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Abstract

This paper empirically analyses airline pricing for short-haul flights in contexts with no credible threat of inter-modal competition. To this end, we explore the southern Italian market since it is less accessible by other transport modes and thus fares are the direct outcome of air-related competition. We show, in fact, that market power matters, depending on the level of intra-modal competition, and that airlines apply differentiated mark-ups. Besides, consistent with the implementation of inter-temporal price discrimination (IPD), we find a non-monotonic inter-temporal profile of fares with a turning point included in the interval of the 43^{th} to 45^{th} days before departure. Finally, we provide evidence that in more competitive markets, airlines are more likely to engage in IPD.

Key words: airfares, market structure, intertemporal price discrimination

JEL: L11, L13, L93

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1 Introduction

There are three sources of competition in the airline market for short-haul flights which jointly affect fares. Airlines compete with other airlines for the same city-pair markets (intra-modal competition). Moreover, airlines compete with other modes of transport (inter-modal competition) such as trains, especially high speed trains, and cars, which have the advantage of allowing travel at any time. Finally, airlines compete with themselves by setting different fares in different time periods prior to departure. This pricing strategy is known as inter-temporal price discrimination (IPD).

Past empirical contributions exploring pricing behaviour and competition in air transportation were not able to control for the effect of inter-modal competition which, we can expect, affected the results. This paper differs from existing works as it attempts to study airline pricing for short-haul flights in contexts with no credible threat of inter-modal competition in order to shed light on pricing behaviour in response to the pure air-related competition. To this end, we analyse a market, southern Italy, which definitely shows a highly limited degree of inter-modal competition. For the connections considered, in fact, services by alternative modes, including road transport, require, on average, more than seven times the same travelling time as airline connections. Thus, for these peripheral areas, air transport is often the only realistic alternative. We can assume, therefore, that airline-pricing strategies are the straight result of air-related competition. The pricing behaviour of airline companies also shows high variability of fares per mile that unlikely can be justified by cost differentials. The fare differentials might, instead, be considered as evidence of different degrees of market power with the capacity to determine mark-ups.

In this paper, we address two issues. The first is to measure the extent to which intra-modal competition determines fares. The second is to shed light on the inter-temporal profile of fares in order to verify whether airlines engage in IPD, and whether IPD is of the monopolistic-type or the competitive-type. As for the former type, market power is required to price discriminate as it enhances the ability of firms to set and maintain higher mark-ups (Tirole, 1988). As for the latter type, market power is not required to sustain price discrimination if consumers show heterogeneity of brand preferences (Borenstein, 1985 and Holmes, 1989) or demand uncertainty about departure time (Dana, 1998).

The dataset we use to address the research question is unique. It covers routes that originate in southern Italy and that operated from November 2006 to February 2011.

Data on fares were collected from airline websites to replicate consumer behaviour when making reservations. Unlike previous contributions, we simulate the purchase of round-trip fares instead of one-way fares. In this way, we effectively replicate the demand side since travellers more often purchase round-trip tickets rather 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 is an effective competitor.

Our results on short-haul markets with no alternative modes of transport show that when there is less intra-modal competition, airlines set higher fares since they exploit the greater market power arising from a concentrated market structure. Specifically, a 10% increase of the market share allows carriers to post up to 6.4% higher fares. Consistent with the implementation of IPD, we find a non-monotonic profile of fares - which can be roughly approximated by a J-curve - with a turning point included in the interval of the 43th to 45th days before departure. We give new interpretations for the non-monotonicity of fares' inter-temporal profile, in addition to the existing ones. Indeed, on the one hand, the non-monotonicity would be the evidence that airlines exploit consumer-bounded rationality. Actually, a common wisdom among travellers is, "the later you buy, the more you pay for the ticket" thus price-sensitive consumers tend to buy in advance. Airlines, aware of this, can extract a greater surplus by setting moderately higher fares for very-early purchasers who will buy the tickets believing they are paying the cheapest fares. On the other hand, a higher fare for very-early purchasers can be seen as a fee for risk-aversion. Indeed, risk-averse travellers usually plan the trip well in advance as they would like to reduce travel uncertainty by making the best choice in terms of departure day and time. Therefore, airlines, by posting moderately higher fares at the very beginning, can extract an additional surplus from risk-averse travellers. Finally, we provide evidence of a competitive-type IPD, as airlines seem to be more likely to engage in IPD in more competitive markets.

The remainder of the paper unfolds as follows. In Section 2 we survey the relevant literature. In Section 3 we present the empirical strategy and in Section 4 we give a description of the data. In Section 5 we discuss the results and in Section 6 we draw conclusions. The robustness check is provided in the Appendix.

2 Literature Review

The literature on which the current work is based concerns pricing in air transportation and the factors influencing it. We initially review papers that analyse the effect of the airline market structure on fares, then we focus on works looking at price discrimination and, in particular, at inter-temporal price discrimination (IPD). We conclude the survey with contributions exploring the relationship between market structure and price discrimination.

The first to study the impact of market structure on fares was Borenstein (1989) on the US airline industry. He develops a model using market share at both route and airport level. Results indicate that market share, whatever measure adopted, influences the carrier's ability to raise fares since 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) point out that, when controlling for inter-route heterogeneity, market share on the route is no longer relevant in determining fares, that are, instead, determined 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 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 applied by British carriers, considering either the route or 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, while at 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 leads 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.

Concerning price discrimination, the main difference between static and inter-temporal price discrimination is that two different markets are covered in the former case, whereas the same market is periodically covered in the latter case. In a theoretical model with two time periods, Logfren (1971) shows that, for the same good, a seller applies higher prices to consumers with higher purchasing power in the first period and lower prices to consumers with lower purchasing power in the second period. Stokey (1979) implicitly extends Logfren's framework to continuous periods. She claims that IPD occurs when goods are "introduced on the market at a relatively high price, at which time they are bought only by individuals who both value them very highly and are very impatient. Over time, as the price declines, consumers to whom the product is less valuable or who are less impatient make their purchases."[1] In her paper, reference is made to commodities such books, movies, computers and related programmes. The concept, however, has had application to the airline industry where IPD consists of setting different fares for different travellers according to how far in advance the ticket is bought. However, in the airline industry, different from markets for commodities, the inter-temporal profile of fares is increasing. Using IPD, airlines exploit travellers' varied willingness to pay and demand uncertainty about departure time. 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. Travellers' heterogeneity appears to be a necessary condition to successfully implement price discrimination strategies. In a theoretical contribution, Alves and Barbot (2009) illustrate that low-high pricing is a dominant strategy for LCCs only if travellers, on a given route, show varied willingness to pay. Actually, 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. More recently, Möller and Watanabe (2010) investigate further on advance-purchase discounts versus clearance sales, showing that the former pricing strategy is preferred to the latter for airline tickets because their value is uncertain to buyers at the time of purchase, and reselling is costly or difficult to implement.

The inter-temporal profile of fares has been also empirically explored. McAfee and te Velde (2006) 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. Instead, Bachis and Piga (2007b), who examine UK connections to

[1] See page 355.

and from Europe, and Alderighi and Piga (2010), who focus on Ryanair pricing in the UK market, find a U-shaped fare inter-temporal profile. Gaggero and Piga (2010) show that fares for Ireland-UK connections follow a J-curve. Gaggero (2010) argues that there are 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 fare inter-temporal profile is J-shaped as it reflects a pattern opposite to that of travellers' demand elasticity.[2]

One strand of literature explores the relationship between market structure and price discrimination to find out whether airlines are more willing to engage in price discrimination strategies when markets are more or less competitive. Traditionally, market power enhances the ability of firms to price discriminate. A monopolist can set and maintain higher mark-ups.[3] In the oligopolistic airline 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 (leisure) travellers. However, Borenstein (1985) and Holmes (1989) show that market power is not required to sustain price discrimination if consumers show heterogeneity of brand preferences. Business travellers prefer the long-run savings given by loyalty programmes, whilst leisure travellers disregard carriers for short-run savings. Sorting consumers based on strength of brand preference is a successful strategy, and competition does not prevent firms from pursuing it. When competition increases, the mark-ups applied to leisure travellers decrease, whereas the mark-ups applied to business travellers remain almost unchanged. As a result, price discrimination increases as competition increases. Further, Gale (1993) proves that competition to conquer less time-sensitive travellers is stronger in an oligopoly than in a monopoly. Competition reduces fares on the lower end of the distribution, thus enhancing price dispersion. Finally, Dana (1998) shows that price discrimination, in the form of advance-purchase

[2] Abrate et al. (2010) show that in the hotel industry, hoteliers undertake IPD with two opposite trends. If a room is booked for the working days, last minute prices are lower. Instead, if a room is reserved for the weekend, last minute prices are higher.

[3] See Tirole (1988) Chapter 3.

discounts, does not require market power to be implemented. Consumers with more certain demands are willing to buy in advance because the presence of consumers with less certain demand could lead to an increase in prices.

Some empirical papers consider price dispersion as the result of price discrimination. Borenstein and Rose (1994) explore the US airline industry and provide evidence of competitive-type price discrimination: lower price dispersion arises in more concentrated markets. Consistent with this, Carbonneau et al. (2004) show that more competition is correlated with more price dispersion. Later, Gerardi and Shapiro (2009) revisit Borenstein and Rose's (1994) analysis.[4] They find the same results when they replicate Borenstein and Rose's (1994) cross-sectional model. However, they have opposite results when performing a panel analysis. Indeed, they provide evidence of monopolistic-type price discrimination: higher price dispersion arises in more concentrated markets.

Stavins (2001), instead, measures price discrimination through ticket restrictions.[5] Consistent with Borenstein and Rose (1994), she provides evidence of competitive-type price discrimination in the US airline industry: ticket restrictions reduce fares although the effect is lower for more concentrated markets. Using the cross-sectional model of Stavins (2001), Giaume and Guillou (2004) get to the same results on intra-European connections.[6]

Gaggero and Piga (2011) provide a seminal contribution on the effect of market structure on inter-temporal pricing-dispersion focussing on the routes connecting Ireland and the UK. Consistent with Gerardi and Shapiro (2009), they find that few companies with a relatively large market share can easily price discriminate.

In contrast to the aforementioned contributions, Hayes and Ross (1998) find no empirical evidence of price discrimination and market structure in the US airline industry. Price dispersion is due to peak load pricing and it is influenced by the characteristics of the carriers operating on a given route. Consistent with this, Mantin and Koo (2009) highlight that price dispersion is not affected by the market structure. Instead, the presence of LCCs among the competitors enhances dispersion by inducing FSCs to

[4] Gerardi and Shapiro (2009) explain that the panel approach allows them to estimate the effect of competition by accounting for changes in the competitive structure of a given route over time rather than changes in competitive structures across routes.

[5] Ticket restrictions are the Saturday-night stay-over requirement and the advance-purchase requirement.

[6] Besides the ticket restrictions used by Stavins (2001), Giaume and Guillou (2004) take into account some exogenous segmentations such as families, age groups, student status, and events.

adopt a more aggressive pricing behaviour.[7]

3 Empirical Strategy

We define two models. The baseline model accounts for the effect of market structure and IPD on fares. The extended model allows for IPD to vary with market structure.[8]

The baseline model:

$$\begin{aligned}\ln\left(P_{it}\right) &= \beta_0+\beta_1 MarketStructure_i+\beta_2 BookingDay_t \\ &+\theta_3 FlightCharacteristics_i+\theta_4 ControlDummies_{it} \\ &+u_{it}\end{aligned} \tag{1}$$

the extended model:

$$\begin{aligned}\ln\left(P_{it}\right) &= \beta_0+\beta_1 MarketStructure_i+\beta_2 BookingDay_t \\ &+\beta_3\left(MarketStructure_i * BookingDay_t\right) \\ &+\theta_4 FlightCharacteristics_i+\theta_5 ControlDummies_{it} \\ &+u_{it}\end{aligned} \tag{2}$$

where i indexes the round-trip flight and t indexes the time. Each flight i is defined by the route, the carrier and the date of departure and return. We have a daily time dimension that goes from 1 to 60.

The dependent variable is the log of the fares. The variable *Booking Day* captures the effect of IPD and ranges from 1 to 60. In order to account for the potential non-linearity of *Booking Day*, we also add *Booking Day* squared to the model.

We use two indices of market structure at city-pair level:[9]

- *Market Share*, the average share of the daily flights operated by an airline at the

[7] Alderighi et al. (2004) find that when an LCC enters a given route, the FSC incumbent reacts by lowering both leisure and business fares. Further, Fageda et al. (2011) note that traditional carriers are progressively adopting the management practices of LCCs. In particular, FSCs, through their low-cost subsidiaries, are able to price more aggressively, and hence successfully compete with LCCs.

[8] The idea of measuring the net effect of price discrimination from varying the market structure has been inspired by the approach of Stavins (2001).

[9] We do not compute market structure variables at route-level because, working with a peripheral area, almost all the carriers could operate as a monopolist on a given route. We need the city-pair level to capture the real competition between carriers.

two endpoints of a city-pair;[10] and

- *Herfindahl-Hirschman Index* (HHI), based on *Market Share*.

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 provided by LCCs, 0 otherwise.

Control dummies are:

- *Route dummies* to capture route-specific effects, demand and cost (or price) differences;
- *Year dummies* to account for macroeconomic factors equally affecting all flights in each year;
- *Month dummies* to capture seasonal effects;
- *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);[11] and
- *Stay dummies* to control for the length of stay (i.e. how many days elapse between departure and return).

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

[10] Market structure would be more appropriately calculated using revenue passenger-miles (RPM), while we base our calculations on the amount of daily flights. This choice is due, basically, to data constraint. At the moment, in fact, data on RPM are not available at flight-level for European connections and, thus, the best proxy of market structure is based on data on the number of flight provided, which are publicly available. For the same reason, a measure based on daily flights is used also by Gaggero and Piga (2010, 2011).

[11] Based on Gaggero and Piga (2011).

We want to estimate coefficients of time-invariant variables, therefore 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_i. The Robust Hausman test using the method of Wooldridge (2002) is performed after each regression to test the validity of that assumption and, hence, the consistency of RE GLS estimates.[12]

We assume that the market structure is exogenous. Basically, we agree with Stavins (2001), claiming 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)."[13] Moreover, in the European Union there are the "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. In the short run, then, market structure can be assumed to be fixed.

However, one might argue that capacity is always designed to accommodate planned demand. Even in a slotted-constrained airport, if demand is clearly below capacity, carriers adjust capacity and reallocate flights between routes. Therefore, even if the overall airport capacity is fixed, route-level capacity is not necessarily fixed, even in the short run. If this applies in our sample, Market Share and HHI are potentially correlated with ε_{it}. Therefore, we also employ the GMM estimator to obtain coefficients. We use instruments designed by Borenstein (1989) and largely adopted in the related literature.[14] *Market Share* is instrumented with *GENP* and Log(*Distance*), whilst *HHI* is instrumented with *QHHI* and Log(*Distance*).

GENP is the observed carrier's geometric mean of enplanements at the endpoints divided by the sum across all carriers of the geometric mean of each carrier's enplanements at the endpoint airports:

$$GENP = \frac{\sqrt{ENP_{k,1} * ENP_{k,2}}}{\sum \sqrt{ENP_{j,1} * ENP_{j,2}}} \tag{3}$$

where k is the observed airline and j refers to all airlines.

QHHI is the square of the market share fitted value plus the rescaled sum of the

[12] See Wooldridge (2002), pp. 290-91

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

[14] See, for instance, Borenstein and Rose (1994), Gerardi and Shapiro (2009), Gaggero and Piga (2010). For a more detailed description of the instruments see Borenstein (1989) pp.351-353.

squares of all other carriers' shares:

$$QHHI = \widehat{MS} + \frac{HHI - MS^2}{(1 - MS)^2}\left(1 - \widehat{MS}\right)^2 \quad (4)$$

where MS stands for the *Market Share* and $\widehat{MS}$ is the fitted value of MS from the first-stage regression.

Log(Distance) is the logarithm of the distance in kilometres between the two route endpoints.

In the extended model we add the interaction between *Booking Day* and *Market Share* or *HHI*. The interaction could be endogenous too, thus we include, as an additional instrument, the interaction between *Booking Day* and *GENP* or *QHHI*, respectively.

4 Data Collection

Data on fares were collected to replicate real travellers' behaviour when making reservations. First, we identify plausible round-trips, then we retrieve data directly from airlines' website by simulating reservations.[15] We observe fares daily, starting generally at sixty booking-days before departure. However, for some round-trip flights we have less than sixty observed fares, thus the panel is unbalanced. We define a dataset comprised of 19,605 observations on 427 round-trip flights from November 2006 to February 2011. Our sample includes 10 city-pairs (see Table 1) and 11 airline companies.

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

Table 1. List of city-pair markets

Origin	*Destination*
Bari	Milan
Bari	Rome
Brindisi	Milan
Brindisi	Rome
Catania	Milan
Catania	Rome
Naples	Milan
Naples	Rome
Palermo	Milan
Palermo	Rome

We consider both FSCs and LCCs (see Table 2); thus we choose the basic services (no add-ons) to make carriers' supply effectively comparable.

Table 2. List of airline companies.

Full Service Carriers	*Low Cost Carriers*		
AirOne	Alpieagles	Meridiana	Volare Web
Alitalia	Blu Express	MyAir	WindJet
Lufthansa	EasyJet	Ryanair	

We simulate the purchase of round-trip tickets, which gives us several advantages. Firstly, we effectively replicate the consumer behaviour since travellers mostly purchase round-trip tickets rather than one-way tickets.[16] In addition to that, we precisely recreate the market structure as we can clearly see whether, for each round-trip flight, a given carrier is a feasible alternative for travellers and an effective competitor. The use of round-trip fares also allows us to account for peak-periods and to verify whether airlines adjust the pricing behaviour during phases of greater travel demand. Further, one-way ticket pricing differs depending on carrier type. For FSCs, a round-trip fare is lower than the sum of the corresponding two one-way fares. This pricing policy is not adopted by LCCs. To avoid distortions, previous contributions, using one-way

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

fares, limit the empirical analysis to LCCs or to a few carriers. Instead, we do not encounter this problem and we are able to carry out a market analysis and compare pricing behaviour of all carrier types. In Table 3 we provide descriptive statistics.

Table 3. Descriptive statistics

Variables	*Obs*	*Mean*	*St. Dev.*	*Min*	*Max*
Fares	19,605	153.80	84.85	11.92	690.49
Market Share	19,605	0.405	0.286	0.065	1
HHI	19,605	0.497	0.203	0.225	1
Booking Day	19,605	24.672	14.889	1	60
Holiday	19,605	0.458	0.498	0	1
LCC	19,605	0.455	0.498	0	1

Our data sample has a good deal of variation in terms of both fares and market structure indices. In fact, we observe either monopolistic or more competitive markets.

Further, in Table 4, we report the average fares per mile posted by the incumbent airline providing services for the city-pair included in the empirical analysis.

Table 4. Average round-trip fares per mile posted by the incumbent airline.[17]

Connection	*Avg fare per mile*	*Connection*	*Avg fare per mile*
BRI-FCO-BRI	0.4260	PMO-LIN-PMO	0.1587
BRI-LIN-BRI	0.1832	PMO-MXP-PMO	0.1225
BRI-MXP-BRI	0.2387	CTA-FCO-CTA	0.2594
BDS-FCO-BDS	0.3086	CTA-MXP-CTA	0.1421
BDS-LIN-BDS	0.1588	NAP-FCO-NAP	0.8788
BDS-MXP-BDS	0.1332	NAP-LIN-NAP	0.1976
PMO-FCO-PMO	0.2548		

From each origin, connections to Rome appear to be comparatively more expensive than connections to Milan, even though point-to-point distances to Rome are shorter than point-to-point distances to Milan. This could be only partially explained by the

[17] BRI = Bari; BDS = Brindisi; CTA = Catania; FCO = Roma Fiumicino; LIN = Milan Linate; MXP = Milan Malpensa; NAP = Naples; PMO = Palermo. Data on the distance between the two route endopoints are taken from the Word Airport Codes web site.

cost of fuel. For short-haul flights, approximately 35% of fuel is used on the take-off. Thus, the cost function is, strictly decreasing with distance. However, differences in fares do not seem to reflect only differences in costs, but, instead, would suggest that the incumbent airline applies different mark-ups to different connections. This preliminary evidence motivates an in-depth discussion on fares' determinants.

It is worth looking at Figure 1 that shows that the relationship between average posted fares and days prior to departure seems to be non-monotonic.

Figure 1. The intertemporal profile of fares.

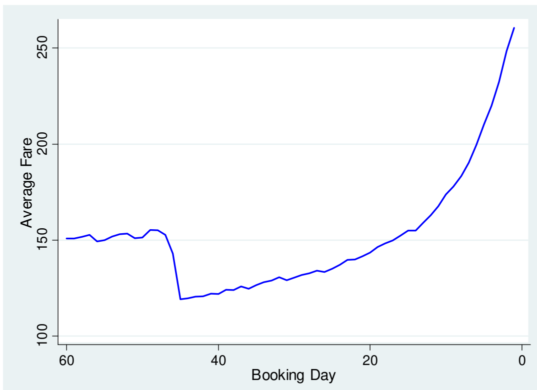
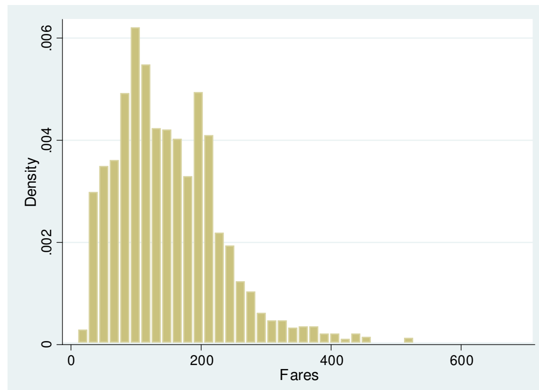


Figure 2. Density distribution of fares.



Airlines set the initial level of fares, subject to slight changes for, roughly, fifteen days, and then fares sharply decrease to the minimum level. Henceforth, airlines increase fares up to the departure day. The increment becomes steeper in the last fifteen days before departure. We look into this in depth when presenting regression results. Figure 2 shows the density distribution of fares. The mass of values is concentrated between 50 and 200 Euros.

5 Results

In each regression table we report both the results from RE GLS estimator and GMM estimator.[18] The results of the Robust Hausman test, which verify the assumption validity of uncorrelation between right-hand side variables and the unobserved heterogeneity, do not lead to the rejection of the null hypothesis, that the RE GLS estimator

[18] Current data on number of enplanements do not cover the whole sample of round-trip fares, so GMM estimations are carried out on a smaller sample.

is consistent.[19] Concerning GMM estimations, we report the results of some tests. The first one concerns the non-weakness of instruments. For all the regressions, the Kleibergen-Paap rk statistic - the robust analog of the Cragg-Donald statistic - is far greater than the critical value, therefore the null of the weakness of instruments is strongly rejected.[20] The second one is the Hansen J Test for the validity of the population moment conditions. For all the regressions, we fail to reject the null hypothesis, that the over-identifying restriction is valid, thus the instruments are not correlated with the error term. Finally, the third one is the Exogeneity Test for market-structure variables. We fail to reject the null hypothesis of exogeneity of either Market Share or HHI for all the specifications. GMM estimates are also very close to the RE GLS estimates. This underlines the robustness of the results.

Estimation results reported in the tables contained in this section are organised as follows: columns (1), (2), (5) and (6) report regressions' output using the variable *Market Share*, whilst columns (3), (4), (7) and (8) report regressions' output using the variable *HHI*.

Table 5 shows the results of the Baseline Model. *Market Share* and *HHI* have a positive and highly significant impact on fares. According to RE GLS estimates, holding constant other variables, a 10% increase in *Market Share* leads to 6.4% higher fares, and a 10% increase of *HHI* leads to 5.7% higher fares. Results are similar to GMM estimates. Indeed, a 10% increase in *Market Share* results in 6.9% higher fares, and a 10% increase of *HHI* results in 8% higher fares.

[19] We find support for the use of the RE-GLS estimator for two main reasons. 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 which might be enough to make the fixed effect unnecessary. Actually, we include in the regressions a rich set of control dummies that, given the Hausman test's results, are able to account for much of the variance in the data. Then, the RE-GLS estimator corresponds to the FE estimator, and 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 consistent as t is equal to infinity.

[20] Critical values were computed by Stock and Yogo (2005) for the Cragg-Donald Statistic which assumes i.i.d errors. Results need to be interpreted with caution only if the Kleibergen-Paap rk Statistic is close to the critical values.

Table 5. Baseline Model.

	RE-GLS Estimates				GMM Estimates			
	Market Share		*HHI*		*Market Share*		*HHI*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Structure	0.0064***	0.0064***	0.0057***	0.0057***	0.0068***	0.0069***	0.0079***	0.0080***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0141***	-0.0353***	-0.0141***	-0.0353***	-0.0136***	-0.0331***	-0.0135***	-0.0331***
	(0.0005)	(0.0013)	(0.0005)	(0.0013)	(0.0005)	(0.0014)	(0.0005)	(0.0014)
Booking Day^2		0.0004***		0.0004***		0.0004***		0.0004***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Holidays	0.2082***	0.2112***	0.2310***	0.2341***	0.1836***	0.1883***	0.1990***	0.2041***
	(0.0521)	(0.0522)	(0.0554)	(0.0554)	(0.0597)	(0.0599)	(0.0623)	(0.0624)
LCC	-0.2249***	-0.2259***	-0.4047***	-0.4058***	-0.2481***	-0.2460***	-0.4281***	-0.4286***
	(0.0426)	(0.0426)	(0.0324)	(0.0325)	(0.0555)	(0.0556)	(0.0374)	(0.0374)
Hausman Test Statistic	0.843	2.141	0.085	1.645				
Hausman Test p-value	0.359	0.343	0.771	0.439				
Kleibergen-Paap Statistic					114.9	114.9	355.2	355.4
Hansen J Test Statistic					0.064	0.054	0.048	0.039
Hansen J Test p-value					0.800	0.817	0.827	0.844
Endogeneity Test Statistic					0.058	0.031	2.780	2.741
Endogeneity Test p-value					0.809	0.860	0.096	0.098
Observations	19,605	19,605	19,605	19,605	16,476	16,476	16,476	16,476

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

Stock-Yogo (2005) critical value is 19.93. *** p<0.01, ** p<0.05, * p<0.1.

Estimations are done, at first, with only the variable *Booking Day*. Its coefficient is negative and significant, meaning that airlines do engage in IPD. Indeed, fares posted the day before appear to be 1.41% lower. We then include *Booking Day* squared to the regression equation to check for the non-linearity, as the graphical investigation suggests. The coefficient of *Booking Day* squared is positive and highly significant. *Booking Day* has a negative effect on fares until the turning point is reached. Beyond that day, it has a positive impact on fares. In the non-linear case, the marginal effect of *Booking Day* on fares is dependent on the level of *Booking Day*: $\frac{\partial \ln(P_{it})}{\partial Booking\ Day_t} = -0.0353 + 2 * (0.0004)\ Booking\ Day_t$. We compute the marginal effect for given values of *Booking Day* which indicates how fares vary with respect to fares posted a day early.

Table 6. The marginal effect (β) of Booking Day (BD) on fares.

BD	β	*BD*	β	*BD*	β	*BD*	β
5	-0.0313***	35	-0.0070***	45	0.0011	51	0.0059***
	(0.0011)		(0.0005)		(0.0008)		(0.0010)
10	-0.0273***	40	-0.0030***	46	0.0019**	52	0.0067***
	(0.0009)		(0.0006)		(0.0008)		(0.0010)
15	-0.0233***	41	-0.0022***	47	0.0027***	53	0.0075
	(0.0008)		(0.0006)		(0.0008)		(0.0011)
20	-0.0192***	42	-0.0014**	48	0.0035***	54	0.0083***
	(0.0006)		(0.0007)		(0.0009)		(0.0011)
25	-0.0151***	43	-0.0006	49	0.0043***	55	0.0091***
	(0.0005)		(0.0007)		(0.0009)		(0.0011)
30	-0.0111***	44	-0.0002	50	0.0051***	60	0.0132***
	(0.0004)		(0.0007)		(0.0009)		(0.0011)

As shown in Table 6, from the 45^{th} day before departure, fares posted a day before are no longer cheaper. The marginal effects are not statistically different from zero at days 43^{th}, 44^{th} and 45^{th} before departure, indicating, thus, that the minimum of the J-curve occurs in the interval of 43^{th} to 45^{th} days.

The non-monotonicity of the fare's inter-temporal profile has received various interpretations in the literature. As stated earlier in the literature review, Gaggero (2010) explains that the non-monotonicity is determined by travellers' demand elasticity. Indeed, he identifies three categories of travellers with different demand elasticity and purchase timing. Early-bookers have a slightly inelastic demand. For instance, families are 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 looking at different holiday destinations. Late-bookers reveal an inelastic demand, such as the business traveller typically booking the ticket a few days before departure, with fixed travel dates and destination. Instead, Bilotkach et al. (2012) claim that fare-drops occur when the actual demand is below the expectation. Therefore, airlines might periodically reduce fares in order to respond to the need of raising the load factor.

Although we share the previous arguments, we propose two new interpretations. We think, in fact, that the J-shaped fare distribution might also be generated by other factors. Travellers generally believe that they can save money by buying in advance. Therefore, setting moderately higher fares for very-early purchasers seems to be a good pricing strategy for airlines since travellers will buy the tickets anyway, believing to be paying the cheapest fare. With this line of reasoning, the non-monotonicity might be seen as the result of consumer-bounded rationality.

Furthermore, travellers are also heterogeneous in terms of risk-aversion. There are risk-averse travellers who do strongly prefer to plan the trip well in advance in order to make the best choice in terms of departure day and time, thus reducing the overall travel uncertainty. Therefore, higher fares at the very beginning of the inter-temporal distribution might be considered as a fee for risk-averse travellers from whom the airline can obtain an additional surplus.

Coefficients of the control variables are those one might expect. The coefficient of Holiday is positive and significant. During peak-periods, airlines exploit the greater travel demand and set 21% to 24% higher fares than off-peak periods. The LLC's coefficient is negative and significant.[21]

In regressions with Market Share, LCCs appear to price 23% lower than FSCs, whilst in regressions with HHI as the predictor, LCCs appear to price 41% lower than FSCs. The different impact is due to the coexistence of Market Share and LCC in the same regressions. Actually, Market Share takes lower values when a carrier is a low cost one, thus it already captures the effect on fares induced by LCC.

Table 7 shows the results of the Extended Model I. Booking Day is still negative and significant, while its interaction with Market Share or HHI is positive and significant.

[21] This is in line with Bergantino (2009). She highlights that LCCs post half the fares of FSCs on some Italian connection at small airports.

The negative impact of Booking Day reduces in less competitive markets, therefore competition does not prevent airlines from using IPD strategies.

Table 7. Extended Model I.

	RE-GLS Estimates				GMM Estimates			
	Market Share		*HHI*		*Market Share*		*HHI*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Structure	0.0049***	0.0051***	0.0043***	0.0047***	0.0055***	0.0057***	0.0067***	0.0068***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0014)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0166***	-0.0375***	-0.0171***	-0.0374***	-0.0159***	-0.0350***	-0.0161***	-0.0354***
	(0.0008)	(0.0015)	(0.0013)	(0.0016)	(0.0011)	(0.0016)	(0.0014)	(0.0018)
Booking Day^2		0.0004***		0.0004***		0.0004***		0.0004***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
*Market Structure*Booking Day*	0.0001***	0.0001***	0.0001**	0.0000**	0.0001**	0.0000**	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Holidays	0.2088***	0.2118***	0.2321***	0.2348***	0.1842***	0.1888***	0.1995***	0.2045***
	(0.0521)	(0.0522)	(0.0554)	(0.0554)	(0.0597)	(0.0598)	(0.0624)	(0.0624)
LCC	-0.2263***	-0.2271***	-0.4049***	-0.4060***	-0.2472***	-0.2452***	-0.4278***	-0.4283***
	(0.0424)	(0.0424)	(0.0324)	(0.0325)	(0.0554)	(0.0554)	(0.0373)	(0.0374)
Hausman Test Statistic	0.942	2.325	0.109	1.709				
Hausman Test p-value	0.624	0.508	0.947	0.635				
Kleibergen-Paap Statistic					76.80	76.82	233.8	233.9
Hansen J Test Statistic					0.062	0.053	0.043	0.035
Hansen J Test p-value					0.803	0.819	0.835	0.852
Endogeneity Test Statistic					0.658	1.064	3.644	2.810
Endogeneity Test p-value					0.720	0.587	0.162	0.245
Observations	19,605	19,605	19,605	19,605	16,476	16,476	16,476	16,476

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

Stock-Yogo (2005) critical value is 14.43. *** p<0.01, ** p<0.05, * p<0.1.

The marginal effect of Booking Day is now given by: $\frac{\partial \ln(P_{it})}{\partial Booking\ Day} = -0.0375 + 2 * (0.0004)\ Booking\ Day_t - (0.0001) Market\ Share_i$ or $\frac{\partial \ln(P_{it})}{\partial Booking\ Day} = -0.0374 + 2 * (0.0004)\ Booking\ Day_t - (0.00004)\ HHI_i$. In Table 8, we report the marginal effects for values of Booking Day, setting Market Share and HHI equal to the sample mean. We compare these results with those obtained from the baseline regression (no interaction).The marginal effect of *Booking Day* is now given by In Table 8 we report the partial effects for values of *Booking Day* setting *Market Share* and *HHI* equal to the sample mean. We compare these results with those obtained from the baseline regression (no interaction).

Table 8. The marginal effect of Booking Day (BD) on fares by a 1% increase of Market Share/HHI

BD	β *(no interaction)*	β *(Market Share)*	β *(HHI)*
5	-0.0313***	-0.0311***	-0.0311***
	(0.0011)	(0.0011)	(0.0011)
10	-0.0273***	-0.0271***	-0.0271***
	(0.0009)	(0.0009)	(0.0009)
15	-0.0233***	-0.0231***	-0.0231***
	(0.0008)	(0.0008)	(0.0008)
20	-0.0192***	-0.0191***	-0.0191***
	(0.0006)	(0.0006)	(0.0006)
25	-0.0151***	-0.0151***	-0.0151***
	(0.0005)	(0.0005)	(0.0005)
30	-0.0111***	-0.0111***	-0.0111***
	(0.0004)	(0.0004)	(0.0004)
35	-0.0070***	-0.0070***	-0.0071***
	(0.0005)	(0.0005)	(0.0005)
40	-0.0030***	-0.0031***	-0.0031***
	(0.0006)	(0.0006)	(0.0006)
45	0.0011	0.0009	0.0009
	(0.0008)	(0.0006)	(0.0007)
50	0.0051***	0.0050***	0.0049***
	(0.0009)	(0.0009)	(0.0009)
55	0.0091***	0.0090***	0.0089***
	(0.0011)	(0.0011)	(0.0011)
60	0.0132***	0.0130***	0.0129***
	(0.0011)	(0.0013)	(0.0013)

In less competitive city-pair markets, the J-curve appears to be flattened. Differences between fares posted on different booking days are less pronounced. This finding is in favour of competitive-type price discrimination, in line with Borestein and Rose (1994), Stavins (2001) and Giaume and Guillou (2004), and in contrast to Gerardi and Shapiro (2007) and Gaggero and Piga (2011).

Table 9 illustrates the results of the Extended Model II by which we investigate IPD further. We test whether airlines adjust their pricing behaviour during phases of a greater travel demand. To this end, we add to the regression equation, the interaction between *Booking Day* and *Holiday*, which has a positive and significant impact on fares. The effect of *Booking Day* on fares for peak periods is 0.56% to 0.64% lower than for off-peak periods. Basically this is due to two facts. One the one hand, the greater travel demand allows airlines to decrease IPD because they can sell all the seats with no need of discounted fares. On the other hand, during holidays, travellers are more homogeneous, as people journey mainly for tourism. IPD, being based on the heterogeneity of travellers, becomes less effective. Furthermore, we focus on IPD strategies implemented by LCCs. To this end we employ the interaction between the *Booking Day* and *LCC*, which has a negative impact on fares. The effect of *Booking Day* on posted fares is 0.34% to 0.42% higher for LCCs than FSCs. LCCs engage in a stronger IPD, in line with the more aggressive pricing behaviour of LCCs.

Table 9. Extended Model II.

	RE-GLS Estimates				GMM Estimates			
	Market Share		*HHI*		*Market Share*		*HHI*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Structure	0.0064***	0.0064***	0.0057***	0.0057***	0.0068***	0.0069***	0.0079***	0.0080***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0154***	-0.0355***	-0.0154***	-0.0355***	-0.0137***	-0.0323***	-0.0133***	-0.0320***
	(0.0009)	(0.0015)	(0.0009)	(0.0015)	(0.0010)	(0.0015)	(0.0010)	(0.0015)
Booking Day^2		0.0004***		0.0004***		0.0003***		0.0003***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Holidays	0.0544	0.0763	0.0773	0.0992*	0.0683	0.0848	0.0880	0.1049
	(0.0572)	(0.0564)	(0.0602)	(0.0594)	(0.0639)	(0.0633)	(0.0666)	(0.0659)
*Holidays*Booking Day*	0.0064***	0.0056***	0.0064***	0.0056***	0.0046***	0.0041***	0.0044***	0.0039***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0010)	(0.0009)
LCC	-0.1279***	-0.1462***	-0.3068***	-0.3255***	-0.1147**	-0.1276**	-0.2855***	-0.3008***
	(0.0476)	(0.0465)	(0.0378)	(0.0364)	(0.0579)	(0.0564)	(0.0407)	(0.0392)
*LCC*Booking Day*	-0.0042***	-0.0034***	-0.0042***	-0.0034***	-0.0054***	-0.0048***	-0.0057***	-0.0051***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Hausman Test Statistic	9.329	10.809	10.505	12.133				
Hausman Test p-value	0.025	0.029	0.015	0.016				
Kleibergen-Paap Statistic					115.2	115.2	356.4	356.6
Hansen J Test Statistic					0.088	0.074	0.070	0.057
Hansen J Test p-value					0.767	0.786	0.791	0.812
Endogeneity Test Statistic					0.032	0.016	3.043	2.967
Endogeneity Test p-value					0.857	0.900	0.081	0.085
Observations	19,605	19,605	19,605	19,605	16,476	16,476	16,476	16,476

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

Stock-Yogo (2005) critical value is 19.93. *** p<0.01, ** p<0.05, * p<0.1.

6 Summary and Conclusions

This paper explores pricing in air transportation for short-haul markets, removing the influence of inter-modal competition. To that end, we use a unique dataset on the southern Italian market that exhibits limited inter-modal competition, thus airline pricing strategies are the straight results of air-related competition.

Basically, we explore two issues. The first is to measure the extent to which intra-modal competition determines fares. The second is to shed light on the inter-temporal profile of fares to verify whether airlines engage in IPD and whether IPD is of a monopolistic-type or a competitive-type. Results are robust across regressions. Further, the robust Hausman test shows that the RE GLS estimator provides consistent estimates.

We find that airlines exploit their dominant position on a city-pair market. When the intra-modal competition reduces, airlines post higher fares. Indeed, a 10% increase in Market Share leads to 6.4% higher fares, and a 10% increase of HHI leads to 5.7% higher fares. Further, we show that airlines do undertake IPD and that the fare inter-temporal profile appears to be non-monotonic, resembling a J-curve with a turning point included in the interval of the 43^{th} to 45^{th} days before departure. In addition to the existing interpretation on the non-monotonicity of fares inter-temporal profile, we set forward two new possible views. On the one hand, the non-monotonicity would be the evidence that airlines exploit consumer-bounded rationality. Travellers generally believe that the later the ticket is bought, the more it costs and, thus price sensitive consumers tend to buy in advance. Thus, airlines can, extract a greater surplus by setting moderately higher fares for very-early purchasers who will buy the tickets believing to pay the cheapest fares. On the other hand, a higher fare for very-early purchasers can be interpreted as a fee for risk-aversion. Airlines can extract additional surplus from risk-averse travellers by posting moderately higher fares at the very beginning of the selling schedule.

The empirical evidence is in favour of competitive-type price discrimination: a more competitive market structure fosters the implementation of IPD. Basically, in less competitive city-pair markets, the J-curve appears to be flattened. Finally, airline pricing strategies differ depending on carrier type. LCCs seem to adopt a more aggressive pricing behaviour as, on average, they set lower fares and undertake stronger IPD strategies.

One might say that price discrimination is only beneficial for airlines. However, in more competitive markets, airlines charge lower fares that, together with the IPD, allow them to target larger segments of demand, which leads to a "democratisation" of air travel. This is very important for areas as southern Italy where the inter-modal competition is limited.

Developments for future research could be an enlargement of the territorial coverage in order to compare different exogenously determined accessibility conditions and, thus, to measure the impact of air-related competition on accessibility. Moreover, it would be interesting to analyse the impact of local government subsidies often granted to low-cost airlines through co-marketing programmes on fares and pricing strategies, thus analysing the net welfare of the area in question.

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Appendix A

We have distinguished between carriers of two types: FSCs and LCCs. Indeed, we have assumed similar operating characteristics and pricing behaviour within types. For the robustness check we verify whether the results hold when a more detailed distinction is made and carrier dummies are added to the model. As shown in Table 10, estimates do not change when we make more specific hypotheses about the behaviour of each carrier.

Table 10. RE GLS estimates with carrier-specific dummies.

	Baseline Model				Extended Model I			
	Market Share		*HHI*		*Market Share*		*HHI*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Structure	0.0068***	0.0063***	0.0051***	0.0051***	0.0047***	0.0049***	0.0036***	0.0041***
	(0.0012)	(0.0011)	(0.0009)	(0.0009)	(0.0012)	(0.0012)	(0.0010)	(0.0010)
Booking Day	-0.0141***	-0.0353***	-0.0141***	-0.0353***	-0.0166***	-0.0375***	-0.0171***	-0.0374***
	(0.0005)	(0.0013)	(0.0005)	(0.0013)	(0.0008)	(0.0015)	(0.0013)	(0.0016)
Booking Day^2		0.0004***		0.0004***		0.0004***		0.0004***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
*Market Structure*Booking Day*					0.0001***	0.0001***	0.0001**	0.0000**
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
Holidays	0.2253***	0.2359***	0.2307***	0.2339***	0.2333***	0.2363***	0.2318***	0.2346***
	(0.0435)	(0.0442)	(0.0448)	(0.0449)	(0.0441)	(0.0442)	(0.0448)	(0.0448)
Hausman Test Statistic	0.011	1.821	0.065	2.541	0.088	2.081	0.119	2.666
Hausman Test p-value	0.916	0.402	0.798	0.281	0.957	0.556	0.942	0.446
Observations	19,605	19,605	19,605	19,605	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

*** p<0.01, ** p<0.05, * p<0.1.