) that maximizes their indirect utility. This two–level nested structure, represented in Figure 4 in Appendix D, allows consumers/travelers to substitute differently between products serving different Italian destination regions.

It can be shown[25] that Equation (7) becomes now

$$\xi_{jm} = \log\left(\frac{s_{jm}}{s_{0m}}\right) - \left(X_{jm}^{\top}\beta + \alpha p_{jm} + \gamma f_{jm} + \sigma_1 \log(s_{jm|r}) + \sigma_2 \log(s_{rm|Italy})\right), \qquad (11)$$

where s_{jm} is the market share of product j in market m, $s_{jm|r}$ is the market share of product j in market m conditional on choosing the Italian region r as final destination (and flying to Italy) and $s_{rm|Italy}$ is the market share of region r in market m conditional on flying to Italy.

Observe that $s_{jm|r} \times s_{rm|Italy}$ is the market share of product j in market m conditional on flying to Italy, i.e., the value $\frac{s_{jm}}{1-s_{0m}}$ in Equation (7). Therefore, our two–level nested model resumes to our original model when $\sigma_1 = \sigma_2$. Interestingly, the same estimation procedure can be implemented to estimate this model since our two BLP instruments used to estimate our demand model can be used for the (now) two endogenous variables $s_{jm|r}$ and $s_{rm|Italy}$ in Equation (11).

We report the estimates of both the demand and supply parameters of this augmented model from a similar GMM procedure in Table 7, in the same manner than Table 4. Note that the two models are both estimated with the same set of instruments which are valid in both cases following our discussion in Section 5.1.

Similar comments can be drawn about the signs and order of magnitudes of the different equilibrium quantities. Note that the demand estimates in Table 4 and in Table 7 are similar. We report in Table 8 the mean values of own–price elasticities, markups, marginal costs with their standard deviation across products as well as the estimated willingness to pay (WTP) for direct flights (and its 95% confidence interval) in both models. It highlights that these two models are very close in their ability to characterize the consumer and airlines behaviour.

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[25] See the notes in `https://www.nathanhmiller.org/nlnotes.pdf` or some details in Appendix D. Like in section 3, we omit the year index t for convenience when introducing the model.

Table 7: Estimates of coefficients, two–level nested demand model

Demand estimates		Marginal cost estimates	
Regressors		Regressors	
$Constant$	-3.1924***	$Constant$	86.5310***
	(0.7597)		(8.8014)
p_{jmt}	-0.0250***	$direct_{jmt}$	-6.4191***
	(0.0049)		(1.6812)
$s_{jmt\|r}$	0.5869***	$fuelcost_{jmt}$	0.1840***
	(0.0614)		(0.0609)
$s_{rmt\|Italy}$	0.4881***	$gateway\_hub\_fsc_{jmt}$	17.0569***
	(0.0897)		(1.7741)
f_{jmt}	-0.0001		
	(0.0003)		
$direct\_fsc_{jmt}$	0.6065***		
	(0.0647)		
gdp_{mt}	0.0418***		
	(0.0043)		
edu_{mt}	-0.0343***		
	(0.0036)		
$expenditure_{mt}$	-0.0537*		
	(0.0317)		
No. observations	6,525	No. observations	6,525
Year dummies	✓	Year dummies	✓
Italian region dummies	✓	Italian region dummies	✓
European country dummies	✓	European country dummies	✓
Airline/Alliance dummies	✓	Airline/Alliance dummies	✓
Standard errors in parentheses ***p-value<0.01, **p-value<0.05, *p-value<0.1			

Table 8: Comparison of outcomes with one– and two– level nested models

	One–level Nested Model	Two–level Nested Model
Mean price elasticity (Std dev)	-5.17 (2.02)	-5.39 (2.59)
Mean Markup (Std dev)	23.01 (6.98)	22.23 (6.93)
Mean Marginal cost (Std dev)	78.29 (52.61)	79.08 (52.50)
WTP direct flight [95% CI]	21.8 [14.4;28.2]	24.26 [16.6;31.9]

In particular, $\widehat{\sigma_1} = 0.5785$ with a standard deviation of 0.0614 and $\widehat{\sigma_2} = 0.4881$ with a standard deviation of 0.0897. Both are significant and close to the estimate of σ in our one–level nested model, i.e., 0.5675.

We run a formal test for the null hypothesis H_0: $\sigma_1 = \sigma_2$ against the alternative H_a: $\sigma_1 \neq \sigma_2$. This hypothesis tests our one–level nested model against the two–level nested model as the second one nests the first one. Using the estimated covariance matrix of $(\widehat{\sigma_1}, \widehat{\sigma_2})$, we can derive the value of the corresponding T–statistic:

$$T = \frac{|\widehat{\sigma_1} - \widehat{\sigma_2}|}{St.dev(\widehat{\sigma_1} - \widehat{\sigma_2})} = 1.102,$$

leading to a p–value of 27%. Therefore, there is no evidence in the data to reject our model in favor if the two–level nested one. In conclusion, in the counterfactual section, we use the one–level nested model.

5.4 Predicting the probability of visiting an Italian region

As mentioned before we estimate the MNL model given in Equation (6) by Maximum Likelihood. Note that since this model is being used to predict which Italian region is visited by air travelers landing in a specific region, we cannot use any specific individual variable other than the country of origin to calculate these probabilities because we do not have personal information in our aviation data. We only observe where do people depart from, which flight they take and where they land.

Our general model encompasses many specifications that can be considered for estimation. Note that the term $\beta_{rl} + \gamma_{rl}^{\top} C_i$ in Equation (6) can be interpreted as the propensity of an individual i with characteristic C_i to visit region r when landing at an Italian airport located in region l.

The first model is probably the less interesting, but can serve as a benchmark. In this model, denoted Model 1, no information is used, neither the country of origin, nor the landing region. Equation (6) becomes:

$$Prob(Y_i = r) = \frac{e^{\beta_r}}{\sum_{r=1}^{R} e^{\beta_r}}, \quad r = 1, \ldots, R \tag{12}$$

with the normalization $\beta_R = 0$. The model is parsimonious, i.e., there are only $R-1$ parameters to estimate. However, Model 1 is predicting the same probability of visiting a given region whatever the landing airport, which seems very unrealistic. Unsurprisingly, the estimates of the parameters leads to estimated probabilities $\widehat{Prob}(Y_i = r)$ equal to the frequency of region r as a vacation destination in the survey observations.

A more interesting specification is to use the information about the landing region l only: we label it as Model 2 and the choice probability is given by the following expression:

$$Prob(Y_i = r|L_i = l) = \frac{e^{\beta_{rl}}}{\sum_{r=1}^{R} e^{\beta_{rl}}},\ \ r = 1, \dots, R,\ \ l = 1, \dots, L, \tag{13}$$

with the normalization $\beta_{Rl} = 0$ for any l. Here, we don't use any specific observable. Model 2 has $(R - 1) \times L$ parameters to be estimated.

The more flexible model we can consider given our constraints is the one in (6), in which the variable C_i is defined as a vector of $k = 25$ dummy variables,[26] where the c^{th} component is equal to 1 if the traveler comes from country c, 0 otherwise. However, this general model includes too many parameters to estimate, $(R - 1) \times L \times k$, from a dataset of 84,225 observations.[27] For this reason, we estimate a more parsimonious model by considering two simplified versions.

In Model 3, we use the following specification:

$$Prob(Y_i = r|L_i = l, C_i) = \frac{e^{\beta_{rl}+\gamma_r^\top C_i}}{\sum_{r=1}^{R} e^{\beta_{rl}+\gamma_r^\top C_i}},\ \ r = 1, \dots, R,\ \ l = 1, \dots, L. \tag{14}$$

Here, we assume that the propensity for an inhabitant of country c to visit region r is the sum of a landing/visiting region fixed effect, β_{rl}, and a country/visiting region fixed effect, the c^{th} component of γ_r. In statistical terms, we assume that all the γ_{rl}s are identical across l. After normalization, there are $(R - 1) \times (L + k)$ parameters to estimate.[28]

In Model 4, we use for C_i a single dummy variable d_i, which equals one if the country sufficiently close to the landing region and zero otherwise.[29] The rationale for this specification is to account for the fact that some people living in nearby countries may drive more systematically to visit nearby Italian regions. Therefore, the specification is:

$$Prob(Y_i = r|L_i = l, d_i = d) = \frac{e^{\beta_{rl}+\gamma_r d}}{\sum_{r=1}^{R} e^{\beta_{rl}+\gamma_r d}},\ \ r = 1, \dots, R,\ \ l = 1, \dots, L. \tag{15}$$

In Model 4 there are only $(R - 1) \times (L + 2)$ parameters to estimate, i.e, 306.

We report the main features of these four models and the summary of the two information criteria used to select the best model in Table 9. It is known that greater flexibility of a model improves the fit but requires more parameters to be estimated. The Akaike Information Criterion

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[26] We have $N_c = 26$ European countries, but because of the dummy variable trap, we need $k = N_c - 1 = 25$ dummies to code the information related to the country of origin.

[27] Recall that $R = 19$, $L = 15$ and $k = 25$, which implies a total of 6,750 parameters to estimate. Note that Umbria is not present in the Bank of Italy Survey, see footnote 31.

[28] This means 720 parameters, and we have 84,225 observations to estimate them.

[29] A country is considered sufficiently close to an Italian region when the distance between their two centroids is smaller than 800 kilometers.

(AIC) and the Bayesian Information Criterion (BIC) are measures that balance these two effects. BIC penalizes additional explanatory variables more severely.

As expected, Model 1 is the worst in terms of fit as no information is taken into account in the estimation of the probability to visit a region. Models 2 to 4 are relatively close to each other but inspection shows that Model 3 generates the lowest AIC/BIC value.

It is therefore used to calculate the probabilities, conditional on the landing region and country of origin, of selecting an Italian region as a vacation destination, which is a crucial factor in linking the results of the air transport sector to changes in tourist flows.

Table 9: Information criteria of the different models

	Model 1	Model 2	Model 3	Model 4
Landing region dummies		✓	✓	✓
Country of origin dummies			✓	
Distance dummy				✓
AIC	4.6547	1.2788	1.2370	1.2554
BIC	4.6547	1.2789	1.2373	1.2555

From the estimation of Model 3, we can derive, for each country of origin, an estimate of the transition matrix which collects the estimates of the probability that a passenger from a European country c landing in region l chooses as final destination region r, denoted $\widehat{Prob}_{rlc}$.[30]

Table 16 in Appendix E presents the weighted average of these transition matrices, using as weight the relative importance of each European country for tourist flows to Italy during the summer. Unsurprisingly this is a frequency version of Table 2.[31]

These probabilities are used to calculate the change in the number of tourists in region r as a result of the change in the number of passengers landing in region l and departing from country c due to the LCC subsidy policy. Then, the variation in the tourist flow in region r is given by the following expression:

$$\Delta TOU_r = \sum_{c=1}^{26} \sum_{l=1}^{16} \widehat{Prob}_{rlc} \times \Delta Pax_{cl} \tag{16}$$

where ΔTOU_r is the variation in tourist flow in region r, and ΔPax_{cl} is the variation in passengers traveling by air from country c to the landing region l. This variation in tourist flows is the final output of our counterfactual analysis and determines the number of additional tourists attracted to Italy and the percentage change in tourists (compared to the situation prior to the subsidy).

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[30] Hence, we have 26 transition matrices. They are available upon request.

[31] Umbria has only one small airport (Perugia Airport), which is not covered by the Bank of Italy's survey data. To estimate the probability of reaching a final destination r conditional on landing in Umbria, we assumed the same distribution of probabilities as observed for the surrounding feeder regions.

6 Analysis of LCC subsidy policies

In this section, we analyze the impact of policy interventions in the aviation sector on the tourism sector. As previously mentioned, we focus on subsidies targeted at LCCs. These subsidies have generated much discussion in the air transport industry, and for decades the European Commission often classified them as state aid, preventing various agreements between regional airport management companies and LCCs (Malavolti and Marty, 2017).[32] The subsidies were considered to distort competition. In 2014, however, the European Commission issued new guidelines that changed the previous assessment of LCC subsidies (Commission, 2014). The guidelines expanded objectives to the dimensions of sustainability and growth, based on a new economic approach in which an LCC subsidy may not be considered state aid if in line with the market economy operator principle (MEOP). In short, it is not state aid if a private agent would adopt the same strategy, i.e., providing discounts to LCCs equal (or similar) to those implemented with public subsidies (Malavolti and Marty, 2019).[33] Similarly, if subsidies are provided by the national government and/or sub–national institutions, they may not be classified as state aid. This scenario therefore makes it interesting to analyze which type of policy (centralized or decentralized) is more effective in terms of tourism growth.

The impact of such a policy is assessed by comparing the actual equilibrium of the air transport market with a counterfactual equilibrium calculated with lower marginal costs. Differences in passenger flows lead to differences in tourist flows according to (16).

More specifically, consider a counterfactual analysis in which a general subsidy is granted to all LCC tickets, which reduces the marginal cost of the corresponding products by the same amount. We calculate the new equilibrium prices charged by the airlines and the new passenger flows under this subsidy policy, by iterating between the pricing equation (Equation (5)) and the market share equations (Equations (2) and (3)). Changes in the market shares of the different airlines, i.e., in the number of passengers landing in different Italian regions, lead to changes in the tourism sector through the predictive model of tourist flows.

Here, we first present the results of two counterfactual analyses comparing the effects of the LCC subsidy policies under centralized and decentralized regimes, both in the aviation sector

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[32] Examples of such agreements are reductions in airport taxes and funding the promotion of new routes, among other initiatives.

[33] Malavolti and Marty (2019) recently show how subsidies to LCCs by airport–operating companies comply with the MEOP. Taking as a reference the fact that decisions of an airport operator can be analyzed via a two–sided economic model, they show that a profit–maximizing company can adopt an optimal policy of providing discounts to LCCs on airport charges because the company can (1) subsidize LCCs through commercial revenues related to non–aviation activities (shops, parking, etc.), and (2) thereby increase profits because the discounts allow to counterbalance the monopoly power of LCCs. Thanks to discounts, a regional airport can attract more passengers, which generates commercial revenues. This decreases the airport operator's dependence on aviation profits and thus the market power of the LCCs.

and in tourist flows. In the first counterfactual analysis, the centralized–uniform policy, the LCC subsidy is controlled by the central government and applied uniformly across all Italian regions. In the second, the decentralized policy, the subsidy is granted by a regional government only to LCCs landing at airports of its region. [34] These two counterfactual scenarios highlight the differences in passenger volumes and changes in tourist flows for the national economy under the two subsidy policies. The decentralized policy, which is currently more widely adopted in Europe, does not internalize the effects on other regions or on the system as a whole. In contrast, the centralized policy provides subsidies to all LCCs operating nationwide, neutralizing any regional competitive advantages.

In the second step of our analysis, we compare the two policy regimes and evaluate their effectiveness for the national tourism system. To ensure a meaningful comparison, we conduct another counterfactual analysis in which the amount of the LCC subsidy is adjusted so that the total budget spent is identical under both the centralized and decentralized policies. This design allows us to assess which regime is more effective in stimulating national tourist flows, the primary objective of LCC subsidy policies. The comparison is based on an indicator measuring the additional number of tourists generated by the subsidy policy.[35]

Finally, to further strengthen the counterfactual analysis, we present the results of a scenario in which the budget for LCC subsidies is set at the national level but may be allocated either uniformly or differentially across areas of the country. The decision–maker is a central planner who can choose to implement the policy by allocating all resources to one or a few areas, thereby generating the typical effects of the decentralized regime, which are discussed below. More specifically, the subsidy to LCCs is distributed across the three macro–regions of Italy: (1) North, (2) Center, and (3) South, that have different tourism attractiveness. The total subsidy budget is fixed and is allocated according to 10 different combinations: for example, the entire budget may be allocated to the South or to the North, divided equally among the three macro–regions, or split unevenly (for example, 2/3 of the budget allocated to the Center and 1/3 to the South).[36]

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[34] Since there are 16 Italian regions to which the LCC subsidy can be applied, under the decentralized policy we analyze 16 region–specific counterfactual outcomes.

[35] It is worth noting that among the people living in the departure regions who do not travel to Italy by air, some may visit Italy using other means of transportation. Here, we are unable to precisely assess the substitution between these two categories (traveling to Italy by air versus by other means) due to a lack of available data. An estimation based on aggregate figures suggests that our results may be overestimated by approximately 7%. Nevertheless, the conclusions drawn in this section remain valid.

[36] We are grateful to the Guest Editor for this suggestion. We cannot analyze the case of a budget breakdown among 16 landing regions, as this would result in over 300,000 combinations.

6.1 The different effects of a LCCs subsidy policy under centralized and decentralized regimes

In this section, we analyze the effects of a uniform subsidy of €1 per LCC passenger. Because the per–passenger subsidy is constant, the effects of the two policies can be compared under an equivalent level of incentive.

Table 10 displays the main outcomes under a centralized–uniform policy. We report the total subsidy in each region, the "pass–through", the percentage variation in passengers (separately for LCCs and FSCs), the variation in annual profits (π), passenger surplus (CS), and welfare (W) in the air transport sector. For the tourism sector, we report the percentage change in tourist arrivals.

First, the total subsidy under this centralized regime is approximately €7.6 million, an amount notably higher than under decentralized policies (see below) because of a size effect. The mean pass–through is equal to €0.91, meaning that most of the €1 subsidy is passed on to LCC passengers in the form of a fare reduction. This indicates that competition in air transport is quite intense. The average percentage reduction in LCC price is –1.24%. FSCs react to the subsidy by decreasing their airfare to compensate for the competitive advantage given to LCCs; on average –0.07%. However, it is not enough to restore the former number of passengers transported. As a result, LCCs have a larger positive variation in passengers, equal to +2.48, while FSCs have less passengers in all region, with –0.88% in total. The subsidy increases the total number of air passengers in Italy by +1.20%, with a positive variation in all regions.

As expected, profits, passenger surplus, and welfare in air transport increase. Welfare increase is always higher than the subsidy amount (about €12 million *vs* €7.7 million overall), and the difference between the two figures is driven by the additional passengers flying to Italy due to the decrease in airfares. In the tourism sector, the global increase in flows is equal to +0.52%, and we also observe increases in all regions. In summary, and this is an important effect, the centralized–uniform policy generates an increase in both the air transport sector's welfare and in tourist flows across all regions.

Under the decentralized policy, we have 16 counterfactual analyses. Table 11 displays the results of the counterfactual analysis with the decentralized regime implemented in Lombardy.[37] The conclusions drawn from the Lombardy case are similar to those in other regions, with differences in magnitude depending on the number of tourists visiting the region, the number of passengers landing there, and the proportion of LCCs operating in the region.

The estimated pass–through is very high in Lombardy, equal to €0.95. It is higher than

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[37] The tables showing the results for the other 15 Italian regions are displayed in the online Supplemental Appendix.

Table 10: Counterfactual analysis: centralized–uniform policy

Region	Air transportation								Tourism
	Total subsidy (€ *year*)	Pass through	Δ % pax	Δ % LCC pax	Δ % FSC pax	$\Delta\pi$ (€ *year*)	ΔCS (€ *year*)	Δ W air (€ *year*)	Δ % tourist
Emilia–Romagna	425,407	-0.90	+1.34	+2.26	-0.81	+279,613	+392,107	+671,720	+0.50
Friuli–Venezia Giulia	16,809	-0.84	+0.37	+1.60	-1.02	+10,447	+14,597	+25,044	+0.04
Liguria	26,325	-0.88	+0.05	+1.91	-0.93	+3,485	+28,561	+32,046	+0.15
Lombardy	2,136,309	-0.91	+1.40	+2.51	-0.83	+1,352,105	+1,981,796	+3,333,901	+0.90
Piedmont	108,544	-0.92	+1.01	+2.34	-0.88	+54,568	+105,443	+160,012	+0.38
Trentino–Alto Adige	-	-	-	-	-	-	-	-	+0.03
Valle d'Aosta	-	-	-	-	-	-	-	-	+0.08
Veneto	869,369	-0.90	+1.00	+2.47	-0.90	+477,240	+833,145	+1,310,385	+0.29
Abruzzo–Molise	55,936	-0.89	+1.98	+2.00	-1.27	+48,031	+49,162	+97,194	+1.20
Lazio	1,754,247	-0.91	+0.99	+2.61	-0.97	+960,134	+1,665,875	+2,626,010	+1.56
Marche	29,759	-0.83	+1.18	+1.69	-0.72	+24,572	+25,002	+49,574	+0.35
Tuscany	581,443	-0.90	+1.28	+2.40	-0.80	+380,264	+540,970	+921,234	+0.44
Umbria	24,337	-0.84	+1.62	+1.62		+21,122	+20,175	+41,297	+0.27
Basilicata	-	-	-	-	-	-	-	-	+0.59
Calabria	53,129	-0.90	+1.14	+2.32	-0.76	+38,708	+48,553	+87,262	+0.71
Campania	498,329	-0.92	+1.37	+2.59	-0.87	+295,041	+474,305	+769,346	+1.10
Puglia	268,587	-0.89	+1.42	+2.22	-0.67	+199,990	+244,038	+444,028	+0.89
Sardinia	300,558	-0.90	+1.23	+2.40	-0.83	+202,999	+276,873	+479,873	+0.52
Sicily	478,747	-0.90	+1.30	+2.59	-0.82	+311,383	+447,256	+758,639	+0.90
Italy	7,627,836	-0.91	+1.20	+2.48	-0.88	+4,659,705	+7,147,859	+11,807,564	+0.52

Table 11: Counterfactual analysis: decentralized subsidy regime in Lombardy

	Air transportation								Tourism
Region	Total subsidy (€ *year*)	Pass through	Δ % pax	Δ % LCC pax	Δ % FSC pax	$\Delta\pi$ (€ *year*)	ΔCS (€ *year*)	Δ W air (€ *year*)	Δ % tourist
Emilia–Romagna	-	-	-0.68	-0.87	-0.23	-116,085	-6,664	-122,749	-0.02
Friuli–Venezia Giulia	-	-	-0.61	-0.89	-0.30	-6,663	-870	-7,533	-0.01
Liguria	-	-	-0.43	-0.74	-0.27	-11,558	+544	-11,014	+0.13
Lombardy	2,171,865	-0.95	+2.74	+4.21	-0.26	+2,503,755	+2,049,291	+4,553,047	+1.70
Piedmont	-	-	-0.54	-0.74	-0.26	-29,361	+540	-28,821	+0.37
Trentino–Alto Adige	-	-	-	-	-	-	-	-	+0.03
Valle d'Aosta	-	-	-	-	-	-	-	-	+0.11
Veneto	-	-	-0.50	-0.67	-0.27	-204,607	-3,873	-208,480	-0.03
Abruzzo–Molise	-	-	-0.54	-0.54	-0.35	-10,681	-1,258	-11,939	-0.32
Lazio	-	-	-0.49	-0.65	-0.30	-406,212	-3,670	-409,882	-0.70
Marche	-	-	-0.58	-0.68	-0.20	-8,832	-1,420	-10,252	-0.12
Tuscany	-	-	-0.51	-0.67	-0.22	-130,220	-5,659	-135,880	-0.10
Umbria	-	-	-0.72	-0.72	-	-7,136	-1,307	-8,443	-0.11
Basilicata	-	-	-	-	-	-	-	-	-0.15
Calabria	-	-	-0.40	-0.55	-0.16	-10,411	-978	-11,389	+0.12
Campania	-	-	-0.53	-0.68	-0.25	-97,857	-5,525	-103,382	-0.35
Puglia	-	-	-0.49	-0.61	-0.17	-55,337	-3,266	-58,603	-0.14
Sardinia	-	-	-0.39	-0.49	-0.21	-49565.2	-2218.54	-51783.7	-0.08
Sicily	-	-	-0.41	-0.53	-0.21	-85,286	-3,030	-88,316	-0.16
Italy	2,171,865	-	+0.34	+0.71	-0.26	+1,273,943	+2,010,637	+3,284,580	+0.15

in the centralized scheme because the comparative advantage given to the LCCs is targeted at flights going to Lombardy. As a result of this high pass–through, the number of LCC passengers increases substantially due to the reduction in LCC fares. Conversely, the number of FSC passengers decreases slightly due to the modest decrease in FSC prices in response to the drop in LCC airfares.

In other regions, there is no subsidy, and the price effects of the centralized and decentralized regimes differ. FSC prices fall, while LCC prices rise, thus leading to a generalized increase in prices in non–subsidized regions. The decrease in FSC prices occurs for the same reason as in the targeted region: FSCs adjust their pricing strategies in response to the (substantial) price reduction introduced by some of their competitors, i.e., the LCCs of the targeted region. However, to understand the increase in LCC prices, recall that in a nested logit model, firms offering multiple products in a market charge the same markup at equilibrium. Consequently, an LCC offering flights from a European region to Lombardy has a higher markup in this scheme because the pass–through is not unitary. As a result, the markup is also higher for flights to other Italian regions, leading to a (very small) rise in prices.

The number of LCC passengers in Lombardy increases by 4.21%, but because the number of LCC passengers decreases in all other regions, the national increase is only +0.71%. The number of FSC passengers decreases in Lombardy as well as in all other regions, resulting in a national decrease of about 0.3%. Overall, the number of passengers increases by 0.34%.

The total subsidy when the policy is implemented only in Lombardy amounts to approximately €2.2 million. As in the centralized regime, airline profits increase slightly above the total subsidy amount (in Lombardy, this amount is approximately €2.5 million) . Once again, the difference between the welfare increase and the policy cost is mainly driven by the additional passengers transported under this new regime, following the reduction in airfares.

The most noteworthy result obtained under the decentralized policy concerns the change in tourist flows, shown in the last column of Table 11. In Lombardy, the subsidy increases the number of tourists in the region by 1.7%, corresponding to 59,903 additional tourists. The effects across the other regions, however, are heterogeneous. In some regions (e.g., Liguria, Piedmont, and Trentino–Alto Adige), the number of tourists also increases. For instance, in Liguria the subsidy generates 1,476 additional tourists because some of the additional passengers who land in Lombardy travel to neighboring regions for tourism, representing a positive spillover effect of regional LCC subsidies. These regions benefit without having to invest. In other words, regions investing in LCC subsidy policies do not internalize all the benefits of their investments. This is a typical case of policy suboptimality.

Conversely, for regions not visited by tourists landing in Lombardy, the spillover effect is negative. For instance, Lazio loses 12,722 tourists, Campania 3,637, and Tuscany 3,057, because of the comparative advantage in costs of LCCs operating in Lombardy. For these regions, we observe a negative subsidy externality. Overall, in regions with positive spillovers, tourist numbers increase by 7,221 in aggregate, while in regions with negative spillovers, the tourist numbers decrease by 26,388. At the national level, the balance remains positive, with a net gain of 40,736 tourists.

6.2 Comparison of LCC subsidy policies

In summary, the two policies examined above have similarities but also important differences. In the aviation market, the effects are similar: the number of passengers increases both in the regions where subsidies are implemented and at the national level, LCCs gain market share, and FSCs lose it. Moreover, the welfare generated by the sector is always greater than the amount invested in subsidies. The important differences between the policies lie in the tourism market. The centralized–uniform policy brings benefits in terms of increased tourism flows for all regions and at the national level. The size of this increase depends on the importance of LCCs in the region. In the decentralized regime, the region proposing the subsidy gives a large comparative advantage to the LCCs landing at its international airports, and thus mainly induces negative spillovers to other regions.[38]

We use an indicator to compare the benefits and costs of these two schemes, namely the number of tourists generated by a fixed amount of subsidy. Table 12 shows the results of the regime comparison based on the counterfactual analyses for a subsidy equal to half a million euros. The top rows refer to to the decentralized regime, while the single bottom row displays the value for the centralized–uniform policy. The discrepancy between the two regimes is evident: in the decentralized regime, a wedge is generated between the change in passengers landing in the subsidized region ("Δ Passengers in the region") and the change in tourists staying in that region ("Δ Tourists in the region") and, more importantly, the change in tourists throughout the country (Δ Tourists in Italy"), which is much smaller due to the decrease in passengers in all other regions caused by the spillover. By contrast, in the centralized–uniform policy there is no difference between the aggregate change in passengers in Italy and the change in tourists.

With the decentralized policy, in the "Δ Passengers in the region" column, we calculate the number of additional passengers attributable to the subsidy in that region. Even with heterogeneity (depending on the usual factors, e.g., region size, LCC product share, etc.), a decentralized policy typically leads to around 20,000–23,000 additional passengers for most regions.

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[38] The centralized regime balances this large advantage given to each region and the induced negative spillovers, thus limiting the variation in competitive advantages between regions. Therefore, the increase in passengers in a region is lower when the subsidy is national than when it is implemented only in that region.

If a region evaluates its policy solely on this metric, it would be misleading. Indeed, some of these additional passengers stay in their landing, while others travel to other regions. The next column ("Δ Tourists in the region") displays the number of additional tourists who land and stay. The figures are lower, with a significant decrease for some regions. For example, around 6,000 tourists land in Lombardy but visit another region. Finally, the last column of Table 12 shows the overall number of additional tourists in Italy under this policy regime. The number of additional tourists generated ranges from 4,400 (Friuli–Venezia Giulia) to 10,300 (Campania). Under the centralized scheme, the number of additional tourists is 9,589, which is generally (but not always) higher than in most decentralized schemes (13 cases out of 16).

As a result, our findings show that, from the perspective of a national policymaker, subsidizing LCCs to stimulate tourism demand under a centralized–uniform policy is more effective than a decentralized approach. Regional policies lead to significant externalities between regions and prevent the full internalization of the effects of subsidies due to spillovers to other regions, thus creating distortions. Furthermore, it is difficult to justify the adoption of subsidies by a single region to public opinion, as this erodes tourism market share in other regions. It could also open a general race to adopt subsidies, tending toward a centralized system (but without uniformity between regions).

Hence, contrary to some theoretical contributions (Oates, 1993, 1999) and in line with related empirical contributions in the health sector (Balia et al., 2018; Di Novi et al., 2019), in the context of the relationship between air transport and tourist flows, a policy of stimulating LCCs to increase the tourist attractiveness of different regions should be uniformly implemented by the central government. In this way, the spillovers generated by a decentralized regime are reduced, competition between regions is limited, and discrimination across regions is avoided.

Finally, after providing evidence that a centralized regime is superior to a decentralized one, we conduct a robustness analysis. We examine how a central planner with a fixed budget for the LCC subsidy policy aims to maximize tourist flows by allocating the budget evenly or unevenly across different areas of the country. In this scenario, we assume that the central planner can allocate the budget not to individual regions (to avoid excessive fragmentation and asymmetries between neighboring regions) but to three macro–regions: in the case of Italy, between the northern, central, and southern regions. Among other things, these macro–regions have different tourist attractions: the southern macro–region has high tourist flows in the summer months, due to the presence of numerous beaches and a favorable climate; the northern macro–region, on the other hand, sees a greater concentration of tourist flows during the winter season, due to the presence of several renowned ski resorts in the Alps. Finally, the central macro–region is characterized by the presence of major cultural cities such as Florence and Rome.

Table 12: Comparison of LCC subsidy policies for a fixed subsidy budget of €0.5 million

	Decentralized policy		
	∆ Passengers in the region	∆ Tourists in the region	∆ Tourists in Italy
Emilia–Romagna	23,244	16,262	8,916
Friuli–Venezia Giulia	17,785	16,006	4,374
Liguria	19,276	16,259	5,662
Lombardy	19,963	14,046	9,534
Piedmont	22,511	20,469	8,986
Veneto	22,709	20,621	9,373
Abruzzo–Molise	21,070	19,305	7,166
Lazio	20,650	18,083	9,753
Marche	19,507	14,323	5,320
Tuscany	23,273	20,932	8,968
Umbria	18,947	17,330	4,968
Calabria	21,036	17,198	7,757
Campania	23,322	21,929	10,264
Puglia	23,539	19,562	8,797
Sardegna	23,117	22,703	9,771
Sicily	23,332	23,033	9,419
	Centralized policy		
	∆ Passengers in Italy		∆ Tourists in Italy
Italy	9,589		9,589

In this case, we first set the budget available to the central planner for the subsidy policy: let us assume that it is equal to €3 million. Second, as shown in Table 13 in the right–hand columns, the central planner has several alternatives for allocating this budget, assuming that the total subsidy funding for an Italian macro–region is in units of €1 million: for example, the top row shows the case where the entire available budget of €3 million is allocated to the North, while the bottom row represents the case where the budget is divided equally among the three macro–regions.

When allocating the budget to only one macro–region, or to two macro–regions while leaving the third without subsidies, the central planner generates, as in the decentralized regime, externalities that determine the wedge between changes in passengers across the country (the column ∆ passengers with spillovers), the variation in passengers in the areas where the subsidy is implemented (the column ∆ passengers without spillovers) and the variation in tourists without taking externalities into account (the column ∆ tourists without spillovers).

For example, if the central planner allocates €1 million to the North and €2 million to the Center, passenger numbers increase by 73,929 in these two macro–regions, but increase by only 56,565 nationwide, due to the negative externality on the South. As a result, in the North and Center, tourist numbers rise by only 70,383 (the difference of 3,546 represents passengers who land at airports in the North and Center but then go on vacation in the South), while in the entire country, the increase in tourists is even lower and coincides with the change in passengers once spillovers are accounted for, i.e., 56,565. Only when the budget is distributed equally among the three macro–regions (similar to the centralized–uniform system) do these three values coincide.

By inspecting Table 13, it is clear that the maximum values of additional tourists are obtained in the two scenarios shown at the bottom of the table, when €1 million is allocated to the Center and €2 million to the South, or when the available budget is distributed equally among the three macro–regions.

At the same time, the distortion generated by an allocation concentrated solely in one geographical area is evident. For example, the third row from the top shows that if the entire budget were allocated to the South, there would be a superficially distorted indication of 115,705 additional tourists, but this figure would not account for externalities, which are mainly negative in the North and South. In fact, these externalities lead to 57,041 additional tourists throughout Italy, a value lower than the 57,568 observed when the subsidy is allocated mainly to the South (€2 million) and partly to the Center (€1 million), and lower than the 57,509 additional tourists observed when it is divided equally. This further counterfactual analysis confirms the superior performance of a centralized and generally uniform policy for a country's tourism sector.

Table 13: Central planner policy with fixed budget at €3 million and possible different allocations among macro–regions

Scenario	Δ passengers with spillovers = Δ tourists	Δ passengers without spillovers	Δ tourists without spillovers	Subsidy allocation (€million)		
				North	Center	South
1	56,045	101,784	92,290	3	0	0
2	55,894	113,992	103,205	0	3	0
3	57,041	120,612	115,705	0	0	3
4	56,622	73,646	70,550	2	1	0
5	57,175	86,234	80,803	2	0	1
6	56,565	73,929	70,383	1	2	0
7	57,197	96,900	91,425	0	2	1
8	57,491	85,946	82,028	1	0	2
9	57,568	95,776	91,725	0	1	2
10	57,509	57,509	57,509	1	1	1

7 Conclusions

This paper analyzes the impact of LCC subsidies on tourism flows, using data on movements from European regions to Italian regions in the 2016–2018 summer seasons. We estimate a two–stage model that links equilibrium in the air transport sector, determined in the first stage by a structural model, to the tourism market. In the second stage, we predict which Italian region passengers landing in an Italian region visit. The counterfactual analysis introduces LCC subsidies, which disrupt the equilibrium in the airline industry and lead to changes in the tourism market. We analyze different implementation regimes for these subsidies, following the literature that analyses the level of policy implementation (national or sub–national) that is most effective. In our paper, we perform a counterfactual simulation in which the LCC subsidy is adopted by the central government and implemented uniformly across all regions. This approach eliminates any possible competition between regions. A second counterfactual simulation examines the effect of subsidies when the policy is implemented in a decentralized manner—i.e. by each region—a scenario that introduces competition between sub–national jurisdictions.

These counterfactual analyses show that LCC subsidies are effective in boosting tourism flows, and that the centralized system produces better results in terms of stimulating tourism demand than the decentralized system. In fact, the latter leads to two mechanisms that reduce its effectiveness. On the one hand, it generates significant externalities in regions that do not implement subsidies; on the other hand, the increase in tourism flows in the subsidizing region occurs partly at the expense of other regions, leading to competition among regions to implement similar policies, potentially resulting in a regime similar to the centralized one.

Subsidizing low–cost carriers (LCCs)—either through reductions in airport taxes or through other financial schemes—is a realistic policy that has already been implemented in some regions across Europe. To the best of our knowledge, the impact of such policies has not yet been formally evaluated. Our paper contributes to filling this gap by assessing their potential effects.

Our use of an airline industry structural model allows us to analyze the impact of exogenous shocks to aircraft operating costs on the volume of passengers carried and hence on tourism flows.

Furthermore, a comprehensive approach should include a structural model of supply and demand in the tourism market, which was not possible due to a lack of data. These extensions are left for future research.

Declaration of interests

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

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A GMM estimation

Let θ_d denote the demand parameters to be estimated, i.e., $\theta_d = (\beta, \alpha, \gamma, \sigma)^\top$. The system of moment restrictions (8) and (10) can be rewritten with obvious notations, reintroducing the time subscript t:

$$E\left(\xi_{jmt} Z_{kjmt}\right) = Em_d\left(\tilde{X}_{jmt}, \tilde{Z}_{k,jmt}; \theta_d\right) = 0, \;\; k = 1, \ldots, K \tag{17}$$

$$E\left(\zeta_{jmt} w_{l,jmt}\right) = Em_s\left(\tilde{X}_{jmt}, \tilde{Z}_{k,jmt}; \theta_d, \psi\right) = 0, \;\; k = K+1, \ldots, K+L \tag{18}$$

where $\tilde{X}$ denotes the vector of all explanatory variables involved in the two equations above and $\tilde{Z}_k$, $k = 1, \ldots, K+L$ denotes the collection of instruments for both the demand and the supply side. $m_d(\cdot)$ and $m_s(\cdot)$ are respectively moments related to the demand and the supply side.

To estimate θ_d and ψ, we build sample analogs of the moment conditions (17) and (18) by averaging across products within a given market, then across markets (we have M markets), and finally across years ($t = 1, 2, 3$):

$$\bar{m}(\theta_d, \psi) = \begin{bmatrix} \frac{1}{3\times M} \sum_{t=1}^{3} \sum_{m=1}^{M} \left(\frac{1}{J_{m,t}} \sum_{j=1}^{J_{m,t}} m_d(\tilde{X}_{jmt}, \tilde{Z}_{1,jmt}; \theta_d) \right) \\ \vdots \\ \frac{1}{3\times M} \sum_{t=1}^{3} \sum_{m=1}^{M} \left(\frac{1}{J_{m,t}} \sum_{j=1}^{J_{m,t}} m_d(\tilde{X}_{jmt}, \tilde{Z}_{K,jmt}; \theta_d) \right) \\ \sum_{t=1}^{3} \sum_{m=1}^{M} \left(\frac{1}{J_{m,t}} \sum_{j=1}^{J_{m,t}} m_s(\tilde{X}_{jmt}, \tilde{Z}_{K+1,jmt}; \theta_d; \psi) \right) \\ \vdots \\ \frac{1}{3\times M} \sum_{t=1}^{3} \sum_{m=1}^{M} \left(\frac{1}{J_{m,t}} \sum_{j=1}^{J_{m,t}} m_s(\tilde{X}_{jmt}, \tilde{Z}_{K+L,jmt}; \theta_d, \psi) \right) \end{bmatrix}.$$

The GMM objective function to be minimized (with respect to θ_d and ψ) is a distance of $\bar{m}(\theta_d, \psi)$ to 0; that is,

$$f(\theta) = \bar{m}(\theta_d, \psi)^\top \Omega \bar{m}(\theta_d, \psi),$$

where Ω is a $(K+L)\times(K+L)$ positive definite weighting matrix. We use a two–step procedure in which we obtain a first set of estimates $(\hat{\theta}_d^{(1)}, \hat{\psi}^{(1)})$ using the identity I_{K+L} as an initial weighting matrix before calculating the final set of estimates using an estimate of the optimal GMM weighting matrix calculated in $(\hat{\theta}_d^{(1)}, \hat{\psi}^{(1)})$.

B Details about the data set treatment

Some general remarks For air transport, we use data from the Official Aviation Guide (OAG), and in particular the information provided by the Scheduled Analyser and the Traffic Analyser. The Scheduled Analyser (SA) provides scheduled timetables of proposed flights and airport locations. A flight with a stopover is the combination of two *O–D* flights. The Traffic Analyser (TA), on the other hand, provides data on flight prices and quantities sold (i.e., actual bookings). Prices and bookings refer to tickets sold by travel agents as well as those bought directly online by consumers. Information on tickets sold by travel agents is provided by a global distribution system (GDS). Information on online sales is made available by dedicated companies working on web–only data. TA information is monthly and at airline level for each individual flight. As we are investigating the relationship between air transport and tourism, we only consider the economy discount booking class.

List of European countries and Italian regions The list of European countries of origin of the passengers included in our data set is shown in Table 14, together with all the Italian regions with at least an airport for international arrivals.

Table 14: European countries and Italian landing regions in our dataset

European countries (A–Z)		**Italian regions (A–Z)**	
Austria	Belgium	Abruzzo	Calabria
Bulgaria	Croatia	Campania	Emilia–Romagna
Denmark	Estonia	Friuli–Venezia Giulia	Lazio
Finland	France	Liguria	Lombardy
Germany	Greece	Marche	Piedmont
Hungary	Ireland	Puglia	Sardinia
Latvia	Lithuania	Sicily	Tuscany
Luxembourg	Malta	Umbria	Veneto
Netherlands	Norway		
Poland	Portugal		
Romania	Slovakia		
Spain	Sweden		
Switzerland	United Kingdom		

Construction of the fuel consumption per seat Our approach is to calculate a proxy for an airline's fuel consumption based on several pieces of information that we collect and multiply by the average yearly price of jet fuel. An airline's annual fuel consumption is calculated from three parameters: (1) the age of the fleet, (2) the distance flown, and (3) the number of seats of the aircraft. The OAG data set provides the aircraft model and the distance flown for each product.

Furthermore, for each aircraft model b, it is possible to identify the age as the difference between the year of observation and the year of that model's first flight. The year of the first flight is taken from various sources, mainly information available on the aircraft manufacturer's website and data available on the internet.

We then calculate a "relative" fuel cost in US$ according to the following equation:

$$fuelcost_{jt} = \sum_{b=1}^{B} \frac{seats_{bjt} \times distance_{bjt} \times (1+0.0288)^{age_{bt}}}{100} \times price_t,$$

where B is the total number of aircraft used to operate flight j, $price_t$ is the average jet fuel price per gallon in year t,[39] $seats_{bjt}$ is the number of available seats (a measure of aircraft capacity), $distance_{bjt}$ is the flight distance, and 0.0288 is an annual penalty for each additional year of age due to the aircraft's technological obsolescence.

In fact, Chèze et al. (2011) shows that energy efficiency improvements over the 1983–2006 period were 2.88% per year. This means that for every year an aircraft is older, it consumes more fuel than a new–generation aircraft by about +3%, a factor that leads to an increase in airline costs. An additional component of this formula is provided by Open-Airlines (2022), which states that fuel consumption in commercial aviation is about 1 gallon of kerosene per seat per 100 kilometers of flight.[40] This explains the factor $\frac{seats}{100}$.

Calculation of the frequency The frequency for connecting flights is not available in the OAG databases. We therefore calculate them using via the connecting flights from the TA database. For example, suppose we have a proposed flight from O to D with a connection at airport G. From the SA data set, we take the frequency of the route O–G and the frequency of the route G–D and the frequency of the product O–G–D is defined as the minimum of the frequency of these two routes.

If the same airline proposes different options for the connecting airport, we define the frequency as the sum of all possible connecting airports of the frequency calculated above. We do not take different gateways and minimum connecting time into account, and therefore the calculated frequency for the connection is slightly overestimated.

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[39] According to the Jet Fuel Price Monitor by IATA, average prices were 1.29 $\frac{US\$}{GAL}$ in 2016, 1.50 in 2017, and 2.11 in 2018.

[40] See the website https://blog.openairlines.com/how-much-fuel-per-passenger-an-aircraft-is-consuming.

Instrument for the frequency The instrument used for frequency, which is endogenous in our demand regression, is given by a median regression conditional on the following independent variables: *latitude_dif*, *distance*, *dep_pop*, *exog_tourist*, *#comp_prod*, *dep_destinations* and *hub_dest*. *latitude_dif* is given by the difference in latitude between the region of origin and the region of destination, and it captures possible climatic differences in summer between the region of origin and the Mediterranean regions; this difference may have a positive effect on frequency, especially for Northern European regions, as there are relevant climatic differences within the Italian regions. *distance* measures the geodesic distance in kilometers between the centroid of the region of origin and the region of destination. *dep_pop* is the population in the origin region, while *exog_tourist* measures the tourist preferences of the destination region by counting the total number of tourists from all countries in the world arriving in the Italian destination region minus those arriving from the European origin region in our data. *#comp_prod* is the number of competing products, *dep_destinations* is the percentage of destinations available at the departure airport that are served by the airline, thus capturing the frequent flyer advantage. Finally, the variable *hub_dest* is a binary variable indicating whether the flight arrives in Rome for the *Skyteam* alliance, which represents the only hub in Italy.

We estimate the conditional median of the frequency given these covariates, and we compute the fitted frequency value $\widehat{f}$ that is used as an instrument in the general demand IV regression.

C First–stage estimation of the endogeneous explanatory variables

Table 15 shows the first stage estimates and highlights in particular that the F–statistic, which could be used to detect the possibility of weak instruments, is so high that we can safely assume that the standard asymptotic approximation for the distribution of the 2SLS estimator is valid.

Table 15: Demand side: first–stage endogenous variables and instruments

	(1)	(2)	(3)
	Dependent variable		
Independent variables	p_{jmt}	f_{jmt}	$\log(s_{jmt\|a})$
$direct\_FSC_{jmt}$	11.4149***	39.3272***	-0.065
	(1.9342)	(13.4412)	(0.0507)
gdp_{mt}	-0.0001	0.0071***	-0.00001***
	(0.0001)	(0.0011)	(0.000003)
edu_{mt}	-0.3127***	-5.3887***	-0.0026
	(0.1091)	(1.0015)	(0.0024)
$fuel\_cost_{jmt}$	0.1445**	-2.4092***	-0.0067***
	(0.0611)	(0.4651)	(0.0013)
$\widehat{f}_{jmt}$	0.0229***	0.9180***	-0.0032***
	(0.0048)	(0.0326)	(0.0001)
$\#\_direct\_comp\_prod_{jmt}$	-4.6255***	6.9061	-0.2756***
	(0.537)	(5.5803)	(0.0131)
$\#\_dir\_comp\_near\_reg_{jmt}$	-0.5308**	2.3114	-0.1091***
	(0.2578)	(2.3426)	(0.0064)
$gateway\_hub\_FSC_{jmt}$	24.1656***	334.2334***	0.1351***
	(2.2007)	(20.2353)	(0.0437)
$Constant$	122.6113***	-210.2659***	-1.4361***
	(10.8201)	(70.5497)	(0.2437)
Observations	6,525	6,525	6,525
F test	77.74	301.04	622.74
Year dummies	✓	✓	✓
Italian region dummies	✓	✓	✓
European country dummies	✓	✓	✓
Airline/Alliance dummies	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

D More on the two–level nested model

Different substitution intensities between products in the same market with different Italian destination regions are allowed for by the two–level nested model. It is equivalent to an ordered decision for the summer European traveler: first, should I fly to Italy for my summer vacation? If yes, which region should I visit? Finally, given that I have chosen a region, which flight should I choose? This process is summarized in Figure 4.

Following the usual terminology of the two–level nested, we have, in this extended model, one group (i.e., Italy) and $R = 16$ subgroups, i.e., the 16 Italian regions which have international airports.

The two–level nested logit can be rationalized from a random utility maximization model with the following indirect utility (omitting the subscript m related to the market for convenience). For a consumer i choosing product j going to region r, its utility is equal to

$$u_{ij} = \delta_{jr} + \zeta_{0,i} + (1 - \sigma_2)\zeta_{r,i} + (1 - \sigma_1)\varepsilon_{ij},$$

where ε_{ij} is the usual idiosyncratic shock, IID extreme value, and where $\zeta_{0,i}, \zeta_{1,i}, \ldots, \zeta_{R,i}$ are shocks specific to the regions which follow specific distributions to ensure the usual parametric form. Note that we require to have $1 \geq \sigma_1 \geq \sigma_2 \geq 0$. Like always, the utility of the outside option is set to $u_{i0} = \varepsilon_{i0}$, where ε_{i0} is iid extreme value.

We call $\mathcal{J}_r$ the set of products proposed in this market landing in region r and we denote a product by its number within the region; its mean utility is δ_{jr}, r being the region. We use the notation $\lambda_i = 1 - \sigma_i$, $i = 1, 2$. We obtain:

$$\begin{aligned}
\exp(I_r) &= \left(\sum_{k \in \mathcal{J}_r} \exp(\delta_{kr}/\lambda_1) \right)^{\lambda_1}, \\
\exp(I_{Italy}) &= \left(\sum_{r=1}^{R} \exp(I_r/\lambda_2) \right)^{\lambda_2}, \\
s_{j|r} &= \frac{\exp(\delta_{jr}/\lambda_1)}{\sum_{k \in \mathcal{J}_r} \exp(\delta_{kr}/\lambda_1)}, \\
s_{r|Italy} &= \frac{\exp(I_r)^{1/\lambda_2}}{\sum_{r=1}^{R} \exp(I_r)^{1/\lambda_2}}, \\
s_{Italy} &= \frac{\exp(I_{Italy})}{1 + \exp(I_{Italy})} = 1 - s_0, \\
s_{jr} &= s_{j|r} s_{r|Italy} s_{Italy}.
\end{aligned}$$

Note that $s_{j|r}$ is the conditional probability of choosing product j given that the travelers fly to region r when s_{jr} is the (unconditional) probability of choosing product j (r is redundant but it is easier to keep it to remind that j goes to region r).

Some calculations show that we get the usual inversion formula (à la Berry):

$$\log \frac{s_{jr}}{s_0} = \delta_{jr} + \sigma_1 \log(s_{j|r}) + \sigma_2 \log(s_{Italy}),$$

which is used to extract the product specific demand characteristic ξ_j to implement our GMM procedure.

Some calculations of interest are necessary in order to compute markups, elasticities:

$$\frac{\partial s_{j|r}}{\partial \delta_{kr'}} = \frac{1}{\lambda_1} s_{j|r}(\mathbf{1}_{j=k} - s_{k|r})\mathbf{1}_{r=r'}, \tag{19}$$

$$\frac{\partial s_{r|Italy}}{\partial \delta_{kr'}} = \frac{1}{\lambda_2} s_{k|r'} s_{r|Italy}(\mathbf{1}_{r=r'} - s_{r'|Italy}), \tag{20}$$

$$\frac{\partial s_{Italy}}{\partial \delta_{kr'}} = s_{kr'}(1 - s_{Italy}). \tag{21}$$

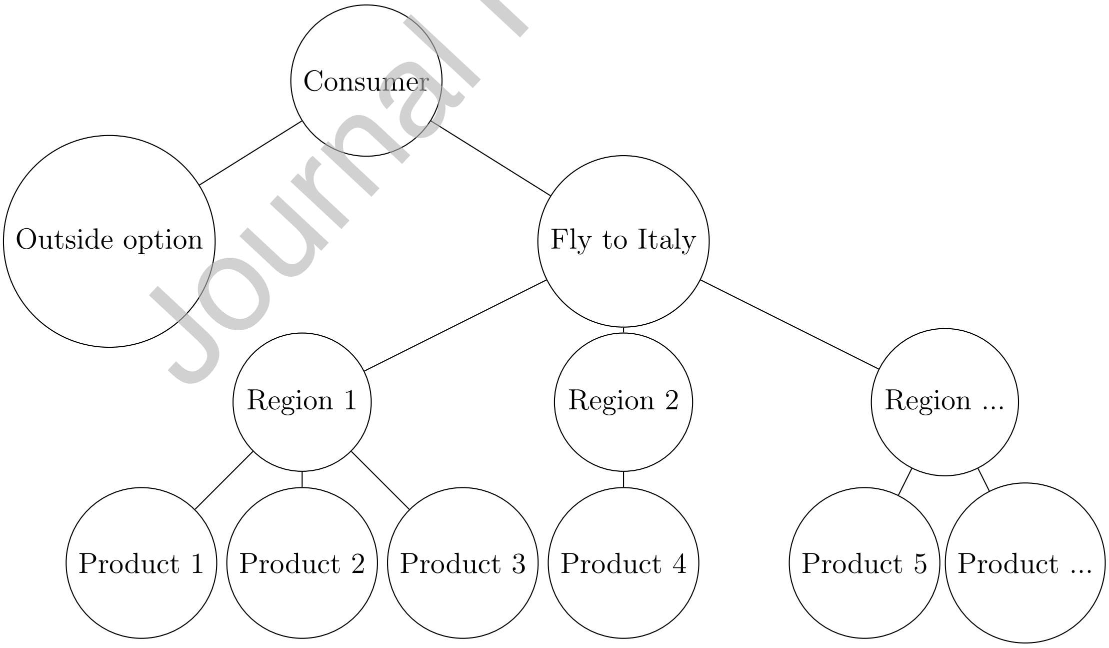

Figure 4: Two–level nested logit model: representation of the choice structure.

E Probability matrix of tourist final destination

Table 16 shows the estimated probability matrix (or transition matrix) of European tourists' regional destinations in Italy. Each figure in the table is the weighted average of the 26 transition matrices.[41] We estimate these probabilities with MNL Model 3 in Table 9; the weights are given by the country's tourists on total European tourists visiting Italy during the summer.

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[41] These 26 transition matrices are available upon request.

Table 16: Summary of conditional probabilities of tourists' final destination (r) given landing regions (l) – percentage values

		Landing region (l)															
		Abruzzo–Molise	Calabria	Campania	Emilia–Romagna	Friuli–Venezia Giulia	Lazio	Liguria	Lombardy	Marche	Piedmont	Puglia	Sardinia	Sicily	Tuscany	Umbria	Veneto
Final destination (r)	Abruzzo–Molise	92.2	-	0.1	0.2	-	0.8	-	0.1	2.1	-	0.6	-	-	0.0	0.2	-
	Basilicata	-	-	0.3	0.1	-	0.0	-	0.0	-	-	5.1	-	-	0.1	-	-
	Calabria	-	75.9	0.3	0.2	0.1	0.5	-	0.7	0.0	0.0	1.5	-	0.1	0.1	-	-
	Campania	0.3	16.4	95.2	0.3	-	3.0	4.1	0.8	0.1	0.4	3.4	0.1	0.0	0.3	0.0	0.2
	Emilia–Romagna	0.0	-	0.0	71.1	0.4	0.3	0.5	3.0	15.2	0.3	0.1	-	-	0.7	0.9	0.2
	Friuli–Venezia Giulia	-	-	-	0.1	93.8	0.1	-	0.2	0.1	-	-	-	-	0.0	-	0.7
	Lazio	0.6	-	1.9	0.9	0.2	87.5	5.8	1.1	0.7	0.5	0.3	0.1	0.1	1.4	0.8	0.3
	Liguria	-	-	0.2	0.7	0.2	0.3	79.4	2.3	-	1.9	-	0.1	-	3.3	-	0.1
	Lombardy	0.1	-	0.3	1.5	0.9	0.3	1.2	71.0	1.1	1.3	0.2	0.2	-	0.3	0.1	2.7
	Marche	2.0	-	0.0	4.0	-	0.2	-	0.1	76.0	0.0	0.1	-	0.1	0.1	3.7	-
	Piedmont	-	-	-	0.2	0.1	0.1	2.2	6.1	0.1	93.0	0.0	0.0	0.2	0.1	-	0.0
	Puglia	1.6	-	0.6	0.6	-	0.4	-	1.0	0.1	0.0	87.4	0.0	-	0.1	0.1	-
	Sardinia	2.8	-	0.0	0.1	-	0.4	0.7	1.3	-	0.1	0.2	98.5	0.1	0.1	0.1	-
	Sicily	0.1	2.5	0.4	0.3	0.1	2.1	4.1	1.7	-	0.2	0.3	0.8	99.4	0.1	-	0.0
	Tuscany	0.2	5.1	0.5	14.1	0.5	2.2	1.6	2.2	0.3	0.1	0.4	0.1	0.0	91.1	0.8	0.2
	Trentino–Alto Adige	0.0	-	0.0	0.7	0.3	0.0	-	2.0	-	-	0.1	-	-	0.4	-	3.5
	Umbria	0.2	-	0.0	0.9	-	0.8	-	0.1	3.7	-	0.1	0.1	-	0.8	93.4	-
	Valle d'Aosta	-	-	-	-	-	-	-	0.4	-	1.8	-	-	-	0.0	-	-
	Veneto	0.0	-	0.2	3.9	3.5	1.1	0.3	5.9	0.4	0.2	0.3	-	-	1.1	-	92.2