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One price for all? Price discrimination and market captivity: Evidence from the Italian city-pair markets ☆

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ABSTRACT

This paper tests whether, and to what extent, airlines exploit market captivity by using price discrimination strategies. The Italian passenger market is particularly fit for this purpose, given the high differentials in the degree of the inter-modal competition amongst domestic connections. Results show that, *ceteris paribus*, airlines adopt a different pricing behaviour depending on the degree of inter-modal market captivity. First, in highly concentrated markets with respect to air competitors, airlines price higher when the inter-modal competition is limited. This proves that inter-modal market captivity strengthens the effect of market power. Second, the inter-temporal price discrimination leads to a J-shaped distribution of fares over time, which is more pronounced when the inter-modal competition is effective. This suggests that airlines need to adopt a pricing technique that allows for a greater market segmentation in order to compete successfully with high-speed rail transport and to extract a larger part of passengers' surplus. These results are relevant in terms of transport-investment implications and competition policy. The indirect benefits that investments in rail infrastructure would yield through downward pressures on competing airline fares should be embedded in any cost-benefit analysis of high-speed networks investments and in any policy evaluation of measures that aim to reduce the territorial gaps in infrastructure endowment and accessibility.

1. Introduction

In the literature, a large number of studies explore pricing behaviour and competition in the air transport sector in various geographical contexts. Special emphasis has been posed on price discrimination, which can be implemented, for instance, through the Saturday-night stay over, the advance purchase discount, etc. More recently, the empirical research has focussed its attention on inter-temporal price discrimination (IPD). This paper differs from existing work, as it attempts to study airline pricing for short-haul flights in response to the different degree of market captivity across city-pairs. A market is said to be captive when consumers have to buy from a particular source, or when they have only one choice. By applying this

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Source: Ministry of Infrastructure and Transport, Italy.

Fig. 1. High speed rail network in Europe, 2012.

definition to this research context, a city-pair market is captive when travellers have no, or highly limited, feasible alternatives to the air transport. In other words, the inter-modal competition is not effective.

The purpose of this work is twofold. First, we would like to understand whether the effect of intra-modal (air-related) competition on fares varies among connections with a different degree of market captivity. Basically, to do this, we empirically test whether the effect of airline market power on fares is curbed or not by competition from rail transport. Second, we verify whether the competitive pressure by the presence of effective rail competition shapes the inter-temporal profile of fares, namely whether airlines modify their IPD strategies, depending on the degree of market captivity.

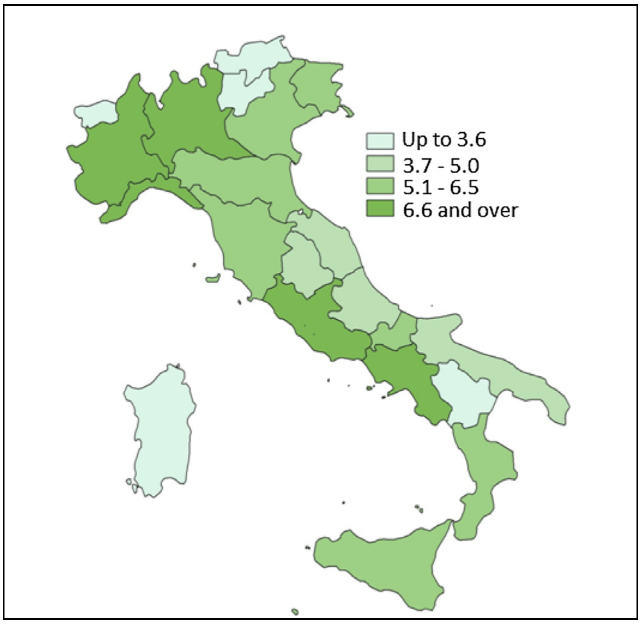
The Italian passenger market is particularly fit to test the research questions we pose, given the strong heterogeneity in inter-modal competition conditions over the territory. In this regard, Fig. 1 is self-explanatory.

At first glance, one might notice that Italy shows a relevant regional gap in rail transport. First, the rail network is less widespread throughout the country – in particular in southern regions – than in the rest of western Europe. Further, high-speed rail (HSR) lines – depicted in red and orange[1] – connect mostly the central and northern regions. With the exception of the Rome–Naples line, HSR services are scant or even lacking in southern regions mainly served by the traditional rails (in grey) and also by connections (in yellow) that are slower than those in red and orange.

[1] The *Union Internationale des Chemins de fer* (UIC) identifies HSR services as those running at minimum of 250 km/h (155 mph).

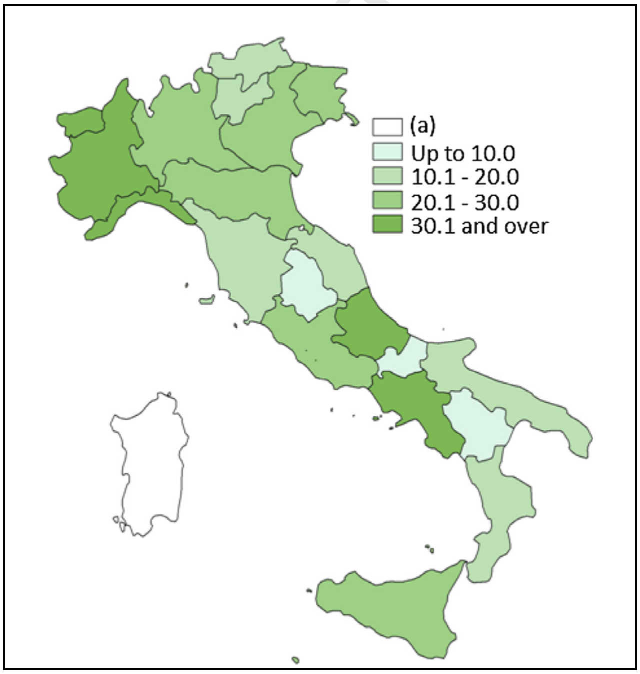
The regional gap in rail transport is not only attributable to the speed of rail services, but also to the extension of the rail network. Fig. 2 shows the Italian rail network.

The rail network is less extensive in southern Italy than in the north and centre. In fact, the northwest and northeast have, on average, 7.2 and 5.3 km of rail network per 100 km^2, respectively. Central Italy has, on average, 6.1 km of rail network per 100 km^2, whereas the south and the isles have only 4.9 km of rail network per 100 km^2. The exception is the Campania region, whose rail network's extension is in line with northern Italy's network.



Source: ISTAT.

Fig. 2. Railway network in operation.



Source: ISTAT.

Fig. 3. Motorway network.

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The main competitor of air transport is rail transport, in particular the HSR transport. However, road transport, by coach or car, could be a non-rail alternative to air transport, thus the motorway endowment in Italy is also worth considering (see Fig. 3).

The regional gap in motorway endowment is similar to the one in the rail network endowment. On average, the north-centre of Italy has 25.5 km of motorway network per 1000 km^2, whilst the south and the isles have 17.2 km. Once again, the Campania region has a motorway network's extension in line with the one in the North-Central Italy.

The regional gap in the transport infrastructures further motivates our interest to develop an empirical analysis to understand whether and to what extent airline fares differ for city-pair markets with a captive demand. Our hypothesis is that airlines exploit the different degrees of market captivity for price discrimination. As suggested by Figs. 1–3, it is natural to sort out city-pair connections into two groups. One group formed by the city-pair connections with *less* captive demand,

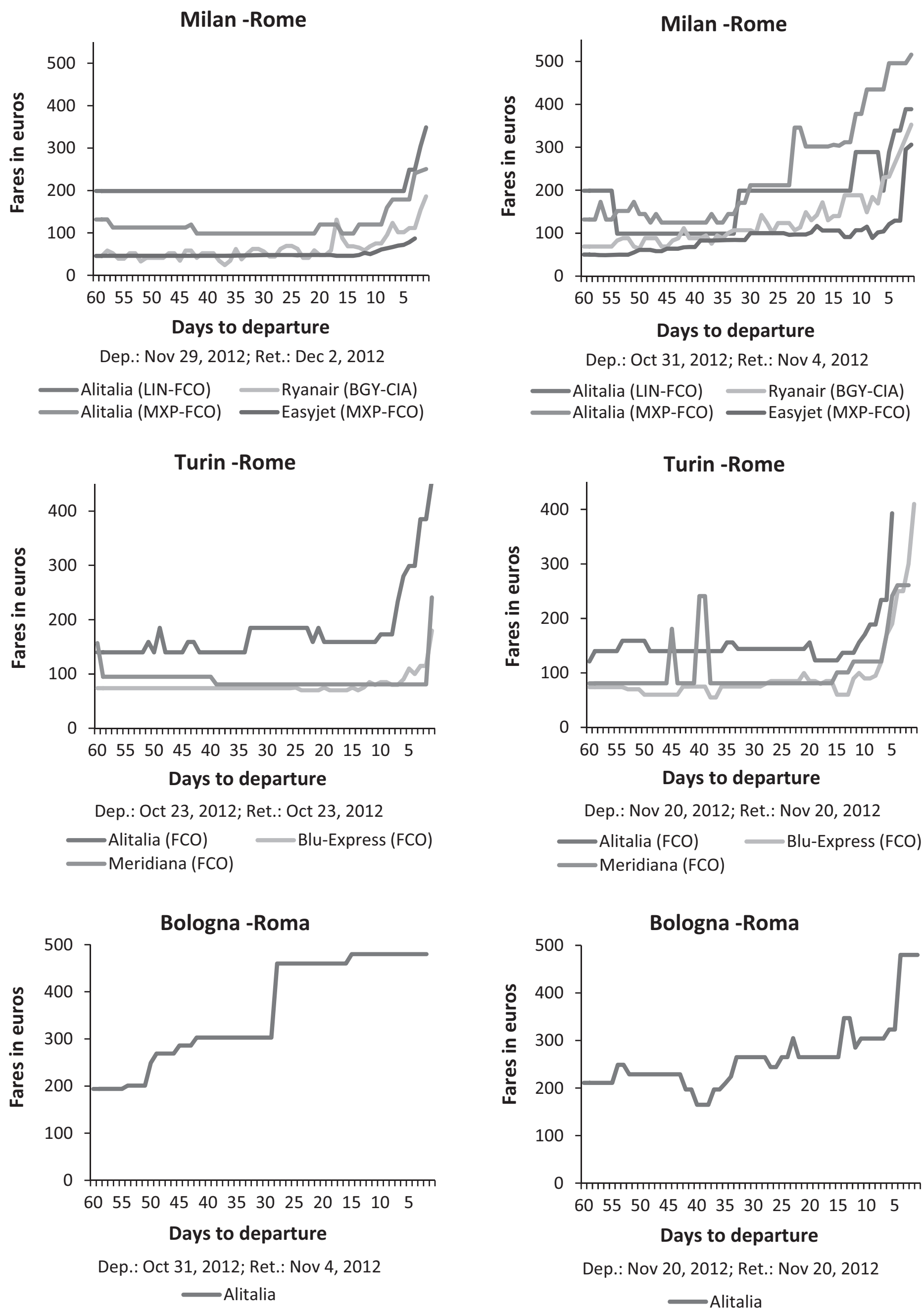

Fig. 4. Actual historic pricing data for markets with a less captive demand.

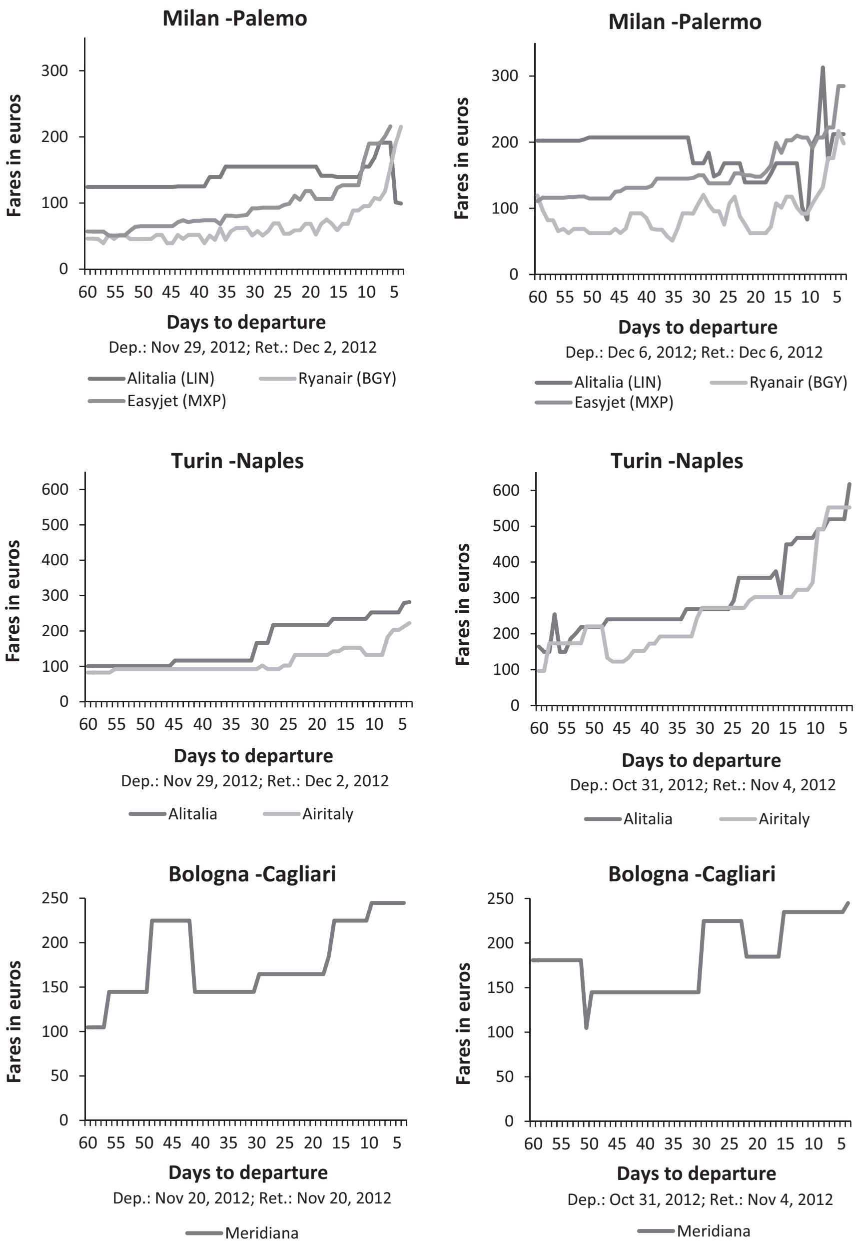

Fig. 5. Actual historic pricing data for markets with a more captive demand.

composed by the links between northern and central Italian cities plus the Naples-Rome city-pair, where the inter-modal competition, especially from HSR services, is effective. The second group characterised by a *more* captive demand, composed by the city-pairs connecting northern and central Italy with the south and the isles (excluding the Naples–Rome city-pair), where the inter-modal competition is not, or only partially, effective.

We use a unique dataset to address the research question. It consists of a sample of Italian domestic flights operated from September to December 2012. For each flight, data on fares were collected by simulating reservations on airline websites, starting at sixty days before departure. This dataset is particularly valuable as it is composed of flight-level data, whilst the bulk of existing papers relies mostly on route-level data, especially those that use the US Department of Transportation's Origin and Destination Survey Databank 1A/1B. Furthermore, to the best of our knowledge, this is the sole dataset with representative geographical coverage containing daily fares for *each* booking day, on *each* flight operated by *any* company in the selected city-pairs. Finally, differently from other institutional databases or from databases created using posted fares, we simulate the purchase of round-trip fares to effectively replicate the demand behaviour as travellers more often purchase round-trip tickets than one-way tickets. In addition, we precisely recreate the supply side as we can clearly see if, for each round-trip flight, a carrier is a feasible alternative for travellers and, thus, an effective competitor.

Our results confirm our intuition that market captivity is exploited by airlines for price discrimination. Indeed, *ceteris paribus*, a 10% increase in the airline market share allows companies to fix fares 7.1% higher in *more* captive markets, i.e., for connections where the inter-modal competition is *not* effective, whereas, their capability of fixing higher fares in less captive markets is statistically lower. There is evidence that airlines' market power is contained by the presence of inter-modal competition. Further, the inter-temporal profile of fares appears to be J-shaped, although we find that the degree market captivity is taken into account by airlines when designing the IPD strategies. Actually, the J-curve of fares is more pronounced for *less* captive markets, whilst it is flatter for *more* captive markets, suggesting that airlines adopt a pricing behaviour that allows for a greater market segmentation when they face effective competition from rail transport.

Investment policy and evaluation strategies for transportation infrastructures can draw important implications from the results. High-speed networks require relevant investments. Being able to identify the indirect benefits of these investments through downward pressures on competing airline fares, adds an important element to their cost-benefit analyses.

The rest of the paper is organised as follows. In Section 2 we survey the relevant literature. In Section 3 we present the empirical strategy and in Section 4 we describe the data. In Section 5 we discuss the results and Section 6 concludes.

2. Literature review

This work contributes to the literature on airline pricing and competition. Following the main points of the paper, we start with the review of works that analyse the effect of intra-modal competition on fares. Thereafter, we focus on works that study the effect of inter-modal competition on fares. We conclude the survey with contributions that explore the inter-temporal price discrimination.

2.1. Airline pricing and intra-modal competition

Borenstein (1989) was the first to study the impact on the US industry of airline market structure on fares. He develops a model using market share at both route and airport level. Results indicate that market share, whatever measure adopted, influences a carrier's ability to raise fares, as the dominant presence of an airline at an airport increases its market share on the routes included in that airport. However, Evans and Kessides (1993) show that, when controlling for inter-route heterogeneity, market share on the route is no longer relevant in determining fares that are, instead, influenced by carriers' market share at the airports. More recently, some contributions explore the European airline markets. Unlike the US market, Carlsson (2004) finds that market power, measured by the Herfindahl index, does not have a significant effect on fares whereas it influences flight frequencies. Consistent with this, Giaume and Guillou (2004) find a negative and, often, non-significant impact of market concentration on fares for connections from Nice Airport (France) to European destinations. Bachis and Piga (2007a) measure the effect of market concentration at the origin airport on fares charged by British carriers, considering both the route and the city-pair level. Their results reveal the existence of a large degree of substitutability between the routes within a city-pair. A greater market share at the route level leads to higher fares, whilst at the city-pair level it does not. Gaggero and Piga (2010) find that a higher market share and the Herfindhal index at the city-pair level lead to higher fares on routes connecting the Republic of Ireland to the UK. Finally, Brueckner et al. (2013) provide a comprehensive analysis of competition and fares in domestic US markets, focussing on the roles of low-cost carriers (LCCs) and full-service carriers (FSCs). They find that FSC competition in an airport-pair market has a limited effect on fares, whilst competition in a city-pair market has no effect. In contrast, LCC competition has a strong impact on fares, whether it occurs in airport-pair markets or in city-pair markets.

2.2. Airline pricing and inter-modal competition

Whilst there is plenty of evidence on the impact of intra-modal competition on fares, relatively few studies examine the impact of inter-modal competition on fares. A stream of research employs game-theoretic models to explore the air-rail competition. Adler et al. (2010) explore the effects of rail infrastructure provision on the competitors' reaction function in the market, and Adler et al. (2014) investigate, among the other aspects, the inter-modal competition effects with an application to the transport market in Northeast Asia. Among the results, a higher level of rail competition is found to negatively affect airlines' market shares. In a theoretical contribution, supported by numerical examples, Yang and Zhang (2012) explore the effect of inter-modal competition on airline fares, using the rail speed as a proxy of rail competition. Airline fares are found to be decreasing in rail speed when the marginal cost of HSR is not too large.

The empirical contributions use mostly stated-preference data and discrete-choice modelling to analyse the effect of inter-modal competition on airline operations and market share. Overall, these studies show that HSR can be a strong competitor for air transport. For instance, Gonzalez-Savignat (2004) predicts a high substitutability between air and rail services on the Madrid-Barcelona connection, arguing that HSR is expected to reach 40% of market shares in the business segment and nearly 60% in the leisure segment. Park and Ha (2006) show a remarkable decline in air transport demand on the Seoul-Daegu route after the opening of the Gyeongbu line of the Korea Train Express (KTX) in 2004. Indeed, only 28% of

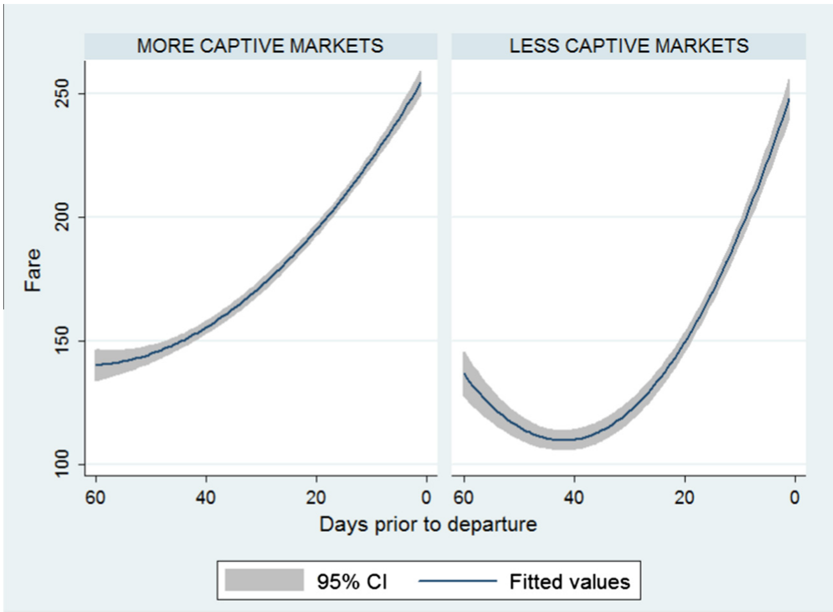

Fig. 6. The J-curve of fares.

air passengers still preferred to travel by air, and fare has been very important in determining the demand reduction. Focussing on Spanish domestic connections, Martin and Nombela (2007) forecast that, if rail infrastructure is upgraded for running HSR services, there would be a substantial modal shift in favour of HSR that would gain 22.8% of the passenger market share, which could even triple in ten years. Betancor and Jiménez (2012) examine air carriers' reaction to the opening of the HSR service in Spain, finding that, on average, the presence of the new service has reduced the number of air transport operations by 17%. Behrens and Pels (2012) analyse inter-modal competition in the London-Paris market. Their results indicate that HSR is a competitor for both FSCs and LCCs insomuch as some FSC are pushed out of the market when they encounter strong competition from HSR.

To our knowledge, there is only one empirical paper on the effect of HSR competition on airline fares. Steer Davies Gleave (2006) carried out this study for the European Commission on the European routes that have HSR lines. Results show that if HSR services are able to capture a relatively large market share on a route, airline fares could drop even below that of HSR services. Our work contributes to the research on the inter-modal competition effects using unique flight-level data, with the aim to shed light on the pricing behaviour of airlines, depending on the extent of the inter-modal competition.

2.3. Airline pricing and inter-temporal price discrimination

In the airline industry, the IPD consists of setting different fares for different travellers according to how far in advance the ticket is bought. By means of IPD, airlines exploit travellers' varied willingness to pay and demand uncertainty about departure time. Indeed, price-inelastic consumers, usually business travellers, most often purchase tickets close to departure date, whilst price-elastic consumers, usually leisure travellers, tend to buy tickets in advance. In a model with travellers' heterogeneity in valuations and demand uncertainty, Dana (1998) shows that airlines offer advance-purchase discounts as travellers with low valuation and more certain demand buy in advance.[2] Moreover, Alves and Barbot (2009) illustrate that the low–high pricing is a dominant strategy for LCCs only if travellers, on a given route, show varied willingness to pay. Travellers' heterogeneity is the necessary condition to successfully implement the price discrimination.[3]

Recently, Möller and Watanabe (2010) show that, for the airline tickets, advance-purchase discounts are preferred to clearance sales because their value is uncertain to buyers at the time of purchase, and reselling is costly or difficult to implement.

Some papers provide empirical evidence that airline fares increase over time. McAfee and te Velde (2007) find out that one week before the departure there is a significant rise in fares, which is on the top of the rise of two weeks before the departure. Bachis and Piga (2007a) show that fares posted by British LCCs follow an increasing inter-temporal profile.

Q4 [2] This finding implies that fares increase over time. In theoretical contributions, Lofgren (1971) and Stokey (1979) show that the IPD occurs when the good is introduced at a high price for very impatient consumers, then its price declines over time to be purchased by less impatient consumers. However, in these papers, reference is made to commodities such books, movies, computers and related programmes.

[3] In theoretical contributions, Gale and Holmes (1992, 1993) prove that, through advance-purchase discounts, a monopoly airline can increase the output by smoothing consumers' demand with weak time preferences over flight times and can extract the surplus of consumers with strong preferences.

However, other empirical contributions show that the distribution of fares over time can be non-monotonic. Bachis and Piga (2007b), examining UK connections to and from Europe, and Alderighi and Piga (2010), focussing on Ryanair pricing in the UK market, find a U-shaped inter-temporal profile of fares. Further, Gaggero and Piga (2010) show that fares for Ireland-UK routes follow a J-curve. Gaggero (2010) justify this finding by the existence of three categories of travellers: early-bookers and middle-bookers, usually leisure travellers, and late-bookers, mostly business travellers. Early-bookers have a slightly inelastic demand. Families planning holidays are, for instance, willing to pay moderately higher fares to travel during vacations. Middle-bookers exhibit the highest demand elasticity, as they are more flexible and search for the cheapest fares. Late-bookers reveal an inelastic demand. A business traveller typically books the ticket a few days before departure, with fixed travel dates and destination. As a result, the inter-temporal profile of fares is J-shaped as it reflects a pattern opposite to that of travellers' demand elasticity. Finally, Bergantino and Capozza (2015), to shed light on pricing behaviour in response to the pure air-related competition, investigate airline pricing for short-haul flights in contexts with no credible threat of inter-modal competition.[4] To that purpose, the authors conduct a case-study analysis focussing on city-pair connections from the main airports of southern Italy to Rome and Milan, where rail and road transport requires, on average, more than seven times the same travelling time as airline connections. They provide further evidence in favour of the J-curve of fares, with the minimum occurring between 43rd and 45th days before departure, though they claim that the J-curve is the evidence that airlines exploit consumer bounded rationality. Moreover, a higher fare for very-early purchasers can be seen as a fee for risk-aversion whilst Bergantino and Capozza (2015) remove the effect of inter-modal competition, in this paper we try to understand whether the presence of an effective inter-modal competition is able to influence, and to what extent, the pricing behaviour of the airlines.

3. Empirical strategy

We define the following equation to be estimated:

$$ln(P_{ijkst}) = \alpha + \beta Market\,Structure_{ijks} + \gamma \cdot f(Booking\,Day_t) + \theta Flight\,Characteristics_{ks} + \rho Control\,Dummies_{ijkst} + u_{ijkst} \quad (1)$$

where i indexes the route, j the carrier, k the departure date and s the return date. We set a daily time dimension t that goes from 1 to 60.

The dependent variable is the log of the fares. We use two indices of market structure at the city-pair level[5] to measure the intensity of the intra-modal competition:

- *Market Share* the number of the daily flights operated by an airline in a city-pair over the total number of flights operated by all the competing airlines in that city-pair; and
- Herfindahl–Hirschman Index (*HHI*): $\sum_{j=1}^{N} Market\,Share_{ijks}^2$.

The variable *Booking Day* captures the effect of IPD and ranges from 1 to 60. As mentioned in the review, the profile of fares over time could also be non-monotonic. Therefore, we do not make any hypothesis on the functional form of *Booking Day* that we empirically identify.

Flight Characteristics includes the following variables:

- *Holiday* is a peak-period dummy equal to 1 for flights occurring during summer holidays, winter holidays, bank holidays and public holidays, 0 otherwise; and
- *LCC* is a carrier dummy equal to 1 for flights operated by LCCs, 0 otherwise.

We also include a set of *Control dummies*:

- *Route-specific dummies* to capture route-specific effects, demand and cost (or price) differences[6];
- *Month dummies* to capture seasonal effects, pertaining to the date of departure;
- *Departure Time*and *Return Time*, two sets of four categorical dummies capturing the effect of the takeoff time: Morning (6:00–10:00), Midday (10:00–14:00), Afternoon (14:00–18:00) and Evening (18:00–24:00);[7] and
- *Stay dummies* to control for the length of stay (i.e., how many days elapse between departure and return).

Finally, u_{ijkst} is the composite error term, where $u_{ijkst} = \alpha_{ijks} + \varepsilon_{ijkst}$. Specifically, α_{ijks} is the unobserved heterogeneity and ε_{ijkst} is the idiosyncratic error term. Standard errors are clustered at flight level since observations on the same flight are not likely to be independent over time.

[4] A previous application concerning minor airports in Italy is contained in: Bergantino, 2009.
[5] Almost all the carriers could operate as a monopolist on a given route, then we need the city-pair level to capture the real competition between carriers.
[6] The route dummies serve to capture the effect of all the variables which are route specific, i.e., have the same value for all the flights referring to the same route. For example, variables such as population and income at the ending cities, proximity of airports to the city centers, airport hub status, flight duration time and distance, etc. Actually, these variables will be collinear with the set of route dummies. By introducing the route dummies in the model we are able to control for the external/exogenous route-specific factors.
[7] Based on Gaggero and Piga (2011).

Our hypothesis is that airlines have a different pricing behaviour depending on the degree of demand captivity. Indeed, we identify two groups of city-pair markets. The first group is composed by the city-pairs from northern to central Italy plus the Rome–Naples line, where the inter-modal competition, especially from HSR services, is effective. Therefore, this group of city-pairs has a less captive demand. The second group is composed of the city-pairs from northern and central Italy to the south and the isles, where the inter-modal competition is not, or only partially, effective. This group of city-pairs has a more captive demand. If airlines have a different pricing behaviour across the two groups of city-pairs, then data should not be pooled in one regression as estimated coefficients differ across the two groups:

$$\ln(P_{\mathrm{lijkst}}) = \alpha_l + \beta_l \mathit{Market\,Structure}_{\mathrm{ijks}} + \gamma_l \cdot f(\mathit{Booking\,Day}_{\mathrm{t}}) + \theta_l \mathit{Flight\,Characteristics}_{ks} + \rho_l \mathit{Control\,Dummies}_{\mathrm{ijkst}} + u_{\mathrm{lijkst}} \tag{2}$$

$$ln(P_{\mathrm{hijkst}}) = \alpha_h + \beta_h \mathit{Market\,Structure}_{\mathrm{ijks}} + \gamma_h \cdot f(\mathit{Booking\,Day}_{\mathrm{t}}) + \theta_h \mathit{Flight\,Characteristics}_{ks} + \rho_h \mathit{Control\,Dummies}_{\mathrm{ijkst}} + u_{\mathrm{hijkst}} \tag{3}$$

where l indexes the group with *low* degree of market captivity (city-pairs from northern to central Italy plus the Rome–Naples line) and h indexes the group with *high* degree of market captivity (city-pairs from northern and central Italy to the south and the isles).

We perform the Chow (1960) test in order to verify whether the coefficients in two regressions on different samples are equal. The test allows us to determine whether the independent variables have different impacts on different city-pair groups. The null hypothesis is that $\alpha_l = \alpha_h$, $\beta_l = \beta_h$, $\gamma_l = \gamma_h$, $\theta_l = \theta_h$ and $\rho_l = \rho_h$. The rejection of the null allows us to claim that coefficients are different across the groups, and, thus, in our case, that airlines have a different pricing behaviour depending on the degree of market captivity.

In our model some regressors, such as market structure variables, are time-invariant. To obtain estimates' coefficients of time-invariant variables, we use the Random Effects (RE) Generalised Least Square (GLS) estimator. The RE GLS estimator to be consistent requires the assumption that the right-hand side variables are not correlated with the unobserved heterogeneity α_{ijks}. We can test the validity of that assumption and, hence, the consistency of RE GLS estimates by performing the Robust Hausman specification error test using Wooldridge's (2002, pp. 290–291) method after each regression.

We assume that the market structure is exogenous. Basically, we agree with Stavins (2001), who claims that elements such as "entry barriers prevent new carriers from entering city-pair routes (e.g., limited gate access, incumbent airlines' hub-and-spoke systems, and scale economies in network size)."[8] Moreover, in the European Union "grandfather rights" – an airline that held and used a slot last year is entitled to do so again in the same season the following year – substantially immobilise the market. In the short run, then, we can assume that market structure is fixed. Finally, in our previous contribution (Bergantino and Capozza, 2015) we prove the exogeneity of market-structure variables using the instruments designed by Borenstein (1989).

4. Data collection

Data on fares were collected to replicate real travellers' behaviour when making reservations. First, we identify plausible round-trip flights,[9] then we retrieve data directly from airlines' website by simulating reservations.[10] For each round-trip flight, we observe fares daily starting, generally, at sixty booking days before departure up to one day before departure. However, for some round-trip flights we have less than sixty observed fares, thus the panel is unbalanced.

We include in the analysis only non-stop flights as fares for flights with a stopover might be influenced by the demand for the intermediate city. We define the market at city-pair level, thus all the alternative airports are included.

The dataset is comprised of 16,837 observations on 354 round-trip flights from September to December 2012. The sample includes 67 routes (listed in Table 1 in the Appendix) and 7 airline companies.[11] Both FSCs and LCCs are considered, thus we choose the basic services (no add-ons) to make carriers' supply effectively comparable.

We simulate the purchase of round-trip tickets as this gives us several advantages. We replicate consumer behaviour because travellers tend to purchase round-trip tickets rather than one-way tickets.[12] In addition, we precisely recreate the market structure as we can clearly see if, for each round-trip flight, a given carrier is a feasible alternative for travellers and an effective competitor.[13] The use of round-trip fares allows us to also account for peak-periods and to verify whether airlines

[8] Stavins follows the approach of Graham et al. (1983).

[9] We define the length of the round-trips on the basis of the tourism statistics provided by the Italian Institute of Statistics (ISTAT) on the residents in Italy in 2012, broken down by the trip motivation (leisure and business). The sample includes only domestic flights, so these statistics can be properly used as an indication to define the length of the round-trip, together with the Italian holiday calendar and the flight scheduling. The average length of a trip is 6.5 days for a leisure trip and 2.1 days for a business trip. We take account of the former information for round-trip flights over the holidays and over the weekend (Saturday-night stay over) and we take account of the latter for round-trip flights on weekdays.

[10] We avoid any potential distortion on pricing strategies caused by online travel agencies that could set discounted fares.

[11] Airitaly, Alitalia-Airone, BluExpress, EasyJet, Meridiana, Ryanair, Volotea.

[12] See, for instance, the analysis on airline travel demand carried out by Belobaba et al. (1987).

[13] Specifically, a carrier is a feasible alternative if it provides flights for the given date of departure and return, in a given time window. Time windows are defined following Gaggero and Piga (2011): Morning (6:00–10:00), Midday (10:00–14:00), Afternoon (14:00–18:00) and Evening (18:00–24:00).

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adjust their pricing behaviour accordingly. By date of departure and return, we set whether each round-trip flight occurs during summer holidays, winter holidays, bank holidays and public holidays, and then we test and measure whether airlines apply higher fares when the demand is greater.

Finally, one-way ticket pricing differs depending on the carrier type. A round-trip fare charged by FSCs is lower than the sum of the corresponding two one-way fares. This pricing policy is not adopted by LCCs. Previous research using one-way fares limit the empirical analysis to LCCs or to a few carriers. Instead, we do not encounter this problem and we carry out the empirical analysis including all the operating carriers.

Data on the number of flights, used to compute market structure variables, are collected from the official airports' timetables.

As already mentioned, previous contributions provide empirical evidence in favour of the non-monotonicity of the temporal distribution of fares. It seems that fares follow a J-curve over booking days (Gaggero and Piga, 2010; Bergantino and Capozza, 2015). In the following figures we show the actual historic pricing data for some markets to see whether the expected J-shape distribution is clear. To check the robustness of the J-shape across data, in the following figures we show for some markets, under different competitive conditions, both the distribution of fares that looks *less* like a J-curve (left column), and the distribution of fares that look *more* like a J-curve (right column).

In Fig. 4, we show flight-level data on some city-pairs with a less captive demand, whilst in Fig. 5 we show flight-level data on some city-pairs with a more captive demand.[14] The J-curve of fares appears to be quite robust across data.

5. Results

The empirical results are shown in Table 2. At the bottom of the table, we report the results of the Robust Hausman specification error test and of the Chow test. The results of the former test do not lead to the rejection of the null hypothesis that the RE GLS estimator is consistent.[15] The results of the latter test lead us to reject the null that estimated coefficients are the same across the two equations. This confirms our initial intuition that airlines have a different pricing behaviour depending on the degree of market captivity.

On the impact of the explanatory variables, *Market Share* has a positive and highly significant impact on fares. When the airline competition reduces and the market power becomes greater, carriers post higher fares. However, the impact size differs across groups. Actually, a 10% increase in *Market Share* leads to 5.6% higher fares for markets with a *less* captive demand and to 7.1% higher fares for markets with a *more* captive demand. The coefficient of the *HHI* for the group of *less* captive markets is not statistically different from zero, whilst it is positive and significant for the group of *more* captive markets, and a 10% increase in *HHI* leads to 4% higher fares. Results support the idea that the higher degree of market captivity strengthens the effect of market power. The same percentage increase in the market concentration leads to a greater increase in price when the inter-modal competition is limited.

In relation to IPD practice, we find that the inter-temporal profile of fares is non-monotonic and follows a J-curve. *Booking Day* has a negative and significant coefficient, thus fares posted the day before are lower. However, the coefficient of *Booking Day*^{2} is positive and highly significant, meaning that fares for very early purchasers are higher than those posted the day after. Basically, *Booking Day* has a negative effect on fares until the turning point is reached. Beyond that day, it has a positive impact on fares.

Besides proving further evidence on the J-curve of fares, we find also that coefficients' size of *Booking Day* notably differs across groups.

In the non-linear case, the marginal effect of *Booking Day* on fares is dependent on the level of *Booking Day*: $\frac{\partial(P_{ijks})}{\partial Booking\, Day_t} = -\gamma_1 + 2 * \gamma_2 Bookind\, Day_t$, where γ_1 indicates the coefficient of *Booking Day* and γ_2 indicates the coefficient of the square of *Booking Day*. In Table 3 we report the marginal effect for values of *Booking Day*, showing fares' variation with respect to fares posted a day early.

By comparing the marginal effects across groups, it appears that the J-curve of fares is more pronounced for *less* captive markets, whilst it is flatter for *more* captive markets, as shown in Fig. 6.

The turning point of the J-curve is included in the interval of the 59th to 50th days before departure for *more* captive markets, whereas it is included in the interval of the 45th to 41th days before departure for *less* captive markets. There is more than a one-week difference. From Fig. 6 it is evident that, consumers in more captive markets pay, on average, higher fares and that they do so for a much longer time. For instance, they reach an average fare of 150 Euros from around the 45th day of booking – and since then the fares they face are on average higher than 150 Euros – whilst passengers on more competitive routes do so only from about the 20th day before departures. In less captive city pairs, passengers face a fare that reaches 150 Euros about 25 days later than in a more captive market. Although the final fare is similar, airlines exploit consumers

[14] In each graph, we specify, in parenthesis to the right of the carrier's name, the destination airport if the city is multiairport one (Rome Fiumicino, FCO; Rome Ciampino, CIA; Milan Linate, LIN; Milan Malpensa, MXP; Milan Orio al Serio, BGY).

[15] The RE GLS estimator is inconsistent if regressors are correlated with individual-specific effect, in our case the flight-specific effect. This is the omitted-variables problem one could try to solve by adding further regressors that might be enough to make the fixed effect unnecessary. Actually, we include in the regressions a rich set of control dummies that, given the test's results, are able to account for much of the variance in the data. Moreover, the RE-GLS estimator corresponds to the Fixed Effect estimator as t goes to infinity. In our data sample, we observe each round-trip fare starting from 60 days before departure, thus $t = 60$ might be fairly considered, as t is equal to infinity.

Table 1
List of connections.

	Origin	Destination
1	Bari (BRI)	Milan Linate (LIN)
2	Bari (BRI)	Milan Malpensa (MXP)
3	Bari (BRI)	Milan Orio al Serio (BGY)
4	Bari (BRI)	Rome Ciampino (CIA)
5	Bari (BRI)	Rome Fiumicino (FCO)
6	Bologna (BLQ)	Bari (BRI)
7	Bologna (BLQ)	Cagliari (CAG)
8	Bologna (BLQ)	Palermo (PMO)
9	Bologna (BLQ)	Rome Fiumicino (FCO)
10	Brindisi (BDS)	Bologna (BLQ)
11	Brindisi (BDS)	Milan Linate (LIN)
12	Brindisi (BDS)	Milan Malpensa (MXP)
13	Brindisi (BDS)	Milan Orio al Serio (BGY)
14	Brindisi (BDS)	Rome Ciampino (CIA)
15	Brindisi (BDS)	Rome Fiumicino (FCO)
16	Brindisi (BDS)	Turin (TRN)
17	Lamezia Terme (SUF)	Bologna (BLQ)
18	Lamezia Terme (SUF)	Milan Linate (LIN)
19	Lamezia Terme (SUF)	Milan Malpensa (MXP)
20	Lamezia Terme (SUF)	Milan Orio al Serio (BGY)
21	Lamezia Terme (SUF)	Rome Fiumicino (FCO)
22	Lamezia Terme (SUF)	Turin (TRN)
23	Milan Linate (LIN)	Bari (BRI)
24	Milan Linate (LIN)	Cagliari (CAG)
25	Milan Linate (LIN)	Lamezia Terme (SUF)
26	Milan Linate (LIN)	Naples (NAP)
27	Milan Linate (LIN)	Palermo (PMO)
28	Milan Linate (LIN)	Pescara (PSR)
29	Milan Linate (LIN)	Reggio Calabria (REG)
30	Milan Linate (LIN)	Rome Fiumicino (FCO)
31	Milan Malpensa (MXP)	Bari (BRI)
32	Milan Malpensa (MXP)	Cagliari (CAG)
33	Milan Malpensa (MXP)	Lamezia Terme (SUF)
34	Milan Malpensa (MXP)	Naples (NAP)
35	Milan Malpensa (MXP)	Palermo (PMO)
36	Milan Malpensa (MXP)	Rome Fiumicino (FCO)
37	Milan Orio al Serio (BGY)	Bari (BRI)
38	Milan Orio al Serio (BGY)	Cagliari (CAG)
39	Milan Orio al Serio (BGY)	Lamezia Terme (SUF)
40	Milan Orio al Serio (BGY)	Palermo (PMO)
41	Milan Orio al Serio (BGY)	Pescara (PSR)
42	Milan Orio al Serio (BGY)	Rome Ciampino (CIA)
43	Naples (NAP)	Milan Linate (LIN)
44	Naples (NAP)	Milan Malpensa (MXP)
45	Naples (NAP)	Rome Fiumicino (FCO)
46	Palermo (PMO)	Bologna (BLQ)
47	Palermo (PMO)	Milan Linate (LIN)
48	Palermo (PMO)	Milan Malpensa (MXP)
49	Palermo (PMO)	Milan Orio al Serio (BGY)
50	Palermo (PMO)	Rome Fiumicino (FCO)
51	Palermo (PMO)	Turin (TRN)
52	Pisa (PSA)	Bari (BRI)
53	Reggio Calabria (REG)	Milan Linate (LIN)
54	Reggio Calabria (REG)	Rome Fiumicino (FCO)
55	Reggio Calabria (REG)	Venice (VCE)
56	Turin (TRN)	Bari (BRI)
57	Turin (TRN)	Cagliari (CAG)
58	Turin (TRN)	Naples (NAP)
59	Turin (TRN)	Palermo (PMO)
60	Turin (TRN)	Rome Fiumicino (FCO)
61	Venice (VCE)	Bari (BRI)
62	Venice (VCE)	Lamezia Terme (SUF)
63	Venice (VCE)	Naples (NAP)
64	Verona (VRN)	Bari (BRI)
65	Verona (VRN)	Cagliari (CAG)
66	Verona (VRN)	Naples (NAP)
67	Verona (VRN)	Palermo (PMO)

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Table 2
RE GLS estimations.

	MARKET SHARE			HHI		
	Pooled	Less captive markets	More captive markets	Pooled	Less captive markets	More captive markets
Market share	0.0061***	0.0056**	0.0071***			
	(0.0015)	(0.0022)	(0.0017)			
HHI				0.0011	−0.0050	0.0040*
				(0.0024)	(0.0047)	(0.0022)
Booking day	−0.0280***	−0.0403***	−0.0251***	−0.0280***	−0.0403***	−0.0251***
	(0.0015)	(0.0036)	(0.0016)	(0.0015)	(0.0036)	(0.0016)
Booking day^2	0.0003***	0.0005***	0.0002***	0.0003***	0.0005***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Holiday	0.2527***	0.1379	0.2502***	0.2543***	0.3077	0.2453***
	(0.0695)	(0.1436)	(0.0755)	(0.0707)	(0.1972)	(0.0763)
LCC	−0.3089***	−0.3013**	−0.2778***	−0.4848***	−0.5459***	−0.4533***
	(0.0581)	(0.1199)	(0.0559)	(0.0390)	(0.0679)	(0.0439)
Robust Hausman test						
Statistics	0.944	0.931	1.005	1.263	0.815	0.897
p-value	0.624	0.628	0.605	0.532	0.815	0.639
Chow test						
Statistics		8.244			9.189	
p-value		0.000			0.000	
Observations	16,837	3180	13,657	16,837	3180	13,657

Standard errors (in parentheses) are clustered at flight-level. Control dummies are always included but not reported.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3
The marginal effect (ME) of Booking Day (BD) on fares.

Low captive markets				High captive markets			
BD	ME	BD	ME	BD	ME	BD	ME
5	−0.0355***	46	0.0033**	5	−0.0228***	46	−0.0036***
	(0.0031)		(0.0018)		(0.0014)		(0.0010)
10	−0.0308***	50	0.0071***	10	−0.0204***	50	−0.0019
	(0.0026)		(0.0022)		(0.0012)		(0.0012)
20	−0.0213***	52	0.0090***	20	−0.0157***	52	−0.0008
	(0.0016)		(0.0024)		(0.0007)		(0.0013)
30	−0.0119***	54	0.0109***	30	−0.0111***	54	−0.0002
	(0.0010)		(0.0026)		(0.0005)		(0.0013)
40	−0.0024**	56	0.0128***	40	−0.0064***	56	0.0011
	(0.0013)		(0.0028)		(0.0007)		(0.0014)
42	−0.0005	58	0.0147***	42	−0.0055***	58	0.0020
	(0.0015)		(0.0030)		(0.0008)		(0.0015)
43	0.0005	59	0.0156***	43	−0.0050***	59	0.0025
	(0.0015)		(0.0031)		(0.0009)		(0.0016)
44	0.0014	60	0.0166***	44	−0.0046***	60	0.0030*
	(0.0016)		(0.0032)		(0.0009)		(0.0016)

for a longer time in the more captive markets, where they charge higher prices mainly to the late buyers who might not have the same availability of alternatives as the early buyers, or who are facing higher prices for the alternative HSR services, or, even, for those who, for a number of reasons, have inelastic demand.

Concerning control variables, the coefficient of *Holiday* is positive although highly significant only in a regression on *more* captive city-pair markets. This implies that during peak-periods, airlines are able to exploit the greater travel demand and post fares higher than off-peak periods for city-pairs with a more captive demand. Once again, the inter-modal competition plays an important role. During peak-periods airlines increase prices up to 25% when the inter-modal competition is limited.

As expected, the coefficient of *LCC* is negative and highly significant across regressions, providing evidence that LCCs apply lower fares than FSCs. However, there is a slight different impact amongst the two groups. The coefficient of *LCC*

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for the less captive markets is, in absolute value, higher than the coefficient for the more captive markets. In fact, in less captive markets LCCs apply 30% lower fares than FSCs, whilst in more captive markets they apply 28% lower fares than FSCs. This finding suggests that the curbing effect on airfares caused by the presence of the effective inter-modal competition is higher, although slightly, on LCCs.

6. Conclusions

In this paper we study airline pricing for short-haul flights on the Italian passenger market, with the purpose of understanding whether, and to what extent, airline companies adjust their pricing strategy, depending on the degree of market captivity. We provide evidence that they do so in two different ways.

First, we find that a more concentrated market structure allows airlines to price even higher when the inter-modal competition is limited. The inter-modal competition, when effective, is able to curb the impact of airline market power on fares.

Second, we find that the inter-temporal profile of fares approximates a J-curve. Comparing the shape of the curves for the *less* and the *more* captive markets clearly shows that the J-curve is more pronounced, and its turning point shifts on the right, for the former. This would indicate that airlines address an IPD strategy to the *less* captive market - where the inter-modal competition is effective - seeking to segment, to a greater extent, demand. In order to fully realise the magnitude of the difference, it is sufficient to refer to Fig. 6. We can see that captive consumers pay - already on the 45th day before departure - the same average fare that consumers on the non-captive markets pay on the 20th day before departure.

Our empirical findings suggest that the inter-modal competition, and thus the degree of market captivity, is taken into account by an airline when designing fares, in both their level and their dynamics.

The results are also particularly relevant in terms of implications for investment policy and evaluation strategies for transportation infrastructures. Actually, from our study, we see the indirect benefits that investments in rail infrastructure would yield through downward pressures on competing airline fares. These considerations should be embedded in any cost-benefit analysis of high speed networks' investments and, in particular, in any policy evaluation of measures that aim to reduce the north–south gap in infrastructure endowment and accessibility in Italy.

Appendix A

Q5 See Table 1

References

Adler, N., Fu, X., Oum, T.H., Yu, C., 2014. Air transport liberalization and airport slot allocation: the case of the Northeast Asian transport market. Transport. Res. Part A: Policy Pract. 62, 3–19.
Adler, N., Pels, E., Nash, C., 2010. High-speed rail and air transport competition: game engineering as tool for cost-benefit analysis. Transport. Res. Part B: Meth. 44 (7), 812–833.
Alderighi, M., Piga, C.A., 2010. On-line booking and revenue management: evidence from a low-cost airline. Rev. Econ. Anal. 2 (3), 272–286.
Alves, C.F., Barbot, C., 2009. Price discrimination strategies of low-cost carriers. J. Transp. Econ. Policy 43 (3), 345–363.
Bachis, E., Piga, C.A., 2007a. Hub Premium, Airport Dominance and Market Power in the European Airline Industry. Discussion Paper Series 2007_11, Department of Economics, Loughborough University.
Bachis, E., Piga, C.A., 2007b. Pricing strategies by European traditional and low cost airlines. Or, when is it the best time to book on line? In: Lee, Darin (Ed.), Advances in Airline Economics, Vol. 2: The Economics of Airline Institutions, Operations and Marketing. Amsterdam, Elsevier, pp. 319–344 (chap. 10).
Betancor, O., Jiménez, J.L., 2012. When trains go faster than planes: the strategic reaction of airlines in Spain. Transp. Policy 23, 34–41.
Belobaba, P.P., 1987. Air Travel Demand and Airline Seat Inventory Management. PhD Dissertation, Massachusetts Institute of Technology.
Behrens, C., Pels, E., 2012. Intermodal competition in the London–Paris passenger market: high-speed rail and air transport. J. Urban Econ. 71 (3), 278–288.
Bergantino A.S., 2009. Le strategie di prezzo delle compagnie tradizionali e delle low cost. In: Marletto, G., Musso, E. (Eds.), Implicazioni per i sistemi aeroportuali minori: il caso della Puglia", Trasporti, ambiente e territorio. La ricerca di un nuovo equilibrio, Milano: FrancoAngeli, pp. 77–91.
Bergantino, A.S., Capozza, C., 2015. Airline pricing behaviour under limited intermodal competition. Econ. Inq. 53 (1), 700–713.
Borenstein, S., 1989. Hubs and high fares: dominance and market power in the U.S. airline industry. RAND J. Econ. 20 (3), 344–365.
Brueckner, J.K., Lee, D., Singer, E.S., 2013. Airline competition and domestic US airfares: a comprehensive reappraisal. Econ. Transport. 2 (1), 1–17.
Carlsson, F., 2004. Prices and departures in european domestic aviation markets. Rev. Ind. Organ. 24 (1), 37–49.
Chow, G.C., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica 28 (3), 591–605.
Dana, J.D., 1998. Advance-purchase discounts and price discrimination in competitive markets. J. Polit. Econ. 106 (2), 395–422.
Evans, W.N., Kessides, J.N., 1993. Localised market power in the U.S. airline industry. Rev. Econ. Stat. 75 (1), 66–75.
Gaggero, A.A. (Ed.), 2010. Airline Pricing and Competition: The J-curve of Airline Fares. Lambert Academic Publishing.
Gaggero, A.A., Piga, C.A., 2010. Airline competition in the British Isles. Transport. Res. Part E 46 (2), 270–279.
Gaggero, A.A., Piga, C.A., 2011. Airline market power and inter-temporal price dispersion. J. Indus. Econ. 59 (4), 552–577.
Gale, I.L., Holmes, T.J., 1992. The efficiency of advance-purchase discounts in the presence of aggregate demand uncertainty. Int. J. Ind. Organ. 10 (3), 413–437.
Gale, I.L., Holmes, T.J., 1993. Advance-purchase discounts and monopoly allocation of capacity. Am. Econ. Rev. 83 (1), 135–146.
Giaume, S., Guillou, S., 2004. Price discrimination and concentration in European airline markets. J. Air Transp. Manage. 10 (5), 305–310.
Gonzalez-Savignat, M., 2004. Competition in air transport: the case of the high speed train. J. Transp. Econ. Policy 38 (1), 77–108.
Graham, D.R., Kaplan, D.P., Sibley, D.S., 1983. Efficiency and competition in the airline industry. Bell J. Econ. 14 (1), 118–138.
Lofgren, K.G., 1971. The theory of inter-temporal price discrimination. An outline. Swed. J. Econ. 73 (3), 333–343.
Martin, J.C., Nombela, G., 2007. Microeconomic impacts of investments in high speed trains in Spain. Ann. Reg. Sci. 41 (3), 715–733.
Möller, M., Watanabe, M., 2010. Advance purchase discounts versus clearance sales. Econ. J. 120 (549), 1125–1148.
McAfee, R.P., te Velde, V., 2007. Dynamic pricing in the airline industry. In: Hendershott, T.J. (Ed.), Economics and Information Systems, vol. I. Elsevier, Amsterdam.

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Park, Y., Ha, H.K., 2006. Analysis of the impact of high-speed railroad service on air transport demand. Transport. Res. Part E: Log. Transport. Rev. 42 (2), 95–104.
Stavins, J., 2001. Price discrimination in the airline market: the effect of market concentration. Rev. Econ. Stat. 83 (1), 200–202.
Steer, Davies Gleave., 2006. Air and rail competition and complementarity. Case study report prepared for European Commission DG Energy and Transport.
Stokey, N., 1979. Intertemporal price discrimination. Quart. J. Econ. 93 (3), 355–371.
Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge, MA.
Yang, H., Zhang, A., 2012. Effects of high-speed rail and air transport competition on prices, profits and welfare. Transp. Res. Part B 46 (10), 1322–1333.

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