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Hub Premium, Airport Dominance and Market Power in the European Airline Industry

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Abstract

Using evidence from an original dataset of more than 12 million fares, this study sheds light on two issues relating to the pricing behaviour of the main European airlines: 1) the extent to which an airline's dominant position at the origin airport, at the route and the city-pair level affects the airlines' market power; 2) whether fares follow a monotonic time path consistent with the pursuing of an inter-temporal price discrimination strategy. Our estimates reveal that enjoying a dominant position within a route is conducive to higher fares, possibly because of the limited size of many "natural monopoly" routes that facilitate the incumbent's engagement in a limit pricing strategy. On the contrary, a larger share within a city-pair does not seem to facilitate the exercise of market power, thereby suggesting the existence of a large degree of substitutability between the routes in a city-pair.

JEL classification: L11, L13, L93

Keywords: on-line pricing; price discrimination; dispersion; yield management.

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1. Introduction

The European aviation sector has gone through dramatic changes in the last decade, due to alterations of the legal, institutional and cultural environment. The legal and institutional transformations have influenced the supply side of the industry whereas new cultural attitudes seem to have changed the way passengers travel.

On the supply side, one cannot ignore the importance of the deregulation process implemented by the European Commission, which has transformed a highly regulated sector into a free-market industry.

The objectives of the air transport liberalization were achieved through different policy packages. In 1987 the Council of Ministers of the European community agreed a more liberal airfares system, declared the end of the principle of the equal sharing of capacity on routes served by airlines of two different member states, and opened up the market access to new companies.[1] In 1990 a second "package" of liberalisation measures reinforced the lifting of constraints on pricing and capacity, and further eased market access by allowing the entry of several companies on routes with high traffic density. More importantly, the European airlines were provided with the freedom of operating on most European routes. A third package finally came into force in 1993, effectively creating an "open skies" regime for the EU air transportation market. All the intra-European routes were finally open to free entry, and companies were allowed to operate without capacity or price restrictions, even on routes outside their own country (Ninth Freedom right). Furthermore, cross-border majority ownership was introduced, paving the way for member states carriers to buy or set up and run an airline in any EU country (Doganis, 2001).

Such new legal frame led inevitably to the privatization of some national carriers and the restructuring of their business model. Traditional airlines intensified the adoption of the hub-and-spoke-system, which, as a consequence of several mergers and acquisitions and the stipulation of alliances, has become in many cases a multi-hub-and-spoke system.[2] The old regulated airfares were replaced by sophisticated yield (also known as revenue) management techniques, whereby carriers improved their ability of managing seats availability and differentiating the product in order to segment the demand and optimize their revenue management. Traditional national airlines have so become known as Full Service Network Carriers or simply Full Service Carriers (FSC, hereafter) in virtue of the several "frills" attached to the different tickets.[3]

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[1] In this paper we define routes as airport-pairs.

[2] Hub and spoke system is a system of air transportation in which local airports offer air transportation to a central airport where long-distance flights are available.

[3] Examples are free on-board catering and newspapers, VIP waiting lounges, late boarding, fast check-in, and in-flight entertainment.

Another major effect of the deregulation within the European civil aviation industry has been the emergence of a new class of companies, known as low-cost carriers (LCC, hereafter).[4] Such companies are characterized by a very simple organization and *modus operandi*, which provide them with a competitive cost advantage with respect to the FSC. Essential to their strategy is the no-frills policy and the running of point-to-point services, preferably from secondary and small airports, where landing tax and handling fees are cheaper, turnarounds are quicker, and therefore better fleet utilisation and staff productivity are achievable. The simplicity of the distribution mainly through the Internet is another key element, as airlines acquire the ability to bypass global distribution systems (GDS) fees and travel agents commissions.

As pointed out by Alderighi *et al.* (2004), however, the LCC's success cannot be fully explained without taking into account the structural changes on the demand side. Indeed, the increased mobility of goods and people accompanying the process of internationalization and globalization has strongly contributed to a rise in the use of air transportation by business travellers. Besides, both a less glamorous view of the flying experience and a shift from long stays to multiple and short holidays, seem to have made no-frills point-to-point short-haul flights the best suitable air service for many tourists (Graham, 2006). Low-cost airlines represent nowadays almost 30% of the European market, after just a decade of their first appearance, with expectations of a 40-50% share in the next future (Tretheway, 2004).

This paper contributes to the growing literature on the determinants of price tickets in the airline industry. The aim is to examine the pricing behaviour of the airlines based in the UK. Thus we will take into account the most relevant aspects of the airlines' price setting emerged in the literature on the US market, and gauge whether such stylized facts apply to the European case. Our empirical findings, based on primary data of more than 10 million fares, support the view of airport and route dominance as drivers facilitating market power and higher fares, although we do not find any evidence of a hub premium since we find LCC tend to set higher fares outside their main hub airport. We also investigate the extent to which fares differ across airlines and at different times before a flight's departure.

In the next section we present a review of the literature on fare setting. In section 3 and 4 we present the data set and the methodology, whereas Section 5 and 6 illustrate the empirical model and results based on the UK aviation market between 2002 and 2005. Section 7 makes some concluding remarks and suggestions for future research.

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[4] Undoubtedly, the heart of the LCC's business model is represented by low costs rather than low fares. However, Piga and Filippi (2002) argue that since their inception, LCC have also pursued a product diffentiation strategy hinging around a careful choice of their departure and arrival airports. See Gil-Molto and Piga (2005) for an analysis of the entry and exit activity by LCC and FSC.

2. Fare setting in theory and practice

A - The role of yield management

Setting airfares and allocating aircraft seats is a complex process. Airlines have to deal with demand fluctuations, consumer heterogeneity, and the uncertainty about when and where passengers want to travel. In addition, aircraft capacity is limited and the nature of the product perishable, as unsold seats cannot be offered once the flight has departed (Alderighi *et al.*, 2004).

To deal with these challenges, airlines have developed over the years a set of techniques known as yield or revenue management (Weatherford and Bodily, 1992). Alderighi *et al.* (2004) distinguish between traditional and simplified yield management. The former is the one developed and implemented over the years by the FSC to cope with the new competitive environment that followed the liberalization process. The latter defines the set of techniques implemented by the LCC. In both cases, a central issue is the need to define and price certain product characteristics in order to accommodate passengers' heterogeneity and different willingness to pay.

Traditional companies, aware of travellers' different preferences, have tried to meet such heterogeneity by offering a differentiated product with a large variety of in-flight and ground services. Different airfares based on the different levels of service quality are therefore offered for the same flight. In addition, to ensure that each segment of travellers acquires its required level of service, companies apply "fences" such as minimum stays at the travel destination, penalties for ticket cancellation or travel date change, or purchase time limits. [5]

FSC offer such differentiated products through reservation classes that reflect the market segmentation. To each fare class a certain number of seats must be allocated in order to optimally accommodate the total demand. This crucial forecasting activity is known as inventory control, and it is applied to all flights operated by each airline in its own network.[6]

In particular, purchase time limit is a "fence" that has gained more and more importance within the yield management. The conventional wisdom holds that carriers tend to attach monotonically increasing airfares to sequential booking classes in order to cope with the uncertainty over demand (Dana, 2001). McGill and Van Ryzin (1999) refer to the latter practice as "low-before-

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[5] Fences are defined as "rules that regulate the ticketing purchase and the conditions imposed on each traveller category" (Alderighi *et al.*, 2004: p 5).

[6] The inventory control is implemented by means of sophisticated computer reservation systems (CRS) and global distribution systems (GDS). CRS and GDS have been used in the past to present biased information to both travel agents and consumers (Borenstein, 1989). By doing that the airlines that own such devices aimed at gaining pricing power over their competitors. Nowadays, however, thanks to *ad hoc* legislation, several mergers, alliances and code-sharing agreements, and the use of the Internet as a sale tool, such practises seem to have lost relevance.

high fares" and explain that it is due to the assumption that booking requests arrive in strict fare sequence, from the lowest to the highest as the date of departure nears.

Many scholars have devoted their attention to the existence of such airfare dynamics both from a theoretical (Belobaba, 1987; Gale and Holmes, 1992 and 1993; Dana, 1998) and an empirical point of view (Borenstein and Rose, 1994; Hayes and Ross, 1998; Stavins, 2001; Giaume and Guillou, 2004; Pels and Rietfeld, 2004; Piga and Bachis, 2007; Pitfield, 2005; Biloktach, 2006).

Belobaba (1987), for example, explains that monotonic fares respond to a situation in which transaction costs of adjusting prices to the incoming information about the actual demand are high for FSC, especially in the context of complex hub-and-spoke systems. Gale and Holmes (1993) argue that in a monopoly with capacity constraints and perfectly predictable demand, advance-purchase discounts (ADP, hereafter) are used to divert demand from peak periods to off-peak periods in order to maximize profits. In doing that airlines price discriminate across customers on the basis of their price elasticity and time valuation. Similarly, when the demand is uncertain APD help to improve profitability by spreading customers evenly across flights before the peak period is known (Gale and Holmes, 1992). Finally, Dana (1998) maintains that in competitive markets where prices are set before the demand is known firms find convenient to implement the "low-before-high-fares" principle in order to cope with uncertain consumer demand.

Stavins (2001) was the first to develop a model in which purchase restrictions and time of booking prior to departure were used as explanatory variables. Although the main objective of her study was to identify the relationship between price dispersion and concentration, her estimates also confirmed the idea that such ticket restrictions as the 14 days requirement, exert a negative and significant effect on fares. Giaume and Guillou (2004 and 2006) applied the same model to flights leaving from Nice (France) to several European destinations, finding further support for the monotonic property. More recently, Escobari (2006) has complemented Stavin's model with the load factors at the moment of ticket purchases concluding that airfares' monotonic increases over time are due to peak load pricing rather than inter-temporal discrimination.

What emerges from the past contributions is the ubiquity of monotonically increasing fares that is assumed to hold even in the simplified yield management developed by the LCC, with fares becoming more and more expensive over time. Such a received wisdom is challenged in Piga and Bachis (2007), who present evidence indicating that for some airlines the early booking fares may be higher than those available from four to two weeks prior to departure. It would therefore seem that the monotonic property does not adequately and fully describe the time profile of many LCCs' pricing schemes when on-line daily fares are used for the analysis.

This is probably related to the easiness with which fares can be changed online, due to low menu costs (Smith *et al.,* 1999). Digital markets possess characteristics that do not appear compatible with a monotonic temporal increase of the offered airfares. It has been argued for example that search and menu costs are very low on the Internet. Customers and competitors are thought to be able to easily track down companies' prices and find the cheapest fare available (Bailey, 1998; Bakos, 1991 and 1997; Baye and Morgan, 2001; Baye et al. 2002a, 2002b, 2003 and 2004; Bailys and Perloff, 2002). A strictly monotonic increase of fares over time does not seem to be compatible with the airline market where demand uncertainty forces the companies to adjust their fares according to demand and makes tacit collusion difficult to sustain.

In this study we have gathered primary data on prices posted at regular intervals before the scheduled departure date. Thus we can follow the inter-temporal variations of prices for each of the 420 company-route combinations in our dataset.

B. The role of market structure

The deregulation of the Civil Aviation sector implemented by the European Commission followed the one that took place in the USA in the late 1970s. The rationale behind the American deregulation process was that in a contestable market the threat of a potential entry by another company would be enough to prevent incumbent companies from wielding pricing power. Entry barriers would be indeed not existent, with free entry into airports and an almost perfect mobility of capital, i.e. aircrafts. The only route-related sunk costs would be represented by the costs of advertising, certainly negligible if compared to non route-specific costs, such as acquiring an aircraft. In such a competitive environment companies were expected to operate efficiently, incrementing travellers' surplus (Graham *et al.*, 1983).

A number of studies thus aimed at verifying whether such liberalization had affected U.S. airlines' ability to exercise market power (Graham *et al.*, 1983; Bailey *et al.*, 1985; Call and Keeler, 1985; Morrison and Winston, 1987; Reiss and Spiller, 1989; Borenstein, 1989 and 1992; Evans and Kessides, 1993; Kim and Singal, 1993; Peteraf and Reed, 1994; Stavins, 2001; Fisher and Kamerschen, 2003). The discovery that such pricing power had not been undermined over time led to move the focus of the analysis on to the sources of it. Graham *et al.* (1983), for example, drew attention to the fact that customers accustomed to a certain carrier and its schedule services would be hesitant to switch to a new operator, at least in the short period when the new company would be still pretty unknown. Borenstein (1989 and 1992) suggested that since incumbent airlines would be able to quickly and easily adapt prices and quantities in response to a new entry, they would be reluctant to take any action before such event had actually occurred. Furthermore, it should have been predicted that the airlines would have reacted to the new legislative system by implementing business strategies aimed at enhancing their competitive positions: such devices as frequent flyer programs (FFP), travel agent commission override bonuses (TACO) or biased booking due to CRS controlled by certain carriers are all institutions created and exploited by companies in order to limit competition and acquire pricing power (Borenstein, 1989).

Although there is general agreement on the failure of the contestability hypothesis and the existence of some market power in the airline industry, there does not appear to be consensus on the way the latter is achieved.

Borenstein (1989) for example developed a structural model whereby prices were regressed on market concentration measures both at airport and route level. Dominance at both levels result in higher fares for passengers, because a company leading at airport level becomes inevitably attractive also at route level thanks to the frequency of its services. Such attractiveness seems to enable dominant airlines to charge more for the same service with respect to its competitors. As for the sources of airport dominance itself, Borenstein (1989) argued that in addition to marketing devices such as FFP, TACOs and CRS, other factors should be considered. In particular, the incumbents' ability to inhibit potential competitors' capacity to obtain the necessary facilities for entry or expansion at a particular airport should not be underestimated.

Evans and Kessides (1993) and Evans *et al.* (1993), however, opposed such results arguing that they were biased by the lack of control for route heterogeneity. The argument goes that "primary impediments to intra- and inter-route mobility within the industry are airport facilities, product differentiation barriers arising from FFP, route-specific irrecoverable advertising and promotional expenditures. Otherwise, aircraft could be easily and costlessly switched among alternative routes rendering them naturally contestable" (Evans and Kessides, 1993: p. 73). Evans and Kessides' (1993) argument is that when inter-route heterogeneity is accounted for, dominance at airport level proves to be the only decisive factor for achieving market power.

That these studies report relatively similar findings suggests that the evidence for market power in the U.S. airline industry is quite strong. Such conclusion, nevertheless, cannot be automatically extended to the European market, for which the few existing contributions seem to rule out the presence of market power both before and after the liberalization process.

Captain and Sickles (1997), for instance, followed a reduced-form approach and showed that although price/cost mark-ups were relatively high between 1976 and 1990, they appeared to be determined more by high cost structures due to technically inefficient use of inputs rather than by the exercise of pricing power.

Carlsson (2004) and Giaume and Guillou (2004 and 2006) followed the common structural approach initiated by Borenstein (1989). By using data on European routes they both implemented a cross-section regression model in which the price of tickets associated with different company-route pairs is regressed on measures of market structure such as market share and concentration. Their results did not support the empirical findings for the U.S. market, as concentration appeared to have an insignificant or negative effect on the levels of price charged by European FSC. Giaume and Guillou (2004 and 2006) tried to find an explanation for such finding, arguing that it might be due to the fact that the European airlines markets are characterized by a small number of carriers on each route, and market share is the major determinant of route concentration. Non-monopolistic concentrated routes are indeed characterized by high inequality of market shares, which leaves the little carriers with the only option of competing on prices.

The most evident limitation of these studies is represented by the fact that they do not take account of the LCC. Such omission is not trivial, as it is legitimate to expect a different relationship between price setting and concentration in an environment where many of the traditional anti-competition devices are employed. Moreover, the papers aforementioned seem to fail from the methodological point of view. Evans *et al.* (1993) warned in fact that cross-section regressions of price on output tend to produce biased estimates for at least two reasons. First of all, concentration proves to be endogenous. Performance feeds back into structure, and this produces simultaneous equations bias. Second, concentration is a function of outputs and therefore endogenous and correlated with determinants of prices such as demand and factor prices. Since these determinants of price are measured with error, concentration measures are correlated with the error term.

The way suggested by Evans *et al.* (1993) to tackle these issues is to combine instrumental variables and fixed-effects in a panel data approach, although both Carlsson (2004) and Giaume and Guillou's (2004 and 2006) could only produce OLS estimates on the European market based on pooled data. The empirical approach in this study uses panel data techniques to shed light on the role played by airport and route dominance in European markets.

3. Data Collection

A- Collection Strategy

Most of the empirical contributions on pricing behaviour in the U.S. Civil Aviation industry have been conducted relying on different cohorts of the same dataset, namely the Databank of the U.S.A. Department of Transportation's Origin and Destination Survey, which is a 10 percent yearly random sample of all tickets that originate in the United States on U.S. carriers (Borenstein, 1989; Evans and Kessides, 1993; Borenstein and Rose, 1994; Hayes and Ross, 1998; Stavins, 2001). In these studies prices are measured as one-way fares and are computed as one-half of the reported fare round-trip tickets. All tickets other than one-way and round trips are excluded.

In contrast, our analysis is based on primary data on fares and secondary data on routes traffic, where a route is identified in this study as an airport-pair combination. The data contain airfares offered by the main British LCC over a span of 37 months, from June 2002 through June 2005. By using an "electronic spider" connected directly to their websites, we retrieved prices posted on 6 budget carriers' websites. We started by collecting airfares from *GoFly*, *Buzz*, *Ryanair* and *Easyjet*'s websites, but over the period of analysis *GoFly* was acquired by *Easyjet* (December 2002) and *Buzz* by *Ryanair* (March 2003). Moreover, new LCC began their operations during the period under investigation. The “spider” was so upgraded in 2003 to retrieve fares also from the *BMIbaby* and *MyTravelLite*’s sites.

Collection of fares for flights operated by Full Service Carriers (i.e., British Airways, Air Lingus, Air France, Lufthansa, KLM, Alitalia, Iberia, SAS, Tap Portugal, Air Europa, BMI British Midland, Czech Airlines and Swiss) started in March 2003: in this case, fares were collected only for flights that Full Service Carriers (FSC) operated on routes similar or identical to those where a LCC also flew.[7] This decision was necessary to reduce the number of queries made by the spider.

Fares from the UK for flights to and from the following Euro-adopting countries were obtained: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. The countries outside the Euro area were: Czech Republic, Norway, Sweden, Switzerland as well as the UK, whose domestic routes were also considered.

In order to account for the heterogeneity of fares offered by airlines at different times prior to departure, every day we instructed the spider to collect the fares for departures due, respectively, 1, 4, 7, 10, 14, 21, 28, 35, 42, 49, 56, 63 and 70 days from the date of the query. Henceforth, these will be referred to as “booking days”. So, for instance, if we consider London Stansted-Rome Ciampino as the route of interest, and assume the query for the flights operated by a given airline was carried out on March 1st 2004, the spider would retrieve the prices for both the London Stansted-Rome Ciampino and the Rome Ciampino-London Stansted routes for departures on 2/3/04, 5/3/04, 8/3/04, 11/3/04 and so on. The return flight for both types of directional journey was scheduled one week after the departure. For those routes where an airline operates more than one flight per day, all fares for every flight were collected. Thus, for every daily flight we managed to obtain up to 13 prices that differ by the time interval from the day of departure. The main reason to do so was to satisfy the need to identify the evolution of fares - from more than two months prior to departure to the day before departure – which has been noted to be very variable for the case of LCC (Pels and Rietveld, 2004; Giaume and Guillou, 2004).The spider could have retrieved any number of prices, but in practice the need to reduce both the number of queries made to an airline server and the time of programme execution to a manageable level, led to the design above. Furthermore, given the site characteristics of Opodo.co.uk, it was impossible to collect Full Service Carriers’ fares 1 and 4 days prior to departure: it was also decided to omit collecting fares from these companies for flights due to depart more than 49 days after the query. Thus, for Full Service Carriers, up to 8 fares per daily flight are available.

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[7] The airfares of the traditional companies were collected from the website www.opodo.co.uk, which is owned and managed by British Airways, Air France, Alitalia, Iberia, KLM, Lufthansa, Aer Lingus, Austrian Airlines, Finnair and the global distribution system Amadeus. Thus, fares listed on Opodo are the official prices of each airline, although Opodo may not report promotional offers that each airline may offer on their web sites.

The collection of the airfares has been carried out everyday at the same time: in addition to airfares we collected the name of the company, the time and date of the query, the departure date, the scheduled departure and arrival time, the origin and destination airports and the flight identification code.

Fares were collected before tax and handling fees for the case of LCC, but inclusive of them for the Full Service Carriers (henceforth FSC). In order to induce comparability between the two sources of fares, we added 10 Sterling pounds to each retrieved fare from a LCC.[8] Furthermore, fares for LCC were one-way, while those for FSC were for a round trip and were therefore halved.

To complement the price data with market structure characteristics, secondary data on the traffic for all the routes and all the airlines flying to the countries indicated above was obtained from the UK Civil Aviation Authority (henceforth, CAA).[9] For each combination of company, route and departure period (i.e., month/year), the CAA provided the number of monthly seats, the number of monthly passengers and the monthly load factors. These were broken down at the flight identification code level, that is, for each flight operated by all the airlines in a given month and route. However, in order to create a more balanced panel, fares and traffic statistics were aggregated at the route level for each airline.

B – Data analysis

A total of more than 10 million daily fares were retrieved, but because of the need to match daily data on airfares with monthly traffic information the sample used for the empirical analysis contains about 650,000 monthly-averaged fares' observations.

Tables 1a and 1b report average one-way fares by airlines and booking days before departure for different days of the week (corresponding to the week days – Tuesday to Thursday - and the week-end – Friday to Monday - timetables). The vast majority of the observations are relative to the LCC, and in particular to *Easyjet* and *Ryanair*, which alone account for more than 350,000 observations. The two main British FSC are also highly represented: *British Airways* with more than 30,000 observations and *BMI* with almost 15,000, to which one should add the observations of its low-cost subsidiary, *BMIbaby*. Recall that routes offered by the FSC were selected only for those markets (identified by city pairs, e.g., London to Paris) where at least a LCC also operated.[10] The number of observations for the traditional companies is understandably reduced.

****TABLES 1a and 1b approximately here ***************

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[8] £10 was in fact the average amount of taxes that customers were asked to pay across companies and routes over the period under investigation.

[9] See www.caa.co.uk

[10] In this paper we define city pairs as vast areas with different airports that serve the same market (Liu and Serfes, 2005).

Table 1a and 1b represent also a straightforward way to compare prices by competing companies in differentiated markets. Generally, airfares offered by the FSC are higher, especially during the week-end. The only exception seems to be *GoFly*, whose fares for early bookings appear constantly higher than those offered by most of the other airlines in our sample. Finally, it is worth noticing how *Air Europa* appears to implement a pricing policy similar to the one of the LCC, with very low levels of fares.

Fares for flights due to depart over the week-ends were on average higher than for services scheduled during the week. This seems to hold for both LCC and FSC, even if the magnitude of such fare-difference varies across companies in virtue of the different cost structures.[11]

An interesting feature of our dataset regards, however, the fact that fares offered for late bookings are consistently higher than those for early bookings. As pointed out by Doganis (2001), flights appear to be opened with low prices, but then fares are monotonically increased until they reach the maximum level right before the departure.

The average increase across companies seems to be within £30, even if important exceptions can be identified. In particular, *Ryanair*'s average fare 4 to 1 days before departure proves to be three times higher than the one offered 70 to 56 days before the scheduled date, for a total difference of around £50. *Easyjet*'s prices more than double their value over time, with an absolute change of around £40. Finally, it is noteworthy the temporal pricing behaviour of *Iberia*, whose fares tend to double in a period of time of just 40 days, and that of *Aer Lingus* and *Air Europa*, for which the offered airfares seem to slightly decrease over time.

These findings are further illustrated in Figures 1 and 2, where initial support for the observation that an airline charges more as the day of departure nears is presented. Figure 1 depicts the temporal evolution of fares offered by the UK-based LCC, and it seems to confirm that also budget airlines monotonically increase their prices over time in line with the traditional yield management. In particular, it is worth noting the pricing behaviour of *Ryanair*, *Easyjet* and *MTL*, whose prices not only steadily increase as the day of departure gets closer, but they also exhibit a large hike in the last week.

FIGURES 1 AND 2 APPROXIMATELY HERE ***********

Figure 2, in contrast, depicts the temporal fare variation of the European FSC operating from the UK. The general picture seems to be validated: prices move from the lowest levels seven weeks before the departure to the highest levels one week before the scheduled date for almost all carriers. Exceptions are represented once again by Aer *Lingus*, *Air Europa* and *Tap Portugal*, which present a flat if not decreasing line over time. As for *Iberia*, the graph backs up the idea that the Spanish carrier is the FSC whose fares are increased the most over time. It is important to compare

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[11] Airlines charge differently for different days of the week in order to maximize revenues. The rationales behind such policies are generally identified with discriminatory pricing and/or peak-load pricing.

the evidence in both figures with the findings in Piga and Bachis (2007), where many exceptions to the monotonic property of fares are shown. Since this study uses the same dataset as in Piga and Bachis (2007) but at a more aggregated level, we conclude that the evidence presented here indicates that the monotonic property holds on average, but it may prove invalid with highly disaggregated fares data where fare levels are driven by contingent demand situations.

Table 2a and 2b describe the UK market by the average number of companies at origin airports, routes and city pairs based on the data collected from the Internet. In order to show the reliability of our sample, we report in brackets the corresponding values do not differ significantly from the population ones, suggesting a good correspondence between our sample and the market as a whole.

***** TABLES 2a and 2b approximately here *********

A notable pattern emerging from Tables 2a and 2b pertains to the small number of airlines per markets. European airline markets are generally geographically small and characterized by short distances between major agglomerations, especially if compared to the U.S. situation (Giaume and Guillou, 2004). This entails that the total demand might not be sufficient to support the presence of many companies on the same route, also because of the presence of alternative transportation such as trains. Moreover, adjacent routes within the same city pair, i.e. London Heathrow-Rome (Ciampino) and London Stansted – Rome (Ciampino), or within a multi-city agglomeration, i.e. Manchester-Rome (Ciampino) and Liverpool-Rome (Ciampino), might be perceived as substitutes by customers, or presented as such by competing carriers, further reducing the room for the presence of many operators in the same market.

Table 2a shows that the average number of companies per routes operated by the LCC is generally less than two, whereas at city level the number rises to more than three. These values are lower than the ones reported in Table 2b for the FSC, in support of the idea that budget airlines tend to serve smaller markets than the traditional carriers. Such finding is further corroborated by the average number of airlines operating at airport level: UK-based LCC seem to operate from airports served by an average of 10 airlines against the average 20 carriers in airports served by the FSC.

This fact might not come as a surprise, but its consequences in terms of the relationship between prices and market structure might be important. By operating from and to small airports LCC are certainly able to avoid the direct competition of other companies, and thus acquire market dominance. Nevertheless, small airports tend to serve small and secondary markets, where demand for air services might not be as strong and continuous as in other bigger markets. Airlines might therefore find themselves in a position to have to create and stimulate the demand by keeping fares constantly low and by launching frequent offers. In such markets companies might indeed struggle to take advantage of their dominant positions, as filling aircrafts becomes the priority. The usual assumptions on the positive relationship between fares and market dominance might not hold, as the capacity to acquire pricing power might be hindered by the modest demand.

Although important, these findings are based on a partial analysis that does not take into account other potential factors affecting the fare-setting process. Furthermore, such an aggregate analysis ignores important information related to route and days of booking heterogeneity, whose fundamental role has already been highlighted in the literature.

4 Methodology

Two reduced-form models are estimated. The first is formally represented as follows:

$$\ln(P_{ijbdt}) = X_{1jt}^{'}\beta_1 + X_{2ijt}^{'}\beta_2 + X_{3it}^{'}\beta_3 + Z_{1i}^{'}\gamma_1 + Z_{2b}^{'}\gamma_2 + Z_{3d}^{'}\gamma_3 + \delta_{ijbd} + \varepsilon_{ijbdt} \qquad (1)$$

where *i* identifies the company, *j* the route, *b* the booking days prior to departure, and *d* the day of the week in which the flight is scheduled and *t* a given month. Thus P_{ijbdt} represents the mean value of all the daily fares observations for each *ijbd* group in month *t*. That is, for each month, average fares for an airline on a given route were thus calculated by using all the fares' observations in the different "booking days" and "days of the week" groups, which constitute important sources of heterogeneity.

The second approach aggregates over "booking days" and therefore considers the determinants of the average monthly price as a result of the different fares available at different points in time. That is:

$$\ln(P_{ijdt}) = X_{1jt}^{'}\beta_1 + X_{2ijt}^{'}\beta_2 + X_{3it}^{'}\beta_3 + Z_{1i}^{'}\gamma_1 + Z_{2b}^{'}\gamma_2 + \delta_{ijd} + \varepsilon_{ijdt} \qquad (2)$$

In both models, regressors may be time variant (the *X*s) and invariant (the *Z*s), while the errors are given by the sum of an unobserved effect (the δ) and an idiosyncratic component (the ε).

Comparisons between the estimates from (1) and (2) are assumed to yield interesting insights into what determines the level of fares offered by airlines, and in particular on the importance of temporal discriminatory pricing.

Equations (1) and (2) present several time-invariant variables, e.g., those reporting the booking days, which in a fixed-effects model would be not identified. At the same time the use of a random-effects model would not be appropriate given the potential correlation of some regressors with the unobserved effects. In order to obtain coefficients for those variables that do not vary over time, we rely on the method developed by Polacheck and Kim (1994) and further studied by Oaxaca and Geisler (2003). It is a two-stage Fixed-Effect (FE) estimation procedure for the consistent estimation of the coefficients of the time-invariant regressors. In the first stage each model is estimated using a panel data FE estimator to obtain the β_k^{FE}, where k=1...3. Then, such estimates are used to run the following heteroschedastic-robust OLS:

$$\ln(P_{ijbd\bullet}) - X'_{K\bullet}\beta_k^{FE} = Z'_{1i}\gamma_1 + Z'_{2b}\gamma_2 + Z'_{3d}\gamma_3 + \delta_{ijbd} + \varepsilon_{ijbd} \quad (1\bullet),$$

where $ln(P_{ijbd\bullet})$ and $X_{k\bullet}$ are the group means of the time variant dependent and independent variables and the β_k^{FE} are the estimated coefficients from the equations (1) and (2), *k=1..3*.

Given the potential endogeneity of some of the time variant and invariant regressors, both first and second stage are based on an Instrumental Variable (IV) procedure.[12] Furthermore, the first stage FE estimates are obtained using a heteroschedastic and panel autocorrelation-consistent variance estimator.

5 The empirical model

In this section, we first describe the variables used to estimate equations (1) and (2). In line with the literature, we estimate a pricing equation as a function of market demand characteristics, costs, discriminatory and peak-load pricing.

Market characteristics

Market structure is commonly seen as an important determinant of ticket prices, and so is market density. Thus, we control for the effect of market concentration and market dominance at airport, route and at city pairs level. Market dominance is generally measured as a company's share of scheduled flights or as its share of transported passengers, whereas market concentration is commonly measured through the Herfindhal index (HHI) of the same variables. Herer we employ the number of flights, in line with Borenstein (1989), Stavins (2001) and Giaume and Guillou (2004). We believe in fact that, since we are dealing with fares offered on-line and not with actual purchased tickets, the number of flights scheduled by airlines might be a better variable to use to reduce a possible endogeneity bias. Indeed, the number of flights is determined well in advance (normally in the preceding semester) and is therefore more dependent on the forecast of future demand rather than on the actual demand of seats. [13] The number of travelled passengers is a less suitable variable as it is recorded after tickets have been sold, and is thus more closely related to the levels of price.

We use the following variables for market concentration: *ORIGIN_HERF* - the HHI at the origin airport, *ROUTE_HERF* - the HHI at route level, and *CITY_HERF* - the HHI at city pairs level. As for market dominance, we define *ORIGIN_SHR* as the market share of each company at the origin airport, *ROUTE_SHR* as the share at route level, and *CITY_SHR* as the share at city pairs

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[12] Oaxaca and Geisler (2003) demonstrate the equivalence between the two-stage FE GLS estimates and the OLS coefficient estimates from a pooled cross-section, time-series model. However, since the estimated standard errors differ, they derive a test to discriminate between the two methods. In this paper, because of the potential endogeneity of some explanatory variables with the unobserved effects, we employ only the two-stage FE estimator.

[13] We are obviously aware of the relationship between past ticket prices, realized load factors and the number of scheduled flights. We will explain later how to tackle such potential endogeneity.

level. As shown in Table 3, a very high correlation characterises each pair of dominance and concentration variables. In order to tackle such multi-collinearity problem we use the market concentration and dominance variables separately.

***** TABLE 3 approximately here *********

Increases in both *ORIGIN_SHR* and *ORIGIN_HERF* are assumed to lead to greater market power and previous findings suggest they are linked to greater pricing power. The evidence on *ROUTE_SHR* and *ROUTE_HERF* is more mixed. Borenstein (1989) initially found a positive and significant relationship between route market power and price tickets within the American market, but then Evans and Kessides (1993) and Evans *et al.* (1994) argued that such result was biased by the lack of control for inter-route heterogeneity. More recently, Stavins (2001), Fischer and Kamerschen (2003) and Escobari (2006) have offered new evidence on the American market, indicating a positive and significant role played by route dominance, but a negative and sometimes insignificant role played by concentration. In line with these papers, Giaume and Guillou (2004 and 2006) found empirical evidence of a negative relationship between concentration and prices also for a subset of European markets.[14] The inequality in the market shares controlled by each airline within routes has been indicated in all these studies as the decisive determinant of carriers' pricing behaviour.

While *ROUTE_SHR*, *ROUTE_HERF*, *ORIGIN_SHR* and *ORIGIN_HERF* have been previously used, the impact of *CITY_SHR* and *CITY_HERF* on ticket prices has never been tested before. This is important because in small markets like the European ones it does make sense in fact to assume that airports within the same city, i.e. Heathrow, Gatwick, City Airport, Stansted and Luton in London, or in neighbouring cities, i.e. Milan-Bergamo and Verona-Brescia, serve the same market. Distances between airports are relatively small and it is therefore legitimate to assume that for travellers close airports might represent good, although somewhat imperfect, substitutes. This implies that it is competition at the market level, and not at the route level, that may limit an airline's ability to increase its fares.

A central econometric issue related to the use of market shares and Herfindhal indexes (HHIs) as right-hand side variables in a price equation is their possible endogeneity (Borenstein, 1989). One would assume in fact that a carrier's share of flights in a market is a function of the price it asks for it and it is therefore correlated with the error term ε In equations (1) and (2). The HHI, having as a component the square of the market shares, is expected to be also endogenous.

In order to tackle such endogeneity issue we have created instruments for market shares and HHIs at all levels of aggregation. The instruments employed for the market shares replicate the ones

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[14] These results might be biased by the fact that they do not take into account market control at airport level, and for Stavins and Fischer and Kamerschen also by the lack of control for routes' heterogeneity.

used by Evans and Kessides (1993): ORIGIN_SHR is instrumented through the intra-airport rank of the ORIGIN_SHR itself, ROUTE_SHR through the intra-route rank of ROUTE_SHR, and CITY_SHR through the intra-city pair rank of CITY_SHR. Ranks are calculated in a descending order, i.e. the largest firm on the market has a rank of one, the second of two, etc., so that the instrument is negatively correlated with market share and orthogonal to the idiosyncratic error ε.[15]

As for the HHIs are concerned, we developed instruments similar to those introduced by Hausman *et al.* (1994) and Hausman (1996), and used by Nevo (2000) and Gayle (2004). Given the specific and peculiar strategies implemented by the European airlines, we can assume that both LCC and FSC pursue a consistent and deliberate choice of which markets to serve. In this sense, the various HHIs can be thought to be influenced by a common strategy component specific to each airline, and therefore somehow correlated across markets. Thus we can assume that the HHI in market *j* is uncorrelated with airfares offered in markets *x* other than *j*. It follows that the HHIs associated to each airline in different markets segmented by type of market structure, i.e. monopoly, duopoly or oligopoly, can be used as instruments for each other. For each observation HHI_{ijbdt} - relative to company *i*, market (i.e. airport, route or city-pair) *j*, booking days prior to departure *b*, and day of the week *d* in month *t* – we therefore use as instrument the average HHIs reported in all the other markets $x \neq j$ operated by company *i* in month *t*, after controlling for the market structure.

In summary, this paper uses average HHIs associated to each airline in other markets to instrument for its HHIs in each market.

Market density is introduced through the variable *N_airports_to_destination*, which identifies the number of UK origin airports from which a flight to a given final destination is operated. *N_airports_to_destination* is a proxy for the importance of each destination and therefore for the popularity of the destination, which is possibly linked with its population size. Its sign is supposed to be positive, as the most served airports are also the most sought-after destinations, where demand is strong and product-elasticity low. Airlines are expected to be able to charge higher fares in these markets without losing customers.

Another variable capable of representing market structure is *D_LCC_FSC*, which is a categorical variable for the simultaneous presence of traditional and budget airlines in the same route. The effect of this variable is unsure. It can be negative as a consequence of an augmented competition brought forward by the LCC; or it can be positive if the LCC decide to charge slightly less than their competitors but still more than in the rest of their own network to take advantage of the strong and continuous demand that usually accompanies routes served by FSC. A positive sign of *D_LCC_FSC*, however, might be just a consequence of the higher fares charged by the FSC. A

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[15] Unlike Evans and Kessides we do not need to set the largest value of the rank at three for the different markets as most of them have already a maximum of 3 companies. More precisely, 90% of airports and routes and 99% of city pairs have less than 3 airlines.

comparison between the regressions for the full sample and those for the LCC-only sample might help to disentangle such intertwined effects.

Costs.

A potential determinant of airfares is represented by the cost of jet-fuel. We collected the Rotterdam (ARA) Kerosene-Type Jet Fuel Spot Price from the U.S. Department of Energy's web site and constructed the variable *ln_fuel_price*.[16] The relationship between changes in the price of air-tickets and the cost of fuel is assumed to be positive. However, two elements might concur to dilute such relationship. First, it is becoming a common practice among airlines to hedge fuel costs. By agreeing the purchase of great quantities of jet kerosene in advance, airlines manage to keep fuel costs constant and be less vulnerable to the unexpected fluctuation of petrol prices. Moreover, takeoffs and landings are highly inefficient and require up to 50% of a flight's fuel. Long routes, on which the fixed cost of the takeoff and landing is spread out, are expected to be less expensive to operate per mile. Thus, when analysing the role played by fuel costs it is essential to control for the economies of scale effect, captured by the route distance. The variable *ln_ROUTE_LENGTH* is thus included.

Both variables are expressed in natural logarithms to reflect the fact that their elasticities are expected to be less than one, as the cost of transporting a passenger increases less than linearly with the distance (Borenstein, 1989). Distance is supposed to have a positive effect on *ln_FARE* (Borenstein, 1989), as the longer the service time the higher the costs incurred to provide such service.

Finally, we use the qualitative variable *D_hub_LCC*, which takes value 1 when the origin airport matches the first hub opened in the UK by one of the LCC under investigation.[17] The hub dummy is usually employed to capture the hub dominance effect. According to Borenstein (1989), hubs are in fact strongholds that seem to insulate the dominant carriers from competition and allow them to charge higher fares to passengers who want to fly from such airports, without any substantial spill-over to the other carriers operating from the same airport. In light of this, one should expect *D_hub_LCC* to positively influence *ln_FARE*. However, we have argued above that one of the main characteristics of the LCC is its cost advantage with respect to the FSC. Such cost advantage is achieved, among other things, by means of favourable agreements with smaller airports, where handling and landing fees are lower, and landing and take-off operations are quicker because of the reduced air traffic and the presence of dedicated infrastructures.[18] This fact, along

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[16] Because these were reported in USD cents per gallon, the prices were converted using the euro/dollar exchange rate from Datastream.

[17] These airports are: East Midlands for BMIbaby; Stansted for Ryanair; Luton for Easyjet; Stansted for GoFly; Stansted for Buzz, and Birmingham for MyTravelLite.

[18] There are also examples of contracts in which airports commit themselves to provide the necessary advertising for the launch of new routes.

with the higher price elasticity of demand assumed in markets served by the LCC, might lead budget airlines to offer lower fares.

Time invariant dummies.

"Booking days" effects were taken into account by allowing the following values for *b* in the *ijbd* groups in equations (1) and (2): 4-1, 10-7, 21-14, 35-28, 49-42, 70-56, where these numbers represent how many days before departure the fares were retrieved. For each of these values a dummy variable was constructed, the first of which is the base case. The rationale for the inclusion of booking days dummies lies on the need to test the validity of the monotonic property: c*eteris paribus*, coefficients should be positive and monotonically increasing with respect to the base case.

By considering two specifications, i.e. one including the booking days dummies, the other without them, we aim at verifying whether failing to control for the fares' temporal profile might affect the interpretation of other regressors.

In order to control for peak-load pricing due to seasonal fluctuations, we introduce two seasonal dummies, the first for the months May and September (i.e. *D_Mid_season*), and the second for the months June, July, August and December (i.e. *D_High_season*), leaving the *D_Low_season* as the base. The dummy *D_weekend* is also thought to capture some peak-load pricing, as the week-ends are generally busier than the week days. *D_weekend* takes value 1 when days correspond to Friday, Saturday, Sunday and Monday. Finally, a dummy for each airline is included.

6 Results

Tables 4 and 5 present the results for equations (1) – where groups are distinguished according to how many days before departure the fares were retrieved - and (2) – where all the fares collected at different points in time before a flight's departure are aggregated - by using different measures of market power: market shares in Table 4 and the Herfindhal indexes in Table 5. Estimates are always reported for the full sample (LCC+FSC) and for the reduced one (LCC only). We begin the comment by looking at the estimates for the booking days' dummies, as these impinge on some of the other findings associated with the other regressors.

**** TABLES 4 and 5 approximately here *********

The role of the inter-temporal profile of fares.

One of the thrusts of this paper is to evaluate the extent to which the fares posted by an airline at different points in time prior to a flight's departure are responsible for fares' dispersion. Dummies for the different booking days before departure seem to suggest that airfares do actually monotonically increase over time. Buying a ticket between 70 to 56 days before the scheduled departure date produces, *ceteris paribus*, a discount of about 72% with respect to a fare posted between 4 and 1 days before the departure. Similarly, and always relative to the latter base case, advance-purchase discounts amount to about 56% for fares posted 35 and 28 days before the flight departs, and to about 30% for the "10 to 7 days" group. These findings confirm the previously discussed descriptive evidence that early booking fares tend to be cheaper, although this holds true only "on average", given the evidence presented in Piga and Bachis (2007). The rationale behind these pricing strategies (that seem to hold for both LCC and FSC) is simple: committing to a steep inter-temporal profile enables the companies to benefit from the implementation of inter-temporal price discrimination, leaving open the possibility of "randomly" (at least in the eye of the potential customer) reducing fares to manage stochastic demand efficiently.

The role of market structure.

The market share that a LCC enjoys in the origin airport (ORIGIN_SHR) appears to be highly correlated with the fare levels: more contrasting evidence is found in the full sample, where no significant impact is revealed in the case of fares aggregated across all booking days. It would seem, therefore, that airport dominance plays a crucial role for the FSC only for the fares associated to a particular set of booking days, i.e., the late booking ones. Table 5 reports that the airlines operating in a highly concentrated origin airport (ORIGIN_HERF) can benefit from a significant fare premium. That is, a 10 percent increase in ORIGIN_HERF is associated with about a 4-6 percent higher level of fares.

In the full sample of Table 4, we show how a fifty percent increase in an airline's market share in a route (this is tantamount to a comparison between a route with two identical firms and a monopolistic route) drives fares up by about 27 percent. The impact of ROUTE_SHR is much smaller in the LCC sample (about 15%) and is significant only when the fares are disaggregated at the booking days level, suggesting that the increase may be associated only with the late booking fares (see above). The latter finding is further supported by the estimates for ROUTE_HERF in Table 5, which are significant only when eq. (1) is estimated.

Enjoying a large market share at the city-pair level (CITY_SHR) does not seem to enable the airlines to post higher fares. This may be because of the large substitutability between routes within a city-pair, or even between routes in bordering city-pairs. A negligible impact is found when we consider the concentration index (CITY_HERF) in Table 5.

The positive sign of *N_airports_to_destination's* coefficient clearly suggests that on routes where demand is strong airlines can afford to offer higher fares, thanks to a low product elasticity of demand. It is noteworthy, though, that the effect on ticket prices is very limited, as the magnitude of the coefficient in both Table 4 and 5 reveals.

In the routes where there is direct competition between a LCC and a FSC (*D_LCC_FSC)*, we observe the effects vary in sign and magnitude depending on the type of sample used. Using the full sample, the coefficient is insignificant in Table 4 when eq. (2) is estimated, but positive and significant for the case of eq. (1). Always in Table 4, but using the LCC sample, the coefficients for both equations become negative: we conclude that fares are generally lower in these routes, but that the presence of a LCC does not deter a FSC from engaging in inter-temporal price discrimination and increasing their late booking fares. A similar conclusion can be reached by looking at the estimates in Table 5, where it is shown that late booking fares by the LCC may also be higher in these routes, suggesting that competition intensity may wane in the periods immediately preceding a flight's departure.

The role of costs.

In Tables 4 and 5, the logarithm of the distance in mile (ln_ROUTE_LENGTH) is as expected positively related to *ln_FARE* as shorter routes are cheaper to run (in absolute terms) than longer ones. The estimates show that an increase of 10 percent in the route's length leads to an increase of about 4 percent in fares. However, such a relationship is hardly linear, and this may be the reason why we find a negative and significant coefficient for *ln_fuel_price.* A complementary explanation may be associated with the long-term contracts that airlines sign with fuel companies, which hedged them from the risk due to the increase in the oil prices which occurred in the second half of our sample period.

The routes that the LCC operate from their hubs (*D_hub_LCC)* appear to be characterised by lower fares, especially in the case of Table 4. Following such statement, we can assume that the agreements signed between airports' authorities and LCC provide the latter with a competitive advantage. Such advantage, however, does not result in higher fares as theorized by Borenstein (1989), but rather in lower fares. Hub dominance by the LCC seems to be more related to the acquisition of cost advantages than to pricing power. As usual, we note that early booking fares for hub routes may drastically differ from late booking ones.

Other control variables

Among the other control variables, *D_season* and *D_weekend* are meant to capture peak-load pricing effects. Both dummies present a positive and significant coefficient, as expected. In particular, we show evidence in Tables 4 and 5 that fares in high season are about 8 percent higher than in mid season, and these are in turn 10-15 percent higher than in the low season (the base case). Similarly, tickets for week-end flights are on average 22-24 percent higher than those for flights scheduled during the week.

Finally, the airline dummies prove to be consistently significant across models and specification, confirming the existence of company specific effects.[19] As expected fares offered by the LCC are, *ceteris paribus*, cheaper than those posted by the FSC. For example, depending on the model's specification, *Ryanair*'s fares are between 11 and 33 percent cheaper than those posted by

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[19] To save space, Tables 4 and 5 report only the coefficients of the LCC and of the main Full Service Carriers. The full set of companies' estimates is available on request from the authors.

the base-case airline, *BMIBaby,* while *Alitalia*'s fares are between 40 and 50 percent higher than the latter. The estimates thus reflect the descriptive evidence discussed in previous sections.

7. Summary and conclusion

Using evidence from about 460 European company-route pairs over a period of 37 months, this study aimed to shed some light on two issues relating to the pricing behaviour of the main European airlines: 1) the extent to which an airline's dominant position at the origin airport, at the route and the city-pair level affects the airlines' market power; 2) whether fares follow a monotonic time path consistent with the pursuing of an inter-temporal price discrimination strategy.

Previous studies deemed the companies' strategic behaviour in the form of Frequent Flyer Programmes, incentivizing contracts to the Travel Agents and the use of Computer Reservation Systems as the source of an airline' airport dominance. Interestingly, we also find a positive relationship between an airline's market share at the origin airport and the fares it charges, especially when we limit the analysis to the sample of Low Cost Carriers. However, the latter do not make use of any of the above forms of strategic and marketing behaviour, suggesting that for the European markets a dominant position at an airport level cannot be based only on the received wisdom from the U.S. experience. Indeed our findings suggest that for the Low Cost Carrier segment, airport dominance is more likely to be a reflection of an airline's ability to operate at lower costs than the result of an airline's strategic behaviour.

Our estimates reveal that enjoying a dominant position within a route is conducive to higher fares, possibly because of the limited size of many "natural monopoly" routes that facilitate the incumbent's engagement in a limit pricing strategy. On the contrary, a larger share within a city-pair does not seem to facilitate the exercise of market power, thereby suggesting the existence of a large degree of substitutability between the routes in a city-pair.

Using fares aggregated at the monthly level, we find robust support to the assumption that fares follow a monotonic time path. The rationale for this strategy is well known: the airlines apply this second-degree price discrimination scheme when they face demand from consumers with more certain demand, who buy at early stage, while travellers with more uncertain demand purchase later and are forced to pay a premium (Gale and Holmes, 1993). We also argue, however, that the monotonic property holds on average, but in some of our previous work - when we consider fares disaggregated at the daily level -, we often observed late booking fares to be cheaper than fares posted earlier (Piga and Bachis, 2007).

From a policy viewpoint, our analysis reveals the dualism that characterises the European airlines' sector. On the one hand, we note the Traditional Carriers' group, which has found enormous difficulties in adjusting to the new post-liberalisation competitive environment. On the other, we find the Low-Cost Carriers segment, which consistently offers highly demanded services at very competitive prices and has been extremely active in expanding its operations by creating real pan-European networks. In particular, the liberalisation has produced two companies, Ryan Air and Easyjet, that after having consolidated their positions in the U.K. markets in the early post-liberalisation years, have expanded by creating hubs in practically every European country. They were also the first to enter massively in the East European countries that have recently enlarged the European Union, by connecting them with most other member States. Unfortunately, the dynamism of the U.K. market constitutes an isolated case in Europe, as no "low-frills company" equivalent in size to Ryan Air or Easyjet, has emerged in such countries as Germany, France, Italy or Spain. This may be due to the dominant position in each of these domestic markets still maintained by their former flag carriers. As discussed by Lee (2003), in the U.S. concentration dropped in the years immediately following deregulation, but then rose steadily starting in the mid 1980s reaching its peak in the early 1990s: this might also happen in Europe unless more effective competition is enabled in every national market.

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Table 1a. Fare breakdown by company, booking day and day of the week. Only LCC.

Company	***Days of the week***	***Days of booking before scheduled departure***						***Total Obs.***
		70-56	**49-42**	**35-28**	**21-14**	**10-7**	**4-1**	
Bmibaby	*week days*	42,41 (6923)	45,43 (4060)	49,54 (4156)	52,46 (4282)	56,67 (4346)	62,86 (4097)	27864
	week-end	52,15 (8849)	55,23 (5110)	59,25 (5171)	63,11 (5338)	67,00 (5484)	71,02 (5114)	35066
Ryanair	*week days*	25,85 (23948)	26,88 (14534)	28,96 (14884)	34,58 (15200)	46,99 (15448)	77,83 (15242)	99256
	week-end	36,90 (32020)	37,98 (19430)	39,96 (19841)	46,76 (20247)	59,48 (20604)	93,65 (20313)	132455
Easyjet	*week days*	39,20 (25124)	44,96 (15111)	49,29 (15420)	49,63 (15792)	55,78 (16129)	80,23 (16055)	103631
	week-end	49,07 (32114)	56,26 (19131)	61,76 (19417)	62,06 (19921)	66,49 (20301)	88,60 (20161)	131045
Buzz	*week days*	47,15 (822)	50,06 (704)	52,71 (758)	59,00 (828)	63,25 (771)	70,55 (762)	4645
	week-end	54,25 (1063)	60,48 (909)	64,05 (977)	72,02 (1060)	75,72 (987)	80,15 (971)	5967
GoFly	*week days*	57,14 (960)	61,67 (748)	63,54 (796)	70,97 (922)	75,40 (871)	84,79 (855)	5152
	week-end	69,33 (1277)	74,19 (996)	77,24 (1059)	83,88 (1227)	87,50 (1160)	90,06 (1138)	6857
MTL	*week days*	50,23 (1176)	49,91 (757)	50,59 (776)	52,22 (798)	55,38 (830)	83,16 (843)	5180
	week-end	55,76 (1829)	54,49 (1151)	55,30 (1184)	57,00 (1230)	59,48 (1284)	85,73 (1272)	7950
Total Obs. LCC		136105	82641	84439	86845	88215	86823	565068

Note: number of observations in parenthesis. Source: Fares retrieved from the airlines' web sites.

Table 1b. Fare breakdown by company, booking day and day of the week. Only FSC.

Company	***Days of the week***	***Days of booking before scheduled departure***				***Total Obs.***
		49-42	**35-28**	**21-14**	**10-7**	
Air Lingus	*week days*	77,55 (720)	75,25 (734)	74,61 (768)	72,93 (744)	2966
	week-end	83,37 (935)	82,66 (923)	84,83 (961)	86,68 (935)	3754
Air Europa	*week days*	47,67 (63)	50,05 (67)	49,45 (73)	50,09 (78)	281
	week-end	58,93 (101)	61,89 (100)	61,82 [(114)	64,45 (112)	427
Air France	*week days*	39,98 (139)	42,00 (139)	46,97 (150)	55,78 (146)	574
	week-end	42,69 (184)	45,28 (178)	50,94 (195)	57,32 (193)	750
Alitalia	*week days*	66,61 (428)	68,65 (439)	76,92 (464)	89,23 (456)	1787
	week-end	72,38 (561)	77,69 (574)	86,44 (591)	98,05 (592)	2318
BMI	*week days*	46,76 (1512)	49,32 (1520)	56,69 (1629)	71,15 (1599)	6260
	week-end	51,57 (2000)	54,50 (1955)	62,28 (2100)	74,16 (2082)	8137
British Airways	*week days*	59,12 (3637)	61,70 (3610)	70,86 (3876)	92,32 (3783)	14906
	week-end	67,07 (4815)	71,28 (4666)	80,42 (4996)	98,26 (4957)	19434
Czech Airlines	*week days*	64,14 (139)	67,19 (138)	71,80 (144)	78,43 (142)	563
	week-end	79,95 (182)	83,70 (172)	88,72 (186)	96,06 (184)	724
Iberia	*week days*	65,27 (461)	70,05 (468)	80,43 (498)	102,14 (499)	1926
	week-end	80,31 (610)	87,89 (601)	98,67 (647)	119,64 (640)	2498
KLM	*week days*	83,54 (275)	84,32 (275)	87,56 (292)	92,87 (288)	1130
	week-end	67,57 (360)	69,90 (351)	75,20 (376)	80,93 (370)	1457
Lufthansa	*week days*	60,28 (461)	61,34 (465)	64,73 (499)	73,87 (493)	1918
	week-end	58,30 (610)	59,48 (596)	63,73 (648)	71,64 (641)	2495
SAS	*week days*	66,78 (402)	68,57 (404)	73,97 (433)	79,40 (420)	1659
	week-end	70,77 (536)	73,01 (516)	79,16 (555)	86,93 (550)	2157
Swiss	*week days*	67,94 (430)	71,05 (431)	79,43 (464)	95,08 (453)	1778
	week-end	75,20 (573)	78,96 (556)	87,21 (596)	100,97 (577)	2302
Total Obs FSC		20228	19985	21366	21046	82625

Note: number of observations in parenthesis. Source: Fares retrieved from the airlines' web sites.

Table 2a. Number of companies by origin airports, routes and city pairs. Low-Cost Carriers.

Company	**Variable**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Obs**
BMIbaby	companies per airport	11 (9.9)	10.6 (9.3)	2 (2)	35 (36)	62930
	companies per route	1.4 (1.4)	0.6 (0.6)	1 (1)	4 (4)	
	companies per city pair	3 (3.1)	1 (1.0)	1 (1)	7 (8)	
Ryanair	companies per airport	8.4 (8.8)	4 (4.5)	1 (1)	36 (36)	231711
	companies per route	1.1 (1.2)	0.4 (0.5)	1 (1)	3 (3)	
	companies per city pair	2.5 (3.1)	1.5 (1.6)	1 (1)	9 (9)	
Easyjet	companies per airport	11.2 (9.7)	7.1 (5.9)	2 (2)	28 (26)	234676
	companies per route	1.4 (1.3)	0.6 (0.5)	1 (1)	5 (5)	
	companies per city pair	3.5 (3.9)	1.5 (1.5)	1 (1)	8 (8)	
Buzz	companies per airport	9.3 (9.1)	1.5 (4.1)	7 (1)	11 (23)	10612
	companies per route	1 (1.2)	0.2 (0.4)	1 (1)	2 (3)	
	companies per city pair	3.4 (3.5)	2.1 (2.3)	1 (1)	8 (8)	
GoFly	companies per airport	8.4 (8.1)	2.1 (2.0)	3 (3)	11 (15)	12009
	companies per route	1.4 (1.4)	0.6 (0.5)	1 (1)	3 (3)	
	companies per city pair	3.8 (4.0)	1.6 (1.6)	1 (1)	7 (7)	
MTL	companies per airport	16.1 (14.0)	2.2 (3.3)	14 (3)	28 (28)	13130
	companies per route	1.6 (1.5)	0.8 (0.8)	1 (1)	4 (4)	
	companies per city pair	3.7 (3.4)	1.4 (1.2)	1 (1)	7 (8)	
Total Obs. LCC						565068

Source: author's calculations based on the fares retrieved from the Internet and traffic data obtained from the Civil Aviation Authority. The latter corresponds to the universe of UK airports, whose values are reported in parentheses.

Table 2b. Number of companies by origin airports, routes and city pairs. Full-Service Carriers.

Company	**Variable**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Obs.**
Aer Lingus	companies per airport	19.5 (18.3)	5.4 (5.6)	11 (8)	36 (36)	6720
	companies per route	2 (1.9)	0.7 (0.7)	1 (1)	3 (3)	
	companies per city pair	3.2 (3.3)	1 (1.1)	2 (1)	5 (5)	
Air Europa	companies per airport	23.2 (20.5)	1.2 (1.7)	20 (17)	25 (23)	708
	companies per route	4 (3.6)	0 (0.5)	4 (3)	4 (4)	
	companies per city pair	6 (5.9)	0 (0.3)	6 (5)	6 (6)	
Air France	companies per airport	20.7 (16.7)	1 (6.9)	19 (4)	22 (36)	1324
	companies per route	3.6 (2.2)	0.6 (1.1)	3 (1)	5 (5)	
	companies per city pair	5.6 (4.1)	0.6 (2.0)	5 (1)	7 (8)	
Alitalia	companies per airport	20.9 (20.6)	1.2 (3.2)	19 (15)	25 (36)	4105
	companies per route	2.6 (2.6)	0.5 (0.6)	2 (2)	4 (4)	
	companies per city pair	5 (4.9)	0.1 (0.8)	5 (2)	6 (6)	
BMI	companies per airport	20.7 (17.6)	0.8 (7.2)	19 (2)	22 (36)	14397
	companies per route	2.4 (2.0)	0.9 (1.0)	1 (1)	5 (5)	
	companies per city pair	5.3 (3.8)	0.9 (2.0)	3 (1)	9 (9)	
British Airways	companies per airport	21.8 (18.9)	3.2 (6.8)	9 (1)	36 (36)	34340
	companies per route	2.1 (1.9)	0.7 (0.8)	1 (1)	4 (5)	
	companies per city pair	4.3 (3.5)	1.1 (1.7)	3 (1)	9 (9)	
Czech Airlines	companies per airport	20.7 (18.1)	1 (7.1)	19 (7)	22 (36)	1287
	companies per route	2 (1.8)	0 (0.7)	2 (1)	2 (5)	
	companies per city pair	3.7 (2.9)	0.7 (1.1)	3 (1)	5 (5)	
Iberia	companies per airport	20.6 (20.4)	1 (2.2)	19 (17)	22 (33)	4424
	companies per route	2.2 (2.1)	0.6 (0.8)	1 (1)	3 (4)	
	companies per city pair	4.4 (4.1)	1 (1.7)	2 (1)	6 (7)	
KLM	companies per airport	16 (13.1)	4.9 (8.0)	9 (1)	22 (36)	2587
	companies per route	2 (1.7)	1 (0.8)	1 (1)	4 (4)	
	companies per city pair	6.1 (3.2)	0.4 (2.1)	6 (1)	8 (9)	
Lufthansa	companies per airport	20.6 (18.4)	1 (6.2)	19 (5)	22 (36)	4413
	companies per route	2 (1.8)	0.1 (0.6)	2 (1)	3 (4)	
	companies per city pair	3.8 (3.1)	1.1 (1.4)	3 (1)	6 (6)	
SAS	companies per airport	20.7 (20.8)	1 (3.9)	19 (1)	22 (36)	3816
	companies per route	1.7 (1.7)	0.4 (0.4)	1 (1)	2 (3)	
	companies per city pair	2.8 (2.7)	0.7 (0.8)	2 (1)	4 (4)	
Swiss	companies per airport	16.2 (16.6)	5.1 (6.9)	9 (3)	22 (36)	4080
	companies per route	1.9 (1.6)	0.8 (0.8)	1 (1)	3 (3)	
	companies per city pair	3.7 (3.3)	0.6 (1.1)	3 (1)	5 (5)	
Tap Portugal	companies per airport	20.7 (20.4)	0.7 (1.4)	20 (17)	22 (23)	424
	companies per route	1 (1.6)	0 (0.5)	1 (1)	1 (3)	
	companies per city pair	4 (2.4)	0 (0.7)	4 (2)	4 (5)	
Total Obs. FSC						82625

Source: author's calculations based on the fares retrieved from the Internet and traffic data obtained from the Civil Aviation Authority. The latter corresponds to the universe of UK airports, whose values are reported in parentheses.

Table 3. Correlation among market concentration and market dominance measures.

	ORGSHARE	ORGHERF	RUTSHARE	RUTHERF	CITYSHARE	CITYHERF
ORGSHARE	1	-	-	-	-	-
ORGHERF	0.7215	1	-	-	-	-
RUTSHARE	0.4798	0.4006	1	-	-	-
RUTHERF	0.4741	0.3809	0.9494	1	-	-
CITYSHARE	0.1796	0.0306	0.3414	0.3122	1	-
CITYHERF	0.2115	0.0363	0.3361	0.3755	0.8916	1

Source: our calculations on both the fares and Civil Aviation Authority datasets.

Table 4. Panel Estimates for market shares on ln_FARE. D_ identifies a Dummy variable. t-statistics in round brackets.

Dependent variable: ln_FARE	**Full Sample (LCC+FSC)**		**Only LCC**	
INDEPENDENT VARIABLES	**2 STAGE FE Eq. (2)**	**2 STAGE FE Eq. (1)**	**2 STAGE FE Eq. (2)**	**2 STAGE FE Eq. (1)**
ln_fuel_cost	-0.101***	-0.003	-0.178***	-0.039***
	(0.010)	(0.000)	(0.009)	(0.00)
ln_ *ROUTE_LENGTH*	0.426***	0.403***	0.385***	0.388***
	(0.000)	(0.000)	(0.006)	(0.00)
D_hub_LCC	-0.044***	-0.091***	-0.426***	-0.106***
	(0.010)	(0.000)	(0.008)	(0.00)
ORIGIN_SHR	-0.100	0.272***	1.298***	0.356***
	(0.300)	(0.020)	(0.252)	(0.02)
ROUTE_SHR	0.546***	0.412***	0.072	0.291***
	(0.080)	(0.010)	(0.075)	(0.01)
CITY_SHR	-0.489***	-0.194***	-0.439***	-0.057**
	(0.090)	(0.020)	(0.086)	(0.02)
N_airports_to_destination	0.004***	0.001***	0.005***	0.001***
	(0.000)	(0.000)	(0.001)	(0.00)
D_LCC_FSC	0.021	0.026***	-0.118***	-0.018***
	(0.020)	(0.000)	(0.019)	(0.00)
D_Mid_season	0.105***	0.133***	0.133***	0.147***
	(0.000)	(0.000)	(0.005)	(0.00)
D_High_season	0.182***	0.201***	0.220***	0.216***
	(0.000)	(0.000)	(0.004)	(0.00)
D_weekend†	0.224***	0.230***	0.246***	0.246***
	(0.000)	(0.000)	(0.005)	(0.00)
D_RYANAIR†	-0.109***	-0.295***	-0.125***	-0.319***
	(0.010)	(0.010)	(0.009)	(0.01)
D_EASYJET†	-0.032***	-0.070***	-0.057***	-0.074***
	(0.010)	(0.000)	(0.007)	(0.00)
D_BUZZ†	0.255***	0.359***	0.879***	0.372***
	(0.010)	(0.010)	(0.013)	(0.01)
D_GOFLY†	0.165***	0.193***	0.490***	0.190***
	(0.010)	(0.010)	(0.013)	(0.01)
D_MTL†	-0.079***	0.034***	0.588***	0.063***
	(0.010)	(0.010)	(0.013)	(0.01)
D_AIR_LINGUS†	0.663***	0.797***	-	-
	(0.030)	(0.020)		
D_AIR_FRANCE†	0.449***	0.519***	-	-
	(0.020)	(0.010)		
D_ALITALIA†	0.394***	0.502***	-	-
	(0.020)	(0.010		
D_BMI	0.337***	0.408***	-	-
	(0.010)	(0.010)		
D_BRITISH_AIRWAYS†	0.473***	0.383***	-	-
	(0.010)	(0.010)		
D_IBERIA†	0.325***	0.461***	-	-
	(0.010)	(0.010)		
D_KLM†	0.659***	0.803***	-	-
	(0.040)	(0.040)		
D_LUFTHANSA†	0.463***	0.513***	-	-
	(0.020)	(0.010)		
D_10-7_days_before_departure†	-	-0.312***	-	-0.314***
		(0.010)		(0.01)
D_21-14_days_before_departure†	-	-0.472***	-	-0.473***
		(0.010)		(0.01)
D_35-28_days_before_departure†	-	-0.557***	-	-0.553***
		(0.010)		(0.01)
D_49_42_days_before_departure†	-	-0.626***	-	-0.625***
		(0.010)		(0.01)
D_70_56_days_before_departure†	-	-0.717***	-	-0.714***
		(0.010)		(0.01)
Constant	-	-	-	-
N	46253	646826	35170	564284
N second stage	25551	37549	21814	33399
R^2	0.1058	0.0852	0.0380	0.0955
R^2 second stage	0.4819	0.7351	0.4817	0.6509

‡ groups defined by company, route and days of the week. *groups defined by company, route, days from departure and days of the week. Standard Errors in the the FE models are robust to heteroscheDasticity and auto-correlation.

†Based on Oaxaca and Geisler (2003) and Polacheck and Kim (1994), the estimates from these time invariant dummies in the FE models are obtained from a second stage OLS estimation with White standard errors clustered over routes.

Note: *** significant at 1%, ** significant at 5%, * significant at 10%. Only the estimates of the most important Full Service Carrier are reported. The full set of estimates available from the authors on request.

Table 5. Panel Estimates for market concentration on ln_FARE. D_ identifies a Dummy variable. t-statistics in round brackets.

Dependent variable: ln_FARE	**Full Sample**			**Only LCC**
INDEPENDENT VARIABLES	**2 STAGE FE Eq. (2)**	**2 STAGE FE Eq. (1)**	**2 STAGE FE Eq. (2)**	**2 STAGE FE Eq. (1)**
ln_fuel_cost	-0.068***	0.032***	-0.159***	-0.010**
	(0.010)	(0.003)	(0.012)	(0.000)
ln_ *ROUTE_LENGTH*	0.407***	0.400***	0.400***	0.400***
	(0.003)	(0.003)	(0.004)	(0.003)
D_hub_LCC	-0.024***	-0.008*	-0.023***	-0.009*
	(0.005)	(0.004)	(0.005)	(0.004)
ORIGIN_HERF	0.596***	0.557***	0.395**	0.480***
	(0.140)	(0.034)	(0.135)	(0.034)
ROUTE_HERF	0.010	0.118***	-0.034	0.123***
	(0.029)	(0.006)	(0.032)	(0.007)
CITY_HERF	0.013	-0.024**	0.002	-0.032***
	(0.032)	(0.007)	(0.032)	(0.008)
N_airports_to_destination	0.008***	0.002***	0.006***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
D_LCC_FSC	0.028	0.068***	-0.032	0.031***
	(0.017)	(0.004)	(0.016)	(0.005)
D_Mid_season	0.100***	0.130***	0.135***	0.143***
	(0.004)	(0.000)	(0.004)	(0.001)
D_High_season	0.182***	0.200***	0.215***	0.214***
	(0.003)	(0.000)	(0.003)	(0.009)
D_weekend[†]	0.223***	0.230***	0.246***	0.246***
	(0.003)	(0.003)	(0.004)	(0.003)
D_RYANAIR[†]	-0.204***	-0.333***	-0.183***	-0.320***
	(0.006)	(0.005)	(0.006)	(0.005)
D_EASYJET[†]	-0.049***	-0.077***	-0.036***	-0.071***
	(0.006)	(0.004)	(0.006)	(0.004)
D_BUZZ[†]	0.368***	0.312***	0.332***	0.300***
	(0.010)	(0.007)	(0.010)	(0.007)
D_GOFLY[†]	0.230***	0.138***	0.193***	0.126***
	(0.012)	(0.006)	(0.013)	(0.006)
D_MTL[†]	0.046***	0.014	0.005	0.000
	(0.011)	(0.008)	(0.012)	(0.009)
D_AIR_LINGUS[†]	0.653***	0.739***	-	-
	(0.027)	(0.020)		
D_AIR_FRANCE[†]	0.340***	0.418***	-	-
	(0.022)	(0.013)		
D_ALITALIA[†]	0.405***	0.407***	-	-
	(0.016)	(0.014)		
D_BMI	0.355***	0.390***	-	-
	(0.010)	(0.008)		
D_BRITISH_AIRWAYS[†]	0.434***	0.422***	-	-
	(0.007)	(0.006)		
D_IBERIA[†]	0.400***	0.424***	-	-
	(0.012)	(0.009)		
D_KLM[†]	0.723***	0.800***	-	-
	(0.050)	(0.044)		
D_LUFTHANSA[†]	0.436***	0.443***	-	-
	(0.014)	(0.012)		
D_10-7_days_before_departure[†]	-	-0.311***	-	-0.313***
		(0.006)		(0.006)
D_21-14_days_before_departure[†]	-	-0.472***	-	-0.473***
		(0.006)		(0.006)
D_35-28_days_before_departure[†]	-	-0.556***	-	-0.553***
		(0.006)		(0.006)
D_49_42_days_before_departure[†]	-	-0.624***	-	-0.625***
		(0.006)		(0.006)
D_70_56_days_before_departure[†]	-	-0.716***	-	-0.714***
		(0.006)		(0.006)
Constant	-	-	-	-
N	46253	646826	35170	564284
N second stage	25551	37549	21814	33399
R^2	0.0801	0.0726	0.1447	0.0873
R^2 second stage	0.5674	0.6826	0.5098	0.6596

[‡] groups defined by company, route and days of the week. [*] groups defined by company, route, days from departure and days of the week. Standard Errors in the the FE models are robust to heteroschedasticity and auto-correlation.

[†] Based on Oaxaca and Geisler (2003) and Polacheck and Kim (1994), the estimates from these time invariant dummies in the FE models are obtained from a second stage OLS estimation with White standard errors clustered over routes.

Note: *** significant at 1%, ** significant at 5%, * significant at 10%. Only the estimates of the most important Full Service Carrier are reported. The full set of estimates available from the authors on request.

Figure 1. Temporal fare variation. LCC.

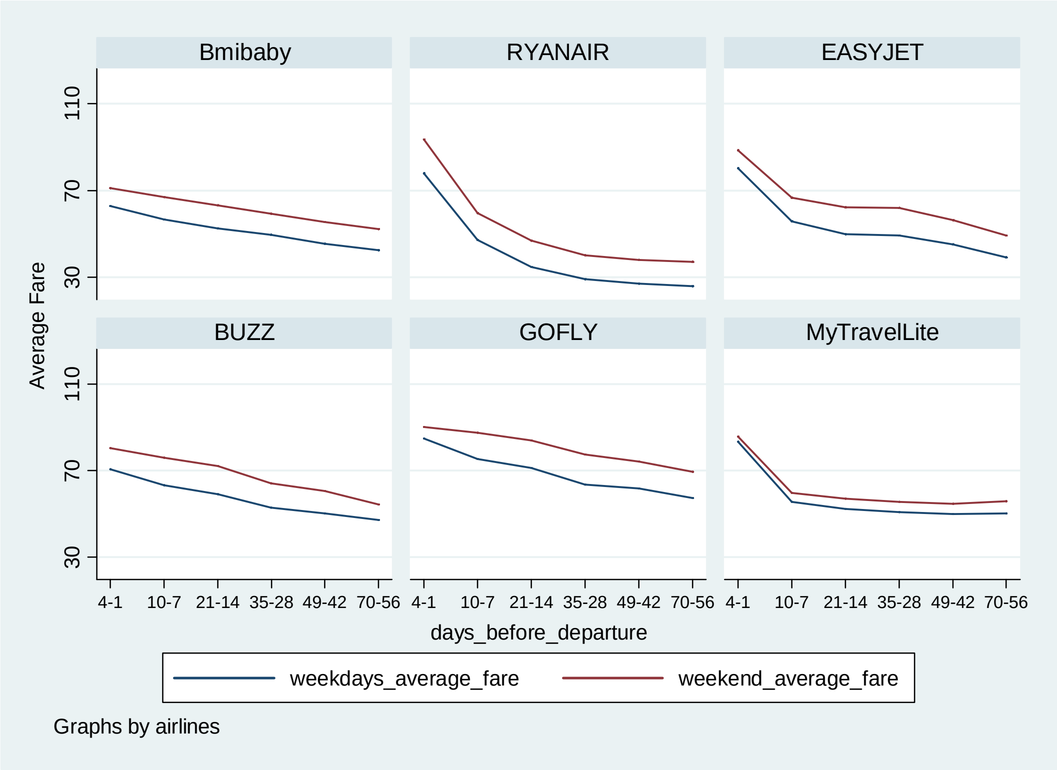

Figure 2. Temporal fare variation. FSC.