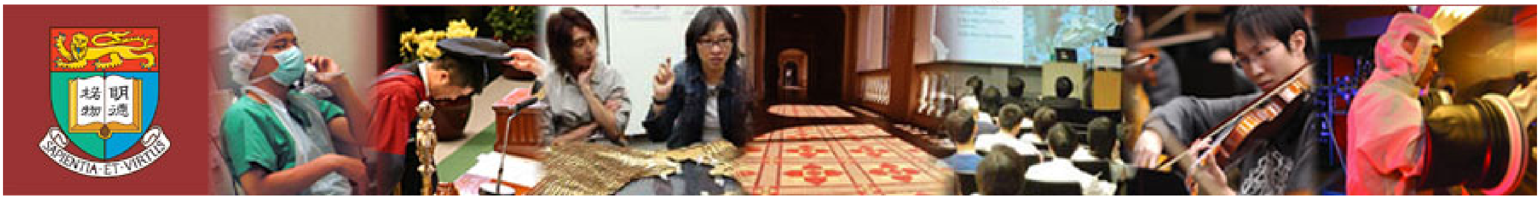

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Pricing Strategy and Technology Choices:
An Empirical Investigation of "Everyday Low Price" in the Domestic US Airline Sector

Extended Abstract

1. Introduction

There is a rich literature in economics on factors that govern airline prices. With approximately 50% of airline tickets sold online, there is now a renewed interest in investigating airline pricing particularly amongst Information Systems (IS) researchers. While market transparency created by online travel agents (OTAs) is a motivation enough to re-examine airline pricing, one missing piece calls for a thorough empirical investigation: In all extant studies (economics, marketing and IS), pricing by two major airlines, Southwest and JetBlue, has been ignored. Of particular interest to IS researchers is the fact that these two airlines practice a unique form of pricing called Everyday Low Price (EDLP) and have made certain technology-related choices that are distinct and different from previously studied carriers.

We test extant theories of price discrimination in the new online context with both posted and transacted prices, including those of the two EDLP airlines. We find that the EDLP airlines demonstrate distinctly different pricing choices – they are very particular about maintaining price consistency, while except in the case of advance purchase, they forgo other conventional opportunities to price discriminate. They also aggressively undercut competition when equipped with certain cost advantages. Further empirical investigation reveals why EDLP airlines forgo participation in OTAs that potentially offer a larger market. In particular, while promising a larger marketplace, OTAs have the ability to reveal the lowest prices in the market; we find that EDLP prices are lowest in the market only 26% of the time – in other words, consumers have 70% chances of obtaining a better deal from other "non-low price" airlines for any given ticket. We also show that EDLP prices, though not necessarily being the lowest in the market, do tend towards the lower end of the market spectrum.

As a first step, we decompose a firm's pricing strategy into two dimensions, namely price consistency and price magnitude. The former captures the frequency of promotions in tickets for the HILO airlines and is a measure of the "everyday" aspect of their EDLP counterparts, while the latter allows us to examine the "low price" element of the pricing strategy. We then develop and estimate a hierarchical model that accounts for partial dependence among prices due to market- and airline-specific factors, using pricing data for over 200,000 tickets offered online by the 14 largest carriers in 268 U.S. domestic air travel markets. In constructing this model, we carefully control for potential endogeneity that may arise from market share-related measures. Further, since our model incorporates a number of dichotomous variables at various levels (e.g. advance purchase and Saturday stay-over, hub operation, route distance), we exercised extreme caution in interpreting related effects and drawing inferences from our statistical analysis. We also repeat all of our analyses with the transacted price data from DB1B (a 10% sample of all tickets sold by reporting carriers, provided by the Bureau of Transportation Statistics) both as a robustness check of our original results and as a means to verify the extent to which the pricing strategies of airlines are absorbed by the market. While existing research typically investigates *either* offered prices *or* transacted prices, our work examines firm-specific strategies (and hence the respective price setting behaviors) and conclude with similar examination of prices at which tickets have actually been purchased.

2. Data

Our data is collected from two primary sources. First, we obtained prices and detailed descriptions of airline tickets from online travel agents and individual airlines' websites in the third quarter of 2004. This raw data was gathered using web-based spiders that we developed using Curl, and later processed by a parser using Perl and other database scripting languages. In addition to the set of fourteen major U.S. carriers[1] and three online travel agents (Orbitz, Travelociy, and Expedia), a list of the top 500 U.S. domestic routes was provided as input to the spiders. These markets represent over 86% of total domestic passenger enplanements (i.e. total number of travelers transported by air within the 50 states) in the U.S. as of 2004. The spiders were sent out on a daily basis to collect prices and other attributes of tickets requiring one- to four-week advance purchases, including weekday as well as weekend departures and returns. Our agents operated in parallel and submitted identical reservation requests to all online travel agents and airlines' websites simultaneously in order to minimize price variations that may arise from the timing of ticket requests.

Consistent with prior research on airline pricing, we consider only coach class, non-refundable, round-trip tickets. Further, to control for any price difference that may be attributed to differences in flight duration or the number of connections on any given route, we restrict our attention to non-stop flights between an origin and a destination. Since non-stop flights were not available in 28 routes, our data set is reduced to 472 markets with 272,362 unique tickets and final prices, including taxes and fees, offered by fourteen largest domestic carriers[2].

Second, we used the Origin and Destination Survey (DB1B) from the Bureau of Transportation Statics (BTS) for the corresponding routes and carriers in the second and third quarters of 2004 to collect prices on transacted tickets and compute the market shares of individual airlines in each origin-destination pair. DB1B is a 10% sample of all tickets sold by reporting carriers, including origin, destination and other itinerary details of passengers transported. This data contains sales from both online and offline channels, and is used in our

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[1] The fourteen major carriers are American, Alaska, Continental, Delta, United, US Airways, Southwest, JetBlue, Frontier, America West, AirTran, ATA, and Spirit.

[2] Spirit Airlines had been dropped from our subsequent analysis due to insufficient number of observations.

later analysis to check the robustness of our findings that are based on the online pricing data we gathered from the Internet. In addition, we used the Air Carrier Statistics (Form 41 Traffic and 298C Summary Data) and Air Carrier Financial Reports (Schedule P-12) provided by the BTS to assemble data on airlines' operational details (e.g. cost per available seat-mile, aircraft types and sizes, frequency of flights, etc.), as well as information on the respective markets (e.g. origin-destination distance, hub information, etc.).

By combining these various sets of data, we yielded a complete profile of all relevant variables at the ticket level that allowed us to examine the effects of various market- and firm-specific factors on airline pricing. We subsequently eliminated routes where the dominant carrier has over 90% market share. Our final data set consists of 209,558 observations from 268 markets. Table 3 reports the descriptive statistics of our data.

3. Models

Our econometric estimation aims to provide an understanding of firms' pricing strategies through two distinct measures. The first is price – which is self-explanatory in its ability to describe pricing strategy. In the price model, a positive (negative) coefficient for an independent variable suggests that the variable is correlated with a higher (lower) ticket price. The second dependent variable is "price variance" – commonly in IS literature this variable has only been used for studying market level dispersion in prices across firms. However, the marketing literature has shown how variance in prices of a single firm is in itself an execution of a corresponding pricing strategy. For example, the work by Hoch et al. (1994), Ho et al. (Ho, Tang et al.), and Shankar and Bolton (2004) use price variance at the firm-level to show some firms vary prices frequently while others do not; the theoretical reasoning behind creating multiple price points is that these different prices can appeal to different segments of consumers, allowing the firm to extract more surplus. Thus an examination of this dependent variable is critical to our understanding of the extent to which airlines like Southwest and JetBlue pursue discrimination compared with the other major carriers.

Model 1: Price level

Consistent with extant literature on airline pricing, we employ log-transformation for most of our explanatory variables to capture their declining marginal effects on prices. The variables that are included in the model without any transformation are the dummy variables, market share $\left(RTshare\right)$, and the corresponding Herfindahl index $\left(RTherf\right)$ (Borenstein 1989).

Level 1 (ticket-level) model:

$$\ln\left(price_{ikmc}\right) = a_{0kmc} + a_{1kmc}BUS_{ikmc} + a_{2kmc}DD7_{ikmc} + a_{3kmc}DD14_{ikmc} + a_{4kmc}DD21_{ikmc} + e_{ikmc} \quad (1)$$
$$e_{ikmc} \sim N\left(0, s^2\right)$$

In this model, the dependent variable $price_{ikmc}$ denotes the price of ticket i offered by carrier k in market (route) m in a given ticket category $\left(c\right)$.

Level 2 (airline- and market-level) model:

$$
\begin{aligned}
\alpha_{0km} &= \beta_0 + \gamma_{01} EDLP_k + \gamma_{02} \ln\left(freq_{km}\right) + \gamma_{03} hub_{km} + \gamma_{04} RTshare_{km} \\
&\quad + \gamma_{05} RTherf_m + \gamma_{06} shorthaul_m + \gamma_{07} \ln\left(CASM_k\right) + \gamma_{08} \ln\left(EQUIPsize_{km}\right) \\
&\quad + \gamma_{09}\left(EDLP_k \times shorthaul_m\right) + \gamma_{10}\left(EDLP_k \times hub_{km}\right) + u_{00k} + u_{00m} + u_{0km} \\
\alpha_{1-4km} &= \gamma_{1-4km} + \delta_{1-4km} EDLP_k \\
u_{00k} &\sim N\left(0, \phi\right) \\
u_{00m} &\sim N\left(0, \tau\right) \\
u_{0km} &\sim N\left(0, \psi\right)
\end{aligned}
\tag{2}
$$

The full model (after rearranging terms and renaming the coefficients):

$$
\begin{aligned}
\ln\left(price_{ikmc}\right) &= \alpha + \beta_1 EDLP_k + \beta_2 BUS_{ikmc} + \beta_3 DD7_{ikmc} + \beta_4 DD14_{ikmc} + \beta_5 DD21_{ikmc} \\
&\quad + \beta_6 \ln\left(freq_{km}\right) + \beta_7 hub_{km} + \beta_8 RTshare_{km} + \beta_9 RTherf_m \\
&\quad + \beta_{10} shorthaul_m + \beta_{11} \ln\left(CASM_k\right) + \beta_{12} \ln\left(EQUIPsize_{km}\right) \\
&\quad + \beta_{13}\left(EDLP_k \times BUS_{ikmc}\right) + \beta_{14}\left(EDLP_k \times DD7_{ikmc}\right) + \beta_{15}\left(EDLP_k \times DD14_{ikmc}\right) \\
&\quad + \beta_{16}\left(EDLP_k \times DD21_{ikmc}\right) + \beta_{17}\left(EDLP_k \times shorthaul_m\right) + \beta_{18}\left(EDLP_k \times hub_{km}\right) + \varepsilon_{ikm}
\end{aligned}
\tag{3}
$$

where

$$\alpha = \beta_0 + u_{00k} + u_{00m} + u_{0km} \tag{4}$$

Equation (3) is the basic model to be estimated. Interactions between the EDLP identifier and various ticket categories (Saturday night stay-over and advance purchase periods) and market characteristics (short-haul and hub) are included to capture any potential differences in the pricing approach of EDLP versus other major carriers due to differences in their segmentation approach and operational/cost differences in various types of markets. β_0 represents the overall intercept; u_{00k} and u_{00m} are the random carrier and route effects, respectively. u_{0km} is the random interaction effect. Finally, ε_{ikm} is the white-noise error particular to the individual observation.

Model 2: Price variance

$$
\begin{aligned}
CV_{kmc} &= \alpha + \beta_1 EDLP_k + \beta_2 BUS_{kmc} + \beta_3 DD7_{kmc} + \beta_4 DD14_{kmc} + \beta_5 DD21_{kmc} \\
&\quad + \beta_6 freq_{km} + \beta_7 hub_{km} + \beta_8 RTshare_{km} + \beta_9 RTherf_m \\
&\quad + \beta_{10} shorthaul_m + \beta_{11} CASM_k + \beta_{12} EQUIPsize_{km} \\
&\quad + \beta_{13}\left(EDLP_k \times BUS_{km}\right) + \beta_{14}\left(EDLP_k \times DD7_{km}\right) + \beta_{15}\left(EDLP_k \times DD14_{km}\right) \\
&\quad + \beta_{16}\left(EDLP_k \times DD21_{km}\right) + \beta_{17}\left(EDLP_k \times shorthaul_m\right) + \beta_{18}\left(EDLP_k \times hub_{km}\right) + \varepsilon_{km}
\end{aligned}
\tag{5}
$$

where

$$\alpha = \beta_0 + u_{0m} \tag{6}$$

The dependent variable in Model 2 is the coefficient of variation of prices, which is measured at the carrier-route-ticket category level and is constructed from the set of tickets written by an airline $\left(k\right)$ in a particular route $\left(m\right)$ for a given ticket category $\left(c\right)$.

4. Discussion

Southwest Airlines completely eschews participation in any of the OTAs while JetBlue does the same while offering some selected fares and participates partially in one OTA. Both airlines primarily rely on selling tickets through their own web sites; in particular, Southwest had created its own GDSs and has generally adopted a posture different from other airlines. We primarily seek to understand the judiciousness of this choice through our empirical analyses particularly since "low" price airlines should benefit from flaunting and even being compared to other airlines. Our results bear out the full story.

The sorting and various other comparison mechanisms offered by the OTAs provide significant improvements in product and price transparency, allowing the consumer to expeditiously determine the lowest price in the marketplace. Such an impact of technology cannot be fully assessed by the standard econometric specification, which concerns the average price of an airline with relations to its competitors. Therefore, in addition to the above estimations, we conduct two empirical analyses: a simple Logit model to assess the probability of these two EDLP airlines offering the lowest fare in the marketplace, and a model that determines how far they usually stray from the market minimum.

It is also interesting to note at this point that American Airlines (AA) have made some very curious moves regarding their participation at OTAs. AA opted out from Orbitz in late 2010, which resulted in Expedia to pull their American offers from their websites. Shortly afterwards (in April 2011), American filed a lawsuit against Orbitz for "exclusionary and anticompetitive business practices" while at the same time reaching an agreement with Expedia to have their offers once again displayed by the OTA. While the industry suspected that AA withdrew from OTAs primarily to cut distribution cost, and later staged a return because they realized that the savings are not worth losing out large marketplaces, American seems to be reformulating their pricing and technology choices. In fact, at the same time AA accused Orbitz of anticompetitive conduct, they also announced the development of their own distribution channel, known as the "Direct Connect". Essentially, American is demanding OTAs to retrieve flight information directly from this new system rather than through the GDSs. Such moves perhaps indicate that American realizes both the potential offered by the OTAs and the threats of transparency associated with such technologies; thus in response, they develop a new channel that allow for the best of both worlds through selectively listing their most competitive offers on OTAs while presenting a different set of choices to consumers who visit their own website.

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