Price competition within and between airlines and high speed trains: the case of the Milan-Rome route

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Keywords: competition; airline; rail; pricing; low cost; strategic behaviour

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ABSTRACT

In the travel industry high-speed trains and airlines are increasingly competing for passengers, and the diffusion of price optimization based on real time demand fluctuations poses new challenges in the analysis of price competition between operators. This paper presents an analysis on how different competitors simultaneously adjust their prices in the short-run. The empirical model accounts for dynamic price variations, exploring both intramodal and intermodal price competition. The results, based on 12.506 price observations, show that intermodal competition presents some kind of asymmetric behavior, with airlines reacting more than trains to competitors' price changes. The paper concludes with the implications of this heterogeneous behavior for tourism and travel industries.

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INTRODUCTION

New dynamic pricing strategies have emerged as a particular useful tool, due to the advances in new technologies and the growing prevalence of Internet transactions between companies and consumers (Haws and Bearden, 2006). Research on revenue management in the travel industry is quite extensive, especially in the tourism industry (Heo and Lee, 2011; Abrate et al., 2012; Schwartz et al., 2012). The extent of the adoption of these technologies depends on a number of internal and external dimensions: temporal, demand and production characteristics, and repurchase intentions.

Aside from the internal use of revenue management, research has recently emphasized the relevance of competitors (Narangajavana et al., 2014) in terms of the interrelated use of revenue management techniques. Price response systems help operators to identify when competitors have introduced new fares into the market, and provide recommendations as how to respond to these changes. This automation is essential, considering that there are more than one million fare changes in any given day (Mumbower et al., 2014). Tsai and Hung (2009) clarify how competitive revenue management is an important issue in practice, while under investigated in the literature. This issue is relevant also in the tourism and hospitality industries. Among the scant evidence, Ropero García (2013) showed a strong impact of competitive scenarios on tourist apartments while Rosselló and Riera (2012) focused on the impact of low cost companies on the traditionally more stable prices of tour operator packages.

In the travel industry, after the liberalisation of the airline market in Europe that took place in the late 1990s, the enormous growth of low cost companies created great pressure on the established European traditional airlines, reducing the profitability of the traditional business model (Dennis, 2007). Furthermore, this competitive arena assists now at the growing presence of high-speed rail, at least in Europe (Castillo-Manzano et al., 2015; Delaplace and Dobruszkes, 2015) and China (Jeng and Su 2013). The Milan-Rome route is a perfect example of this new form of competition, with a traditional airline operator, two low cost operators and two high-speed rail operators. To exemplify the growing relevance of the high-speed rail in this market consider that, in the first trimester of 2012, the market proportion of train over air between

Milan and Rome (and vice versa) was 38%, while in the fourth trimester of 2014 train surpassed air in this route with a 54% market share (Uvet, 2015).

This paper tests the application of revenue management and price discrimination techniques (e.g., different fares between classes and in different time periods prior to departure) of different companies. While doing so, it enriches the previous literature by investigating the complex short-run price interrelations among intra-modal competition (airlines competing with other airlines – as well as train carriers competing with other train carriers – for the same city-pair market) and intermodal competition (airlines versus trains).

The empirical application is based on the Milan-Rome route, which represents a suitable case for analysing both intramodal and intermodal competition. The next section presents the conceptual framework, revising the literature on price competition and presenting the hypotheses that will be tested in the empirical part of the paper. The subsequent sections describe the data and the empirical model adopted to test the hypotheses, and then discuss the findings. Finally, the last section presents the limitations and the conclusions of the paper with the implications for tourism and travel industries.

CONCEPTUAL FRAMEWORK

The framework is based on two strands of literature. First, the article presents the application of revenue management and price discrimination techniques by the travel operators to maximize their revenues. Then, the paper thoroughly discusses how competition – and, specifically intramodal and intermodal competition – shapes these strategies. In this sense the main contribution here is on the supply side, by investigating the factors that influence the price set by operators in the short run.

The travel industry has to cope with heterogeneity, perishability with high sunk costs, cyclical demand and segments with different price elasticities (Bull, 2006). In this context, Dana (1998) claims that since consumers are heterogeneous in both their valuation and their demand uncertainty, a pattern of advance-purchase discounts can increase load-factors and profits. This is due to the low valuations of consumers that are more likely to buy in advance and, from the supply side, the certainty of allocations of a given number of seats well into advance. Gaggero (2010) explains the non-monotonic intertemporal profile of fares as follows: early bookers show a slightly inelastic demand, middle-bookers exhibit the highest demand elasticity and late-bookers book tickets only a few days before the departure. This last category is mainly composed by business travellers, with fixed travel dates and destination while the two former categories are composed mainly by standard and tourism customers, who are more flexible and desire to plan ahead their travel. While a monopolist can set and maintain high mark-ups for both category, in the oligopolistic industry, when competition increases, carriers lose this ability: mark-ups associated with the fares paid by the less price-sensitive (business) travellers decrease and align with the ones of the more price-sensitive standard travellers. Bergantino and Capozza (2015) discuss that this should be avoided because of the need to preserve, through price discrimination, the mark-ups applied to business travellers.

Aside from advance purchase behaviour, the supply can benefit from offering different attributes to account for the heterogeneity of customers' preferences with respect to travel choice (price, access time, comfort). Although Park and Ha (2006) mention fares as one of the most important driver of customers' mode choice and predict a decline in the aviation demand, at least business travellers were shown to be willing to pay more to improve connectivity, access and journey time (O'Connell and Williams, 2005; Jung and Yoo, 2014). It follows that for some segments low prices might not be sufficient to compensate the consumer additional effort to reach secondary airports and to fly at inconvenient time slots during the day, as for example a portion of Ryanair flight requires to do. For instance, when looking at revealed preference data provided by travellers, Wang et al. (2014) found that the magnitude of elasticity for travel time is higher than the magnitude of elasticity for trip costs in the business segment while the opposite holds in the leisure segment. Thus, despite a highly competitive context, the heterogeneity of product valuations across customers can allow many companies to remain profitable (Kim et al., 2009).

Recently, investments in high-speed rail infrastructures have significantly reduced travel time, enhancing mode competition between airlines and trains also for the business segment (Ivaldi and Vibes, 2008). Roman et al. (2007) investigates an example of this type of infrastructure in Europe, the Madrid-Barcelona high-speed line. These authors paid attention to the willingness to pay of customers and the level of demand needed to cover the high investment costs of such an infrastructure. Behrens and Pels (2012), examining the consumers' modal preferences on the Paris-London route, highlight how the lack of data for the high-speed train market does not allow drawing definitive conclusion on the interrelated competition mechanisms. In particular, there is no evidence regarding the intramodal competition between different high-speed train carriers.

The competition between airlines and trains needs to be addressed in light of the application of revenue management techniques, which allow operators to rapidly adjust their prices in the short-run. There are two main ways to apply revenue management in practice. The first, generally named supply or quantity-based perspective, places special emphasis on inventory capacity allocation. The second, named price-based perspective uses prices as the primary tactical tool for managing demand. Gallego and van Ryzin (1994) shows that a mixture of both pricing and allocation schemes is practical to receive the best revenues and to reach the optimal results. We claim that the weight of this mixture is different between airlines and high-speed trains. There is growing evidence that airlines apply a mix of quantity and price based Revenue Management to maximize their revenues in a competitive context (Bitran and Caldentey, 2003; Vinod, 2005; Chiang et al., 2007; Luo and Peng, 2007). This phenomenon is explained in Netessine and Shumsky (2005). The basic idea is that, to account for competition, airlines tend to base the allocation of set inventory adopting typical price-based measure. More specifically, they adjust for the demand distribution of each class and account for the level of prices of competition. While airlines, especially low cost airlines, adopt massively price changes depending on demand and purchase date (Alderighi et al., 2011; Piga et al., 2015), in the high-speed train context various tariffs and classes are set way into advance, favouring more traditional allocations based on the remaining seats for each class.

The framework above let us to draw the following hypotheses:

H1: Travel companies offer advanced-purchased discounts to capture travellers with low valuations.

H2: Both intramodal and intermodal price competition are intense, but only within similar target segments (business travellers and standard travellers).

H3: The use of revenue management techniques is different between airline and train industries.

H3a: Due to the number of tariffs and classes, high-speed trains apply mainly quantity-based techniques

H3b: Airlines react more than high-speed trains to changes in competitors' prices due to Revenue Management systems built on price-based techniques

While the core of the analysis is devoted to investigate the strategic behaviors of operators in terms of advance booking policies and price reactions to changes in competitors' prices, the regression model includes a control for other two variables that were shown to have a general impact on tariffs: peak-load vs. off-peak load pricing *and* week day vs. weekend price levels. There is extensive literature on peak-load vs. off-peak load pricing strategies in transport and tourism (for a review see Pan et al., 2015) and on the variation of tariffs depending on the day in which the travel will take place (Stavins, 2001; Park and Ha, 2006). Nonetheless, it is an interesting research question to assess if and how operators deal differently with these variables, depending on the customer segment to reach and on the mode of transport.

DATA AND EMPIRICAL MODEL

The Milan-Rome route represents an ideal case study for the empirical analysis. It is a route that attracts both business commuters and tourism customers (Holloway and Taylor, 2006). There are several options for getting from Milan to Rome. Aside from driving, five main options are available for a hypothetical tourist or business traveller: three airline companies (one traditional carrier, Alitalia, and two low-cost carriers, EasyJet and Ryanair) and two high-speed train operators – Trenitalia ("Frecciarossa") and NTV ("Italo"). This setting is suitable for a comprehensive analysis of both intramodal (within airlines and within trains) and intermodal (between airlines and trains) competition.

This study makes use of publicly available information on prices. All available options were monitored in a period aimed at representing a typical week without any special events or festivity (20^{th} to 26^{th} May 2013). In order to simulate the customer advance booking process, prices were checked at different points in time, in particular: 1, 7, 15, 30, 45 and 60 days before the date of the journey. For each travel option, all available fares – each characterised by some kind of peculiarity in terms of restrictions or in terms of travel class – were collected.

In order to ensure to reduce biases in the comparison between the different companies, the analysis was limited to the "one-way" ticket options[1]. Table 1 shows summary statistics of the main fares available for the five operators, providing a first picture of the revenue management strategies. In general, moving from the left to the right of the table, fares are characterised by tariffs with lower prices but more restrictions in terms of possible ticket changes or refund as well as other frills (such, for example, snacks). There is some heterogeneity between airlines and trains price differentiation. In the case of Alitalia, the highest fare might be considered as the business class service, because it guarantees more leg space and no one sitting next to the customer. In the case of trains, the distinction is even clearer, with the class of the service associated to distinct coaches characterised by different quality levels.

[INSERT TABLE 1 HERE]

A first look at the descriptive statistics provides a first support to hypothesis H3. Airline prices are characterised by high within-fare variability. On the contrary, the different train fares show a low variability (sometimes even zero), but the quantity of available tickets reduces significantly moving from the left to the right of Table 1. For instance, the super-economy ticket in the Frecciarossa standard class is available in less than 20% of occasions, likewise the promo ticket in the Italo smart class is available around once every three times. Thus, train operators prevalently apply quantity-based revenue management strategies.

Overall, Table 1 describes a rather complex set of options available for a typical traveller. To deal with such complexity, a set of more standardised alternative travel modes and associated prices (*p*), ending up with a total number of 12.506 price observations. The eight travel modes are the following:

1) Traditional carrier airline (Alitalia), standard class, operationalized as the minimum available fare for booking a specific flight with Alitalia.
2) Traditional carrier airline (Alitalia), business class, operationalized as the Comfort Fullflex fare.
3) Low cost airline mode (Easyjet, minimum available fare)
4) Low cost airline mode (Ryanair)

5) Frecciarossa train, standard class, minimum available fare

6) Frecciarossa train, business class, minimum available fare

7) Italo train, standard class ("Smart"), mimimum available fare

8) Italo train, business class ("Prima"), minimum available fare.

Individual preferences will drive the ultimate choice of which ticket (if any) to buy. Some people might consider as valid options only the more comfortable business class tickets, others might instead just look at the most convenient options; some people might strictly prefer travelling by train (or by plane), others might be more flexible. By looking at dynamic price evolutions in the above-defined categories, the main research question is whether (and how much) an operator cares about price variations in competing segments when defining its revenue management strategy. Implicitly, it is reasonable to expect a higher degree of price correlations when customers exhibit a higher degree of substitutability between the alternative options.

We propose a model where the price depends on the day of the week, the hour of the day, the booking time and the competitors' prices, and where all these covariates are interacted with the travel modes above defined, in order to examine specific price patterns. More specifically:

$$p = \sum_{n} \beta_n * Type_n + \sum_{j,n} \beta_{jn} * Weekday_j * Type_n + \sum_{l,n} \beta_{ln} * Hour_l * Type_n$$
$$+ \sum_{m,n} \beta_{mn} * Adbook_m * Type_n + \sum_{r \neq n} \beta_{rn} * Compprice_r * Type_n$$

Where:

- The dependent variable (*p*) is expressed in logarithm.
- *Type* indicates a set of 8 dummies characterising each of the eight above defined travel modes (i.e. Alitalia standard and business, Easyjet, Ryanair, Frecciarossa standard and business, Italo standard and business):
- *Weekday* indicates the day of the week (7 dummies).

- *Hour* indicates a set of 5 dummies characterising the different time slots during the day (6-10a.m.; 10a.m.-1p.m.; 1p.m.-4p.m.; 4p.m.-7p.m.; later than 7p.m.).
- *Adbook* indicates a set of 6 dummies defined according to the number of days of advance booking before traveling (e.g. 60 days means that the price refers to a ticket booked 60 days in advance).
- *Compprice* indicates the minimum price available (in logarithm) for each of the alternative travel *Type* within the same time slot (*Hour*). Thus, it reflects the presence of price promotions in the potentially competing segments[2].

The estimation strategy is based on a random effect panel data specification. In particular, we aim at capturing unobserved heterogeneity across each specific train or flight departure (and, across different travel categories within the same train/flight departure). One major potential source of unobserved heterogeneity is related to the occupancy rate: for example, we do not observe how many passengers have travelled in business class on the 6 o'clock Frecciarossa train. The time dimension of the panel is instead given by the 6 advance booking options simulated for each journey (i.e. by the fact that price information for each journey was retrieved at 1, 7, 15, 30, 45 and 60 days before the date of the journey).

Following our hypotheses development, the main interest is measuring β_{mn}, the impact of advance booking on prices (H1), and β_{rn}, the relations between the prices of competitors (H2 and H3). While doing so, the regression model includes a control for possible asymmetric behaviour across operators between weekdays and weekends (β_{jn}), and variations within the transport option in peak-hours and off-peak hours (β_{ln}).

RESULTS AND DISCUSSION

Table 2 presents the estimated coefficients of the random effect panel regression (R-squared: overall = 0.9250; within = 0.7226; between = 0.9584). First, control variables concerning the average difference between travel modes and the impact of weekday and peak hours have usually intuitive interpretation. Not surprisingly, Ryanair is the cheapest option while, on average, Alitalia is the most expensive career (especially in the case of business class), followed by Frecciarossa business. As to the day of the week, almost in all cases fares tend to be lower in the central days of the week, with a more accentuated discount associated to the less expensive travel modes (in particular, Ryanair, Italo standard and Frecciarossa standard). This might be due to less expensive travel modes being the preferred option for leisure customers, whose demand peak is on the weekend. However, this discounting behaviour does not seem significant in the case of the most expensive business tariffs (Alitalia business and Frecciarossa business), with the extreme case of Alitalia which places the most convenient price promotions during the weekend. This is coherent with the target segment of Alitalia mainly composed by business customers mostly travelling during working days. As to the within-day price variations, flights in the morning slot and in the evening slot tend to be more expensive. In the case of trains the highest fares can be found in late afternoon (4pm-7pm), with lower prices registered after 7pm. A possible explanation for such a finding is that peak-hours are slightly different for flights and trains, as peak-hours for trains are anticipated (i.e., trains depart directly from the city centre).

[INSERT TABLE 2 HERE]

Table 2 highlights the core results concerning the advance booking (β_{nt}) and competitor price effects (β_{nn}), quantifying such relationships. Analysing the dynamic of a flight with respect to the booking date, one can observe that, as expected, booking last minute is more expensive for all types of travel (H1). However, the price difference with respect to booking in advance is maximum for low cost carriers (64.8% and 51.7% for Ryanair and Easyjet, respectively) and minimum in the case of Alitalia business and Italo business, supporting the idea that intensive dynamic revenue management is more common among the cheapest categories that offer advanced-purchased discounts.

As to the competitors' effect on price, a positive sign suggests a potential substitution between the two categories: since competitors' prices are in log, the coefficients can be interpreted as elasticities. The coefficients describing intramodal competition are highlighted in light grey in the matrix. Alitalia business fares move independently, while low cost carriers and the lowest Alitalia fare tend to have similar moves. On the other hand, also within-train competition presents several significant coefficients. Italo adjusts both its two tariffs to the corresponding class level of Frecciarossa, and the same strategic behaviour can be seen in the case of Frecciarossa standard. On the whole, these coefficients provide support to H2, but, as an anomaly, Frecciarossa business fare seems to depend on Italo standard fare rather than on the business one.

The results for intermodal competition (highlighted in dark grey) show some kind of asymmetric behaviour and provide further support to the presence of different revenue management strategies between trains and airlines (H3). While train prices seem not to react significantly to airline ones, the prices of low cost carriers seem to adjust depending on the moves of Italo. Also, the minimum available fare of Alitalia is significantly affected by both Frecciarossa business and Italo standard tariffs. Regarding the intermodal competition within similar target segments, the findings support H2 only partially. There are some cases where this hypothesis holds, i.e. the reaction of Ryanair, Easyjet and the minimum tariff of Alitalia to the Italo standard tariff. Nonetheless, there are other relations that are more counterintuitive, like the effect of Italo business tariff on the Ryanair pricing strategy.

CONCLUSIONS AND LIMITATIONS

The adoption of revenue and yield management techniques is very popular in the tourism and travel industries and was shown to have a positive effect on load factors (Bilotkach et al., 2015). Nonetheless, the way operators react to short-term competitors' price variations is rather unexplored in the empirical literature. This paper attempts at filling this gap, providing a pricing regression model applied to the passenger transport market. Specifically, it focuses on the characteristics of intramodal and intermodal competition between airlines and high-speed trains. Advance-purchase discounts tend to be higher for low-cost products. In general, prices evolve coherently within business and leisure segments, but with some exceptions. Finally, price competition tends to be asymmetric between trains and airlines, since only the latter appears to be reactive to competitors' price changes. These results suggest the adoption of heterogeneous pricing strategies depending on the different type of supplier. Interestingly, it appears that traditional carriers (Alitalia in our case) tend to move independently from low cost airlines, while low cost airlines are following them in their pricing strategies. This finding confirms the different supply strategies adopted to increase revenues.

Through an examination of the impact of our control variables on the empirical model, it appears that business-oriented operators generally present higher prices during weekdays and peak-hours, while low cost operators present higher prices during the weekend, coherently with tourism population preferences.

The travel and tourism arena has started to investigate the advantages of the adoption of dynamic pricing in different routes. Our contribution suggests that to have a complete picture the analysis has to jointly investigate intramodal and intermodal options when present, as travellers are generally flexible and willing to switch to another mode of transport (Behrens and Pels 2012; Ivaldi and Vibes, 2008). On the whole, these interrelated results suggest the need of further studies to disentangle the complexity of relations between different modes in tourism and transport settings. As found in the hospitality industry by Lee and Jang (2013), revenue managers have to find the best profit maximization strategy. This can be obtained by monitoring the decisions of competitors of similar quality and by accounting for asymmetric price dynamics in decision-making processes.

Studying only a route made it possible to consider properly all the set of prices that are very difficult to gather for a large set of routes (Dobruszkes et al., 2014). Nonetheless, this study might raise the issue of representativeness in the complex relationships within and between modal competitions.

Analysts and researchers have to improve the quality of the prediction models when conducting research on a specific competition set. Based on a priori theory, structural equation model (SEM) would have allowed measuring indirect effects (Bentler, 2006). This is left for future research.

Notes

[1] Frecciarossa offers in addition some extra class differentiation: a “Premium” option is available as an intermediate level between standard and business service, while among the business category it is possible to book the “business silence area”. Moreover, Alitalia, Frecciarossa and Italo do offer some discount in case of “Return tickets” (on average, around 6-7 percent of the one-way ticket); however, the dynamic of return ticket prices strictly follows the dynamic of one-way ticket prices.

[2] When an alternative was not available in a particular time slot, in order to simulate such a “scarcity” in the supply without losing observations, we considered the highest price for that travel type (actually, this mainly happened because Ryanair flights are not available in the central hours of the day).

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List of Tables and Figures

Table 1. Available fares and travel modes.

ALITALIA		COMFORT Fullflex	COMFORT	EASY Flex	EASY
	N. obs.	1793	2296	2311	1910
	Mean price	320.37	238.06	138.14	97.87
	S.d.	63.93	63.19	30.61	14.88
EASYJET				FLEXY	STANDARD
	N. obs.			602	603
	Mean price			118.25	53.02
	S.d.			43.22	23.51
RYANAIR					STANDARD
	N. obs.				235
	Mean price				43.42
	S.d.				34.86
ITALO		BASE	ECONOMY	LOW COST	PROMO
SMART	N. obs.	1407	1329	901	517
	Mean price	88	58	45	31.6
	S.d.	0	6.24	0.71	2.33
PRIMA	N. obs.	1407	1397	1049	678
	Mean price	117	73.6	55	48
	S.d.	0	7.53	0	0
CLUB	N. obs.	1403	1365		
	Mean price	130	117		
	S.d.	0	0		
FRECCIAROSSA		BASE	ECONOMY		SUPERECON.
STANDARD	N. obs.	2423	1606		468
	Mean price	86	51.68		35.35
	S.d.	0	4.46		4.9
BUSINESS	N. obs.	2295	2157		1107
	Mean price	116	80.57		49.07
	S.d.	0	3.09		0.85
EXECUTIVE	N. obs.	2431	1560		
	Mean price	200	160		
	S.d.	0	0		

Table 2. Matrix of coefficients from the regression model.

	Ryanair	Easyjet	Alitalia standard	Alitalia business	Freccia standard	Freccia business	Italo standard	Italo business
Type (1)	0.000	1.005	1.941**	4.708***	0.860	1.743*	0.596	1.136
Weekday x Type(2)								
Mon	-0.116	0.054	0.110**	-0.04	-0.002	-0.019	-0.100*	-0.035
Tue	-0.232**	-0.059	0.141***	-0.054*	-0.112***	-0.051	-0.205***	-0.040*
Wed	-0.248**	-0.065*	0.174***	-0.046	-0.131***	-0.028	-0.202***	-0.043*
Thu	-0.185**	-0.047	0.153***	-0.035	-0.072***	0.001	-0.166***	-0.039*
Fri	-0.058	0.069	0.078	-0.026	0.037	0.039	-0.017	-0.011
Sat	-0.193*	-0.027	0.041	0.021	0.020	-0.067*	-0.104	-0.051**
Sun	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hour x Type (3)								
Before 10am	0.119**	-0.036	0.041	-0.020	0.052**	0.003	0.061**	0.019
10am-1pm	-	-0.088*	-0.158***	-0.008	0.081**	0.047	0.023	-0.024
1pm-4pm	-	-0.006	-0.240***	0.021	0.091*	0.075**	0.058	-0.018
4pm-7pm	0.031	0.034	0.036	-0.031	0.108***	0.123***	0.061**	0.027
After 7pm	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adbook x Type (4)								
Day1	0.648***	0.517***	0.384***	0.154***	0.380***	0.297***	0.321***	0.182***
Day7	0.184*	0.280***	0.047**	0.099***	0.297***	0.241***	0.289***	-0.101***
Day15	-0.168***	0.000	0.079***	0.026***	0.260***	0.155***	0.156***	-0.098***
Day30	-0.161***	0.022	0.061***	0.008	0.127***	0.048**	0.015	-0.093***
Day45	-0.124***	0.023	0.061***	0.008*	0.104***	0.029	-0.102***	-0.093***
Day60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Compprice x Type (5)								
Ryanair		-0.003	0.062**	0.002	-0.018	-0.005	0.007	0.019
Easyjet	0.183***		0.048**	-0.010	0.017	0.036*	0.018	0.004
Alitalia standard	0.135**	0.126***		-0.018*	0.004	0.012	0.017	-0.001
Alitalia business	0.017	0.013	0.064*		0.042	0.011	-0.046*	0.013
Freccia standard	-0.129	-0.036	0.017	0.011		0.140***	0.191***	-0.011
Freccia business	-0.084	-0.014	0.097**	-0.001	0.313***		-0.026	0.226***
Italo standard	0.202*	0.255***	0.125***	-0.004	0.258***	0.116**		0.267***
Italo business	0.344*	0.117	-0.035	0.051*	-0.116*	0.035	0.421***	

*** Significant at 1%; ** Significant at 5%; * Significant at 10%
R-squared: overall = 0.9250; within = 0.7226; between = 0.9584

(1) The dummy for Ryanair was omitted to avoid collinearity. Thus, the coefficients for other operators indicate the average price differences with respect to a Ryanair ticket.
(2) The dummy for Sunday was omitted to avoid collinearity. Thus, the coefficients indicate, for each travel type, the average price differences with respect to travelling on Sunday.
(3) The dummy for the time slot "After 7pm" was omitted to avoid collinearity. Thus, the coefficients indicate, for each travel type, the average price differences with respect to travelling after 7pm.
(4) The dummy for "Day60" was omitted to avoid collinearity. Thus, the coefficients indicate, for each travel type, the average price differences with respect to booking 60 days in advance.
(5) For each travel type, the coefficients, multiplied by 100, represent the estimated percentage price reaction to a percentage change of price by another travel type.