Dynamic Price Competition in the Air Transport Market: An Analysis on Long-Haul Routes

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Preliminary version

Abstract

The pricing policy of airlines is based on revenue management. Revenue management analysts daily observe competitive prices and strategically adjust their own tariffs. One could expect this behavior to lead to a sound homogenization of airline prices evolution while competing on a market. We test empirically whether airline pricing strategies evolve on a similar manner, on a particular set of long-haul routes. Using new and original data including information on ticket prices paid, purchasing and departure dates, we estimate a model for the effect of dynamic factors on the evolution of ticket prices, based on economic theory. We use a 3rd degree polynomial regression between prices and number of days to departure for each airline operating on the routes, and control for key revenue management variables, competition factors and individual effects. Our results show that competing airlines pricing strategies are statistically distinct during their ticket sale period. Airlines maximize their profits by sequentially increasing or decreasing their prices, but they do so in a non-synchronized fashion, and with different magnitudes.

Keywords: Air transportation, Price discrimination, Revenue management, Panel data;

JEL codes: L93, L110, L130, C33

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1. Introduction

Airlines tend to differentiate their products and use complex pricing discriminatory practices on the basis of their Revenue Management (RM) process. Revenue managers open or close tariff classes during a flight booking period, taking into account the load factor and the level of demand. Also, to address competitive pressure during this optimization process, they observe daily prices of competitors and adjust their tariffs accordingly.[1] This practice should lead to similar pricing strategies across time for similar products, however we show that airlines choose to significantly differentiate their tariffs and sometimes even alternate high and low prices in an opposite way.

The literature tries to explain the evolution of observed prices and their dispersion over time. However, most studies are built on databases that either lack information on dates of purchase and dates of departure (primarily articles based on the DB1B database from the US government) or are built according to data on posted fares (usually collected through spider programs[2]) rather than actual prices paid. In this article we have access to a unique and confidential database gathering information on the tickets purchased on four long-haul routes for which sales are registered since the moment they are proposed, i.e. one year in advance. This distinctive database allows us to analyze how pricing behavior differs across airlines in some competitive markets. However its confidentiality rules prevent us from giving any specific information on the markets and competing airlines.

To our knowledge, there is a limited number of articles that use observed purchased tickets; Sengupta and Wiggins (2012; 2014), Hernandez and Wiggins (2014), Puller, Sengupta and Wiggins (2009) or Puller and Taylor (2012). They all have access to tickets bought between June and December 2004 for flights in the fourth quarter of the same year for the US domestic market. They use fixed effects or airlines market shares to control for airlines specificities, however none of these studies differentiates pricing strategies among airlines.

With our dataset we observe distinct patterns among airlines in the evolution of their prices over time. Figure 1 depicts the average of the prices paid for all economy tickets sold a specific number of days prior to the departure of any flights in our sample.[3] We observe individual changes in trends and magnitudes. In this paper, we empirically show that airlines, while dynamically taking pricing decisions of their competitors into account: i) internalize the number of days prior to departure to increase their revenue; but ii) do not engage in similar price patterns over a booking period. More specifically, not only carriers differentiate the products they are offering on the market but they also adopt different pricing strategies, even if punctually adjusting for competing tariffs (thanks to RM technics). These findings could also explain some of the contradictory results observed in the literature. For example Borenstein and Rose (1994) show that price dispersion increases on more competitive routes, using 1989 cross section data from the US DB1B database. Gerardi and Shapiro (2009) find the opposite result: competition has a negative impact on dispersion. They use panel data, rather than cross-sectional data, from

[1] For instance Amadeus announces in its website: "*Based on real-time shopping session information (e.g. trip context), market information (e.g. competitor offers), and the airline's revenue management and pricing strategy (e.g. product consistency), Amadeus Dynamic Pricing is modelling customer behavior and decision, considering his willingness to pay, to calculate the optimum price and instantly adjusts the available fares and taxes"* ('Amadeus Dynamic Pricing' 2017). All these practices are described in Talluri and Van Ryzin (2004) among others.

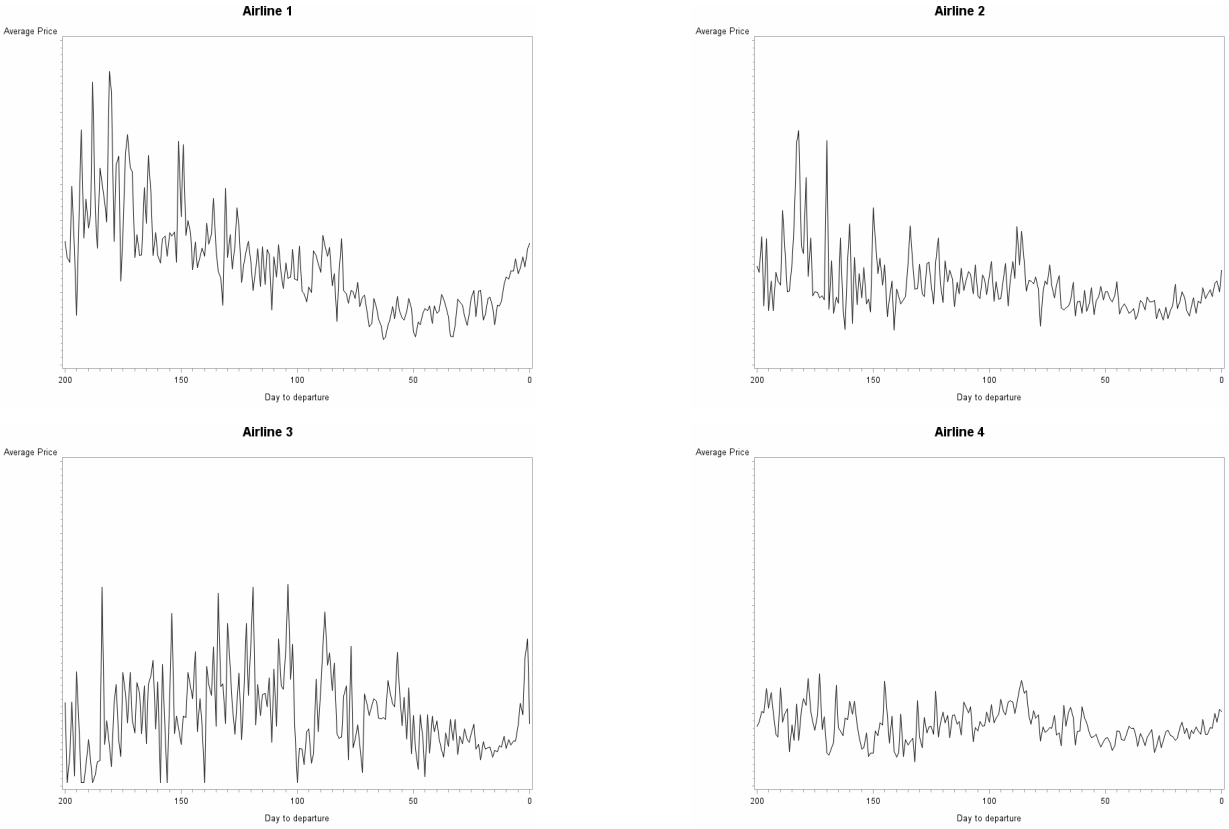
[2] Spider programs, also called website crawlers or 'bots' are software programs created to gather information from all the websites they visit.

[3] See Section 3 for more details on the average price computation.

the same US DB1B database on the period 1993-2006. Our approach illustrates that price dispersion measures could be biased if pricing strategies are not well specified.

The paper is organized as follows. In Section 2 we present the data, then we describe the model and estimation method in Section 3. Section 4 summarizes the results and Section 5 concludes.

Figure 1. Average Price Evolution per Day Prior to Departure, on a Given Market



2. A Rich Dataset

We use a database gathering information on purchased tickets for four airlines, all operating on the same four long-haul routes. We observe individual tickets from the Computer Reservation System, purchased between September 1, 2012 and February 1, 2014.[4] This period of observed booking corresponds to 2541 flights departing from September 1, 2013 to February 1, 2014. A route is a one way Origin-Destination market at the airport level. This ticket-level information is provided for all four airlines operating on those markets. Three of them are Full Cost Carriers (FCC), and one is a Low Cost Carrier (LCC).[5]

The tickets in our sample are collected and observed daily. Such a disaggregated database opens a large scope of research. To begin with, we observe the date of purchase of each ticket

[4] Our dataset does not include tickets bought directly from the airlines websites.

[5] The Low Cost business model for airlines focuses on strongly reducing costs in order to offer significantly lower prices to customers.

and the date of the flight departure. Second, the dataset avoids the restrictions imposed by the usual US DB1B database, which restricts the empirical analysis to the domestic US market and more importantly presents the limitation of quarterly aggregated data. Third, our observations contain information on the ticket characteristics[6] and the flight arguments.[7] In particular we observe ticket classes.[8] The classes are used by revenue managers to determine the price to offer according to their revenue maximization objective. .

The date of purchase and the date of departure allow us to recover the number of days prior to departure which is crucial information for the analysis of dynamic price competition. We restrict the analysis to direct flights and to a booking period of 200 days before departure. Before these 200 days the number of tickets purchased represents only 2.5% of the total tickets sold. We focus on economy cabin tariffs only, to derive consistent results based on a homogenous service quality. The strength of our dataset lies in the observation of the two above mentioned dates, jointly with ticket classes. Some competition mechanisms on the market can be partly inferred from these observations.

Each observation in our dataset is defined as a combination of a route, an airline and a number of days prior to departure (DTD). We compute an average price per observation, weighted by the corresponding number of passengers: For flights departing between days *1* and *T,* we compute the average of all the transactions realized at dates *1- DTD*, *2- DTD*,…and *T- DTD*. Our dataset contains 3198 observations for the booking period under scrutiny. Our sample covers 30% of the offered seats.

3. The model

The equation we fit on this data is a reduced form based on an economic model, even though it does not explain the full behavior of airlines. The theoretical foundations of our model are that airlines offer varying prices over the booking period for a flight, to maximize their profit by trading off between attracting more passengers and generating a higher margin. Airlines take into account the dynamics of their cumulative revenue on a flight as well as their competitors' prices. We control for these dynamics to better identify and measure the impact of the number of days prior to departure for the different airlines, and consequently better distinguish their differentiated strategic pricing behavior.

First, as displayed in Figure 1, the dynamic evolution of prices according to the days to departure seems to follow a non-linear relationship. We introduce in our model the days to departure as a third-order polynomial to match this behavior as in Escobari (2009). Second, in order to test whether airlines implement different pricing strategies across time, we interact the number of days to departure with each airline, allowing for a different effect of time on each competitor's decision, as in Bilotkach et al (2010). Third, to capture the effect of competition on prices, we build a variable measuring the average competitors' price for a ticket, for the day preceding the observed booking. We are then able to address the main (but not only) component

[6] More precisely: Hour, date and city of purchase, city and country of departure and arrival, day and hour of departure and arrival.

[7] More precisely: Flight number, number and date of stops, marketing and operating airlines, aircraft type.

[8] Using RM wording, the distinction between Economy and Business tickets corresponds to a distinction in terms of cabin layout and quality. Several fare classes are distinguished within each Economy or Business. RM pricers open or close classes during the booking period according to their objectives in terms of revenue while taking into account the behavior of competitors on the market.

of RM, which is the permanent adjustment of prices to the competitors'. Obviously matching closely competitors' prices is only optimal for an airline when it also takes into account its cumulated revenue up until the previous day. Indeed, the urge to fill an aircraft close to the departure date might drive airlines to lower their prices, or on the contrary to maintain a high level of prices if revenue is already significant. We introduce a variable measuring the sum of all past revenues for a flight (the cumulative revenue), until the previous day of booking. We finally control for seasonal effects, as the markets under consideration are likely to be sensitive to national holidays, implying different demands, and therefore different prices.

To control for unobserved route and airline individual effects that could affect prices (like reputation, costs specificities…), we perform a standard within group estimation. This technique, described in details in Wooldridge (2010) allows solving for potential endogeneity issues when no good instrumental variables are available..

Our model is presented in the equation below. The subscripts *i*, *j* and *DTD* refer to an airline, an OD pair and a number of days prior to departure, respectively:

$$\ln\left(P_{ijDTD}\right) = \alpha + \beta_{1i}\, DTD + \beta_{2i}\, DTD^2 + \beta_{3i}\, DTD^3 + \beta_{4FCC} \ln\left(P_{-ijDTD+1}\right) FCC + \beta_{4LCC} \ln\left(P_{-ijDTD+1}\right) LCC$$
$$+ \beta_{5FCC}\ \ln\left(CR_{ijDTD+1}\right) FCC + \beta_{5LCC}\ \ln\left(CR_{ijDTD+1}\right) LCC + \beta_6\ LowSeason_{ijDTD} + u_{ijDTD}$$

where P_{ijDTD} is the average price paid for flights operated by airline *i*, on the route *j*, at a certain number of days prior to departure *DTD*. [9]*DTD* belongs to the $[0; 200]$ interval. It is equal to 0 when customers purchase tickets on the flight departure day. It is equal to 200 when tickets are purchased 200 days before the departure of the flight. $P_{-ijDTD+1}$ and $CR_{ijDTD+1}$ are respectively the average price of competing airlines' tickets and airline *i*'s cumulated revenue on route *j* at *DTD*+1 (that is to say the cumulative revenue up until the day before). The variables $P_{-ijDTD+1}$ and $CR_{ijDTD+1}$ are interacted with dummy variables capturing each airline's business model, characterizing respectively FCCs and LCCs (the dummy takes the value one if the airline is an LCC). $LowSeason_{ijDTD}$ is a variable for low season periods. It indicates the percentage of tickets, for a given combination of airline, route and *DTD*, for which the corresponding departure date does not fall into a holiday period. This exogenous variable controls for price adjustments relative to exogenous demand patterns.

We estimate the model with the Generalized Least Squares approach, which aims at correcting for potential heteroskedasticity. This is the appropriate estimation method with the panel nature of our dataset. We use the SAS software for data treatment and estimation.

4. Empirical Results

The results of our estimation are presented in Table 1. The global fit of our model to the data is good, with an R-square of 0.54, and most parameters significant at the 1% level.

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[9] Let $t=1 \ldots T$ be the date for departing flights. $P_{ijDTD} = \dfrac{\sum_{t=1}^{T} P_{ijt-DTD} * pax_{ijt-DTD}}{\sum_{t=1}^{T} pax_{ijt-DTD}}$ where $pax_{ijt-DTD}$ represents the number of tickets bought at date *t-DTD* at price $P_{ijt-DTD}$.

The first parameters of interest are those capturing the effect of days prior to departure on prices, for each airline. We find that the polynomial specification fits the behavior of three airlines in the list, as most of the parameters are strongly significant, although interestingly they present opposite signs or different magnitudes. For the third full cost carrier, no particular trend is observed. Wald tests were conducted and statistically confirm these different price dynamics across airlines. These results highlight a significantly distinct pricing behavior among airlines, over a booking period. Airlines do not all choose to apply the same strategy over the period, some starting to sell with lower prices than others, then making prices vary in different or even opposite directions, when getting closer to the departure date. This result is crucial in better understanding airlines' pricing decisions, which are not solely based on short term RM adjustments. We believe this result has not been consistently estimated in the literature so far, and also calls for a more structural model including a pricing equation for airlines, derived from game theory models. This is left for further research.

Our specification is reinforced by the additional variables we introduce. The two variables capturing the typical strategic dimensions of RM are interacted with the airlines' business model and exhibit reasonable and informative effects. Indeed, the parameter for the cumulative revenue $CR_{ijDTD+1}$ is only significant for LCCs and indicates that if the average cumulative revenue of an LCC for a flight increases, the price for this flight the next day will increase as well. Simultaneously, the parameter for competing price $P_{-ijDTD+1}$ is only significant for FCCs, and has a positive sign. These findings are in line with RM objectives applied to the distinct business models. Because of their market positioning implying relatively constant low prices, LCCs have lower incentives to fill an aircraft at any cost when they already have generated certain revenue. They would rather increase their margin on the remaining seats, taking advantage of passengers' lower sensitivity to price as the departure date gets closer. For instance Piga & Bachis (2011) show that LCC's fares do not necessarily increase monotonically over time, peaking a few days before departure. Due to their market positioning, LCCs pricing is barely affected by the fares set by FCCs. Indeed the prices set in the previous period by the FCCs do not have a significant impact on the LCCs pricing strategy.

Oppositely FCCs adjust their prices in the same direction as their competitors' in the previous period, always trading off the sale of an additional seat and the highest possible margin: If the competing prices increase, no need to decrease their own price to sell a ticket as increasing the price a little might still make them sell the seat and generate a higher marginal profit at the same time. The intense price competition between the FCCs could explain why the cumulated revenue does not have a significant impact over the FCCs pricing strategy.

Finally, prices decrease during low season, which is intuitive and consistent with empirical observation.

Table 1. Estimation Results

Variable	Parameter Estimate	t Value[(1)]
Intercept	3.563***	3.95
Days to Departure [(2)]		
$\beta_{11} DTD$	-0.016***	-5.23
$\beta_{21} DTD^2$	$2e^{-4}$***	9.74
$\beta_{31} DTD^3$	$-5.78e^{-7}$***	-9.34
$\beta_{12} DTD$	-0.004	-1.44
$\beta_{22} DTD^2$	$7.35e^{-5}$***	2.95
$\beta_{32} DTD^3$	$-2.15e^{-7}$***	-3.09
$\beta_{13} DTD$	0.018	0.87
$\beta_{23} DTD^2$	$-9.43e^{-6}$	-0.91
$\beta_{33} DTD^3$	$3.14e^{-8}$	0.87
$\beta_{14} DTD$	0.015***	16.08
$\beta_{24} DTD^2$	$-1.02e^{-4}$***	-10.82
$\beta_{34} DTD^3$	$2.33e^{-7}$***	5.94
Competitors' prices on the route - previous period		
$\beta_{4LCC} \ln\left(P_{-ijDTD+1}\right) LCC$	0.124	1.55
$\beta_{4FCC} \ln\left(P_{-ijDTD+1}\right) FCC$	0.171***	10.18
Airline Cumulative Revenue - previous period		
$\beta_{5LCC} \ln\left(CR_{ijDTD+1}\right) LCC$	0.304***	11.41
$\beta_{5FCC} \ln\left(CR_{ijDTD+1}\right) FCC$	0.102	1.42
β_6 ***Low Season***	-1.233***	-11.74
N=3198	R^2=0.5392	

*Note: *** significant at the 1% level*

(1) Computed with Robust GLS

(2) Airlines 1, 2, 3 are FCCs and Airline 4 is an LCC.

5. Conclusion

In this article we estimate the direct effect of competition on the daily prices for economy tickets supplied by four airlines, three Full Cost Carriers and one Low Cost Carrier. We focus our analysis on measuring the impact of the number of days prior to departure on prices, while controlling for airlines, routes, seasonality and competitive pressure. The days to departure are introduced with a 3rd degree polynomial form, for each airline. We show that the polynomial form between the days to departure and the price level is statistically significant and that the coefficients of the polynomial differ from one airline to the other. These results confirm the differences in pricing strategies implemented by airlines during the booking period for a flight. Moreover we also observe differences while identifying the RM analysts' behavior. We show that the FCCs adapt their current prices to competitors' prices charged during the previous period, while LCCs would rather focus on their cumulative revenue.

The available data open a large scope of extensions for further analysis. First, our model, based on average price per route, airline and days to departure, fails to account for the airlines' price dispersion for a given day prior to departure. The next step of our analysis will consist in using price dispersion per airline as an endogenous variable and better assessing discriminatory practices linked to the booking day. This will lead to the estimation of a more sophisticated system of equations where the endogenous variables would be the average price and the price dispersion. The different strategies adopted by the airlines could explain the controversial results found in the literature with respect to price dispersion.

Second, given the limits of a reduced form model, we will use structural models to better identify the type of competition between airlines. In particular we will use game theory models to study airline's strategic interactions and coordinated effects.

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