Pricing strategies by European traditional and low cost airlines: or, when is it the best time to book on line?

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July 2006

Abstract

It is often assumed that the airlines' fares increase monotonically over time, peaking a few days before the departure. Using fares for about 650 thousand flights operated by both Low-Cost and Full Service Carriers, we show several instances in which the monotonic property does not hold. We also show that the volatility of fares increase in the last four weeks before departure, which is the period when the airlines can formulate a better prediction for a flight's load factor. Finally, especially within the last two weeks, Full Service Carriers may offer lower fares than those posted by Low Cost Carriers.

JEL classification: L11, L13, L93

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

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1. Introduction

The conventional wisdom on the temporal profile of airlines' prices holds that carriers facing uncertain demand can enhance their profits by assigning a monotonically increasing price to different batches of seats (Dana, 2001). Such a recommendation arises from the fact that airlines have to set their price before demand is known, and that the transaction costs of adjusting prices in response to current information about demand are high. It is thus important to verify if the monotonic property is observed in situations where transaction costs are less relevant, i.e., for fares offered on the Internet.

In this article we use price information for about 650 thousands flights, collected from both some European Low-Cost Carriers' web sites and an online travel agent. The latter was used to retrieve prices for flights operated by traditional carriers. An important characteristic of our dataset is that for each flight operated by a Low-Cost Carrier (hereafter, LCC) we have up to 13 fares collected at regular intervals before departure, while for Full Service Carriers (FSCs) we could collect up to 9 fares posted before the flight's departure. Although other studies have used fares posted a number of days prior to departure (see, for instance, Pels and Rietfeld, 2004; Pitfield, 2005), these were usually for a very limited number of routes. A distinguishing feature of our approach is that we retrieved data for a large proportion of routes operated by the main LCCs, where they either are monopolists or face competition by other LCCs or FSCs. Therefore our analysis, by focussing on the features which are common across routes, enables us to draw general conclusions on the different online pricing schemes adopted by the airlines in our sample.

To this purpose, we present evidence that we directly relate to some recent contributions on pricing in electronic markets. More precisely, we try to address the following issues:

- Do fares increase monotonically as the date of departure approaches (Klein and Loebbecke, 2003)?
- Do fares change frequently, i.e., are there menu costs on-line (Brynjolfsson and Smith, 2000; Smith *et al.*, 1999)?
- Is it true that LCCs always offer the cheapest fares, or, consistent with a hit-and-run strategy, there is significant variation in the identity of the low-price firm in a competitive route (Baye *et al*, 2004b)?

While we observe consistent hikes for fares posted less than a week prior to departure, we also find 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. This is probably related to the easiness with which fares can be changed online, due to low menu costs (Smith *et al.*, 1999). Interestingly, prices tend to remain more stable when departure is further away in the future, while volatility increases as the date of departure approaches. Unexpectedly, FSCs tend to change their fares more frequently than LCCs.

As far as the identity of the low-price firm is concerned, the evidence confirms the notion that a LCC offers the lowest price in a competitive route. However, considerable differences are observed across LCCs, especially in conjunction to the distinction between early and late booking fares. Indeed, the same airline may offer the cheapest early booking fares but the dearest late booking fares. Furthermore, we show that a few days before departure it is not unlikely that a FSC may offer the cheapest fare.

The strategy used to collect the data has exploited some of the innovative features of the pricing schemes followed by LCCs (Pender and Baum, 2000; Piga and Filippi, 2002; Shon *et al.* 2003). For instance, consider some of the forms of price discrimination that have dominated the industry and that are highly documented in the literature: the Saturday night stay-over requirement, the surcharge for one-way tickets and the advance-purchase discounts (Stavins, 2001; Giaume and Guillou, 2004). The European LCCs have eliminated completely the first two forms: e.g., departing on a Monday and returning on a Thursday is likely to cost less than returning on a Sunday. In any case, each leg is priced independently and the same price would be shown on-line for the Monday flight if one tried to book a one-way ticket. An important implication of pricing each leg independently without any penalization for one-way tickets is to have severed the links between airport dominance and market power (Borenstein, 1989 and 1991). Indeed, the above-mentioned invariance of fares when booking a round-trip or two one-way tickets implicitly impedes the possibility to take advantage of airport dominance.[1] Furthermore, the European LCCs in our sample do not practice any of the marketing strategies indicated as the source of airport dominance (i.e., Frequent Flyer Programme, Travel Agents' Commissions Override programme etc).

As far as the advance-purchase discount tactic is concerned, it arises from the airlines' need to derive schemes in situations where demands or travellers' preferences are uncertain (Dana, 2001; Gale and Holmes, 1993). A central contribution of this paper is to show that the LCCs follow it in a rather flexible manner.

[1] Assume that airline 1 dominates airport A, and airline 2 airport B. Both airlines operate a service on the route. In the traditional case where airlines impose a penalty for one-way tickets, airline 1 could charge more for round-trip tickets originating in A, and airline 2 would do the same for round-trips originating in B. Absent the penalty and all else equal, arbitrage would significantly erode the airlines' market power.

It is also widely known that all LCCs offer “no-frills” flights with no class distinction for seats, thus excluding any form of discrimination based on quality (Mussa and Rosen, 1978). Finally, price variations due to the inclusion of connecting flights are ruled out by the fact that LCCs issue only “point to point” tickets (Clemons *et al*., 2002).

In the next section we illustrate the data collection strategy. This is followed by three sections where we address the questions listed above and present some supporting evidence. Some business strategy implications are discussed in the concluding section.

2. Data Collection

Most of the empirical contributions on pricing behaviour in the Civil Aviation industry have focused, so far, mainly on the U.S. market. Such studies have been mostly 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 and 1991; 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. Since the start of this research project in May 2002, fares were collected using an “ electronic spider”, which connected directly to the websites of only the main LCC (i.e., Ryanair, Buzz, Easyjet, GoFly) operating in Great Britain at the time. 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 and Maersk) 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.[2] This decision was necessary to reduce the number of routes under study, where each route is identified in this study as an airport pair combination.

The dataset includes daily flights information from June 2002 up to, and including, June 2004, for a total of 25 months. Over such a period, a number of important events took place, which are reflected in the dataset. First, a series of takeovers occurred: Easyjet acquired GoFly (December 2002) and Ryan Air took over Buzz (March 2003). Second, new LCC began their

[2] 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.

operations: the “spider” was upgraded to retrieve fares from the Bmibaby and MyTravelLite sites. However, due to technical difficulties, fares from Flybe, which was already an established LCC, and Thomson Fly, a new entrant could not be obtained.

Over the 25 months period, fares from UK for flights to and from the following Euro-adopting countries were obtained: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. A term of comparison is provided by fares for flights to the following countries outside the Euro area: Czech Republic, Norway, Sweden, Switzerland as well as UK, whose domestic routes were also considered.

In order to account for the variety 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). While the spider could have retrieved any number of prices, 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, 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 FSCs, up to 8 fares per daily flight are available.

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. 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).[3] 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 each airline operated in a given month on a route. However, in order to create a more balanced panel, fares and traffic statistics were aggregated at the route level for each airline.

Table 1 illustrates how the data retrieved from the Internet represent an accurate sample of the activity of each of the LCCs in the markets we consider. It compares the number of routes for which we have price data with the actual total number of routes by each airline. The latter figure is taken from the CAA dataset, which also provides the number of routes where our LCCs face competition by either a major FSC or another LCC. To test the spider's functionality, initially we limited the number of surveyed routes. Indeed, in August 2002 the percentage of routes with prices was 63% (37 over 59) of the total number operated by Ryan Air, 50% for Easyjet, 64% for Buzz and 46% for GoFly. However, thanks to the speed of the programme, within a few months such percentages could be increased significantly for all the airlines, to cover 80% or more of the total routes they operated. Considering that the spider took all the prices for all the daily flights, the price dataset provides an exhaustive illustration of the on-line pricing activity of each airline.

Table 1 also shows that the airlines differ in the amount of competition they face. For instance, in about 25% of EasyJet's routes at least another competitor (FSC or LCC) is also present. At the other extreme, Ryan Air (and Buzz to a lesser extent) faced competition in a very limited subset of routes. The other airlines lie somewhere in between, with competitive routes accounting for about 33% of the total. Such differences may be driven by the choice of the arrival destinations. Ryan Air and Buzz chose almost exclusively secondary airports that may be many miles away from the city of arrival, while the other airlines also fly to major airports where FSC also land.

3. The temporal profile of fares

Existing theoretical literature like Gale and Holmes (1992,1993) and Dana (1998, 2001) state various reasons for the airlines to offer lower-priced seats to earlier purchasers. Gale and Holmes (1993) use a mechanism design approach to explain the adoption of Advance-Purchase

[3] See www.caa.co.uk

Discounts (APD) in a monopoly model with capacity constraints and perfectly predictable demand. They show that firms using APD practice a form of second-degree price discrimination where travellers self-select according to their preference for a peak or an off-peak flight. The advice they offer is to set a low fare for the off-peak flight at an early stage. Such a result hinges around the assumption of certain demand, implying that the airlines can tell an off-peak flight from a peak one. Moreover, its practical implications are that we should expect a flatter temporal profile of fares for the peak flights, and a monotonically increasing profile for the off-peak flights. With demand uncertainty, Gale and Holmes (1992) show that APD can promote efficiency by spreading consumers evenly across flights before timing of the peak period is known. The implication is that ex-post, both types of flight will exhibit a monotonically increasing time profile. For competitive markets where firms set prices before demand in known, Dana (1998) shows that firms may offer APD because travellers with more certain demand and weaker departure time preferences are better off buying in advance due to the presence of other consumers with higher valuations and more uncertain aggregate demand. To drive this result is the assumption that the airlines commit to a rationing rule that limits the number of cheaper seats and thus reduces the incentive of consumers with more certain demand to postpone purchase.

From an empirical viewpoint, price dispersion may be due to such forms of inter-temporal price discrimination as the APD, as well as to systematic and stochastic peak-load pricing (Borenstein and Rose, 1994). Using an original dataset with information on seats availability at each advertised fare, Escobari (2006) finds that the difference in prices paid between earlier purchasers and later purchasers is mostly explained by flights' capacity constraints, i.e., peak-load pricing seems to be a highly relevant factor in the determination of the shape of the temporal profile of airlines' fares.

In the present setting, lack of data on a flight's load factor at the time the fares were retrieved makes it impossible to distinguish the factors behind the temporal price dispersion. The size of our dataset however enables us to address the commonly held belief that fares increase as the date of departure approaches. Recall how for each flight we obtained up to 13 fares, collected at regular intervals from 70 days up to the day prior to departure. Table 2 shows the mean fares across all routes by booking day and airlines. Even when using such a highly aggregate measure, some interesting features arise. For Bmibaby, the mean price offered 42 days before departure is lower than that posted in the three preceding weeks. Subsequently, BMIbaby's fares increase monotonically, but in a rather flat manner. One could still argue that discounts offered 42 days before departure may still be considered within the advance-purchase category, but in any case we find the first violation of the monotonic property. Furthermore, considering that mean fares increase only by 5.4 British Sterling between 35 and 10 days prior to departure, it is also possible that for a number of flights within this period the monotonic property did not hold. As far as Ryan Air's mean fares are concerned, similarly to BMIbaby we observe marginally lower fares 35 days prior to departure, relative to those posted a week earlier. However, Ryan Air presents a steeper time profile in the week preceding departure, where the fare available four days before departure is more than twice as high as that available two months before the flight departs. Such a finding is both consistent with an explanation based on the fact that Ryan Air realizes higher load factors (hence, the higher fares are due to peak-load pricing) or simply due to its willingness to implement a second-degree form of price discrimination as suggested in the previous discussion.

The mean fares shown in Table 2 for Easyjet provide compelling evidence that the monotonic property does not always constitute a precise way to describe the evolution of fares. Indeed, those posted 21 and 10 days are lower than those available in the preceding booking day. Interestingly, this is consistent with similar evidence for the same airline shown in Pitfield (2005) and Pels and Rietveld (2004). The combination of our evidence, which includes a high number of routes, with that collected on specific routes seems to suggest the existence of a company fixed effect playing a crucial role in the shaping of the temporal price profile in a route.

GoFly is another airlines whose fares' time profile violates the monotonic property in various instances. Indeed, fares available 42, 14 and 7 days before departure are lower than those in the preceding periods. The column for MyTravelLite (MTL) exhibits another type of pricing behaviour, one that tends to be U-shaped. For this airline we record fares that decline every week from 70 up to 35 days before departure, and then rise at first rather smoothly but then quite sharply in the last four days. Finally, Buzz seems to be the only LCC in our sample whose aggregate fares follow a monotonically increasing, although at a relatively small gradient, path.

Figures 1 and 2 show clearly how the conclusions from Table 1 continue to hold when we consider specific routes. Each box in these figures provides a graphical summary of the distribution of the fares for each booking day. We focus the attention on the line inside each box, which represents the median of the distribution (the lower hinge in the box represent the 25^{th} percentile, the top hinge the 75^{th} percentile). It is evident how the monotonic property is often violated. For instance, in Figure 1 the median price for 21 and 14 days is below that of 28 days; the 10 days fare is also below the immediately preceding ones. Interestingly, the 10 days fare is at the level of the 49 days median price. In Figure 2 the median prices offered 4 and 63 days before departure are of equal magnitude: within this time interval, fares fluctuate widely.

The evidence presented so far suggests that for the LCCs in our sample the commonly held belief of airlines' fares increasing over time misrepresents the actual temporal profile of fares. Although the lack of sales data at each point in time does not allow us to identify the reasons behind price dispersion, our findings suggest a rather complex relationship between fares and load factors. Indeed, exceptions to the monotonic rules often occur between two and one month before departure: these may be considered advance-purchase discounts. However, they are also observed only a few days before departure, something that is hard to reconcile with the recommendations of theoretical models. In the next section we will further investigate the extent to which fares change over the booking period.

Quite interestingly, there seems to be a mismatch between what the airlines preach and what they practice. Consider for instance this quote, taken from http://www.easyjet.com/EN/Book/aboutourfares.html: "In general, our fares increase as the departure date gets nearer, so to get the best deals make sure you book as early as possible". Ryan Air allows itself more leeway when it states: "Our lowest fares generally require an advance purchase of 14 days; however this can vary up to 28 days". Both quotes suggest a preference for early bookings, possibly because of the associated financial benefits as a ticket purchased 60 days before departure is equivalent to an interest-free loan. In the next section we show that such a preference for early booking may be one of the possible reasons behind the frequency with which fares change from one booking day to another.

4. Menu Costs on line?

As discussed in Smith *et al (*1999*)*, in an electronic market menu costs, i.e., the costs incurred by retailers in making price changes, should be lower, since they are comprised primarily of the cost of making a single price change in a central database. Evidence supporting this hypothesis can be found in Brynjolfsson and Smith (2000), where it is shown that 1) on-line retailers change prices of books and CDs more frequently than their conventional counterparts, and 2) changes are often of negligible size on-line.

In Table 3 we show the percentage of times in which we observe a fare change from one booking day to the next one. That is, we first calculate all the fare changes between two consecutive booking days: e.g., between the 70 and 63 days fares For each airline, we then identify the total number of possible changes in the entire dataset, and work out the averages in Table 3. Among the LCCs, Ryan Air and MyTravelLite are the ones that are more likely to revise their posted fares with, respectively, a probability of 0.65 and 0.62 that two consecutive fares may not be identical. For such LCCs as Go Fly and Bmibaby, however, fares tend to change less frequently. A surprising feature is that most FSCs exhibit a stronger tendency to revise their fares, with probabilities ranging from 77% for British Airways up to 90% for Scandinavian. Although a number of factors may be responsible for such observed variability, our main aim in this chapter is to present evidence that is consistent with the hypothesis of small menu costs. Table 3 clearly provides support to this hypothesis: what it does not reveal is when fare changes are more likely to occur, something we now address. In this sense, the following analysis is directly related to that presented in the previous section on the temporal profile on fares.

Figures 3 to 7 illustrate the percentage of flights in which fares between two booking periods either remained the same or changed by either increasing or decreasing. Flights are for the year 2003. Figure 3 considers the case for fares posted by BMIbaby. About 65% of times there is no change between 70 and 63 days: the average fare is £.49.16. About 22% and 13% of times fares increased or decreased in this time interval, when mean decreases amount to £9.75, while increases to £10.38. A characteristic of Bmibaby is that the probability of a price reduction remains relatively stable (and not very high) throughout the whole booking period while price increases become more likely as the date of departure approaches. However, about 35% of flights keep their fares stable in the last week. The relative stability of fares for BMIbaby seems to suggest little role for peak-load pricing and a pricing scheme that is independent of the realisation of current load factors.

The case for Ryan Air, illustrated in Figure 4, tells a rather different story. The highest percentage of stable fares (about 40%) is obtained in the 63-56 days period. In all other cases, the proportion of stable fares is lower. Up until 28 days before departure, we observe a similar probability for an increase or a decrease, which tend to be of similar magnitude. From 28 days onwards, increases become more likely and of larger size than decreases, which however still account for about 25% and 20% of flights in the periods 21-14 and 14-7 days, respectively. This contradicts Ryan Air's quote in the previous section that the lowest fares are available before 14 or 28 days prior to departure. Conspicuous and almost certain price hikes are observed in the last week.

Figure 5 shows that EasyJet kept its fares stable about 55-60% of times up to 28 days prior to departure: a huge jump from 20 to 40% in the probability of observing a discount of about £14.8 relative to the price in the previous week is found in the 28-21 days period (see also the discussion of Table 2 above). In the last three weeks EasyJet fares are frequently increased, and they hardly stay stable in the last seven days. Generally, the evidence for the 3 LCCs above is indicative of small menu costs. It also suggests that the enhanced volatility observed within four weeks from departure may reflect a more intense use of pricing as an yield management tool aimed at increasing a flight's load factor.

The intense variability in posted fares is confirmed in Figures 6 and 7, which consider the Summer timetable fares of two FSCs: BMI British Midland and British Airways. The probability of a fare decrease falls steadily as the date of departure approaches, although, quite surprisingly, for quite a large proportion of BMI flights (about 15%) fares declined in the 14-7 days period. For both FSCs fares tend to remain less stable than those of BMIbaby and Easyjet, and generally the magnitude of changes is smaller than that recorded for the LCCs. Recall how the fares for the FSCs were taken from an on-line travel agent, which is also owned by Amadeus, the computer reservation service. Thus, it is likely that the fares posted on-line are the same as the ones available on Amadeus. The small and highly frequent fare changes even from an on-line travel agent supports the hypothesis of small menu costs even in cases where the airlines are feeding their fares through a computer reservation system.

The discussion in this and the previous section highlights some important characteristics of airlines' pricing behaviour on-line. The low menu costs facilitate price changes, an important factor that enables companies to gauge current demand by trying out different fares. Note however, that while fares may vary across booking days, it is not likely that they change frequently within each day. As Ellison and Ellison (2005) discuss, inertia in Internet prices is often observed, suggesting that companies do not continually monitor the market situation and re-optimize.[4] Nonetheless, the variability we observe over the booking period is probably one of the reasons why the temporal profile of fares hardly replicates a monotonically increasing curve. This reflects the airlines' ability to combine recommendations from on-line pricing with the more traditional schemes typically used in the industry. Indeed, sometimes the airlines may want to reconsider the planned pricing scheme they are adopting, in order to reflect and better adjust to demand conditions. This is highly facilitated by the Internet technology. Although this also suggests the airlines' preference not to commit strictly to a temporal price discrimination scheme, traditional pricing schemes still play a central role. Indeed, in line with the conventional wisdom fares generally grow over time and last-minute offers are virtually non-existent. This makes it highly risky for a traveller to choose to postpone purchase hoping for a lower fare to become available. Thus, the prospect of future discounts will not deter low-evaluation, risk-averse consumers with more certain demand from buying at an early date. Therefore the traditional second-degree price discrimination schemes still remain a very effective managerial tool even when applied on-line.

[4] Moreover, we casually noted that after buying tickets on-line from the LCCs in our study, fares remained unchanged despite the obvious reduction in the seat availability.

5. Which airline is the cheapest, and when?

The previous sections have revealed a synergetic relationship between the traditional pricing schemes in the airlines' industry and the opportunities presented by the Internet. It is thus worth looking at our data from the perspective offered by some recent theoretical and empirical contributions on pricing in on-line markets. Baye *et al* (2004a) present a model where firms using a price comparison site (a "*clearinghouse*") must try to sell to two types of consumers: "Shoppers" (S), who actively engage in searches on the comparison site and buy at the lowest possible price, and "Loyals" (L), who do not search and pay up to their reservation value for the service offered by their preferred brand. In a clearinghouse model, the Law of One Price does not hold and persistent price dispersion will be observed (Baye *et al*. 2006). More relevant for our purposes, the identity of the firm offering the lowest price will vary unpredictably over time (Baye *et al*. 2004b). This is because randomisation arising from a "hit-and-run" strategy will be used to prevent rivals from being able to systematically undercut a fixed high price. Indeed, should all firms set a high price to extract the maximum surplus from Shoppers and Loyals, the predictability of such a scheme would give an incentive to each firm to reduce its price by an arbitrarily small amount to attract the Shoppers. To prevent systematic undercutting by rivals, firms in highly competitive e-retail markets adopt "hit-and-run" sales promotions, which in turn leads to the absence of a persistent "low-price" firm in the market.

The clearinghouse model can be related to our analysis. We can think of Shoppers as those travellers who search for the lowest price in many airlines' web site, even if they offer differentiated routes, while Loyals may be those who do not consider alternative airlines maybe because of their preference for a route or type of service (e.g., they may prefer FSCs to LCCs). It is clear, however, that some aspects of the clearinghouse model do not directly translate into the airlines' setting.[5] A comparison site lists all the available prices for exactly the same product. In the airlines industry, flights are differentiated along many horizontal dimensions, namely, time of departure and endpoints airports, as well as vertical ones (e.g., the FSCs vs. the LCCs business concept).[6]

We tried to account for such sources of product differentiation in the preparation of Tables 4 to 7, where we show the percentage of times an airline offers the cheapest or the most expensive fare over different booking days. We assigned flights into 8 time bands groups of similar size and within each time band, we compared fares posted by the airlines operating in a

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[5] Nonetheless, search engines, e.g. www.traveljungle.co.uk or www.skyscanner.net, are present in the European Airlines' market but they do not operate as the comparison site illustrated in Baye et al (2004a, 2004b and 2006).

[6] The time of booking is also a source of differentiation, which we account for by using the booking days described above.

market defined as a city-pair (e.g., London-Rome). While we are aware that to eliminate any effect due to geographical differentiation we should have used the flights within a route (i.e., an airport pair), we have shown in Table 1 that the number of competitive routes is very limited, especially if we intend to analyse competition between FSCs and LCCs. Therefore, in the following analysis we assume that a flight, say, from London Stansted to Rome Ciampino at 9:30 a.m. can be usefully compared with a flight leaving from London Luton for the same destination at 10:00 a.m. However, imperfect substitutability across routes is likely to drive some of the results we will present. Another limitation of the present analysis is that, although we compare fares for the same booking day, the load factors of each flight at each point in time, and thus the cost conditions, may differ.

Tables 4 and 5 show the percentage of times an airline offers the cheapest or the most expensive fare over different booking days in markets where LCCs and FSCs are both present. A first interesting result is that LCCs do not always post the cheapest price: this is even more surprising when we consider that FSCs operate in major airports that are often considered to be able to enhance the quality of a journey's experience. Most likely, such a finding hinges around the imperfect substitutability of the routes in a city-pair. Furthermore, the likelihood to observe a cheaper fare by a FSC increases as the date of departure approaches. This may be explained by the results in the previous section, where we show that FSCs' fares are more stable than those by LCCs and exhibit smaller changes between consecutive booking periods.

In addition to helping explaining why sometimes FSCs are cheaper than LCCs, product differentiation may also be responsible for the fact that such LCCs as Ryan Air, MyTravelLite and EasyJet to a lesser extent, very often turn out to be the "lowest-price" companies in the markets where they operate, while the other LCCs quite rarely offer the cheapest fare. That is, if differentiation did not matter, the identity of the low- and high price firm would be more difficult to predict, as easier substitutability across routes would tend to smooth the differences across airlines in Tables 4 to 7. [7] On the contrary, within each booking day in these Tables important differences across firms are observed, making the above identities easier to forecast. That is, in market where either Ryan Air or MyTravelLite operate, it would be a safe bet to expect them to be the low-price companies, especially as far as early booking is concerned.

Across booking days, the same identities may however vary, thereby further suggesting that product differentiation may matter less than the airlines' idiosyncratic on-line pricing behaviour. That is, since the same routes are evaluated for the same airlines, the effects of product differentiation are fixed: changes across booking days may be ascribed to the airlines'

[7] That is, if an airline operates a route with better attributes and that therefore the travellers prefer, then that airline should always be the one with the highest fares across booking days.

pricing schemes. Consider the cases of BMIbaby and GoFly. Especially for the latter, early fares tend to be among the highest on the market, but the probability to be the "low-price" firm increases as the date of departure approaches. This is even more evident in Tables 6 and 7, where we consider the market where only LCCs compete. The probability that BMIbaby offers the cheapest fare one day before departure is almost 0.62 (the highest across the companies), but it falls to less than 30 % about two months before departure. The same probabilities for Go Fly are, respectively, about 40% and 7.5%. A reverse example is given by MyTravelLite, whose probability to be the cheapest company falls to 8.3% four days before departure, from more than 83% in one of the previous booking days. Ryan Air behaves similarly to MyTravelLite, although with less drastic variations.

To conclude, our analysis seems to confirm the hypothesis put forward in Baye *et al* 2004b) that the identity of the firm offering the lowest price exhibit some degree of unpredictability over time. Such results seem to be independent of the fact that we compare fares for imperfectly substitutable flights and can be mainly attributed to the way the airlines set their fares over time, a topic we have discussed at length in the previous two sections. Nonetheless, within each booking day the low- and high-fare firms are easier to predict, partly because of the imperfect substitutability of the routes in a city-pair. Overall, the two results combined point at the conclusion that the airlines do not seem to adjust their fares to match their closer rivals' offers. If they did, within each booking day identifying the low-price firm would be more difficult than it would seem to be. This confirms the importance of product differentiation as a strategic weapon to reduce the incentive to engage in tough price competition (Tirole, 1988). The enhanced unpredictability across booking days suggests that the heterogeneity of the airlines' idiosyncratic pricing schemes is thus likely to be mostly motivated by the aim to maximise a flight's load factor and not by concerns about the fares offered by the immediate rivals.

6. Conclusions.

Using evidence from about 650 thousand flights, for which up to 13 fares were available, the present article addressed three highly interrelated topics on the behaviour of fares over time: 1) whether airlines' fares grow monotonically, as it is often assumed; 2) how often and when fares change; and 3) which companies offer the lowest price, and when. First, we show violations to the monotonic property both when we aggregate fares over all the airlines' routes, and when we consider fares in specific routes. Second, we observe higher volatility of fares in the four weeks preceding the departure date. Both findings contrast with the statements on some LCCs' web sites declaring that the best deals are available before 28 days before departure. It would seem that these announcements might be aimed at consumers with more certain demands to induce them to purchases early. The high variability of fares serves the purpose of discouraging such consumers to postpone the ticket purchase, as the probability of the availability of a discounted price in the future is often more than offset by the probability of ending up paying a higher price. In this respect, the airlines manage to apply the traditional schemes based on a second-degree price discrimination strategy where consumers with more certain demand buy at an early stage, while later purchasers with uncertain demand pay a premium. A contribution of this article is to show that such traditional schemes are adjusted to reflect the innovative features offered by the Internet. Thus, the investigation of the first and the second issue leads to conclude that a potential area for future research is a deeper evaluation of how the airlines' traditional pricing schemes can be applied to reflect such prevailing conditions on the Internet as low search and transaction costs and high price transparency. A first step in this direction is offered in Bachis and Piga (2006), which shows evidence of a form of on-line price discrimination entailing the airlines charging, at the same time and for the same flight, fares expressed in different currencies that violate the law of One Price.

The third part of this study explicitly relates airline pricing to some recent theoretical and empirical contributions on pricing in electronic markets. In line with the predictions in Baye *et al* (2004b), we find that the identity of the airline offering the lowest price in a market changes with the booking day, although within each booking day it tends to remain the same and is therefore easier to predict. The former result is obviously related to the first two issues analysed in the paper, i.e., the fares' temporal profile and frequency and timing of their change. In Baye *et al.* (2004b) the unpredictability of the low-price firm is a consequence of the intense on-line competition. In our case the identity of the low-price airline changes because of the different inter-temporal pricing schemes used by the airlines. These different approaches seem to be less driven by competitive pressure, given that the airlines are often protected by product differentiation, and more by distinctive strategies used by the airlines to maximise a flight's load factor.

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Figure 1 – The temporal profile of fares offered by Easyjet on a specific route

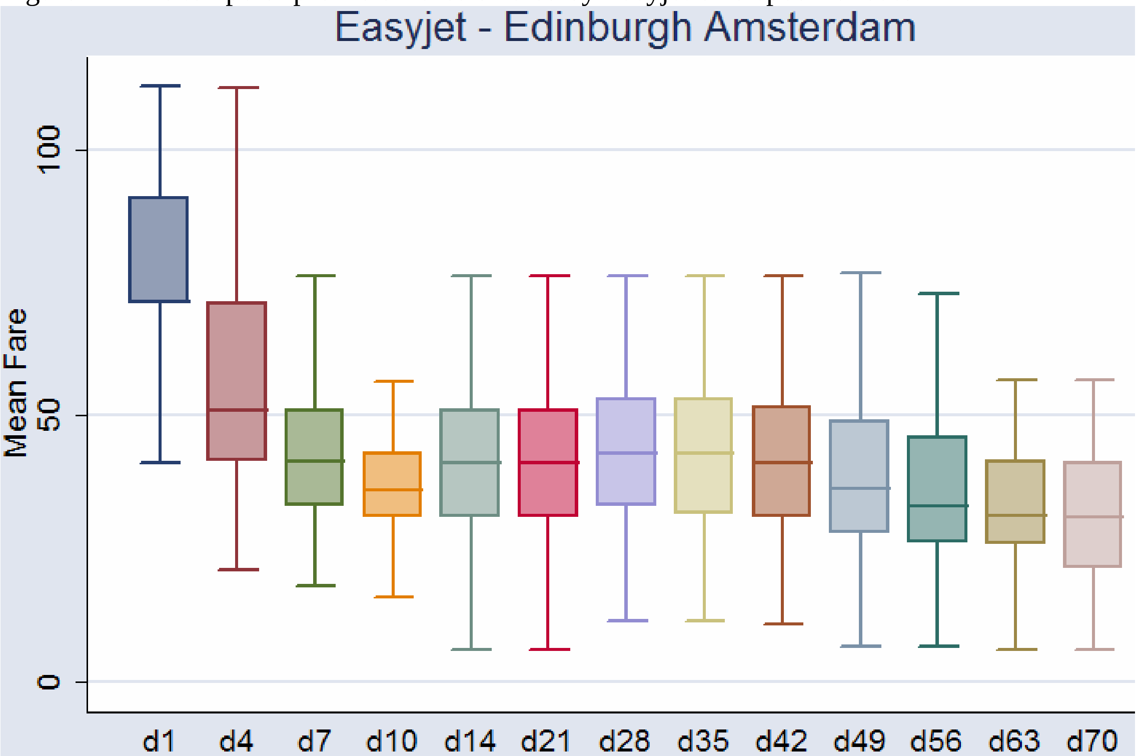


Figure 2 – The temporal profile of fares offered by Go Fly on a specific route.

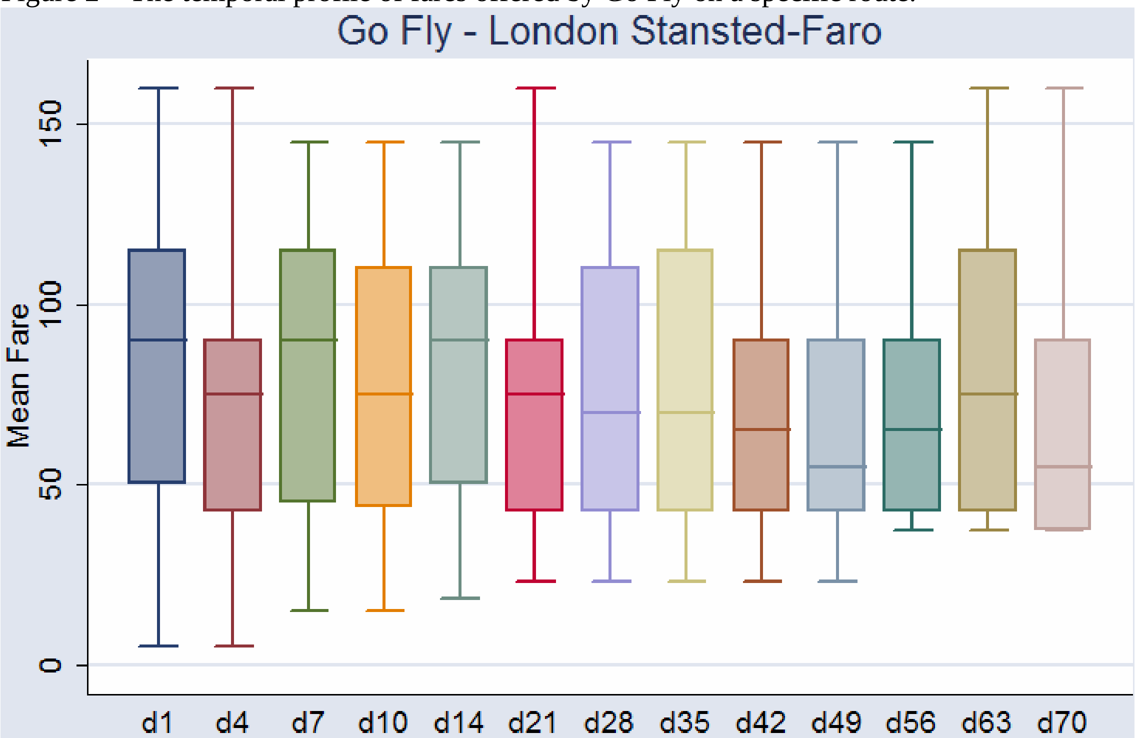


Figure 3.

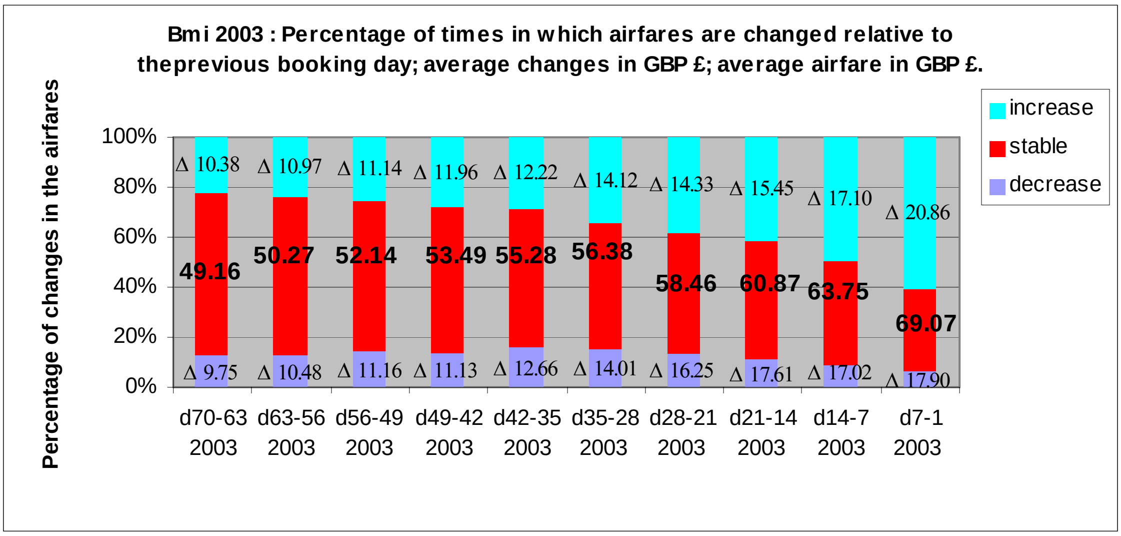


Figure 4

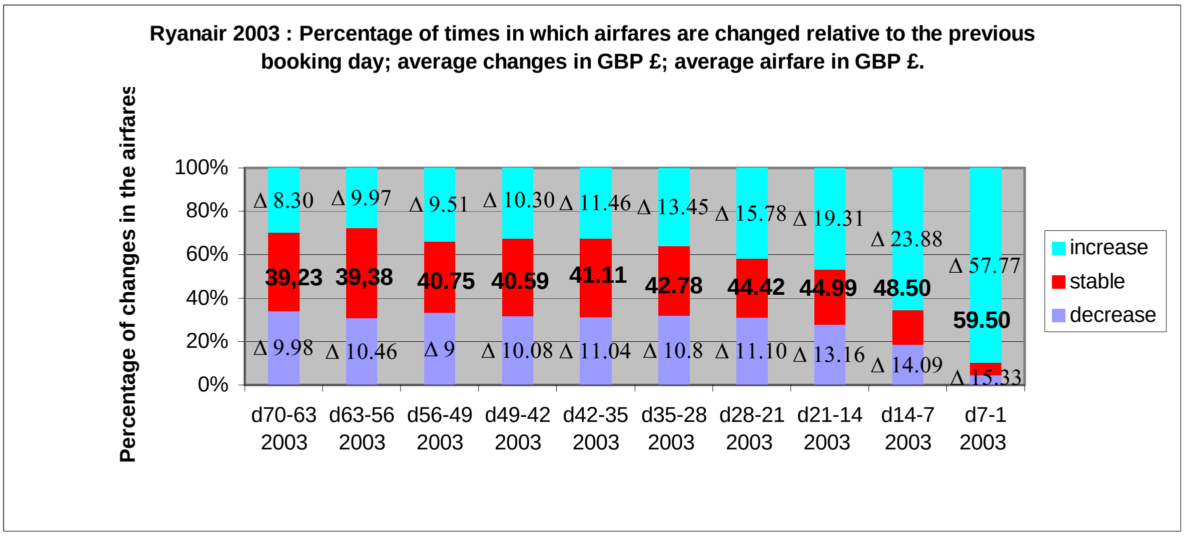
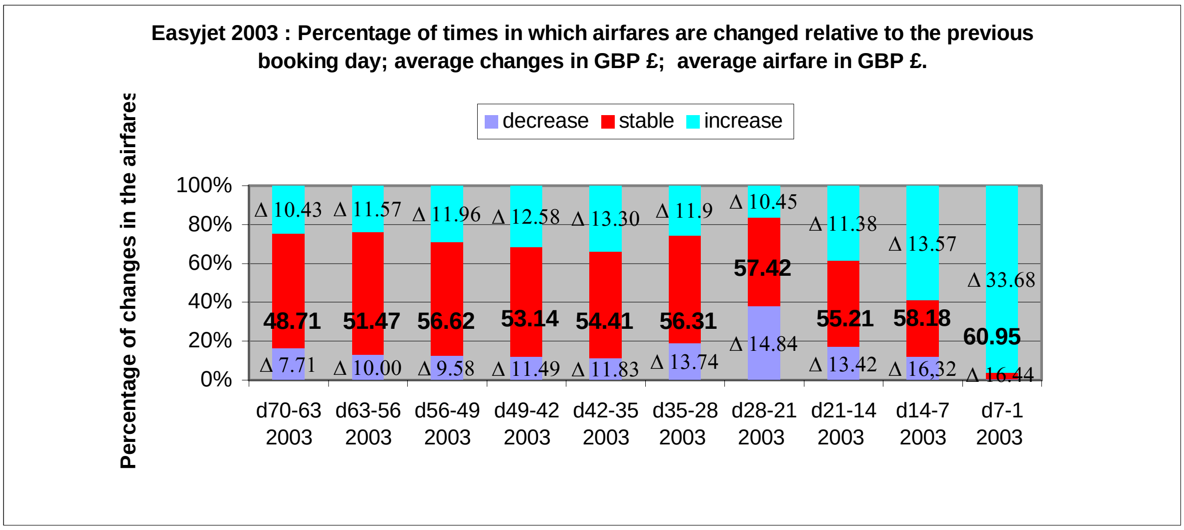


Figure 5



Easyjet 2003 : Percentage of times in which airfares are changed relative to the previous booking day; average changes in GBP £; average airfare in GBP £.
decrease
stable
increase
Percentage of changes in the airfares
100%
80%
60%
40%
20%
0%
Δ 10.43
Δ 11.57
Δ 11.96
Δ 12.58
Δ 13.30
Δ 11.9
Δ 10.45
Δ 11.38
Δ 13.57
Δ 33.68
48.71
51.47
56.62
53.14
54.41
56.31
57.42
55.21
58.18
60.95
Δ 7.71
Δ 10.00
Δ 9.58
Δ 11.49
Δ 11.83
Δ 13.74
Δ 14.84
Δ 13.42
Δ 16,32
Δ 16.44
d70-63 2003
d63-56 2003
d56-49 2003
d49-42 2003
d42-35 2003
d35-28 2003
d28-21 2003
d21-14 2003
d14-7 2003
d7-1 2003

Figure 6

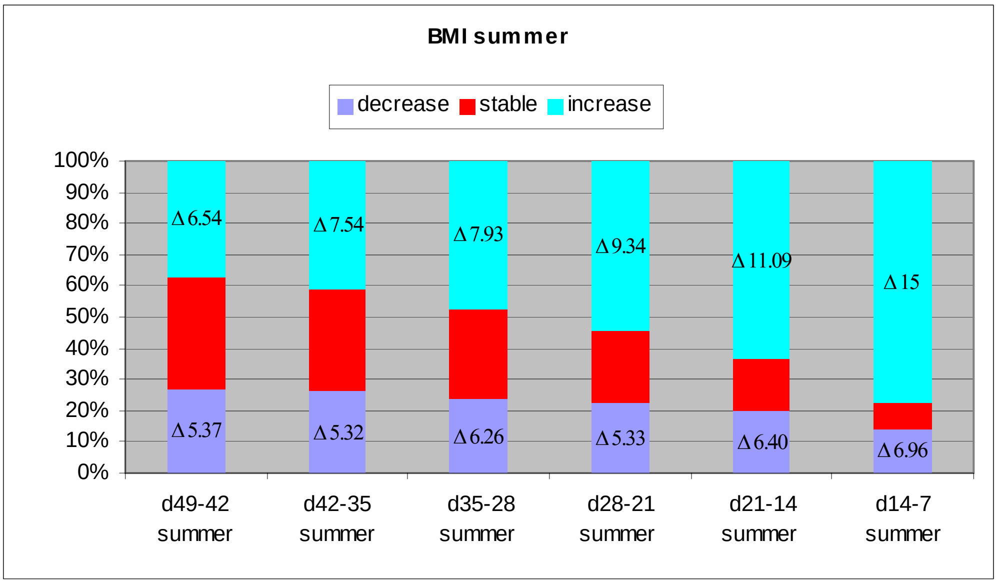


Figure 7

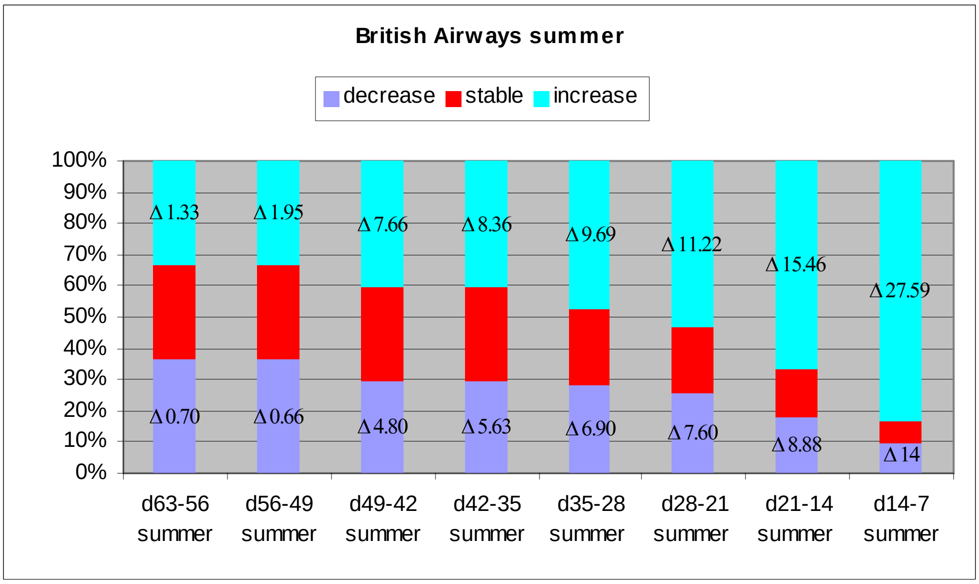


Table 1 – Number of routes by type of sample, airline and period.

	BMIBABY			RYAN AIR			EASYJET		
Year_ month	Routes Price Sample	Routes CAA Sample	Comp. Routes CAA Sample	Routes Price Sample	Routes CAA Sample	Comp. Routes CAA Sample	Routes Price Sample	Routes CAA Sample	Comp. Routes CAA Sample
02_07				34	59	7	19	38	9
02_08				37	59	8	19	38	9
02_09				37	59	7	28	40	9
02_10				37	59	7	28	41	10
02_11				37	60	8	29	41	9
02_12				37	60	8	61	79	20
03_01	26	35	10	49	61	9	61	80	20
03_02	26	35	11	50	64	7	63	82	21
03_03	30	37	12	50	64	7	66	84	22
03_04	26	37	9	56	65	7	66	88	19
03_05	31	40	10	69	88	6	67	89	19
03_06	32	43	10	69	88	6	67	89	20
03_07	33	45	11	69	88	6	67	89	21
03_08	34	45	11	83	89	8	88	92	24
03_09	35	44	11	83	89	6	88	92	23
03_10	35	48	13	84	92	8	89	96	26
03_11	37	42	12	87	93	8	88	95	23
03_12	38	47	15	87	94	8	88	98	25
04_01	33	49	15	42	98	8	46	98	25
04_02	36	47	14	84	94	8	88	98	25
04_03	38	43	13	84	94	8	89	101	25
04_04	34	48	17	87	99	10	89	107	27
04_05	34	50	16	81	94	9	89	110	27
04_06	34	55	18	84	96	9	88	114	29
	BUZZ			GOFLY			MYTRAVELLITE		
02_07	21	33	3	17	37	11			
02_08	21	33	5	17	37	11			
02_09	21	33	5	30	35	9			
02_10	21	32	5	30	39	11			
02_11	20	20	0	32	38	11			
02_12	22	22	0	32	38	11			
03_01	22	22	1						
03_02	22	21	0						
03_03	22	26	4						
03_12							13	14	5
04_01							13	14	5
04_02							13	13	5
04_03							13	11	4
04_04							13	11	4
04_05							10	9	3
04_06							9	9	3

Source: Price sample is retrieved from the airlines' web sites, Total routes and competitive routes are from the Civil Aviation Authority dataset.

Table 2 – Mean fares by airline and booking days. Fares in British Sterling

	BMI Baby		Ryan Air		Easy Jet		Buzz		Go Fly		MTL	
	N	Fare	N	Fare	N	Fare	N	Fare	N	Fare	N	Fare
1	24659	68.5	233880	99.4	170810	91.0	6617	84.0	11708	88.5	2841	107.1
4	25073	65.3	245460	79.0	163589	72.9	5889	76.8	10804	71.8	2837	82.6
7	25919	60.2	245583	63.2	177324	62.9	6842	72.5	15816	62.6	2972	56.1
10	25802	58.4	240143	58.5	160884	56.7	6012	68.1	11106	67.3	2923	54.0
14	25725	56.7	238375	51.2	164496	59.3	6647	66.6	15345	58.9	2871	52.7
21	25292	54.5	225967	45.4	162229	55.7	6441	62.3	11464	64.6	2764	51.6
28	24729	54.2	226578	42.7	159942	57.5	6262	59.0	11041	62.4	2665	51.2
35	24171	53.0	227183	41.2	157437	56.2	5983	56.5	10561	59.9	2560	50.6
42	23498	47.6	210423	42.1	151369	53.1	5840	55.0	10049	57.9	2402	50.8
49	22852	49.8	210751	38.2	152408	51.0	5642	53.5	6197	70.5	2210	51.3
56	18742	49.8	200317	37.3	143147	50.3	5381	51.7	5812	69.5	1978	52.4
63	21563	48.2	197461	37.8	140777	49.6	5155	49.5	8856	52.7	1819	53.6
70	21299	45.8	197253	35.9	141639	47.7	4874	48.0	8315	50.6	1610	53.9

Source: data retrieved from the airlines' web sites from June 2002 until June 2004.

Table 3. Percentage of times in which each company changes the airfare offered on its website (number of changes in prices, flight by flight, divided by total number of potential price changes).

Company	**Mean**	**S.D.**	**N**
Bmibaby	.44	.185	29248
Ryanair	.65	.198	268584
Easjet	.56	.191	181644
Buzz	.50	.233	6987
GoFly	.39	.283	12466
MyTravelLite	.62	.215	3179
Aer Lingus	.57	.278	8046
Air Europa	.54	.260	296
Air France	.67	.274	8061
Alitalia	.81	.139	6448
BMI	.78	.268	33068
British Airways	.77	.264	35683
Czech Airlines	.80	.204	547
Finnair	.87	.192	1298
Iberia	.72	.302	4896
KLM	.90	.199	6624
Lufthansa	.76	.241	18597
MaerskAir	.79	.224	683
Scandinavian Airlines	.90	.213	12033
Swiss	.82	.234	4228
TapPortugal	.75	.240	126
Volare	.85	.188	270
Total	.63	.234	643012

Table 4***. Percentage of times in which an airline offers the cheapest airfare.***

Company	***Days before departure***								***Mean***
	7	***10***	***14***	***21***	***28***	***35***	***42***	***49***	
Low-cost companies									
Bmibaby	37	28	28	26	30	32	32	32	31
Ryanair	74	75	77	79	84	86	85	84	80
Easyjet	57	61	59	59	52	52	53	55	56
Buzz	20	19	18	16	24	25	22	21	21
MyTravel	76	75	65	66	68	68	65	66	69
GoFly	22	18	16	12	14	15	11	9	15
Traditional Full Service companies									
Aer Lingus	30	25	23	20	19	17	17	17	20
Air France	16	13	12	15	10	9	10	9	11
Alitalia	21	15	13	11	9	9	9	9	12
BMI	17	17	16	16	17	17	18	18	18
BA	11	12	13	14	15	14	14	14	14
Finnair	17	13	11	11	9	9	8	7	10
Iberia	13	12	12	11	12	12	11	10	11
KLM	15	10	9	8	7	5	6	5	8
Lufthansa	8	6	6	5	5	5	5	5	6
Maersk Air	28	28	21	20	20	23	28	27	23
SAS	31	30	29	26	25	23	23	23	26
Swiss	32	42	32	29	29	27	25	26	27

These percentages are drawn from competitive markets in which 2 to 5 different companies, both LCA and traditional carriers, operate. Data for the LCC are for the period running from June 2002 to December 2003. Data for FSC are from April 2003 to December 2003.

Table 5. ***Percentage of times in which an airline offers the dearest airfare.***

Company	***Booking days before departure***								***Mean***
	7	***10***	***14***	***21***	***28***	***35***	***42***	***49***	
Low-cost companies									
Bmibaby	60	66	67	69	64	57	58	57	62
Ryanair	13	11	9	7	5	4	4	3	7
Easyjet	9	7	8	8	11	12	11	11	10
Buzz	80	81	82	84	76	75	78	79	79
MyTravel	22	25	30	19	17	18	21	16	21
GoFly	70	76	79	83	81	80	85	87	80
Traditional Full Service companies									
Aer Lingus	18	20	22	25	28	31	33	34	26
Air France	40	53	56	69	73	73	75	75	64
Alitalia	20	22	23	14	13	15	13	13	17
BMI	22	22	21	21	20	15	18	21	20
BA	47	43	38	40	41	41	42	42	42
Finnair	35	33	54	59	63	63	64	64	54
Iberia	41	71	73	72	75	74	77	74	70
KLM	48	60	69	75	78	80	82	84	72
Lufthansa	62	64	68	64	61	62	61	62	63
Maersk Air	53	62	57	65	59	54	53	52	57
SAS	36	38	39	41	42	44	45	46	41
Swiss	19	42	45	51	47	59	60	62	48

* These percentages are drawn from those markets in which operate from 2 to 5 different companies, including both LCA and traditional carriers.
** Data for the LCA are for the period running from June 2002 to December 2003. Data for traditional carriers are from April 2002 to December 2003.
***Air Europa, TapPortugal and Volare are not included because of the low number of observations.

Table 6. ***Percentage of times in which an airline offers the cheapest airfare, when competing with other low-cost airlines. %***

Company	***Booking days before departure***													***Mean***
	1	***4***	***7***	***10***	***14***	***21***	***28***	***35***	***42***	***49***	***56***	***63***	***70***	
Bmibaby	61.73	47.70	25.67	19.46	17.53	14.95	22.39	32.57	31.47	33.05	29.82	29.38	34.62	30.79
Ryanair	51.54	58.87	65.43	67.54	71.17	74.10	80.18	78.63	77.30	79.76	77.21	75.89	69.54	71.32
Easyjet	49.44	49.09	51.00	51.84	51.37	48.26	37.82	36.36	40.67	38.02	41.42	42.24	47.33	44.99
Buzz	35.58	26.88	16.57	14.56	16.48	13.86	24.22	27.04	20.13	16.22	15.65	20.28	18.12	20.43
GoFly	40.30	34.18	30.22	26.23	18.48	19.22	21.79	19.69	11.97	11.82	9.84	7.51	6.88	19.86
My Travel	16.67	8.33	73.33	60.00	46.67	80.00	73.33	78.57	70.00	83.33	60.00	-	-	50.02

* These percentages are drawn from markets in which at most 2, and not more than 3, LCA operate.

** Data for the LCA are for the period running from June 2002 to December 2003.

Table 7. ***Percentage of times in which an airline offers the dearest airfare, when competing with other low-cost airlines. %***

Company	***Booking days before departure***													***Mean***
	1	***4***	***7***	***10***	***14***	***21***	***28***	***35***	***42***	***49***	***56***	***63***	***70***	
Bmibaby	38.27	51.94	74.00	80.20	82.13	84.70	77.24	67.43	68.13	66.95	70.18	70.62	65.38	69.01
Ryanair	47.82	40.71	34.20	32.06	28.35	25.71	19.62	21.17	22.60	20.24	22.79	24.11	30.46	28.45
Easyjet	49.85	50.40	48.36	48.16	48.63	51.74	62.18	63.64	59.33	61.98	58.58	57.64	52.31	54.83
Buzz	64.42	73.13	83.43	85.44	83.52	86.14	75.78	72.96	79.87	83.78	84.35	79.72	81.88	79.57
GoFly	55.60	61.54	64.49	67.62	75.25	74.02	71.60	72.05	79.91	79.55	82.38	86.71	86.88	73.66
My Travel	83.33	91.67	26.67	40.00	53.33	20.00	26.67	21.43	30.00	16.67	40.00	-	-	34.60

* These percentages are drawn from markets in which at most 2, and not more than 3, LCA operate.

** Data for the LCA are for the period running from June 2002 to December 2003.