

An airline-based multilevel analysis of airfare elasticity for passenger demand

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Abstract

Price elasticity of passenger demand for a specific airline is estimated. The main drivers affecting passenger demand for air transportation are identified. First, an Ordinary Least Squares regression analysis is performed. Then, a multilevel analysis-based methodology to investigate the pattern of variation of price elasticity of demand among the various routes of the airline under study is proposed. The experienced daily passenger demands on each fare-class are grouped for each considered route. 9 routes were studied for the months of February and May in years from 1999 to 2002, and two fare-classes were defined (business and economy). The analysis has revealed that the airfare elasticity of passenger demand significantly varies among the different routes of the airline.

KEYWORDS: Price Elasticity, Passenger Demand, Multi-level Analysis

1. INTRODUCTION

The liberalisation of the aviation sector and the continuously increasing demand for air transportation have determined a deep transformation in the air transport market, particularly characterised by the access of many new airspace users. In this context, customers of air traffic services show very different behaviours and characteristics (see, e.g., [10] and [11]). Moreover, their reactions to exogenous factors might be very different. In this framework, the careful understanding of the characteristics of the final demand for passenger air transportation plays a key role to assess and predict the behaviours of airspace users.

Passenger attitudes, and in particular price elasticity of demand for air transportation, vary essentially because they fly for different reasons; a broad distinction is generally made between business travellers and leisure travellers. Leisure travellers aim to maximise the utility derived from the air travel and from the associated holiday experiences, subject to a given budget constraint. Business travellers use air travel as an input to final production; generally, comfort and time constraints play a key role in their decisions for flights. The different marginal utility of the air travel for the two categories yields different sensibilities to factors affecting demand for it; in particular, many studies have pointed out that demand for business travel tends to be less price elastic than demand for leisure travel [3], [18], and [19].

This paper addresses the issue to determine price elasticity for passenger demand for a specific airline. Airfare elasticity of passenger demand is generally estimated with respect to a specific market (e.g., domestic, international, European, North-American) considering the aggregate demand to all the airlines operating in that market. Our study differs from this approach because it focuses on the passenger demand of a single airline.

First, an Ordinary Least Squares (OLS) regression analysis is proposed. It takes into account usual drivers affecting passenger air transportation demand. Then the different behaviours passenger demand may show on routes with different characteristics are investigated. To this end, a statistical multilevel approach is used. To the best of the authors' knowledge, no similar methods have been reported in the literature for air transportation problems. In particular, we determine fare elasticities for each route considered in the OLS sample. It turns out that their values largely vary from one route to another one, and such a variation is statistically significant.

This is a relevant result as it implies that the passenger behaviour may significantly differ for different routes of a same company. In turn, the reaction of an airline to perturbations of the values of the driver factors, and especially of prices, may be expected to sensibly vary for different routes. In particular, this means that routes on which a larger share of business customers may be expected, not only have lower elasticity, as everyone would expect, but also that such a difference can be numerically large (experienced elasticities more than double) and statistically relevant, even within a same company. Such a wide spread of elasticity values is a meaningful and not obvious result of the study.

The paper is organised as follows. A literature analysis on the methodologies to assess passenger demand elasticity and on the main drivers affecting demand for air transportation is proposed in Section 2. Section 3 describes the general model, introduces the main factors taken into account, and presents the network under study and the available data. In Section 4 the OLS model is specified, the results are shown and discussed. Section 5 introduces the multi-level model, and analyses its results. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

Literature provides many studies where determinants of air travel demand are investigated and methodologies to assess their influence are proposed. Important works in this field include, among others: Abrahams [2], Fridström and Thune-Larsen [7], Oum, Waters and Yong [19], Ghobrial and Kanafani [8], Jorge-Calderón [12], Abed, Ba-Fail and Jasimuddin [1], Brons, Pels, Nijkamp and Rietveld [3].

Abrahams [2] presents an econometric model to estimate the air travel demand for the domestic USA market. Unlike previous studies, besides geo-economical factors, demand is expressed also in terms of quality of service and intermodal competition terms. Coefficients are determined using a two-stage least squares procedure. Results suggest that demand is elastic with respect to airfares. In particular, long-haul routes demand is more price elastic than short-haul routes demand and vacation traffic demand is more price elastic than business one.

The study of Fridström and Thune-Larsen [7] presents an econometric air travel demand model for the entire conventional domestic network of Norway. In addition to population and income factors, airfares, travel time and inter-modal competition factors are taken into account and short-medium and long term demand elasticities are estimated. Demand results inelastic in

the short-medium term (estimated elasticity: -0.69) and elastic in the long term (estimated elasticity: -1.63) with respect to airfares and elastic with respect to travel time.

Oum, Waters and Yong [19] carry out a survey on the state-of-the-art of the research in the estimation of transport demand price elasticity. After a theoretical introduction of the concepts of elasticity, a survey on price elasticity of demand for various transportation modes is presented and the influence of some factors on demand is discussed. It turns out that demand for business travel is less elastic with respect to prices than demand for leisure travel and that price elasticity estimates from cross-section data generally are higher than those from time-series data.

The study of Ghobrial and Kanafani [8] presents an econometric model for the intercity air travel demand in USA. The model incorporates some quality of service measures as explanatory variables and coefficients are estimated using post-deregulation data. A distinction is made between services offered by airlines in peak and off-peak hours and a dummy variable is introduced for capacity-constrained airports. Results suggest that demand is elastic with respect to airfare (estimated elasticity: -1.2) and highly dependent on flight schedule and travel time.

Jorge-Calderón [12] presents a demand model for scheduled airline services for the entire network of international European routes in 1989. The model includes variables describing both geo-economic characteristics of the area where transportation took place and patterns of airline services. Flight data are also divided in three sub-samples by distance of the end-points. Results suggest that demand is inelastic respect to fares on shortest sectors and price elasticity increases with distance. In addition, short haul markets seem to be more sensitive to frequency of flights.

Abed, Ba-Fail and Jasimuddin [1] provide an econometric analysis of international air travel demand in Saudi Arabia. As explanatory variables they consider only macro-economic and demographic indicators and a detailed description of the steps followed for the development of the model is given. Results suggest that population size and total expenditures are the main determinants of international demand in Saudi Arabia.

Brons, Pels, Nijkamp and Rietveld [3] present a meta-analysis of the price elasticity estimates of demand for passenger air travel. After a description of determinants of demand for passenger air transport, they carry out a comparative re-evaluation of previous research on price elasticities for passenger air transport. They find an overall demand mean price elasticity of -1.146 with passengers becoming more price sensitive over time. Business passengers show lower price

sensitivity, with an average price elasticity of -0.8 . Passengers are becoming more price sensitive over time.

To the best of authors' knowledge, the multilevel analysis introduced in this paper is a new methodology in the air transportation context.

3. MODEL DESCRIPTION

Demand for air transportation between two cities is assumed to be dependent on two main groups of drivers [7] [8] [12]. The first one is composed of the geo-economic variables determined by the economic activities, the population and the geographical or locational characteristics of the two cities between which the transportation takes place. The second group is composed of the service-related factors, determined by the quality and price characteristics of the air transport system connecting them.

The functional form selected for the estimating model is generally log-linear, as suggested among the others by [7], [8], and [12]. The relationship between demand for air transportation D and the explanatory variables is assumed to take the following functional form:

$$D = A \times \prod_g G_g^{\beta_g} \times \prod_s S_s^{\gamma_s} \quad (1)$$

where A is a constant, and G_g and S_s represent the geo-economic and service-related factors, respectively. Taking the logarithm on both sides, equation (1) becomes linear in the exponents of the factors. This allows the use of linear regression techniques for their assessment. The values of the parameters β_g and γ_s represent the variation rate of the demand with respect to the percentage variation of the corresponding factors, all other conditions being equal.

3.1 DEPENDENT VARIABLE

The dependent variable used in the model is the number of passengers D_{ift} travelling on route i in the fare-class f at day t . For this specification of the dependent variable, the demand considered is the sum of demands for all the flights on a given route and fare-class in a day. In this model a distinction is made between two main groups of fare classes, as it is explained in subsection 4.2. Moreover, here we aggregate both origin-destination and transfer traffic. As discussed below, dummy variables were included to explain the extra-traffic expected in hub airports, where the volume of transfer traffic is supposed higher. Finally, the model is non-

directional: no distinction is made between origin and destination city. This is justified by the set of data used, which revealed no significant difference in the passenger flows of the two directions of the route.

3.2 EXPLANATORY VARIABLES

According to the literature, population and regional Gross Domestic Product per capita have been introduced in the model as proxies for socio-economic characteristics of the passengers on the different routes. In our model we consider population of the total metropolitan area served by the airports. Population factor *POP* has been defined as the product of the populations of the two airport catchment areas. Also for GDP per capita in the two airport catchment areas, their product has been chosen as the explanatory factor *GDP*. As geographical and locational factors of the two cities, many explanatory variables have been tested in the model. According to the literature, the distance between the two airports was introduced (*DIST*). To take into account the inter-modal competition, a measure of the cost faced by the travellers in other modes of transportation has been taken into account. The direct competitor of airline services in the routes considered is the car (except in one case where the substitute of aeroplane is the ferry). The costs of alternative transportation modes have been considered in the *ALTCOS* factor.

Service-related variables were also included in the model. As explanatory of the service quality provided, daily frequency of flights (*FREQ*) and aircraft size used for each flight (*CAPA*) were inserted. A dummy variable *HUB* was introduced to identify «hubbing activity», and was set to one for routes from or to a hub airport for the considered airline. This variable was expected to have a positive effect on demand as hub airports handle a relevant part of transfer traffic. As regards pricing patterns, a variable *FARE* was included in the model. Since the dependent variable is demand for each fare-class in a given day, the corresponding fare introduced in each sample was the average airfare paid by travellers of the given fare-class.

Moreover, a dummy variable *COMP* was introduced to identify direct intra-modal competition. The dummy variable was set to 1 for airport pairs among which other airlines perform direct flights. A dummy variable *WEND* was introduced and set to 1 for flights performed on Saturdays or Sundays and a dummy variable *MAY* was introduced and set to 1 for flights performed in May (see Subsection 3.3). Finally, a control variable *YEAR* has been included in the model to capture the influence of the year of observation on the demand.

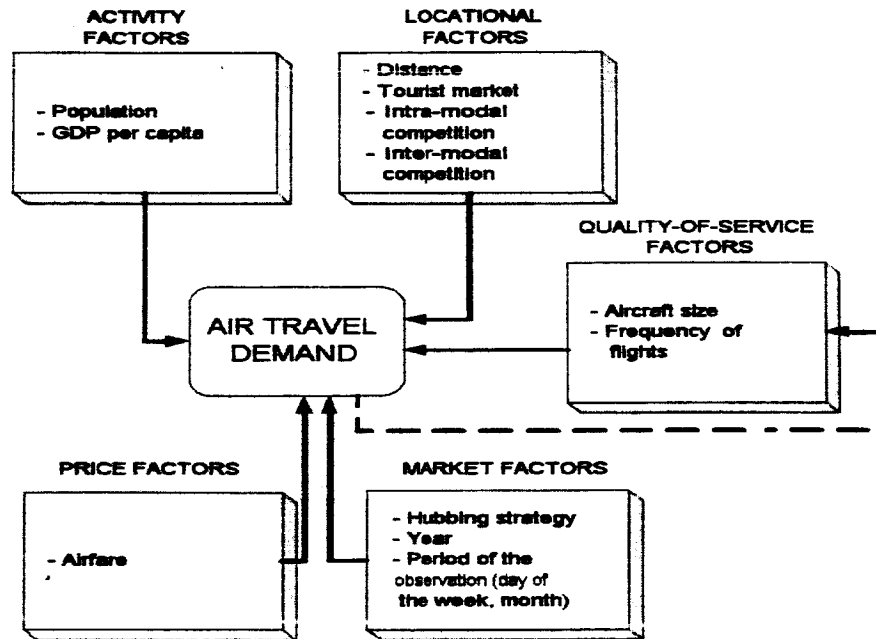


Figure 1: Drivers of air travel demand

3.3 NETWORK AND PERIOD OF TIME UNDER STUDY

Daily passenger demand for air transportation was considered using data about 9 routes of Air Dolomiti (the largest Italian regional carrier, partner of Lufthansa), for the months of February and May in years from 1999 to 2002 and from 1999 to 2001, respectively. The 9 routes used for the analysis are: Ancona-Munich, Barcelona-Torino, Barcelona-Verona, Cagliari-Genova, Paris-Verona, Frankfurt-Verona, Genova-Munich, Munich-Trieste and Munich-Venezia. These routes present different characteristics, considering Air Dolomiti network structure and market position. Some routes have, as end-point cities, one of the hubs of the airline: Munich and Frankfurt. Moreover, a group of routes is directed to a holiday resort or touristic destination. On some routes there was also a direct competition with another airline serving with a direct link the same cities. The choice to analyse passenger demand in the months of February and May has been done to capture the seasonal variation of demand, characteristic of the air travel market (to see this trends

for year 2000 in the overall European air market see [6]). February is a month of low passenger demand, while May is a month with a high level of demand; to cope with that, Air Dolomiti schedule and passenger offer is different in these two months. Moreover, the unavailability of data for the passenger demand in an electronic form has limited the analysis to data about flights performed not before 1999.

3.4 DATA SOURCES

Data of passengers flown in each fare-class, airfare paid by each passenger, aircraft used and frequency of flights have been provided by Air Dolomiti for the 9 routes. Geo-economic data (GDP per capita in the catchment area of the airports, cost of fuel) and demographic data (population in the area served by the airports) have been taken from the National Institutes of Statistics and other Statistical organisations of the countries which the respective airports belong to (see [4] for details). Distance between two cities was considered as the length of the shortest segment between pertaining airports.

3.5 AGGREGATION OF FARE CLASSES

The available data give the detail of the number of passengers for each fare-class in each flight on the routes considered in the sample. Moreover, for each passenger they give the fare paid for the flight. The data have been first aggregated by fare-class and day: the demand for each fare-class on the same origin-destination pair has been grouped through the various flights of each day. The regression analysis carried out using these aggregated data gives many unreliable coefficient estimates with an overall low explanatory power of the regression. The key factor for these bad results is that data are too much dispersed. In fact, the analysis reveals that on average there are 7-8 different fare classes per flight, a kind of "dispersion" that is mainly due to revenue management strategies of the airline, and not to substantial differences in passenger service offered. To cope with this problem, we decided to collapse all these fare-classes in only two "usual" groups: business classes and economy classes. This final aggregation is reasonable and easy to implement, since there is a clear distinction between "economic" fare-classes and "business" fare-classes. The corresponding airfare variable is the average airfare paid by passengers travelling on that class.

4. ORDINARY LEAST SQUARES MODEL

When OLS regression analysis is performed, multi-collinearity and endogeneity issues may arise. In our case, multi-collinearity analysis proved *DIST* and *ALTCOST* to be redundant factors, and therefore they have been dropped. As regards the endogeneity of factors, possible endogenous problematic variables could be frequency of flights [2] [12], airfares [8] [12] and aircraft size [12]. In our analysis we consider both airfare and aircraft size as exogenous factors affecting demand. Frequency of flights has been considered endogenous (see [4] for details).

4.1 MODEL SPECIFICATION

The estimated model is displayed in equation (2); it has been linearised taking the logarithm on both sides of the equation, as shown in (3):

$$D_{if} = A \times POP_u^{\beta_1} \times GDP_u^{\beta_2} \times FREQ_u^{\beta_3} \times FARE_{if}^{\beta_4} \times CAPA_u^{\beta_5} \times YEAR_t^{\beta_6} \times \exp(\gamma_1 HUB_i + \gamma_2 TOUR_i + \gamma_3 COMP_u + \gamma_4 WEND_t + \gamma_5 MAY_t + \varepsilon) \quad (2)$$

$$\ln D_{if} = \alpha + \beta_1 \ln POP_u + \beta_2 \ln GDP_u + \beta_3 \ln FREQ_u + \beta_4 \ln FARE_{if} + \beta_5 \ln CAPA_u + \beta_6 \ln YEAR_t + \gamma_1 HUB_i + \gamma_2 TOUR_i + \gamma_3 COMP_u + \gamma_4 WEND_t + \gamma_5 MAY_t + \varepsilon \quad (3)$$

where subscript *i* represents route, *f* represents fare-class (“business” or “economy”) and *t* is a progressive index that indicates the day of the observation. Greek letters are the estimated factors. Coefficients β_n of the *n* quantitative variables represent the direct elasticity of demand with respect to a change in the corresponding factor, γ_m are the coefficients of the *m* qualitative variables, α is the constant term and ε is the error term of the estimation.

4.2 EMPIRICAL RESULTS

The results of the OLS regression analysis are presented in Table 1.

Explanatory variable	Coefficient	Estimated coefficient	t-statistic
Constant	α	-1.226	-1.680
Population (<i>POP</i>)	β_1	0.128	6.285
GDP per-capita (<i>GDP</i>)	β_2	0.127	3.342
Frequency of flights (<i>FREQ</i>)	β_3	0.862	31.884

Airfare (<i>FARE</i>)	β_4	-1.058	-71.479
Aircraft seat capacity (<i>CAPA</i>)	β_5	0.636	13.936
Year (<i>YEAR</i>)	β_6	0.070	4.164
Hub airport (<i>HUB</i>)	γ_1	0.241	3.564
Tourist market (<i>TOUR</i>)	γ_2	0.312	4.598
Direct competition (<i>COMP</i>)	γ_3	-0.088	-3.227
Weekend (<i>WEND</i>)	γ_4	-0.442	-25.566
May (<i>MAY</i>)	γ_5	0.080	5.198
Observations	6700		
R^2_{adj}	0.627		
Fisher Test	1024.59		

Table 1: Estimation results

The adjusted multiple determination coefficient R^2_{adj} , that indicates the percentage of variance in passengers demand explained by the selected drivers, is 62.7% for our model. This result, although lower than the ones found in [2] and [12], is higher than the values found in [8] and only slightly lower than the results in [7]. The *Fisher Test* value F , that indicates the overall significance of the estimated regression line, is 1024.59. Considering such value for the *F Test*, the F distribution, with 10 ($k-1$) and 6689 ($n-k$) degrees of freedom, allows the rejection of the null hypothesis, i.e., all partial slopes are simultaneously equal to zero or, alternatively, $R^2 = 0$.

The results of the regression analysis show that all the estimated coefficients are of the expected sign and all are statistically significant at the 0.05 level. In the following, the impact on the passenger demand of the main drivers is described in more detail.

4.3 ANALYSIS OF THE RESULTS

4.3.1 Price Elasticity

With regard to prices, the estimated elasticity of passenger demand for air transportation with respect to airfare is -1.058 . This coefficient is associated to a very high value for the *t-test* ($|t| > 70$) that implies a very high significance of the elasticity coefficient. The literature provides a slightly higher value for the overall market; a recent meta-analysis [3] [13] indicates that studies published on this topic reveal a mean price elasticity of -1.146 . Nevertheless, Air Dolomiti is an airline oriented to the business travellers, which is a segment less sensitive to changes in airfares

than the leisure travellers. In fact, studies focused on business class passengers on the past years revealed an average price elasticity of travel demand of -0.8 [3]. However, this latter figure refers to the whole business passenger market. Instead, competition reasons imply that the price elasticity of demand for a single company is generally higher than the price elasticity of demand for the whole market where it operates. Moreover, in the latter years, faced with the liberalisation of the European air market [11] and an increased choice of airlines and prices, the business travel market is becoming more and more price sensitive. Recent studies indicate an increasing tendency for business travellers to travel economic and discounted classes, as it is also proved by the fact that airlines are developing various economic measures and marketing strategies to maintain their loyalty (frequent flyers programmes, web check-in, etc.) [14] [15].

4.3.2 Other factors

Frequency of flights on a route is found to have a positive effect on passengers demand, with an elasticity coefficient of 0.862. GDP per-capita and Population factors have a small positive effect on passenger demand. The estimated coefficient of aircraft seat capacity is 0.636. All these elasticity results are in line with the findings in [8] (see [4] for more details).

4.3.3 Dummy Variables

Dummy variables to characterise hubbing activity and holiday resort destinations have a positive coefficient that indicates the presence of a larger volume of traffic due to the role of connecting point of the hub and the attractiveness of tourist destinations respectively. Both coefficients are significant at the 0.05 level, but the *t-test* coefficient is not high, thus implying a large variance in the coefficients estimation.

The dummy variable introduced to take into account the direct competition with another airline on the same route has, as expected, a negative coefficient of -0.088 . Also in this case, the considerations about the low value of the *t-test* coefficient apply.

The dummy variable introduced to consider flights performed in the week-ends has a coefficient of -0.442 . This implies that, other conditions being equal, the demand for air transportation on Saturdays and Sundays is 35.7% lower than in the other days of the week.

Finally, *MAY* dummy variable reveals an 8.3% increase in passenger demand during the month of May respect to February. Moreover, there is a positive trend in passenger demand for air transportation for Air Dolomiti (all other conditions being equal) during these last years.

5 A TWO-LEVEL MODEL FOR AIR TRAVEL DEMAND

According to the analysis of the literature and also to the results of the OLS model estimation performed in Section 4, it turns out that passenger demand for air transportation seems to be elastic with respect to airfares. Then, in order to refine these findings, we study the pattern of variability of price elasticity of demand along the different routes of the airline. In our analysis of Air Dolomiti data, airfare paid by passengers explains more than 30% of the variance in the passenger demand. Therefore, for our qualitative “route-variability” analysis we decided to focus our attention only on the effect of the paid airfares on the passenger demand for air travel on each route. In this framework, the multilevel structure in the data sample must be considered. The final daily passenger demands on each fare-class, that constitute the level 1 units of the population, are grouped in a level 2 units defined by the pertaining route to which demand is referred. Therefore, our model can be seen as a two-level model. The level 2 macro-units are the routes of the airline network, while the level 1 units are the daily demand for a given fare-class on the route. For the analysis of such a model, multilevel statistical methodologies are used [17], as described in the following.

5.1 MODEL SPECIFICATION

The purpose of this investigation is to consider the pattern of variation among the Air Dolomiti routes of price elasticity of passenger demand. To this end, our approach is to consider only the effects of a single predictor x , airfare, to the response variable y , passenger demand. According to the exponential functional form selected in the previous analysis (see subsection 4.1), the two variables are subject to a logarithmic transformation. Since price elasticity is represented by the slope of the regression line in the (x,y) graph, the multilevel functional form selected for the model has to allow both intercepts and slopes of the predicted regression lines to vary across level 2 units. Therefore, the mathematical specification of the model is the following:

$$y_{ij} = a_j + b_j x_{ij} + \varepsilon_{ij}$$

with

$$a_j = a + u_{0j}$$

$$b_j = b + u_{1j}$$

and

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N \left(0, \begin{bmatrix} \sigma_{u0}^2 & \sigma_{u01} \\ \sigma_{u01} & \sigma_{u1}^2 \end{bmatrix} \right)$$

$$e_{ij} \sim N(0, \Omega_{ij})$$

where y_{ijf} is the logarithm of passenger demand for a given fare-class f in the day i on route j and x_{ijf} is the corresponding logarithm of average airfare paid for the transportation. Subscripts j on the coefficients a and b denote that both intercept and slope of the regression line are allowed to vary across the level 2 units, i.e., the different routes.

5.2 EMPIRICAL RESULTS

The empirical results of the multilevel regression analysis are presented in the following equations:

$$y_{ijf} = a_j + b_j x_{ijf} + \varepsilon_{ijf}$$

$$a_j = 8.366(0.483) + u_{0j}$$

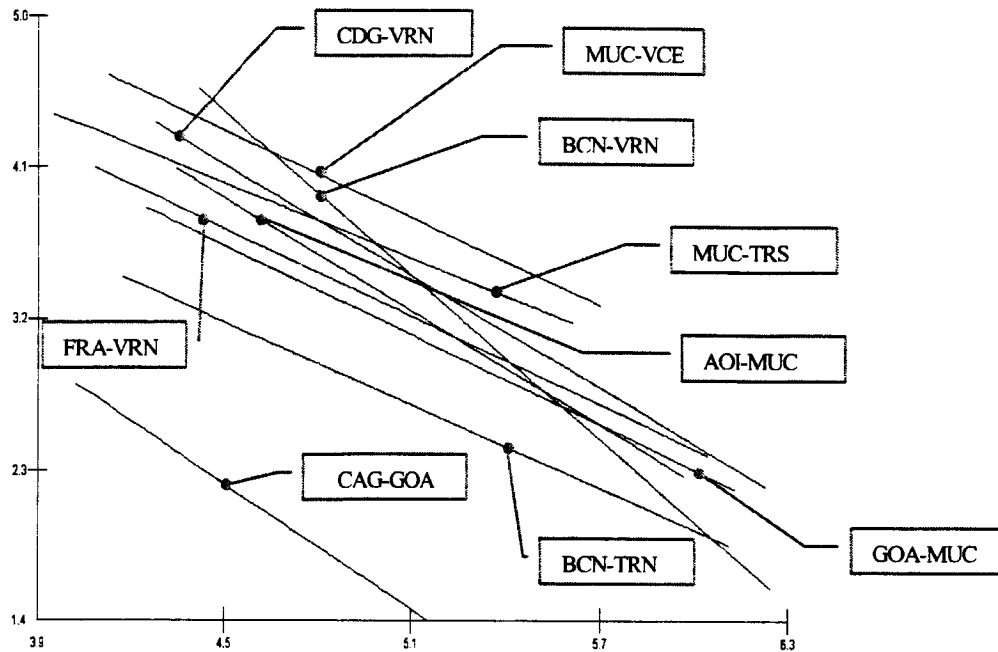
$$b_j = -1.031(0.092) + u_{1j}$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N \left(0, \begin{bmatrix} 1.986(0.989) & -0.337(0.178) \\ -0.337(0.178) & 0.072(0.036) \end{bmatrix} \right)$$

$$e_{ij} \sim N(0, \Omega_{ij} = 0.466(0.008))$$

The estimated mean price elasticity coefficient, b , is -1.031 (with a standard error 0.092 indicated within parentheses) and does not differ significantly from the value of -1.058 found in the multiple OLS regression analysis. The individual route slopes vary about this mean with a variance estimated as 0.072 (standard error 0.036). The intercepts of the individual route lines also differ. Their mean is 8.366 (standard error 0.483) and their variance is 1.986 (standard error 0.989). In addition there is a negative covariance between intercepts and slopes, estimated as -0.337 (standard error 0.178), suggesting that routes with higher intercepts tend to have lower slopes (in absolute value). The observed passenger demands vary around their routes' lines by quantities ε_{ijf} , whose variance is estimated as 0.466 (standard error 0.008).

The estimated regression lines for each route are also plotted in the Graph 1 where the x axis represents the logarithm of the average airfare paid and the y axis represents the logarithm of the demand.



Graph 1: Price elasticity of the demand for each route

The analysis of Graph 1 reveals that demand for flights involving a hub for the airline (Munich or Frankfurt) is relatively more price inelastic than demand for other, point-to-point, routes. This is probably due to the fact that the point-to-point flights attract more leisure travellers, whose price sensitivity is higher. A peculiar case is constituted by the Barcelona-Torino route, which is a point-to-point route for Air Dolomiti and shows a relatively low price elasticity of passenger demand, typical for business routes. This is due to the fact that between the Barcelona and Torino areas there are many important industrial and commercial links, which generate a peculiarly higher demand for business travels between the two cities.

For flights from or to a hub, it should also be considered that a significant fraction (over 40% on the average) of their traffic is transit traffic, in connection with other flights. Then it must be pointed out that the elasticity figures derived in this chapter are based on fares paid for the Air Dolomiti connection only, and not on the total cost of the whole route of transit passengers, which involves other flights, operated by other airlines.

In Table 2 the estimated passenger demand price elasticity coefficients for the various routes are provided.

Route	Estimated passenger price elasticity of demand
Munich-Trieste (MUC-TRS)	-0.746

Barcelona-Torino (BCN-TRN)	-0.821
Munich-Venice (MUC-VCE)	-0.866
Frankfurt-Verona (FRA-VRN)	-0.868
Genova-Munich (GOA-MUC)	-0.884
Paris-Verona (CDG-VRN)	-1.103
Ancona-Munich (AOI-MUC)	-1.122
Cagliari-Genova (CAG-GOA)	-1.243
Barcelona-Verona (BCN-VRN)	-1.624

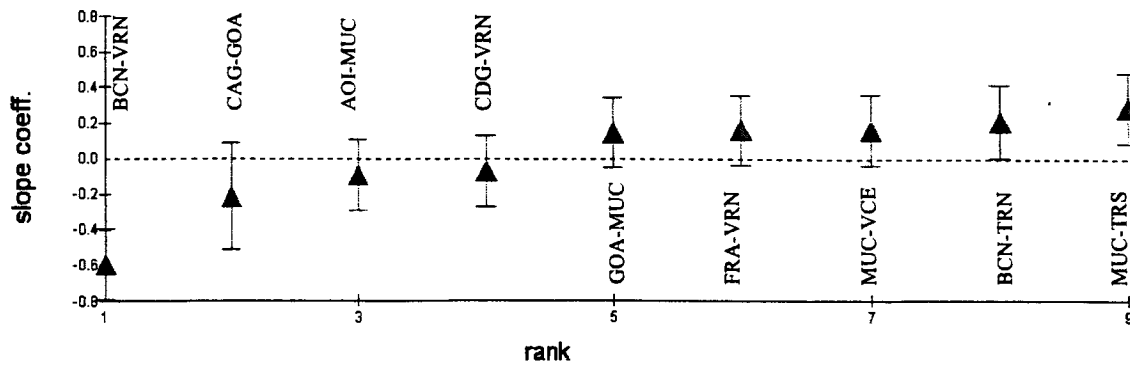
Table 2: Price elasticity of passenger demand for the various routes

5.3 ANALYSIS OF THE RESULTS

Table 2 shows that there is a great variability among the estimated values of airfare elasticity of passenger demand on the sampled routes ranging from -0.746 for the Munich-Trieste route to -1.624 for the Barcelona-Verona route. In order to investigate in deeper detail the significance of the differences in the airfare elasticity of passenger demand among the different considered routes, the confidence intervals around the values presented in the table above have been studied.

The overall mean slope coefficient (i.e., the airfare elasticity of passenger demand) estimated for the whole data set was -1.031 . The residuals, calculated for each route, are defined as the difference between the slope coefficient found for the route (reported in table 2) and the overall mean value; for example, the residual for the Ancona-Munich route was -0.091 . Around these residuals (whose mean is zero), the 95% confidence intervals have been calculated. To this end, in [9] and [16] Goldstein, Rasbash *et al.* discussed the circumstances where the value of 1.4 rather the conventional 1.96 standard deviation is used to calculate 95% intervals. They pointed out that to analyse whether a route is significantly different from the overall mean, the conventional 1.96 interval can be used in terms of whether or not it overlaps the zero line. Conversely, if intervals are used to make comparisons between pairs of routes, then we can judge significance at the 5% level by whether or not the 1.4 times standard error intervals overlap.

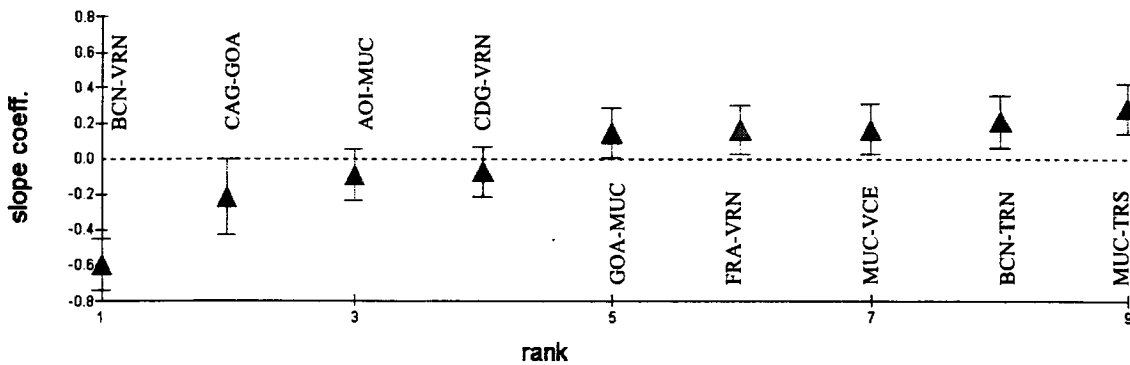
In Graph 2, the residuals for the slopes are ordered from smallest (-0.593 for the Barcelona-Verona route) to larger (0.285 for the Munich-Trieste route). Then the 1.96 standard deviation intervals are calculated.



Graph 2: Residual confidence intervals (1.96 standard deviations)

It turns out that the confidence intervals for the Barcelona-Verona route (on the extreme left) and for the Munich-Trieste and Barcelona-Torino routes (on the extreme right) do not overlap the zero line and, therefore, with more than 95% of probability they differ from the overall mean value of -1.031.

If we consider the 1.4 standard deviation, the confidence intervals around the residuals (ordered from smallest to larger, as in the previous case) are presented in Graph 3:



Graph 3: Residual confidence intervals (1.4 standard deviations)

Graph 3 evidences that the routes in the sample could be clustered in three distinct groups, with similar characteristics in terms of airfare elasticity of passenger demand. The first group is constituted by only the Barcelona-Verona route, whose confidence interval does not overlap any other one for the other routes. A second group is constituted by the Cagliari-Genova, Ancona-Munich and Paris-Verona routes, whose slope coefficient is higher than one (in absolute value). The third group is finally constituted by Genova-Munich, Frankfurt-Verona, Munich-Venice, Barcelona-Torino and Munich-Trieste routes, whose price elasticity of demand with respect to airfares is lower than one (in absolute value).

From the analysis of Graphs 2 and 3 we could also note that the Cagliari-Genova route shows larger confidence intervals for the residual than other routes. This is due to the smaller data set used (flights on that route in past years were performed only for two days per week) that also makes the intercept and slope coefficients more “sensible” to outlier observations.

6 CONCLUSIONS

This paper presents an application of an Ordinary Least Squares model to assess passenger air transportation demand for a single airline. The model follows the main guidelines described in the literature taking into account usual drivers affecting passenger air transportation demand. However, the attention is not focused on passenger air travel demand for a given market (as it generally happens, see Section 2), but on the passenger demand of a single airline. The model has been verified and validated on a relatively large sample of flights taken from the Air Dolomiti network. According to the statistical tests performed, the obtained results do not vary from the expected theoretical ones and prove the correctness of the proposed approach.

However, for most airlines passenger price sensitivity may be different (on the average) on different routes. OLS analysis only provides an aggregate view and cannot capture these effects. Hence a multilevel statistical approach has been used to analyse the airfare elasticity of passengers demand on the different routes of the Air Dolomiti data set. The analysis has revealed a significant variability of the elasticity of passenger demand for air transportation with respect to the airfares paid among the different routes of the airline, ranging from -0.746 for the Munich-Trieste route to -1.624 for the Barcelona-Verona route. The study has also been extended through the analysis of the confidence of the results obtained. Their analysis has revealed that the routes in the sample could be clustered in different groups, with different characteristics in terms of price elasticity of passenger demand and, therefore, different expected behaviours of the airline.

The results obtained by the innovative application of the multilevel analysis in the air transportation context seem to be encouraging and suggest to extend the study to more complex models with further explanatory variables and a larger sample of routes. Furthermore, analyses could be led to a more detailed level to investigate, e.g., the effect on fare elasticities of the fact that a larger share of passengers flying to a hub may be expected to continue their journey on other flights, paying a cumulative fare.

REFERENCES

- [1] Seraj Y. Abed, Abdullah O. Ba-Fail, Sajjad M. Jasimuddin, "An econometric analysis of international air travel demand in Saudi Arabia", *Journal of Air Transport Management*, Vol. 7, pp. 143-148, 2001
- [2] M. Abrahams, "A service quality model of air travel demand: an empirical study", *Transportation Research, Part B*, Vol. 23B, pp. 213-223, 1989
- [3] M. Brons, E. Pels, P. Nijkamp, P. Rietveld, "Price Elasticities of Demand for Passenger Air Travel: A Meta-Analysis" *Journal of Air Transport Management*, Vol. 8, pp. 165-175, 2002
- [4] L. Castelli, R. Pesenti, S. Schiratti, W. Ukovich, "Study of the impact of innovative route charges schemes considering ATC and airlines new perspectives", Final Report of the CARE Innovative Action Project, 2001,
<http://www.eurocontrol.int/care/innovative/projects2002/ircs/ircs-wp1finalreport.pdf>
- [5] EUROCONTROL Experimental Centre, *Review of Research Relevant to Rail Competition for Short Haul Air Routes*, Ref. EEC/ENV/2002/003, March 2002
- [6] EUROCONTROL Performance Review Commission, *Performance Review Report PRR4-Year 2000*, April 2001
- [7] L. Fridström, H. Thune-Larsen, "An econometric air travel demand model for the entire conventional domestic network: the case of Norway", *Transportation Research, Part A* Vol.17A, pp. 385-393, 1983
- [8] A. Ghobrial, A. Kanafani, "Quality-of-Service model of Intercity Air-Travel Demand", *Journal of Transportation Engineering*, Vol.121, pp. 135-140, 1995
- [9] H. Goldstein, "Multilevel Statistical Models", Kendall's Library of Statistics 3, Arnold Publishers, London, 1995
- [10] B. Graham, "Regional airline services in the liberalized European Union single aviation market", *Journal of Air Transport Management*, Vol.3, No.4, pp. 227-238, 1997
- [11] M. Janić, "Liberalisation of European aviation: analysis and modelling of the airline behaviour", *Journal of Air Transport Management*, Vol.3, pp. 167-180, 1997
- [12] J. D. Jorge-Calderón, "A demand model for scheduled airline services on international European routes", *Journal of Air Transport Management*, Vol.3, pp. 23-35, 1997
- [13] H. Kremers, P. Nijkamp, P. Rietveld, "A meta-analysis of price elasticities of transport demand in a general equilibrium framework", *Economic Modelling* Vol.19, pp. 463-485, 2002

- [14] K. J. Mason, "The propensity of business travellers to use low cost airlines", *Journal of Transport Geography*, Vol.8, pp. 107-119, 2000
- [15] K. J. Mason, R. Gray, "Short haul business travel in the European Union: a segmentation profile", *Journal of Air Transport Management*, Vol.2, No 3/4, pp. 197-205, 1995
- [16] J. Rasbash, W Browne, H. Goldstein M. Yang *et al*, "A user's guide to MLwiN", Version 2.1c, Centre for Multilevel Modelling, Institute of Education, University of London, 2001
- [17] T. A. B. Snijders, R. J. Bosker, "Multilevel Analysis. An introduction to basic and advanced multilevel modeling", Sage Publications, London, 1999
- [18] Tae Hoon Oum, D. W. Gillen, S. E. Noble, "Demand for fareclasses and pricing in airline markets", *Journal of Transportation Review*, Vol.22, No. 3, pp.195-222, 1986
- [19] Tae Hoon Oum, W. G. Waters II, Jong-Say Yong, "Concepts of price elasticities of transport demand and recent empirical estimates an interpretative survey", *Journal of Transport Economics and Policy*, Vol.26, pp.139-154 and 164-169, 1992