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# *Low-cost pricing strategies in leasure markets*

by

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# Low-cost pricing strategies in leasure markets

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## ABSTRACT

The practice of dynamic pricing, so typical of low cost carriers, is generally regarded as a form of price discrimination between "leisure" and "business" travellers on the single flight or on the single route. Across different routes, however, things may go differently. If price increases in the last 15 days prior to departure are meant to discriminate business demand, leisure demand should account for earlier price variations. Working on a database including the daily fare over the 3 months prior to each flights operated by easyJet during 2009, we assign to each route its own "leisure index", defined as the difference between the rate of price change during the ninety days prior to departure and the one during the last 15 days. Empirical results can be summarized by saying that "business" routes have lower average prices per kilometre, while "leisure" routes show a less dynamic price behaviour, with higher minimum prices and lower maximum prices per kilometre.

**KEYWORDS:** price differentiation, price discrimination, market segmentation, dynamic pricing, low cost carriers.

# 1. Introduction

Strategies of price differentiation as traditionally pursued by flag carriers were used to be one of the favored examples of price discrimination under monopolistic conditions by authors of introductory/intermediate microeconomics textbooks. The two markets with different demand elasticities, which carriers are assumed to be able to keep separated, were almost invariably indicated as given by people travelling for business and people travelling for tourism, leisure, or other personal reasons. From such a kind of explanation it would had naturally followed the prediction that deregulation, via increasing competition, should have mitigated the practice of discriminatory pricing.

As is nowadays well-known, if only from manifest factual evidence, things have by no means gone that way. As frequently happens in a discipline like economics, different answers to the same question have been given at different times. Indeed, since the early 1980's authors like Robert Frank (1983) have begun to warning against the habit of equating differential pricing with discriminatory pricing allowed by market concentration[1]. Subsequent literature has shown that demand uncertainty (Dana 1999) and the competitive environment (Gerardi and Shapiro 2009) can be taken as sufficient reasons to induce airlines to offer advance discounts and, more generally, that these variables affect price dispersion both among and within airlines fares structure. Regarding low-cost carriers (LCC's) in particular, several studies have also convincingly shown that their offered fares systematically tend to increase as the departure day approximates[2]. All this should imply that travellers' willingness to pay increases over time. However, willingness to pay may increase with the booking irrespective of the customer type, simply because of a shift in perceptions and expectations about fares and flight availability in the remaining days (Chen and Schwartz, 2008).

Among specialists in air transport economics it survives nonetheless the idea that differential pricing, whatever its origin, ultimately discriminates between, broadly speaking,

[1] Additional references to more recent literature on competition and discriminatory pricing can be found in Baumol (2005, section 1). Baumol's lecture contains one of the most resolute invitations not to take for granted the necessity of regulatory intervention whenever discriminatory pricing is observed. The author, indeed, goes so far as to maintaining that "[I]n a broad range of market types and conditions, where consumers can be separated into distinct groups with different demand elasticities and in which the market's commodity cannot easily be resold by one group to another, *market pressures will prevent any equilibrium in which the product price is uniform*." (p. 2, italics added).

[2] See, for example, Button and Vega (2007), Piga and Bachis (2007), and, Malighetti *et. al*. 2009.

business and leisure travellers. Discussions of discriminatory pricing more practically oriented, usually under the more palatable heading of "revenue (or/and yield) management", draw a distinction between quantity-based and price-based approaches to revenue management (see, for example, Holloway 2008). The former usually produces the well-known array of fare bases and booking classes utilized by traditional carriers, while the latter generates that practice of dynamic pricing so typical of low cost carriers and consisting, roughly speaking, in the practice of raising fares as the date of booking approaches the date of flight[3]. If we assume, as it seems reasonable to do, that leisure travellers – differently from business ones – are inclined to book well in advance, we may well conclude, as plainly stated by Button and Ison (2008, p. 3), that

> The airline can maximize its revenues by fare differentiation, and in particular, charging higher fares to those who book closer to take-off time – these are often business travellers that are fairly fare insensitive because they have to make the flight at short notice.

Focusing on the single flight such a conclusion seems almost undisputable, and paves the way to some considerations about the welfare effects of dynamic pricing based on the implicit cross-subsidizing mechanism. In fact, from a welfare perspective,

> [I]t is interesting to observe that not all travellers are affected in the same way with a decrease in the level of competition. Business travellers, who purchase high-price tickets, end up paying relatively lower fares in less competitive markets while leisure travellers pay more. Conversely, leisure travellers end up paying relatively lower fares with more competition. (Hernandez and Wiggins 2008, p. 20)

Otherwise, if we consider the single route, it seems equally appropriate to observe that

> Even if differences in air fares are explicitly discriminatory […] they can improve profits and welfare. Low prices directed at leisure travellers, with elastic demand, can lead to an increase in the overall size of the market; this results in higher frequency, which is valued by the business travellers paying highest fares, and may also lead to larger aircrafts with lower unit costs. (Forsyth et al. 2002, p. xiv).

The same conclusions, however, cannot be straightforwardly extended to the whole set of routes operated by a single carrier, if only because we cannot assume the same shares of business/leisure passengers on every route. On the contrary, due to the diverse nature of the different destinations, we may well expect a widely divergent composition of business/leisure traffic on different routes. Moreover, in this case it does not seem that we have sufficient *a*

[3] For a comprehensive discussion of the rationale behind the practice of dynamic pricing, see McAfee and te Velde (2006).

*priori* reasons to predict lower fares (on average) for "leisure" destinations than on "business" ones.

The aim of this paper is to investigate this last issue, which so far has been somewhat neglected even in specialized literature, with reference to one of the two major European low-cost carriers.

Working on a database which includes the daily fares over the 3 months prior to each flights operated by easyJet during 2009 (on 902 routes for a total of 321,538 flights), we trace the fare variation for each individual route as the flight date approaches. Our hypothesis is that price increases in the last 15 days before departure are meant to discriminate business demand, whereas leisure demand should account for earlier price variations, and that the relative weight of the two effects cannot be established *a priori*.

In that way we are able to classify each route by a "leisure index", defined as the percentage of offered flights where major price increases are in the earlier period. If this presumption is correct, it should be expected that: *(i)* such a leisure index allows to distinguish between routes typically "leisure" and routes more "business concerned", and *(ii)*, on average, the leisure index intensifies for week-end and midday flights, whereas longer term seasonal effects depend on the specific route characteristics. This will permit to estimate different pricing dynamics for the two kinds of flights/routes, so obtaining some interesting results.

The content of the paper is organised as follows. Section 1 reports the details of the construction of the above mentioned index. Section 2 describes the database as well as the methodology employed in this study and presents the main econometric results, while Section 3 offers some concluding remarks.

## 2. A "leisure index" defined

The "leisure index" as defined below has been constructed in order to distinguish "leisure" from "business" routes. It is based on the idea that the intertemporal price discrimination implemented by carriers reflects, in some way or another, different motivations for travelling. Since the LCC's business model does not entail any further restriction on fares, a business traveller is induced to reveal its nature and to buy late expensive tickets if this choice maximise her own surplus. This implies that intertemporal fare discrimination succeeds in separating the two type of customers if the willingness to pay of the business traveller increases with the booking time faster than that of the leisure travellers (or, more generally, if the spread between the willingness to pay of the two kinds of customers increase over time).

The rationale behind this presumption stands on observing that in early stages business travellers typically support an higher uncertainty cost about the real need to flight, while, after the meeting/business event is fixed, the cost of missing the flight is higher for her than for a tourist who might have to change the date and/or the destination if the first chosen flight is not available.

Hence our assumption here is that on those flights/routes where the intertemporal fare curve is expected to discriminate between the two types of customers we ought to see an increase in the fares offered during the last two weeks more than proportional to what could be derived looking at the fares trend in the early weeks. In order to check this conjecture, we proceed as follows.

First, for each flight we fit the temporal fare curve as in Malighetti *et al.* (2009, 2010). This permits to estimate a coefficient (β) of dynamic pricing, derived from the following price function:

$$p_x = \frac{1}{\alpha \cdot (1 + \beta_{1\_90} \cdot x)} \qquad x = 1..90 \qquad [1]$$

where x is the number of days between the advance reservation and the flight date and $p_x$ is the corresponding price. The referred price function is a hyperbola with the price going up as the flight date approaches. To a low β value it corresponds a steady price trend as the number of advance booking days increases, whereas a high β value indicates a more significantly discounted fare, in comparison with the highest fare ever offered, on advance purchases.

Second, we estimate the value of β in the last two weeks before departure only, that is

$$p_x = \frac{1}{\alpha \cdot (1 + \beta_{1\_15} \cdot x)} \qquad x = 1..15 \qquad [2]$$

For each flight i,t (on route i departing at date/time t) the "leisure index" is then defined as the difference between $\beta_{1\_90}$ and $\beta_{1\_15}$

$$L_{i,t} = \beta_{1\_90,i,t} - \beta_{1\_15,i,t} \qquad [3]$$

A significantly negative L-index means that in the last 15 days fares progression tend to be higher than what could be expected looking at the overall trend, thus suggesting that in the last 15 days the airline is targeting a new group of customer with higher late booking willingness to pay.

Figure 1 reports two examples of specific flights, including the spot price offered by easyJet as well as the two betas and the resulting L index.

<Figure 1 about here>

Table 1 below reports the average statistic of our Leisure index at flight level.

<Table 1 about here>

Table 2 reports the top and the last 20 routes by average L index. The routes with the higher average L-index, as well as with a higher share of flights with L>0, pretty well correspond to typical leisure routes. Indeed, the top 20 routes typically connect the main UK and some German airports to Mediterranean touristic destination in Greece, Egypt, Turkey, and Spain islands.

Conversely, among the routes with strong negative L-index we find connections between the main European capital (Milan, Paris, London and Brussels) as well as domestic connections like Toulouse-Lyon, Newcastle-Bristol or Milan-Rome which evoke typical business trips.

<Table 2 about here>

## 3. Empirical analysis

The above defined “leisure index” has an obvious empirical content. We can make use of it in order to analyze the main fare differences between “leisure” and “business routes”. In particular, we will study the relationship between L- index and some price characteristics of single routes (average price, minimum and maximum prices per kilometre) and the associated intensity of dynamic pricing.

The database at our disposal includes fares for each easyJet flight offered in 2009, from 90 days to the day before flight departure. Figure 2 shows the relation between average price per kilometre and distances for all flights considered. Average prices per kilometre drop from 0.2€ for short-haul routes to less than 0.05€ for routes longer than 2,000 kilometres[4].

<Figure 2 about here>

### *3.1 The model*

A possible impact of the leisure index on prices can be detected only if a number of other variables affecting fares that could be in some ways correlated with the leisure index (such as route distances, demand intensity, competition, the typology of territories connected, and, last but not least, the time of the day, the day of the week and the month in which the flight is scheduled) are taken into due account[5]. Furthermore, since both the dependent and the independent variables could be partially determined by the same factors, a problem of endogeneity may arise due to omitted variables.

To solve these problems, we employ a two-stage procedure. In the first place, we create a panel for the dependant variable, i.e. average fares per kilometre in the three months before departure, and for the leisure variable. In this phase, we consider 321,538 different flights operated by easyJet in 2009 on 902 different routes. The models to be estimated are as follows:

$$P_{i,t} = \alpha X_{i,t} + uP_i + \varepsilon_{i,t} \qquad [4]$$

$$L_{i,t} = \gamma X_{i,t} + uL_i + \varepsilon'_{i,t} \qquad [5]$$

where $P_{i,t}$ is the average price per kilometre of a flight on the route i starting at the time t[6], $L_{i,t}$ is the leisure variable, as defined in previous section, computed for a flight on the route i and

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[4] Data are obtained through a three steps procedure. First, we calculate for each flight its average price as the average of offered fares over a 90-day period before departure; then we compute the average price for each route calculated as the average of fares on all related flights; finally, for each distance x in the figure we report the moving average of fares on all routes with a distance included in the interval x +/- 50km.

[5] So, for example, a significant relationship between fares per kilometre and leisure attitude could result from a higher concentration of leisure flights on weekends or summer months rather than on a different revenue management between business and leisure flights.

[6] $P_{i,t}$ is defined as the average of the flight fares offered over a 90-day period before departure divided by the flight distance.

starting at time t. The $X_{i,t}$ vector represents the set of n independent variables which are meant to consider, for each route i, the effects of the time and date of departure and demand intensity.

Solving the equations employing the fixed-effects methodology, allows us to estimate the specific effects $uP_i$ and $uL_i$ that represent the average price per kilometre and the leisure effect at a route level, filtered from the departure time and demand intensity effects, respectively. The explanatory variables $X_{i,t}$ employed at this stage are as follows:

- FirstDay represents the day closest to departure after which tickets are no longer available. Thus, this variable is the day the flight can be considered fully booked. It is used as a proxy for the intensity of demand.
- Month1-Month12 are dummies for the month in which the observation occurs. For example, a flight in January sets 'Month1' to one, and all other dummies to zero.
- Day1-Day7 are dummies for the day of the week. For example, a flight taking place on Sunday sets 'Day1' to one and all other dummies to zero.
- Hour1-Hour24 are dummies for the time of the day. For example, a flight taking departing at 11:00 sets 'Hour11' to one and all other dummies to zero.
- BankHoliday is set to one if the flight occurs on a bank holiday, and zero otherwise.

The first stage of the model aims to obtain time-independent and route-related variables, after separating the effects of time and date of departure of the single flights together with their specific demand intensities. After solving the first stage model (assuming fixed effects), we correlate the specific effects $uP_i$ at a route level with the following set of explanatory variables. All these variables are related to specific characteristics of single routes. For the second stage of the analysis, as mentioned above, we rely on a total of 902 observations.

- The fixed effect $uL_i$ accounting for the leisure attitude of the route i, as computed at previous step.
- Distance is the route length.
- Frequency is the average weekly frequency of flights between the two airports.
- DirectCompetition is the number of competitors offering the same route.
- IndirectCompetition is the number of alternative routes departing from and/or arriving at airports within 100 kilometres of the observation's origin and destination airports.
- DepartureGDP is Gross Domestic Product generated in the departure airport region (as reported by Eurostat, 2007).

- ArrivalGDP is Gross Domestic Product generated in the arrival airport region (as reported by Eurostat, 2007).

The regression results of the second stage allow us to find the relationship between the average price per kilometre and the leisure variable, with no interference due to demand intensity and departure time and date.

### *3.2 Empirical results*

We are mainly interested on the results of the second stage of the methodology to understand whether pricing strategies vary from leisure to business routes. However, since in this paper we also define an innovative way to indentify leisure flights, it is of interest to look at the results of the first stage of the analyses in which the leisure index (equation [2]), is regressed to its explanatory variables at a flight level. The results are in table 1. The base case against which those coefficients and p-values are determined is that of a flight departing on Wednesday (Day4) of January (Month1), at five in the morning (Hour5), representing a typical business day and time.

Results fully confirm the statistical description in the previous section, with Saturday (Day7) and Sunday (Day1) as the days of the week in which the leisure index reaches its peak. As expected, the summer period including August (Month8) is that in which leisure flights are more frequent, followed by April (Month4). The later occurrence could be explained by considering that Eastern 2009 happened in this month. Looking at hours of the day, the midday period from 12a.m. to 3p.m. has the highest impact on leisure activities. The BankHoliday variable shows a significant and positive coefficient confirming that, other things being equal, leisure flights are more frequent on bank holyday. Interestingly enough, once time and date of the flight are accounted for, the relation between the leisure index and demand intensity measured by the FirstDay variable is negative, meaning that the earlier the flight becomes fully-booked the likelier for it to be classified as business. These results confirm once again the validity of the index constructed in the previous section.

<Table 3 about here>

**** indicates a statistical significance lower than 0.001; ** lower than 0.01 and * lower than 0.05.*

In the second phase of the empirical analysis, we regress the average price for kilometre at a route level, $uP_i$ from equation [4], to a second set of explanatory variables all related to single routes, including the leisure index at a route level, $uL_{i,}$ obtained from equation [5].

In order to reach a better understanding of the different pricing policies carried out by easyJet to leisure and business routes, we also study the determinants of the maximum and minimum prices per kilometre ($uPmax_i$ and $uPmin_i$, respectively) at route level, as well as the beta coefficients ($uBeta_i$, which summarizes the particular dynamic pricing pattern of each route). Values for this last variable are obtained according to a procedure analogous to the one followed for the average price per kilometre at a route level (uPi), repeating the first stage of the econometric analysis as from equation [4][7].

Table 2 reports the correlation matrix among the four dependant variables and their determinants in the second stage of the analysis. It is worth noting that the leisure index at a route level ($uL_i$) is weakly correlated to all other variables. Its correlation coefficient regarding average price per kilometre ($uP_i$) at a route level is zero, while the highest coefficients are associated with the distance and the Gross Domestic Product generated in the departure airport region variables. On average, therefore, leisure routes are longer than business routes.

On the whole, the correlation analysis dispels any possible remaining doubt about our definition of the leisure index as endogenously depending on average prices. The highest correlation coefficients in the table are between the price-related dependant variables and distance, as one would expect.

<Table 4 about here>

Table 3 reports the results of the second stage of the analysis. In the first column we have the determinants of the average price per kilometre at a route level. The only two variables statistically significant are the route distance, whose coefficient is negative, and the leisure index at a route level, whose coefficient is positive. This means that on average prices per kilometre are higher for leisure routes than for business routes.

<Table 5 about here>

[7] That is: $\beta_{i,t} = \alpha' X_{i,t} + u' \beta_i + \varepsilon'_{i,t}$

The second column reports results for the maximum price per kilometre. In this case, the coefficient of the leisure index at a route level is negative with statistical significance. So, when looking at maximum prices per kilometre, which we usually observe during the last days before departure, business routes reach higher levels than leisure routes. Distance remains significantly negative and frequency also shows some positive statistical significance. The higher the frequency on the route, the higher the maximum price per kilometre.

Results for the minimum price per kilometre (third column) at a route level, which usually occurs 60-90 days prior to departure, mirror those of model 1 with a positive relationship with the leisure index on a route level. Prices for leisure routes usually start higher, reach lower peaks but have higher averages than those for business routes. Another interesting result is that prices per kilometre on leisure routes show a less dynamic behaviour than those on business routes. This finding is also confirmed by the result of the fourth model regarding the beta determinants at a route level. Other things being equal, the higher the leisure index at a route level, the less intense the dynamic pricing activities. Discounts on advance booking happen mainly for stimulating (leisure) demand on business routes. Beta also appears (weakly) correlated to the direct competition variable, measured as the number of competitors on the route. Other things being equal, a higher direct level of competition induces the carrier to increase discounts for advanced bookings. This result confirms Malighetti et al. (2009 and 2010) where a similar relationship for Ryanair fares has been found.

### *3.3 Sensitivity Analysis*

The main result of the empirical analysis is that travellers on leasure routes are offered higher average fares than on business routes, other things being equal. Let us note, however, that from this we cannot conclude that “leisure” routes are more profitable for the carrier than the “business” ones, neither that the average revenues per passengers are higher.

Indeed, there are three factors that must be accounted for in order to assess overall revenues on leasure and business routes:

1. The number of offered seats could be different between leasure and business flights. EasyJet has a fleet mainly composed of Airbus A319-111 with 156 seats. However, it partially still employs Airbus A320 and A321 and Boeing 737-700. We easily accounted for this factor by looking at the average aircraft size for each route in the OAG data.

2. It may well happen that the higher fares which are charged on leasure routes are aimed at counterbalancing lower load factors. Results in table 3 confirm that. The variable Firstday, which accounts for demand intensity and is indirectly related to load factors, is negatively correlated to the leasure index. So, the lower the leasure index, the earlier the flight is fully booked.
3. We computed average fares as the simple mean of fares offered from 90 days to the day before departure. Anjos et al. (2005) proved that the optimal dynamic pricing strategy by low-cost carrier is that by which in each day the same quantity is sold. However, since here on each flight there are two different kinds of demand, leasure and business, it may happen that the quantity of tickets sold during the last 15 days is higher than the related proportion of days, 15/90. So, by computing the simple average of offered fares one would underestimate the average price paid on business routes.

In this section we aim to carry out a sensitivity analysis to determine under which conditions revenues for leasure routes are higher than for business routes, other things being equal. We consider two variables in the sensitivity analysis: i) the percentage of seats sold during the 15 days before departure for business route, that is allowed to be higher than 15/90 and ii) the increase in load factors for business routes. For each combination of the two variables we solved equation [4] and find whether the leasure index is still significantly positive, as it is in Model 1 of table 5. Figure 3 shows the results of the sensitivity analysis. It reports the curves under which revenues for leasure routes is higher than for business routes with a statistical significance (p-value) lower than 5%, 1% and 0.1%.

If seats sold during the last 15 days for business routes double from 15/90 to 30/90, revenue for leasure routes is still significantly higher than that of business routes with a p-value less than 0.1%. If load factors for business routes is above that of leasure routes by 7%, with bookings unchanged, revenues for leasure routes is still significantly higher. To make the difference between revenues of leasure and business routes not significantly different from zero, with a p-value of 5%, seats sold in the last 15 days for business routes must double to 30/90 and load factors for business routes must be at least 8% higher than those of leasure routes.

So, the assumption that overall revenues on leasure routes is higher than that on business routes appears statistically robust.

<Figure 3 about here>

## 4. Concluding Remarks

The main differences of revenue management between leisure and business routes, as they emerge from the above empirical results, can be summarized by saying that: *i)* leisure routes have higher average prices for kilometre, and *(ii)* prices on leisure routes show a less dynamic behaviour than on business routes, with higher minimum prices and lower maximum prices per kilometre.

These findings can be easily understood from the carrier's point of view. Dynamic pricing eventually aims to approximate for each flight the high-fare demand (that is, business demand) reserving its seats requirement for the last days before departure. The other seats are sold at lower prices in earlier periods. So, if a flight has a higher level of expected business demand, the carrier can afford to sell the other seats at lower fares. This explains why maximum prices for business flights reach higher level and dynamic pricing activities appear to be more pronounced than for leisure flights. In the latter case, since expected business demand is low or not existent, price dispersion for leisure passengers must be lower to allow carriers to reach the target revenue. However, we also robust find evidence of higher average fares on leisure routes, suggesting a much less obvious form of price discrimination between leasure and business routes. Sensitivity analysis in section 2.3 shows under which conditions the carrier's revenues on leasure routes is higher than that on business routes and appears to confirm the robustness of our conclusions.

Finally, from the point of view of leisure travellers, these findings bring intriguing insides. The best deals can be found on business routes, especially for advanced bookings. So, on average, it is cheaper to fly to big capital cities (typical destinations of business travellers too) than to exotic islands in Greece or Egypt. Furthermore, it is better change the travelling behaviour towards those of business passengers, flying during the week working days and departing earlier in the morning or later in the evening. In other words, it pays to stick as close as possible to business travellers since they are taking a bigger share of the burden. In this respect, temporal price discrimination is not so different from traditional quantity discrimination, after all.

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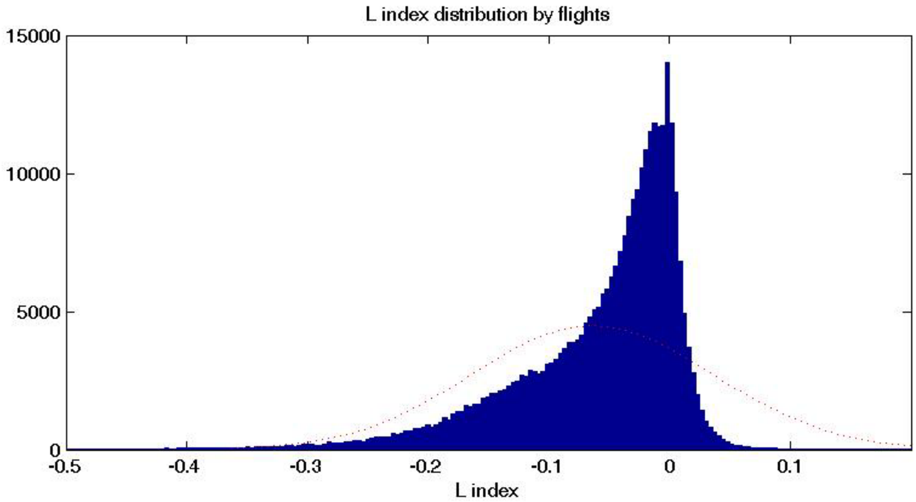
**L index by flights**

| | |
|---|---|
| N. flights | 317572 |
| Mean | -0.0638 |
| Std. Dev. | 0.0998 |
| Max | 1 |
| Min | -1 |
| $10^{th}$ percentile | -0.4107 |
| $25^{th}$ percentile | -0.0917 |
| $50^{th}$ percentile | -0.0364 |
| $75^{th}$ percentile | -0.0088 |
| $90^{th}$ percentile | 0.0051 |




**Average L index by routes**

| | |
|---|---|
| N. routes | 744 |
| Mean | -0.0516 |
| Std. Dev. | 0.0336 |
| Max | -0.0006 |
| Min | -0.2421 |
| $10^{th}$ percentile | -0.1510 |
| $25^{th}$ percentile | -0.0663 |
| $50^{th}$ percentile | -0.0415 |
| $75^{th}$ percentile | -0.0280 |
| $90^{th}$ percentile | -0.0190 |

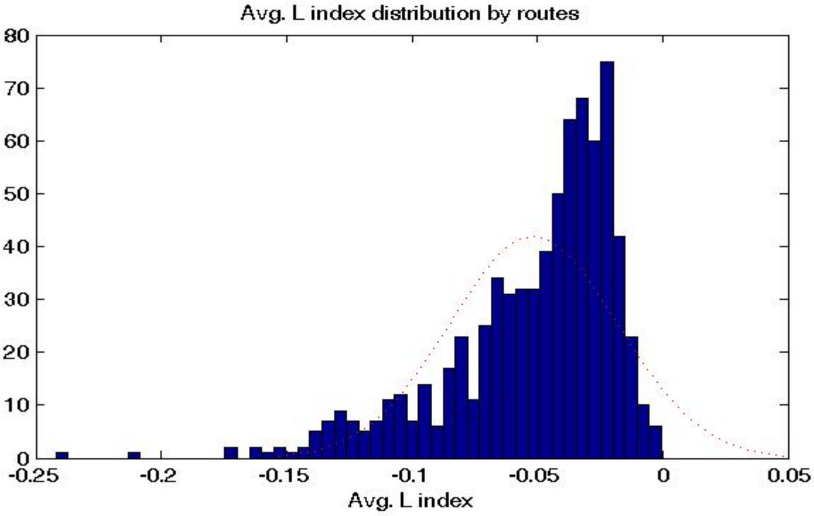



*Table 1 L-index summary statistic and distribution (Only routes with at least 50 flights have been considered here).*

| Last 20 routes by Average L index | | | | Top 20 routes by average L index | | | |
|---|---|---|---|---|---|---|---|
| **Route** | **Avg L index** | **St Dev Lindex** | **% flights L >0** | **Route** | **Avg L index** | **St Dev Lindex** | **% flights L>0** |
| Basel-Dusseldorf | -0.242 | 0.149 | 3.9% | Dubrovnik-London LGW | -0.001 | 0.043 | 66.0% |
| Toulouse-Lyon | -0.212 | 0.266 | 8.9% | Thira-London LGW | -0.003 | 0.009 | 49.0% |
| Rome FCO-Bari | -0.172 | 0.132 | 4.4% | Berlin SXF-Pisa | -0.003 | 0.035 | 48.3% |
| Milan MXP-Bristol | -0.170 | 0.167 | 5.8% | Sharm el Sheikh - London LGW | -0.004 | 0.015 | 58.2% |
| Rome FCO-Milan MXP | -0.160 | 0.160 | 5.2% | Bodrum-London LGW | -0.005 | 0.015 | 54.4% |
| Newcastle-Bristol | -0.156 | 0.130 | 1.8% | Dalaman-Manchester | -0.005 | 0.015 | 58.6% |
| Milan MXP-London LTN | -0.142 | 0.169 | 9.4% | Hurghada-London LGW | -0.006 | 0.021 | 61.5% |
| Newcastle-London STN | -0.141 | 0.109 | 2.8% | Dalaman-London LGW | -0.007 | 0.024 | 62.9% |
| Milan MXP-Brussels | -0.140 | 0.119 | 5.4% | Rhodes-London LGW | -0.007 | 0.029 | 62.5% |
| Bristol-Glasgow | -0.139 | 0.109 | 2.0% | Palermo-London LGW | -0.008 | 0.033 | 40.6% |
| Milan MXP-Paris CDG | -0.136 | 0.161 | 6.9% | Madrid-Fuerteventura | -0.008 | 0.032 | 43.9% |
| Madrid-Lisbon | -0.136 | 0.141 | 5.2% | Las Palmas-Geneva | -0.009 | 0.023 | 41.0% |
| London LTN-Glasgow | -0.134 | 0.115 | 2.7% | La Rochelle-Bristol | -0.009 | 0.059 | 78.6% |
| Paris CDG-London LTN | -0.133 | 0.117 | 3.1% | London LGW-Mikonos | -0.009 | 0.022 | 40.8% |
| Geneva-Birmingham | -0.131 | 0.143 | 11.0% | Palma De Mall.-Belfast | -0.010 | 0.040 | 46.2% |
| Dortmund-London LTN | -0.131 | 0.121 | 11.0% | Berlin-Thessaloniki | -0.010 | 0.020 | 32.5% |
| Lyon-London LGW | -0.130 | 0.173 | 13.5% | Faro-Belfast | -0.011 | 0.074 | 61.3% |
| London STN-Glasgow | -0.130 | 0.104 | 2.9% | Alicante-Belfast | -0.011 | 0.036 | 43.9% |
| Edinburgh-London STN | -0.127 | 0.114 | 1.8% | Thessaloniki-Dortmund | -0.011 | 0.025 | 43.6% |
| Brussels-Milan MXP | -0.116 | 0.107 | 5.1% | Madeira-Bristol | -0.011 | 0.043 | 65.5% |

*Table 2 Top and last 20 routes ranking by Average L index*

| **Explanatory Variables** | **Coefficient (*1000)** | **P-value** | **Explanatory Variables** | **Coefficient (*1000)** | **P-value** |
|---|---|---|---|---|---|
| FirstDay | -2.60 | 0*** | Hour6 | -7.39 | 0.002** |
| Day1 | 49.15 | 0*** | Hour7 | -11.67 | 0*** |
| Day2 | 16.61 | 0*** | Hour8 | -2.51 | 0.289 |
| Day3 | 1.86 | 0.002** | Hour9 | 9.27 | 0*** |
| Day5 | 10.19 | 0*** | Hour10 | 10.23 | 0*** |
| Day6 | 31.60 | 0*** | Hour11 | 13.05 | 0*** |
| Day7 | 40.34 | 0*** | Hour12 | 16.90 | 0*** |
| Month2 | -10.10 | 0*** | Hour13 | 14.95 | 0*** |
| Month3 | 10.72 | 0*** | Hour14 | 16.41 | 0*** |
| Month4 | 30.59 | 0*** | Hour15 | 18.03 | 0*** |
| Month5 | 16.73 | 0*** | Hour16 | 11.27 | 0*** |
| Month6 | 23.09 | 0*** | Hour17 | 11.08 | 0*** |
| Month7 | 24.99 | 0*** | Hour18 | 4.85 | 0.039* |
| Month8 | 35.42 | 0*** | Hour19 | 11.13 | 0*** |
| Month9 | 23.40 | 0*** | Hour20 | 8.34 | 0*** |
| Month10 | 19.46 | 0*** | Hour21 | 6.82 | 0.004** |
| Month11 | 13.41 | 0*** | Hour22 | 3.77 | 0.207 |
| Month12 | 16.94 | 0*** | Hour23 | 2.57 | 0.431 |
| Constant | -105.01 | 0*** | BankHoliday | 7.49 | 0*** |

*Table 3.Results of the first stage (equation[5]). Explanatory variables of the leisure index.*

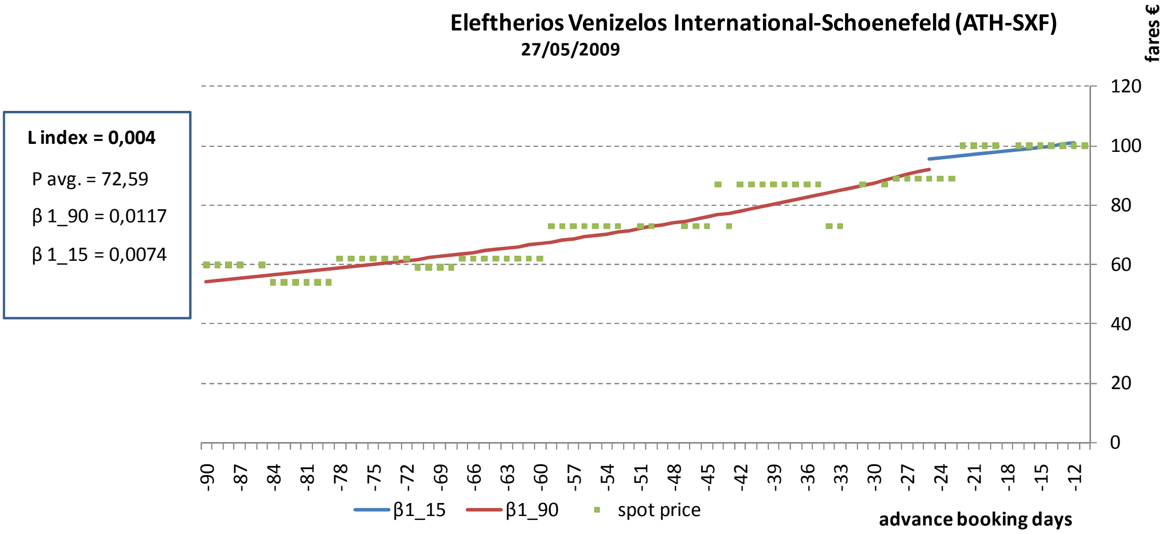
| | | Correlation matrix | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Dependant variables | AveragePrice/km($uP_i$) | 1.00 | | | | | | | | | | |
| 2 | | Maxprice/Km($uPmax_i$) | 0.87 | 1.00 | | | | | | | | | |
| 3 | | Minprice/km($uPmin_i$) | 0.96 | 0.77 | 1.00 | | | | | | | | |
| 4 | | Beta($uBeta_i$) | 0.14 | 0.50 | -0.04 | 1.00 | | | | | | | |
| 5 | Explanatory variables | Leisure($uL_i$) | 0.00 | -0.22 | 0.01 | -0.16 | 1.00 | | | | | | |
| 6 | | Distance | -0.59 | -0.74 | -0.48 | -0.49 | 0.37 | 1.00 | | | | | |
| 7 | | Frequency | 0.11 | 0.33 | 0.04 | 0.45 | -0.23 | -0.31 | 1.00 | | | | |
| 8 | | DirectCompetition | 0.00 | 0.07 | -0.03 | 0.18 | -0.08 | -0.06 | 0.41 | 1.00 | | | |
| 9 | | IndirectCompetition | 0.03 | 0.13 | 0.02 | 0.08 | -0.20 | -0.14 | 0.10 | 0.27 | 1.00 | | |
| 10 | | DepartureGDP | -0.04 | -0.02 | 0.02 | -0.12 | -0.32 | -0.03 | 0.03 | -0.05 | 0.03 | 1.00 | |
| 11 | | ArrivalGDP | -0.01 | 0.07 | -0.05 | 0.19 | 0.14 | -0.03 | 0.03 | 0.00 | 0.33 | -0.40 | 1.00 |

*Table 4 .Correlation matrix among the variable employed in the second stage of the analysis.*

| | **Model1 Average price/km($uP_i$)** | | **Model2 Maximum price/km($uPmax_i$)** | | **Model3 Minimum price/km ($uPmin_i$)** | | **Model4 Beta ($uBeta_i$)** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Coeff.** | **P-value** | **Coeff.** | **P-value** | **Coeff.** | **P-value** | **Coeff.** | **P-value** |
| **Leisure($uL_i$)** | 1.4E-01 | 0.000*** | -1.4E-01 | 0.019* | 7.3E-02 | 0.000*** | -1.1E-01 | 0.000*** |
| **Distance** | -2.7E-05 | 0.000*** | -5.9E-05 | 0.000*** | -1.4E-05 | 0.000*** | -5.3E-06 | 0.000*** |
| **Frequency** | 4.3E-05 | 0.208 | 3.5E-04 | 0.000** | 1.4E-05 | 0.557 | 9.1E-05 | 0.052 |
| **Direct Competition** | -6.8E-04 | 0.368 | -1.5E-03 | 0.358 | -7.3E-04 | 0.155 | 1.0E-03 | 0.014* |
| **Indirect Competition** | 1.7E-04 | 0.591 | 5.3E-04 | 0.452 | 3.2E-04 | 0.142 | -7.0E-04 | 0.067 |
| **DepartureGDP** | -4.4E-09 | 0.109 | -7.4E-09 | 0.215 | 6.1E-11 | 0.974 | -6.7E-09 | 0.100 |
| **ArrivalGDP** | -4.4E-09 | 0.133 | -5.7E-10 | 0.930 | -4.5E-09 | 0.026* | 4.2E-09 | 0.09 |
| **Constant** | 3.1E-02 | 0.000*** | 5.5E-02 | 0.000*** | 1.6E-02 | 0.000*** | 3.4E-03 | 0.009** |
| **Adjusted $R^2$** | 43% | | 57% | | 32% | | 39% | |

*Table 5. Empirical results of the second stage of the analysis for the four estimated models.*

**Example of Lindex on single flights**



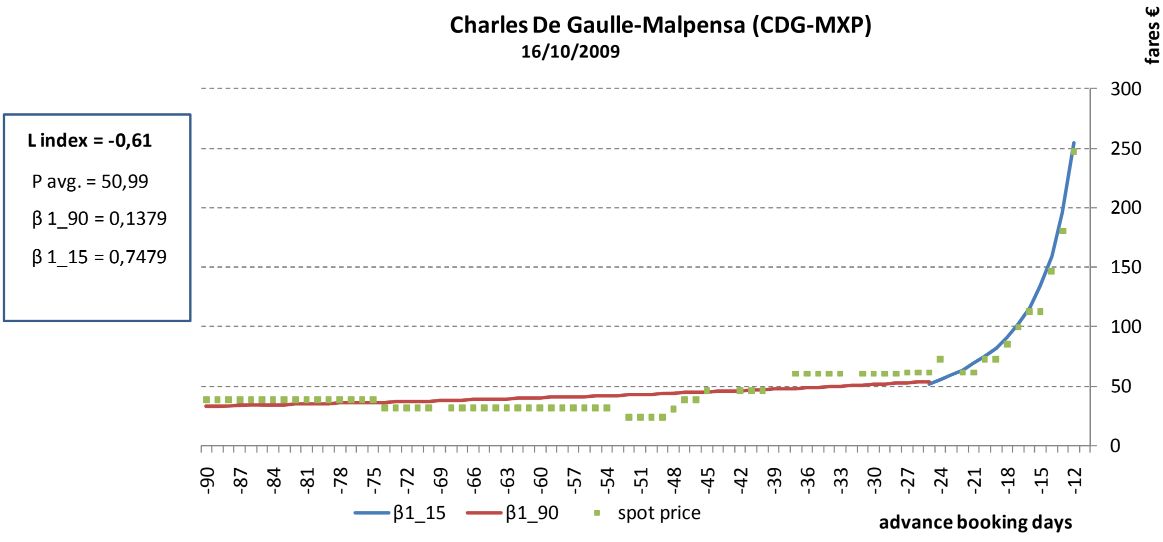




*Figure 1. Examples of spot price offered on specific flights, and plot of fare curves estimated (β1_90, β1_15 and derived Lindex )*

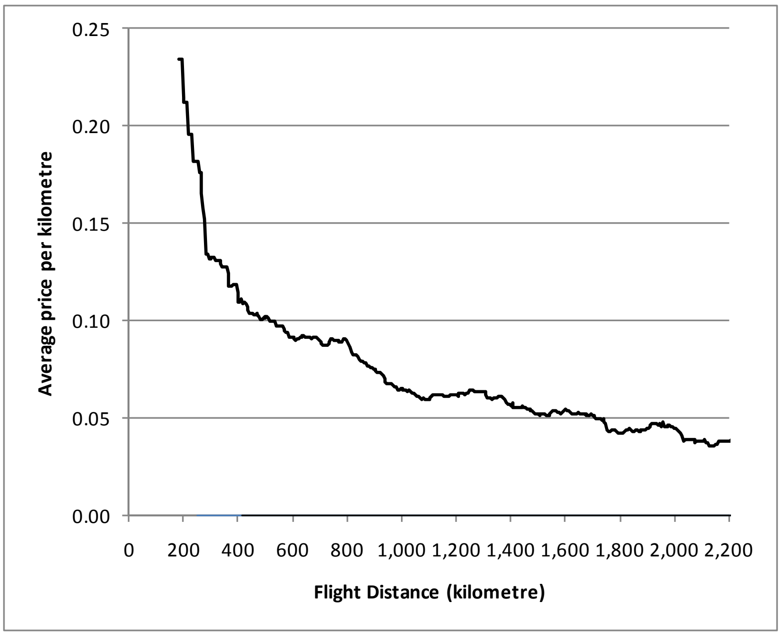



*Figure 2. Average fares per kilometre and distances for all flights operated by easyJet in 2009.*

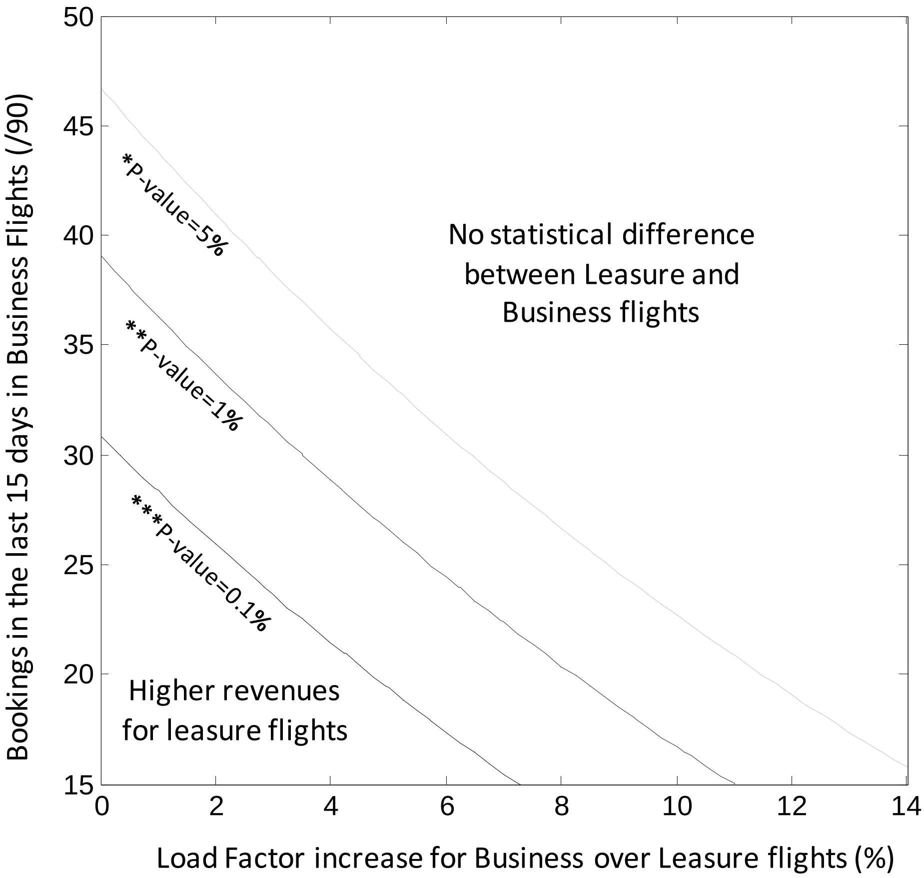



*Figure 3. Sensitivity analysis on the difference between revenues for leasure and business routes.*