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Optimal purchase timing in the airline market

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ABSTRACT

This paper presents general patterns in airline pricing behaviour and a methodology for analysing different routes and/or carriers. The purpose is to provide customers with the relevant information they need to decide the best time to purchase a ticket, striking a balance between the desire to save money and any time restraints the buyer may have.

The study shows how non-parametric isotonic regression techniques, as opposed to standard parametric techniques, are particularly useful. Most importantly, we can determine the margin of time consumers may delay their purchase without significant price increase, specify the economic loss for each day the purchase is delayed and detect when it is better to wait until the last day to make a purchase.

As an application, we analysed air fares for routes from Madrid to London, Frankfurt, New York and Paris over the course of two months, taking into account advance-purchase ticket sales of up to 30 days. We found that the consumer has a margin of 18 days prior to departure within which to purchase a ticket without any significant economic penalty.

1. Introduction

The arrival of the Internet to millions of homes around the world, coupled with the development of new technologies, has allowed people to purchases of all types goods and services on-line. Tourism is one of the most important sectors in terms of on-line demand, with airline tickets one of its greatest exponents. Air fares fluctuates daily, and prices can even change several times in a single day.

The goal of the consumer is to purchase a ticket at the lowest possible price. Logic would suggest that the earlier the purchase date, the lower the fare. However, nothing indicates this to be the case, and even if it were, customers are generally not certain of their travel plans until a few weeks prior to departure. Every airline has a specific pattern for setting ticket prices at different times. People not involved in this task are not privy to the rules on price variation and therefore do not know when the best time is to purchase tickets.

When consumers are concerned about value for lower prices, they tend to purchase from an Internet retail channel (Yu, 2008). In fact, Alderighi et al. (2011) stated that passengers who booked well in advance were more concerned about paying lower prices than those who bought their airline tickets closer to the departure date. Therefore, airlines employ a high-low pricing mechanism based on this inter-temporal segmentation, especially among low-cost companies.

This practice of inter-temporal price discrimination variation has been detailed in several papers (see for instance Gallego and van Ryzin, 1994; Su, 2007). In general, there is compelling evidence that the characteristic path slopes upwards in the last 20–30 days before the departure date (Alderighi, 2010; Alderighi et al., 2011; Gaggero and Piga, 2010; Giaume and Guillou, 2004; Mantin and Koo, 2009).

Other studies reinforce this idea. Law et al. (2011) examined the temporal changes of air fares toward the set departure date. The authors presented a descriptive study of the prices collected but showed no modelling. Puller and Taylor (2012) focused their study on the day of the week a ticket is purchased. Mantin and Koo (2010) found a strong weekend effect for airfare dispersion, but not for price level. Salanti et al. (2012) considered two different time intervals and the implicit interpolating functions are hyperbola. Etzioni et al. (2003) analysed price dynamics as a function of whether the carrier was a small or large airline, using a system based on rule learning, reinforcement learning and time series. Roos et al. (2010) used a mixed linear model to analyse the pricing dynamics in the Australian Airline Market, and Alderighi et al. (2011) used a linear model, including variables such as amount of

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time before departure the ticket is bought and duration of stay, using a logarithmic transformation.

The approach closest to our study is that of Piga and Bachis (2007) and Bachis and Piga (2011). These authors analysed the daily change in airfare for routes operated by low-cost carriers departing from several European airports. For each route, they collected a sample of daily airfare data on several days prior to departure and showed that each airline's distribution of the lowest fares tended to increase as the departure date approached. A more complex model may be found in Mantin and Koo (2009), who included in the linear model several variables of route characteristics (distance, origin and destination, per capita income and population, number of passengers boarded at the two endpoints, etc.).

However, none of the aforementioned references suggest possible purchaser strategies; this is precisely the aim of the present study. Using non-parametric techniques (known as isotonic regression techniques) our model includes the monotone relationships between fare distribution and departure date, which provides us an innovative method to obtain a purchasing strategy for the consumer. We can calculate the margin of time consumers can delay their purchase without a significant price increase, the daily increase from that point on, and when it is better to wait until the last moment to make a purchase.

Isotonic regression techniques have been used successfully in the field of tourism in Domínguez-Menchero and González-Rodríguez (2007), Torres and Domínguez-Menchero (2006) and Valdés et al. (2007), and in situations associated with the management of airports, Torres et al. (2005). The methodology is easy to implement and requires less additional information than other methods; moreover, the piecewise linear models obtained are easy to interpret and analyse by managers who are not specialised in statistical techniques.

General patterns in price behaviour are obtained and the methodology enables us to extract particular patterns from data on specific routes, time periods and airlines. In this study we analysed four routes defined between city-pairs, all departing from the Madrid airport with destinations either on the European continent (Frankfurt, London, Paris) or in North America (New York). Both direct flights and flights with one stop were considered. Over a two-month period the daily price fluctuation was studied for 30 days prior to the travel date. The departure dates were between 14 June 2012 and 14 July 2012. Ticket prices were based on the lowest fare generated by the search engine on the website www.atrapalo.com. The search was conducted every day at the same time so that the factors mentioned above would have the least possible impact on price change.

The market structure and, in particular, the presence of low-cost carriers on the analysed routes influenced the data collected. For each route, there were at least eleven airlines and a high presence of low-cost carriers. For each case, the most economic fare was selected. The following airlines were observed using the atrapalo.com service (companies are listed by decreasing average fare): i) Madrid-Frankurt: Lan Airlines, Swiss, Lufthansa, Vueling, Scandinavian Airlines, Iberia, KLM Royal Dutch Airlines, Air France, Sn Brussels, Airberlin, TAP Air Portugal, British Airways, LowCost, Austrian Airlines, Alitalia; ii) Madrid–London: LowCost, Vueling, Air Europa, British Airways, Swiss, Lufthansa, TAP Air Portugal, Iberia, Sn Brussels, KLM Royal Dutch Airlines, Air France, Scandinavian Airlines, Austrian Airlines, Alitalia, Airberlin; iii) Madrid–New York: US Airways, British Airways, Finnair, Iberia, American Airlines, Delta, Air France, KLM Royal Dutch Airlines, United Airlines, Lufthansa, Turkish Airlines, Royal Air Maroc, Aeroflot, Aerlingus, Airberlin, Swiss, LowCost, Scandinavian Airlines, Avian-ca, TAP Air Portugal, Virgin Atlantic Airways, Sn Brussels, Air Europa, Alitalia, Air Canada, Austrian Airlines, Jet Airways; iv) Madrid–Paris: LowCost, Iberia, Swiss, Lufthansa, Vueling, KLM Royal Dutch Airlines, Air France, Air Europa, British Airways, TAP Air Portugal, Alitalia.

The remainder of the paper is structured as follows: In Section 2 we detail the mathematical model and the results for the routes analysed. In Section 3 we discuss the limitation of the research, and in Section 4 we offer concluding remarks.

2. Methodology

As mentioned in the introduction, the price analysis begins one month before the travel date. Thus, the price of the ticket for day t_0 is represented by $p_{t_0,l}$, with $|l|$ being the number of days of advance purchase, $l = -31, -30, \ldots, -2, -1, 0$.

The savings rate

$$\Delta_{t_0,l} = 100\left(1 - \frac{p_{t_0,l}}{p_{t_0,0}}\right) \quad l = -31, -30, \ldots, -2, -1$$

measures the percentage of savings if the consumer purchased the ticket $|l|$ days before the departure date (i.e., a $|l|$ day lag) as opposed to a same-day purchase.

For each route studied, there are 31 savings rate values for each day t_0 from 14 June to 14 July 2012, amounting to a total of 961 rates per route. Fig. 1 shows the rates for the four routes in an interval that covers at least 80% of the rates observed.

If the relationship between the savings rate and the lag time is modelled using an explanatory function g, then the model is

$$\Delta_{t_0,l} = g(l) + \varepsilon_{t_0,l} \tag{1}$$

where $\varepsilon_{t_0,l}$ is the model error.

First, a parametric linear model, $\widehat{g}_{\text{linear}}$, is fitted to the cloud of points. Such a naive model would obviously not be used in practice, but it does allow us to draw initial conclusions about the savings rate trend with increased lag time. For each of the routes observed the function g would be estimated by the linear regression of the 961 rates observed $\Delta_{t_0,l}$. The results are shown below in Fig. 2.

$$\text{Frankfurt} \quad \widehat{g}_{\text{linear}}(l) = -1.63\, l + 25.49 \tag{2}$$

$$\text{London} \quad \widehat{g}_{\text{linear}}(l) = -1.63\, l + 19.75 \tag{3}$$

$$\text{New York} \quad \widehat{g}_{\text{linear}}(l) = -0.57\, l - 2.02 \tag{4}$$

$$\text{Paris} \quad \widehat{g}_{\text{linear}}(l) = -1.57\, l + 39.45 \tag{5}$$

The respective R^2 coefficients are 0.17, 0.23, 0.09 and 0.45.

The previous naive strategy would always be to buy as soon as possible. In fact, the initial fare, although tending to increase as the days pass, is more likely to remain the same or experience irrelevant changes during a period of time. Therefore, purchasing earlier does not provide the traveller any economic benefit but does cause inconvenience. For the consumer, it is particularly relevant to know when the savings rate begins to drop, since it is at that time that the decision should regarding purchase. One of our aims is to estimate this moment.

With linear regression, however, we can conclude that the savings rate trend is non-increasing in terms of lag time. In recent years, statistical techniques have been developed for estimating non-increasing (or alternatively non-decreasing) regressions, known as isotonic regressions. These are particularly important in the area of economics (see, for example, Härdle, 1991); in Colubi et al. (2006) isotonic regression is applied to the consumption of essential goods in terms of family income in the UK.