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IMAGE PRICING: AIRLINE COMPETITION ON THE INTERNET

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Abstract

Pricing and positioning are among the most important strategic decisions for every online firm in today's competitive environment. Traditionally retailers adopt different price formats as store positioning and segmentation strategies by signaling to consumers their specific pricing structures. In particular, "everyday low price" (EDLP) has proved to be a successful strategy for vendors in physical markets in creating a "low price" image and persuading consumers that regardless of what item they buy or when they buy it, they can always expect below average prices. While managing this perception is much easier when it is costly for consumers to compare prices across geographically separated stores, the advent of electronic commerce has significantly reduced search and menu costs, allowing consumers to search multiple stores with a few mouse clicks and competitors to immediately react to any price change at the individual-product level, hence posing serious challenges to sellers adopting EDLP in electronic markets. Using a hierarchical modeling approach and 272,406 unique price observations on airline tickets obtained from seventeen U.S. carriers online, this study examines the role of price format adoption in competition in electronic markets. Specifically, this research aims to address the following questions: 1) Do self-declared EDLP airlines indeed charge stable, low prices online? 2) Is EDLP being adopted in electronic markets in the same fashion as in physical markets? 3) Do they adopt different price formats in different product categories?

Our findings offer the first formal evidence of the adoption of a "hybrid" strategy of implementing different price formats in different product categories in electronic markets. Further, online EDLP airlines focus more on the "within-market" characteristics of this pricing strategy rather than the temporal characteristics, implying a diminishing role of intertemporal price consistency to EDLP in online markets. This suggests that reduction in search cost in electronic markets may have differential effects on consumers' price elasticity along two dimensions: by making price information more accessible, consumers may focus on the comparison of "spot prices" when they perform the search. However, due to the large amounts of information available at the time of search, recall may be poor. As a result, electronic markets may increase consumers' price sensitivity at any given point in time when they perform price comparison but have a negative effect on consumers' intertemporal price sensitivity, suggesting that even sellers who pursue an everyday low price strategy online may find temporal price discrimination profitable.

Keywords: Price image, everyday low price, hierarchical model, airline competition

Introduction

Price formats have long been understood as important strategic tools for traditional brick-and-mortar retailers. The most popular formats are "Everyday Low Price" (EDLP) and "Promotional Pricing" (HILO). Sellers who adopt promotional pricing aim to attract consumers with frequent "deals" and discounts. Vendors who adopt EDLP, on the other hand, focus on creating a "low price" image to persuade consumers that regardless of what item they buy or when they buy it, they can always expect below average prices. EDLP has proved to be a successful strategy in the physical context. A classic example is Wal-Mart, the retail giant famous for its "always low prices" motto. Coupling with its EDLP strategy, Wal-Mart deliberately locates its stores away from malls and other competitors who engage in frequent price discounts. By making price comparison costly to consumers, Wal-Mart is able to avoid head-to-head competition and maintain a low price reputation even when its prices are not the lowest in the area.

Since EDLP is a conscious pricing strategy that aims to create a "low price" perception, it is the goal of this strategy to impart such a perception in consumer's mind – even if the *actual* pricing behaviors of sellers adopting this strategy were not consistent with their claim. Therefore, a basic premise for the success of EDLP appears to be that it is difficult for consumers to locate the lowest price. While managing this perception in the physical context is much easier given the relatively higher cost required to uncover price differences across stores, the advent of electronic commerce and the ability of consumers to price-search multiple stores with a few mouse-clicks pose new challenges to sellers adopting this particular price format. The absence of physical separation among firms leads us to naturally ask the question: does it even make sense to adopt "Everyday Low Price" in the online environment?

This research examines price format as an important strategic tool for competition in electronic markets and offers insights on alternative explanations for persistent price dispersion online. Further, it provides managerial guidelines to online firms in adopting different pricing strategies, taking into account the specific nature of electronic markets. Using a hierarchical modeling approach, this research aims to address the following questions: 1) Are the prices of self-declared EDLP airlines indeed more stable and less variable? 2) Is EDLP being adopted in electronic markets in the same fashion as in physical markets? 3) Do EDLP airlines employ this strategy on a universal basis, or vary with respect to different markets and product categories?

Our study is the first to explicitly contrast the actual pricing practices of firms with their advertised price images along the dimensions identified by existing price format research. Further, we offer the first formal investigation of category-level implementation of price format in electronic markets. The results of this study shed light on the specific ways in which EDLP is manifested in the online environment, and provide important managerial insights to online vendors by offering a more thorough understanding of employing EDLP as both pricing and positioning strategies in electronic markets. This research enriches the marketing theories on competitive pricing strategy and contributes to information systems literature by providing a better understanding of price format as an important element in online pricing.

The paper is organized as follows: section two presents an overview of literature from economics, information systems, and marketing on pricing and pricing strategy. Section three discusses the conceptual development. Section four presents the domain of analysis and data collection, which is followed by empirical models and analyses in section five. The paper concludes with a summary of findings and extensions.

Literature Review

The theory on pricing in competitive markets begins with the most simplistic assumptions: homogeneous products, identical sellers, and transparent prices. Under these conditions, competing sellers would undercut each others' prices, resulting in the classical Bertrand competition where equilibrium prices converge to marginal costs (Bertrand 1883; Spulber, 1995). However, such an outcome is unlikely in the real world because prices are rarely transparent. The difficulty of obtaining or comparing prices arises when vendors employ various differentiation strategies, based on factors such as consumers' prior price knowledge (Baye et al., 2001; Varian, 1980), brand loyalty (Chen et al., 2001; Iyer et al. 2003; Narasimhan, 1988; Raju et al., 1990), location proximity (Hotelling, 1929; Salop, 1979), and switching cost (Chen et al., 2002).

It is argued that lowered search and frictional costs in electronic markets can make vendor strategies more transparent (Bakos, 1997), which may possibly lead to convergence of prices. However, empirical research in information systems consistently observes dispersion in prices online in markets for both homogeneous products, such as books and CDs (Brynjolfsson et al., 2000), and differentiated products, such as airline tickets (Clemons et al., 2002). Clearly, there are other ways in which online vendors can differentiate themselves; one such possibility is by adopting different price formats.

Price formats in retail industry have been studied extensively in marketing (e.g. Bell et al., 1998; Hoch et al., 1994). According to existing literature, the two basic price formats are Everyday Low Price (EDLP) and Promotional Pricing (HILO). Although researchers argue that these formats are more appropriately regarded as a continuum rather than a dichotomy (Hoch et al., 1994), it is commonly agreed that sellers who declare to adopt EDLP tend to charge relatively stable and below-average prices. These sellers aim to attract consumers who expect "good deals" by creating credibility and a low price image (Bell et al., 1998; Ortmeyer et al., 1991; Tang et al., 2001). On the other hand, HILO sellers are promotion-oriented and charge higher prices on average but engage in frequent promotions that allow prices to fall temporarily below the EDLP price level (Lal et al., 1997). These sellers aim to price discriminate consumers of different preferences and price knowledge (Blattberg et al., 1981; Pigou, 1920; Varian, 1980). Therefore, researchers suggest that EDLP and HILO are more than mere price formats but rather positioning strategies that target different types of consumers, such as large-basket shoppers versus small-basket shoppers (Bell et al., 1998), and time-constrained consumers versus cherry-picking consumers (Ortmeyer et al., 1991). Further, research suggests that the coexistence of EDLP and HILO relies heavily on the choice of physical locations by sellers adopting the two strategies (Lal et al., 1997).

While location has long been recognized as the most important factor in a seller's consideration (Alba et al., 1997), it is particularly critical for those who adopt the EDLP strategy. Since the low price image created by EDLP is protected in part by the physical distance that creates costs for comparison shopping, an important element in the success of EDLP sellers in the offline world is the physical separation from other sellers in the market. Other things being equal, the dominant strategy for an EDLP seller would be to locate at a distance from promotion-oriented sellers. In the online environment, however, such a physical distance is absent. To sell products through the electronic channel, an EDLP seller would have to risk the possibility of damaging its low price image in return for potential increase in customer exposure. Existing literature has offered very limited understanding as to whether or not vendors would still adopt EDLP strategy as a means to build a low price image when there is no physical separation among sellers.

In sum, theories suggest that in the online environment, consumers' ability to search and compare is high and the coexistence of different price formats can no longer be supported by physical separation. Interestingly, while it may appear that EDLP is difficult to pursue in electronic markets, we observe that self-declared EDLP sellers do exist and, in the airline industry in particular, these sellers (e.g. Southwest Airlines, Jetblue Airways) are enjoying tremendous success. The following section investigates the potential explanations for this phenomenon and develops a set of testable hypotheses that examine the actual pricing behaviors of these self-declared EDLP sellers in electronic markets.

Conceptual Development

Price Level

Search cost literature suggests that due to the low cost of search, online consumers are able to engage in more aggressive price comparison than in the offline context (Bakos, 1997). Further, the existence of intermediated electronic marketplaces (IEM) (Chircu et al., 2001), such as Orbitz and Travelocity, allows consumers to receive multiple price quotes and product information from different airlines with a single Web site visit. EDLP airlines are therefore subjected to relatively costless and direct price comparison with other vendors online, and are at a much disadvantaged situation compared to operating in physical markets. These characteristics of electronic markets would likely discourage the adoption of the EDLP strategy. Empirical studies on electronic markets, however, find substantial evidence that price dispersion persists online even in homogeneous product markets (Brynjolfsson et al., 2000). Others also suggest that despite the low search costs, not all online consumers would search extensively or buy from the seller with the lowest price (Barua et al., 1997). Results from existing empirical research point to the existence of a barrier to perfect price competition, suggesting the possibility of EDLP strategy in maintaining a low price image even in the online context. Therefore, we expect to find differences between online EDLP and HILO prices in a similar fashion as observed in the offline context.

Hypothesis 1 (H1): Online prices of tickets written by EDLP airlines are lower than those obtained from HILO airlines.

Price Variability

Most of the existing research in retail price format focuses on the measure of price level and intertemporal price variability; i.e., the comparison is based on average price levels and the change in prices of the same products over a period. In contrast to supermarket purchases on which the majority of price format research is based, however, airline ticket purchase may not be repetitive. While some consumers (i.e., business travelers) make routine trips between specific cities and thus are more concerned about the frequency and magnitude of temporal price changes of the same set of tickets that they routinely purchase, others may not repeatedly purchase tickets for the same routes over time. These consumers are more concerned about whether they can get a good deal for *any* ticket of interest at a given point in time, not necessarily how the prices of a specific set of tickets change over time. Therefore, in addition to low temporal price variability, airlines that adopt the EDLP strategy may build their low price image by offering low and less volatile prices in any given market as means to signal to consumers that they can expect a "high probability of getting a good deal", regardless of which specific routes they are considering. Further, some EDLP airlines, most notably the Southwest Airlines, emphasize their offering of low prices not only for certain products in particular markets but low prices for *any* ticket in *any* market. For example, Southwest Airlines follows a strategy similar to that of "99 cents" stores by routinely advertising a fixed price for flying from anywhere to a particular city or between any two cities within a region. Therefore, EDLP airlines may appeal to online consumers by maintaining low variability in prices i) across time, ii) within a market for any given time, and iii) across markets.

Hypothesis 2a (H2a): The temporal price variability of any given ticket offered by an EDLP airline is lower compared to that offered a HILO airline.

Hypothesis 2b (H2b): The prices of comparable tickets offered by EDLP airlines within a market are more similar to each other than those offered by HILO airlines.

Hypothesis 2c (H2c): The prices of tickets offered by EDLP airlines across different markets are less variable compared to those offered by HILO airlines.

Category-specific Price Format Implementation

Industry reports suggest that pure EDLP/HILO seldom exists, and they point toward the adoption of various elements in the two price formats (Radice, 1998). The views on a "hybrid" price format adoption in academia, however, are mixed. While some argue that sellers may introduce variations to EDLP for certain product categories to take advantage of differences in consumer demand within and across categories so as to maximize revenue (Ho et al., 1998; Shankar & Bolton, 2004), others believe that implementing EDLP on a category-by-category basis would not work well because it has to be implemented on a chainwide basis to benefit from overall store price image (Hoch et al., 1994). In the online context, the existence of IEM makes price information more transparent and thus threatens the ability of EDLP airlines to vary their pricing strategy across product categories. This has two effects on the online pricing behavior of EDLP airlines: on one hand, it is less feasible for them to adopt EDLP for certain tickets while HILO for others because it would be easy for consumers to discover the discrepancy in their pricing practice, hence undermining the low price image of these airlines; on the other hand, given that the protection of a low price image is now more costly, consistent EDLP pricing may become less attractive.

However, because of cost transparency (Sinha, 2000; Zhu, 2004), the opportunity cost for sellers in employing everyday low price on all product categories in electronic markets is much higher because EDLP sellers are no longer competing locally with two or three HILO sellers. Further, the lack of physical separation from HILO sellers makes their pricing strategy more vulnerable, and EDLP sellers are at greater risk of losing sales from consumers who switch to the competitors when they discover better deals elsewhere. Intensified competitions along with weakening of barriers that protect the low price image would cause online EDLP airlines to adopt the everyday low price strategy selectively on a limited set of products.

Hypothesis 3 (H3): Airlines that adopt EDLP implement the strategy to different extents with respect to various ticket and market characteristics.

Data and Method

Data

Two sets of data are employed in this research. The first data set contains prices and descriptions of airline tickets obtained from both online travel agents and individual airline Web sites. Consistent with existing research that uses computer agents to collect airline ticket prices from the Internet, our agents operated in parallel and sent out identical reservation requests[1] to all airline Web sites and online travel agents simultaneously to minimize any price variation due to the timing of ticket requests (Clemons et al., 2002). All prices obtained are on restricted coach class tickets, and are final prices that consumers see and compare, including all taxes and fees. Our first set of data includes one-to-four-week advance purchase tickets with weekday as well as weekend departures from the 126 busiest routes[2] in which EDLP airlines operate. Two markets in which the dominant airline has over 98% of market share are excluded to control for any bias in estimations caused by potential monopolistic pricing behaviors in those markets. The resulting data consists of tickets written by the fourteen largest domestic carriers and three regional airlines in 124 unique, origin-destination pairs in the domestic U.S. airline market. The total numbers of observations on individual ticket prices are 138,514 and 133,892 for business and leisure travel[3], respectively. The second data set is a collection of the Origin and Destination Survey provided by the U.S. Bureau of Transportation Statistics. The data contains cost per available seat mile, equipment sizes, and other operational information on all domestic U.S. carriers. In our model, we incorporate all known factors that affect airline pricing based on an extensive literature review on airline competition.[4] Explanations of the corresponding variables are summarized in Table 1.

Table 1: Explanation of Variables

Variable	Description
EDLP[5]	Dummy = 1 if the ticket is written by an “Everyday Low Price” airline; 0 otherwise
fwcon	Number of connections from origin to destination on the forward journey
retcon	Number of connections from destination to origin on the return journey

[1] All ticket requests were generated within the same (third) quarter in 2004 to eliminate potential seasonal effects on ticket prices.
[2] These 126 routes account for over 90% of traffic in all markets served by EDLP airlines.
[3] Leisure travels are characterized by Saturday night stay-over; business travels are characterized by weekday departure and return. The proportions of tickets offered by EDLP versus HILO airlines are approximately the same.
[4] Due to space limitation, details are relegated to the appendix.
[5] For an airline to be identified as adopting the EDLP strategy, it must 1) emphasize such a practice in their advertising messages; and 2) consciously refer to their pricing practice as “everyday low price” in their financial reports and communications to investors.

fwPEAK[6]	Dummy = 1 if the flight departs between 6am to 10am or 3pm to 7pm on the forward journey; 0 otherwise
retPEAK	Dummy = 1 if the flight departs between 6am to 10am or 3pm to 7pm on the return journey; 0 otherwise
redeye	Dummy = 1 if the flight departs after 10pm or arrives between midnight and 6am on either forward or return journey; 0 otherwise
multicarr	Dummy = 1 if it is a ticket combined of multiple legs from different carriers; 0 otherwise
DD7	Dummy = 1 if the ticket is requested 1 week before departure date; 0 otherwise
DD14	Dummy = 1 if the ticket is requested 2 weeks before departure date; 0 otherwise
DD21	Dummy = 1 if the ticket is requested 3 week before departure date; 0 otherwise
freq	Average daily frequency of (round-trip) flights offered by a particular airline on the given route
hub	Dummy = 1 if either the origin or destination (or both) airport is a hub airport for the carrier writing the ticket; 0 otherwise
shorthaul	Dummy = 1 if the non-stop distance between the origin and destination airports is less than or equal to 500 miles; 0 otherwise
slot	Dummy = 1 if either the origin or destination (or both) airport is a slot-constrained airport; 0 otherwise
mktcon	Dummy = 1 the total number of airlines offering services (non-stop or indirect) on the observed route
CASM	Cost per available seat mile for the carrier serving on the observed route
avgEQUIP	Average equipment (aircraft) size for the carrier serving on the observed route
EDLP × DD7	Interaction Dummy = 1 if the ticket is written by an EDLP airline *and* is requested 1 week before departure date; 0 otherwise
EDLP × DD14	Interaction Dummy = 1 if the ticket is written by an EDLP airline *and* is requested 2 weeks before departure date; 0 otherwise
EDLP × DD21	Interaction Dummy = 1 if the ticket is written by an EDLP airline *and* is requested 3 weeks before departure date; 0 otherwise
EDLP × shorthaul	Interaction Dummy = 1 if the ticket is written by an EDLP airline *and* the observed route is characterized by shorthaul; 0 otherwise
EDLP × hub	Interaction Dummy = 1 if the ticket is written by an EDLP airline *and* either the origin or destination (or both) airport is a hub airport for the carrier; 0 otherwise

Empirical Method

We employ hierarchical modeling (HM) for this research as opposed to the traditional least square approach due to potential violation of two critical assumptions of OLS – the independence and homoscedasticity of random errors.

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[6] Numbers of connections on the forward and return trips are used to control for flight duration; tickets with more than two connections each way are excluded.

Prices of tickets offered by a particular carrier are likely to be correlated because they are written by the same airline with the specific cost structure and pricing strategy. The dependence among observations is also referred to as Intra-Class Correlation (ICC). The OLS assumption of independent errors is violated in the presence of ICC (Kreft et al,. 1998), and the standard errors of the coefficients are underestimated. This raises the risk of type-I error (Pedhazur, 1997). Further, since unit-level random error varies across airlines, the assumption of homoscedasticity is also likely to be violated. Hierarchical models extend traditional regression models by taking into account the partial independence of individual observations within the same group as well as the fact that these observations may be more similar to one another compared to those belong to another group.

The fundamental idea behind hierarchical modeling is that there are separate analyses for each of the units at the lowest level of a hierarchical structure, while both individual-level and group-level unit variances are examined in the outcome measure by estimating variance between groups and examining the effect of variables at each level simultaneously. The total variance in the outcome is divided into the parameter variance and error variance components. Unlike OLS, hierarchical models estimate residuals from different levels separately and account for the covariance structure among group-level regression estimates, giving more accurate group effect estimates than traditional methods that systematically underestimate them (Raudenbush et al., 1989). This also allows one to model explicitly both within- and between-group variances as well as their effects on the outcome while maintaining the appropriate level of analysis (Griffin et al., 1997).

For the purpose of this research, one critical advantage of hierarchical models is that they allow for incorporation of airline and market characteristics into the model of individual ticket prices while at the same time producing accurate estimates of the group-level effects and with the corresponding valid tests and confidence intervals (Mendro et al., 1995), which are typically ignored by the OLS (Bryk et al., 1989). Traditional fixed effects models use the dummy variable approach to "absorb" all observable and unobservable heterogeneity across different group units; hence, the inclusion of any group level-specific characteristics will cause multicollinearity problems. In other words, when using fixed effects models to address the multilevel nature of hierarchical data, level-two variables cannot be included into the model specification because they will be confounded with the group fixed effects and the parameters of the model will be unidentifiable. In the airline pricing context, this implies that airline and market-specific attributes cannot be explicitly accounted for in the model, limiting a researcher's ability in drawing inferences on the mediating effects of these characteristics on the relationship between other explanatory variables (such as pricing strategy) and ticket prices. While typically such effects can be incorporated into the model using interactions between the explanatory variables and group-level dummies, when the number of groups (such as origin-destination pairs) is large, the interaction approach becomes impractical and will result in a large number of parameters and overidentification of the model.

Two maximum likelihood methods are commonly used in estimating hierarchical models: the full maximum likelihood (ML) and the restricted maximum likelihood (REML). In ML, both fixed effects and variance components are included in the likelihood function. Variance-covariance parameters and second-level fixed coefficients are estimated by maximizing the joint likelihood. In REML, variance-covariance components are first estimated with maximum likelihood that integrates over all possible values of the fixed effects, which are then recovered using generalized least square (GLS) given the variance-covariance estimates obtained from the first step (Goldstein, 1995; Raudenbush et al., 2002; Raudenbush et al., 2001). REML minimizes the deviance of the least squares residuals as opposed to minimizing deviance of the data.

We choose to adopt REML in this research because ML, though consistent and asymptotically efficient, does not adjust for the number of fixed effects that are being estimated; as a result, the variance components will tend to be underestimated with small sample sizes or when the number of groups is small (Jones et al., 1997). Although the data sets we use in this research do not fall into the "small sample size" category, some of our dependent variables are aggregated measures (such as the coefficient of variation); thus the number of observations reduce to several hundreds in certain cases. As a precautionary measure and to be consistent with the majority of research using hierarchical models, REML is employed in our analyses.

Model

We model the relationship between price, product quality, and a firm's pricing strategy by considering the most relevant and observable dimensions of the tickets and information on the respective routes and carriers. The functional forms and variables included are based on extensive research on airline pricing (Borenstein, 1989;

Morrison & Winston, 1990; Brueckner et al., 1992; Borenstein & Rose, 1994; Berry et al., 1997; Stavins, 2001) and online price dispersion in the airline industry (Clemons et al., 2002). A particular nature of the data is that it is "clustered" in different classes. For example, prices of tickets in the same route will be more similar to each other compared to those of tickets from different routes. This implies that the data does not exhibit a pure hierarchical structure – i.e., two tickets can belong to the same airline but different routes. Such a lack of unique identity of members within each class is known as cross-classification.[7] Further, we employ log-linear form in our cross-classified model for two main reasons. First, this formulation is consistent with existing research on airline pricing, and is flexible in allowing for proportional and declining marginal effects of the explanatory variables. Second, it captures the percentage change in price as opposed to absolute change, which is consistent with actual pricing behavior in the market.

This section presents the models employed in testing the hypotheses discussed earlier in this chapter. Although some of the hypotheses (hypotheses 2c and 3) do not require separate models to be analyzed, for notational convenience and ease of reference, the models are named according to the relevant hypotheses.

Test of Hypothesis 1: Price Levels

Model 1:

$$\begin{aligned}\ln\left(price_{ikm}\right) = {} & \alpha + \beta_1 EDLP_k + \beta_2 fwcon_{ikm} + \beta_3 retcon_{ikm} + \beta_4 fwPEAK_{ikm} \\ & + \beta_5 retPEAK_{ikm} + \beta_6 redeye_{ikm} + \beta_7 multicarr_{ikm} \\ & + \beta_8 DD7 + \beta_9 DD14 + \beta_{10} DD21 \\ & + \beta_{11}\ln\left(freq_{km}\right) + \beta_{12} hub_{km} + \beta_{13} shorthaul_m \\ & + \beta_{14} slot_m + \beta_{15}\ln\left(mktcon_m\right) + \beta_{16}\ln\left(CASM_k\right) + \beta_{17}\ln\left(avgEQUIP_k\right) \\ & + \beta_{18}\left(EDLP_k \times DD7\right) + \beta_{19}\left(EDLP_k \times DD14\right) + \beta_{20}\left(EDLP_k \times DD21\right) \\ & + \beta_{21}\left(EDLP_k \times shorthaul_m\right) + \beta_{22}\left(EDLP_k \times hub_{km}\right) + \varepsilon_{ikm}\end{aligned} \tag{1}$$

where

$$\alpha = \gamma_0 + u_{0k} + u_{0m} \tag{2}$$

$$\beta_1 = \gamma_1 + u_{1m} \tag{3}$$

$$u_{0k} \sim N\left(0, \varphi\right) \tag{4}$$

$$\begin{pmatrix} u_{0m} \\ u_{1m} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{pmatrix}\right] \tag{5}$$

$$\varepsilon_{ikm} \sim N\left(0, \sigma^2\right) \tag{6}$$

Equation (1) is the basic model to be estimated. Dependent variable $price_{ikm}$ denotes the price of ticket i offered by carrier k in market (route) m at time t[8]. Time is represented by the number of weeks between the date at which the ticket is requested and the departure date (i.e., number of weeks of advance purchase). For expositional simplicity, subscript that denotes product category (i.e., business and leisure) is suppressed from all variables. Interactions between EDLP and advance purchase, EDLP and market characteristic (short-haul), and EDLP and market power characteristic (hub) are included to capture any variation in airlines' adoption of this pricing strategy[9].

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[7] Notice that cross-classification structure of the data is observed only in model 1a, where the dependent variable is individual ticket prices. For the remaining models, unless stated otherwise, observations are nested only within a particular group (route) due to aggregated measures (such as range and coefficient of variation). Therefore, only one random effect will be modeled.

[8] For ease of exposition, subscript t is suppressed from the equations.

[9] Preliminary analysis suggests a substantial amount of variations of adoption of EDLP strategy across different routes; a set of interaction variables between (EDLP and market characteristics) were selected based on industry

The hierarchical structure of the model is presented in equations (2) and (3). γ_0 represents the overall intercept; u_{0k} and u_{0m} are the random carrier and route effects, respectively. u_{0k} is assumed to be distributed normally with mean zero and variance φ (equation (4)). The slope of *EDLP* is considered to be composed of both fixed (γ_1) and random (u_{1m}) effects. In other words, not only are prices related to the carrier's pricing strategy, but this relationship is hypothesized to also vary across routes. The variance and covariance components for u_{0m} and u_{1m} are presented in (5). Finally, (6) specifies the white-noise error particular to the individual observation.

Test of Hypotheses 2a: Temporal Price Variability

Model 2a:

$$\begin{aligned} pvar_{ikm} &= \alpha + \beta_1 fwcon_{ikm} + \beta_2 retcon_{ikm} + \beta_3 multicarr_{ikm} \\ &+ \beta_4 freq_{km} + \beta_5 hub_{km} + \beta_6 shorthaul_m + \beta_7 slot_m \\ &+ \beta_8 mktcon_m + \beta_9 EDLP \times shorthaul_{km} + \beta_{10} EDLP \times hub_{km} + \varepsilon_{ikm} \end{aligned} \tag{7}$$

where

$$\alpha = \gamma_0 + u_{0k} + u_{0m} \tag{8}$$

$$u_{0m} \sim N(0, \varphi) \tag{9}$$

$$\varepsilon_{ikm} \sim N(0, \sigma^2) \tag{10}$$

and u_{0k} denotes the airline fixed-effects and u_{0m} represents the random route effects[10]. Dependent variable $pvar_{ikm}$ is the coefficient of variation of the four prices of a particular ticket *i* offered by carrier *k* in market (route) *m*. It is computed as:

$$pvar_{ikm} = \frac{\sum_t^T \left(T^* price_{ikm,t} - \sum_t^T price_{ikm,t} \right)}{\sqrt{T} * \sum_t^T price_{ikm,t}}$$

$pvar_{km}^i$ of a given ticket is the coefficient of variation, measured by the standard deviation of its prices across weeks $(t = 1, ..., T)$ divided by the mean of these prices.

It should be noted that there are several major differences between this model and the previous one (model 1a). First, since airline effects are treated as fixed, all airline-specific but time- and market-invariant variables (CASM and avgEQUIP) are excluded from the model. Second, several temporal attributes of the ticket have also been removed from the model. This is because the data used in this model is composed of the *identical* tickets that are observable throughout the four-week period. The resulting data consists of only tickets that have departure times at peak hours on both journeys. Therefore, the variables "fwPEAK", "retPEAK", and "redeye" are not included. Finally, because the unit of analysis is variability of prices across four time periods, dummies that represent time (weeks of advance purchase) are therefore omitted from the model as well.

Test of Hypothesis 2b: Price Variability within Markets

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knowledge as potential candidates to improve the fit of data. Stepwise regressions were then performed and the interactions yielding the most improvement were selected.

[10] Unless otherwise indicated, the interpretation of u_{0m} remains the same in the rest of the models.

Model 2b:

$$\begin{aligned} p\,\mathrm{var}_{km} &= \alpha + \beta_1 DD7 + \beta_2 DD14 + \beta_3 DD21 + \beta_4 freq_{km} \\ &+ \beta_5 hub_{km} + \beta_6 shorthaul_m + \beta_7 slot_m + \beta_8 mktcon_m \\ &+ \beta_9 EDLP \times DD7 + \beta_{10} EDLP \times DD14 + \beta_{11} EDLP \times DD21 \\ &+ \beta_{12} EDLP \times shorthaul_{km} + \beta_{13} EDLP \times hub_{km} + \varepsilon_{ikm} \end{aligned} \quad (11)$$

where

$$\alpha = \gamma_0 + u_{0k} + u_{0m} \quad (12)$$

$$u_{0m} \sim N(0, \varphi) \quad (13)$$

$$\varepsilon_{ikm} \sim N(0, \sigma^2) \quad (14)$$

and u_{0k} denotes the airline fixed-effects. Dependent variable $pvar_{km}$ is the coefficient of variation of prices of a set of tickets *I* offered by carrier *k* in market (route) *m* at a given time. It is computed as:

$$pvar_{km} = \frac{\sum_i^I \left(I{*}price_{ikm} - \sum_i^I price_{ikm} \right)}{\sqrt{I} * \sum_i^I price_{ikm}}$$

Model 2b is similar to model 2a in that airline-specific but time- and market-invariant variables are not included in the model because of the airline fixed-effects. Notice that the unit of analysis is variability across all tickets that are written by each airline in a market at a given point in time; therefore two modifications are made: First, because individual ticket-specific attributes are lost in pooling the tickets for the aggregate measure, fwcon, retcon, fwPEAK, retPEAK, redeye, and multicarr are omitted. Second, time dummies (DD7, DD14, DD21) and their interactions with EDLP are added back to this model.

Results

Test of Model Specification and Robustness

Model Specification

Multicollinearity and Hausman tests were performed to check for misspecification of the models. The results indicate that multicollinearity is not an issue in the models. The highest value of VIF is 8.86, with the next highest VIF being 4.29. Both values fall below the critical level of 10. Further, Hausman tests were performed separately for route random effects and airline random effects. The Chi-square values for the two random effects are 0.001 and 0.002, well below the critical value of 30.58 for the 1 percent significance level at 15 degrees of freedom.

These statistics indicate that the coefficient estimates from the random effects model are not significantly different from those obtained from the fixed effects model. A comparison on the coefficients of the set of variables used in the Hausman test is presented in table 2, with the first column indicating results from the fixed effects model, and the second column indicating results from the hierarchical model with both route and airline effects being treated as random.

Table 2: Hausman Test

	OLS	**HM**
fwcon	0.1398***	0.1400***
retcon	0.1741***	0.1743***
fwPEAK	-0.0111***	-0.0111***
retPEAK	0.0135***	0.0135***
redeye	0.0050	0.0052
multicarr	0.3042***	0.3042***
DD7	0.2359***	0.2360***
DD14	0.0454***	0.0454***
DD21	0.0068**	0.0068**
lnfreq	-0.0537***	-0.0535***
hub	0.0501***	0.0503***
EDLP*DD7	-0.0718***	-0.0718***
EDLP*DD14	0.0198***	0.0197***
EDLP*DD21	0.0385***	0.0384***
EDLP*shorthaul	-0.4922***	-0.4927***
EDLP*hub	0.0889***	0.0882***
$\hat{\varphi}$	--	0.0355***
$\hat{\tau}_{00}$	--	0.0473***
$\hat{\sigma}^2$	0.1177***	0.1177***
N	138514	138514
-2LL	97739.9	97720.2
BIC	97751.7	97755.7

Significance at 1% (***), 5%(**), and 10% (*) levels[11]

Robustness

Tables 3 and 4 summarize the results of model 1, including the coefficient estimates, covariance parameter estimates for the random effects, and goodness of fit indexes for business and leisure tickets, respectively. Bayesian Information Criteria (BIC) is reported in addition to the conventional reporting of log likelihood in light of the large sample size. Two baseline models are also presented along with the full cross-classified hierarchical model (HM).

[11] The same notations are used in all remaining tables.

Both BIC and χ^2/df tests show that the full HM model offers superior fit to the data compared to the fixed effects model and the null model for both types of tickets. Additional robust checks were performed by comparing the sum of residual-squared of the fixed-effects model (OLS) and HM based on the differences between actual (y) and predicted $(\hat{y})$ values of the dependent variable. HM outperforms the OLS by a difference of 7.14% and 4.65% lower in the sum of residual-squared for business and leisure tickets, respectively. Furthermore, the intra-class correlations $(\hat{\rho})$ for carrier $\left(\frac{\hat{\varphi}}{\hat{\varphi}+\hat{\tau}_{00}+\hat{\sigma}^2}\right)$= 0.22 (0.23) and route $\left(\frac{\hat{\tau}_{00}}{\hat{\varphi}+\hat{\tau}_{00}+\hat{\sigma}^2}\right)$= 0.34 (0.23) from the null model suggest that there are fair amounts of clustering of prices within both carrier and route for business (leisure) tickets. This implies that results obtained from OLS analysis of this data would likely be misleading.

The amounts of reduction in variance components $\hat{\varphi}$ and $\hat{\tau}_{00}$ suggest that 70.95% (67.28%) of explainable variation in carrier means and 23.59% (29.65%) of explainable variation in route means are explained by the variables incorporated in the full model for business (leisure) tickets. Further, the random error is reduced by 32.88% and 29.16% compared to the second baseline model for the two types of tickets respectively. All statistics indicate that the chosen variables provide excellent explanation of the pricing of airline tickets in the sample.

Table 3: Results of Model 1 – Price Levels (Business Tickets)

	BUSINESS		
	OLS	**HM NULL**	**HM FULL**
Intercept	--	5.7760***	6.5681
EDLP	--		0.0284
fwcon	0.1398***		0.1083***
retcon	0.1741***		0.1466***
retPEAK	0.01347***		0.0124***
redeye	0.0050		0.0074**
multicarr	0.3042***		0.2916***
DD7	0.2359***		0.2335***
DD14	0.04541***		0.0444***
DD21	0.006821**		0.0047*
lnfreq	-0.05366***		-0.1278***
hub	0.05005***		0.0790***
shorthaul	--		-0.0286
slot	--		0.0161
lnMktCon	--		0.1533***
lnCASM	--		0.1172
lnavgEQUIP	--		-0.2834
EDLP*DD7	-0.07175***		-0.0691***
EDLP*DD14	0.01976***		0.0163***

EDLP*DD21	0.03845***		0.0404***
EDLP*shorthaul	-0.4922***		-0.5104***
EDLP*hub	0.08891***		0.2759***
$\hat{\varphi}$	--	0.1277***	0.0371***
$\hat{\tau}_{00}$	--	0.0831***	0.0635***
$\hat{\tau}_{01}$	--	--	-0.0435***
$\hat{\tau}_{11}$	--	--	0.1039***
$\hat{\sigma}^2$	0.1177***	0.1630***	0.1094***
N	138514	138514	138514
-2LL	97739.9	142740	88134.7
BIC	97751.7	142775.5	88193.9
Sum of Residual-Sq	16284.5		15121.4

Table 4: Results of Model 1 – Price Levels (Leisure Tickets)

	LEISURE		
	OLS	**HM NULL**	**HM FULL**
Intercept	--	5.8525***	5.8972***
EDLP	--		-0.0199
fwcon	0.1487***		0.1236***
retcon	0.1677***		0.1485***
fwPEAK	-0.0144***		-0.0170***
retPEAK	-0.0359***		-0.0396***
redeye	-0.0178***		-0.0138***
multicarr	0.2214***		0.2189***
DD7	0.2602***		0.2608***
DD14	0.0914***		0.0911***
DD21	-0.0035		-0.0030
lnfreq	-0.0732***		-0.1324***
hub	0.0467***		0.0721***
shorthaul	--		-0.1607***
slot	--		-0.0118
lnMktCon	--		0.1019*

lnCASM	--		0.0604
lnavgEQUIP	--		-0.0651
EDLP*DD7	0.0249***		0.0278***
EDLP*DD14	-0.0606***		-0.0604***
EDLP*DD21	0.0898***		0.0880***
EDLP*shorthaul	-0.4587***		-0.4282***
EDLP*hub	0.0188**		0.2094***
$\hat{\varphi}$	--	0.07426***	0.0243***
$\hat{\tau}_{00}$	--	0.07434***	0.0523***
$\hat{\tau}_{01}$	--	--	-0.0327***
$\hat{\tau}_{11}$	--	--	0.0896***
$\hat{\sigma}^2$	0.1250***	0.1684***	0.1193***
N	133892	133892	133892
-2LL	102550.8	142290.6	96768.5
BIC	102562.6	142326.0	96827.5
Sum of Residual-Sq	16716.4		15938.6

Results of Hypothesis 1: Price Levels

The results from model 1 (tables 3 and 4) offers partial support for the hypothesis that prices of online EDLP airlines are lower compared to those of their HILO competitors. One interesting observation is that the main effects of EDLP are insignificant in both types of tickets, implying that there does not exist an "overall" low price strategy.

The most striking difference between EDLP and HILO prices are observed in tickets for routes less than 500 miles and those in which EDLP airlines have hub airport(s). EDLP prices in short-haul markets are on average 39.97% and 34.83% cheaper than HILO prices for business and leisure tickets, respectively[12]. On the other hand, prices offered by EDLP airlines are higher compared to those by their HILO competitors in hub markets. For business tickets, EDLP prices in hub markets are 31.77% higher compared to HILO prices while 23.29% higher for leisure tickets.

The pricing of EDLP airlines is more complicated along the temporal dimension – their prices are higher for two- and three-week advance purchase business tickets than those of HILO airlines by 1.64% and 4.12%, respectively. For leisure tickets, their prices are higher for one- and three-week advance purchase tickets by 2.82% and 9.2%. Lower prices are found in EDLP airlines' one-week advance business tickets (6.68% cheaper) and two-week advance leisure tickets (5.86% cheaper).

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[12] The relative effect of a dichotomous variable coefficient (c) on the dependent variable in semilogarithmic equations is 100*(exp(c)-1) (Halvorsen, R., and Palmquist, R. "The Interpretation of Dummy Variables in Semilogarithmic Equations," *American Economic Review* (70:3) 1980, pp 474-475, Hann, I.-H., Roberts, J., Slaughter, S., and Fielding, R. "An Empirical Analysis of Economic Returns to Open Source Participation," *Working Paper*) 2004.

The relative magnitudes of coefficient estimates for the interactions among EDLP and weeks of advance purchase compared to those among EDLP and market specific attributes reveal that, in terms of the "low price" component, EDLP airlines employ "everyday low price" strategy more extensively in the market-specific rather than the temporal-specific dimension.

Results of Hypothesis 2a: Temporal Price Variability

Table 5: Results of Model 2a – Temporal Price Variability

	Business	**Leisure**
Intercept	0.1435***	0.2315***
fwcon	0.0075**	0.0055
retcon	0.0117***	0.0032
multicarr	-0.0345***	-0.0682***
freq	0.0004***	-0.0001
hub	0.0103**	-0.0118
shorthaul	0.0288**	0.0550**
slot	-0.0045	-0.0196
mktcon	-0.0024	-0.0025
EDLP*shorthaul	-0.1039**	0.0447
EDLP*hub	-0.0687	0.0996***
EDLP1	0.000[13]	-0.0925*
EDLP2	0.0195	-0.0652*
$\hat{\varphi}$	0.0032***	0.0077***
$\hat{\sigma}^2$	0.0096***	0.0138***
N	7368	2690
-2LL	-12783.1	-3518
BIC	-12765.3	-3502.2

The results of model 2a are summarized in table 5. Coefficients for the EDLP main effects suggest that price variability between EDLP and HILO airlines across time are significantly different only in leisure tickets. For business tickets, the only observable difference is in short-haul markets, where the variability of prices offered by EDLP carriers is lower than that of HILO carriers. While price variability is generally lower for leisure tickets

[13] No tickets have been identified for this airline.

offered by the EDLP airlines, in markets where the origin and/or destination is their hub airport, prices are found to be more variable than those of their HILO counterparts. These results offer partial support for hypothesis 2a.

Results of Hypothesis 2b: Price Variability within Markets

Table 6: Results of Model 2b – Price Variability within Markets

	Business	**Leisure**
Intercept	0.1329***	0.1613***
DD7	0.0555***	0.0656***
DD14	0.0231**	0.0465***
DD21	0.0011	-0.0099
freq	0.0006***	0.0010***
hub	0.0508***	0.0311***
shorthaul	0.0207	-0.0124
slot	0.0535***	0.0269*
mktcon	0.0039	0.0028
EDLP*DD7	-0.0032	-0.0503***
EDLP*DD14	-0.0040	-0.0339*
EDLP*DD21	0.0211	0.0328*
EDLP*shorthaul	-0.0677***	-0.0248
EDLP*hub	-0.0600***	-0.0463**
EDLP1	-0.1288***	-0.1208***
EDLP2	-0.1511***	-0.1168***
$\hat{\varphi}$	0.0046***	0.0023***
$\hat{\sigma}^2$	0.0213***	0.0187***
N	2954	2944
-2LL	-2597	-3026.3
BIC	-2581.0	-3010.3

Results from model 2b (table 6) indicate strong support for the hypothesis that prices of EDLP airlines are less variable in the market compared to others that do not adopt this strategy. The main effects of EDLP are negative and significant for both business and leisure tickets. This implies that prices offered by EDLP airlines are more consistent compared to those offered by HILO carriers, regardless of whether the Saturday-night stay restriction is imposed on the tickets and how many days prior to departure when the tickets were requested. Further, the low price variability is even more observable in markets where there is a hub airport for the EDLP airlines, for both business and leisure tickets, and in one- and two-week advance purchase leisure tickets. For business ticket, the low price variability of EDLP airlines is being emphasized in short-haul markets but not with respect to the number of weeks of advance purchase.

Results of Hypothesis 2c: Price Variability Across Markets

In order to investigate whether price variability of EDLP airlines are low across markets, we need to verify whether the *absolute* difference in prices of any two tickets written by EDLP airlines drawn from any given two markets is low. One way to test this hypothesis is by examining whether the standard deviations of median prices of EDLP airlines are low across different markets.

Table 7: Variability in Median Prices Across Markets

	Standard Deviation of Median Prices Across Markets			
	Business			
	1-wk adv	2-wk adv	3-wk adv	4-wk adv
EDLP	107.49	108.73	100.48	90.66
HILO	274.04	215.50	222.32	216.48
	Leisure			
	1-wk adv	2-wk adv	3-wk adv	4-wk adv
EDLP	133.79	104.67	124.80	95.18
HILO	228.13	171.01	179.27	177.84

Analysis of the standard deviation of median prices across markets (table 7) offers support to hypothesis 2c. The median price variations across markets for EDLP airlines are consistently lower than those for their HILO counterparts, for both business and leisure tickets and regardless of the number of weeks of advance purchase.

Category-level Implementation of EDLP

Strong evidence is found on the hypothesis that EDLP airlines adopt price format differently in different markets and product categories (results are summarized in table 8). The most consistent pricing behavior is observed in short-haul markets, where online EDLP pricing exhibit the characteristics that are consistent with the "everyday low price" image in both dimensions (price level and price variability) for both business and leisure tickets (tables 3-5). However, the pricing practice of EDLP airlines differs largely with respect to the number of weeks of advance purchase for business and leisure tickets. For example, while EDLP prices generally exhibit low price variability, the effects are more pronounced for one- and two-week advance purchase leisure tickets (tables 3 and 4). On the other hand, in terms of the "low price" dimension, general price levels between EDLP and HILO carriers are not significantly different. Further, EDLP airlines focus on charging low prices exclusively in specific product categories – one-week advance purchase for business tickets, and two-week advance purchase for leisure tickets – and specific types of markets (short-haul) for both business and leisure tickets.

Table 8: EDLP Pricing Dimension with respect to Various Market Segments and Product Categories

Market Segment/Product Category			EDLP Pricing Dimension	
			Price Level	Price Consistency[14]
High Willingness to Pay Segment (Business Travelers)	Market-specific Pricing	High Share (Hub) Markets	+	+
		Low Cost (Short-haul) Markets	-	+
	Category-specific Pricing	1-wk advance Purchase	-	n.s.[15]
		2-wk advance Purchase	+	n.s.
		3-wk advance Purchase	+	n.s.
Low Willingness to Pay Segment (Leisure Travelers)	Market-specific Pricing	High Share (Hub) Markets	+	+
		Low Cost (Short-haul) Markets	-	n.s.
	Category-specific Pricing	1-wk advance Purchase	+	+
		2-wk advance Purchase	-	+
		3-wk advance Purchase	+	-

Table 8: EDLP Pricing Dimension with respect to Various Market Segments and Product Categories

Conclusion

Our results suggest that EDLP airlines focus less on maintaining low average prices in general (model 1) and more on offering the lowest prices that undercut those of their competitors. Further, we find that EDLP airlines adopt this low price strategy selectively in certain types of market and product categories, particularly in markets where they have cost advantage. These results offer evidence for the prediction based on Lal and Rao's (1997) model on EDLP and HILO competition that, as the distance between the two types of firms decreases – due to either decrease in physical distance or lowering of search costs for the consumers in the context of electronic markets – EDLP sellers need to lower their overall level to keep their prices attractive to time-constrained consumers who still have higher search costs relative to the cherry-picking consumers.

Results from models 1 and 2 suggest that EDLP airlines adopt the everyday low price strategy to different extents depending on the type of market as well as product categories. While they compete aggressively on price level in a limited set of markets and products, EDLP airlines' adoption of the low price variability dimension of the strategy exhibits an "umbrella effect" that covers most markets and types of products. These findings suggest that EDLP sellers may find maintaining stable prices to be more effective than offering low prices in building an "everyday low price" online, as it is costly to compete on price level in electronic markets due to high price transparency. These results also offer a potential explanation for why research in online price dispersion finds contradictory evidence on random pricing theory (Baye et al., 2004; Baylis et al., 2002) – in markets where both types of sellers coexist, the

[14] Positive sign represents EDLP prices being more consistent than HILO prices.
[15] No significant difference between EDLP and HILO prices.

price-rank of sellers appears stable (Baylis et al.), while in other markets where only HILO sellers compete, substantial evidence of "hit and run" strategy and randomness in price-rank may be observed (Baye et al., 2004).

EDLP airlines' pricing are most consistent with their image in markets where they have cost advantage. Their prices in these markets exhibit the classical behavior of an "ideal" everyday low price practice in both price level and variability. On the other hand, the most "consistently inconsistent" behavior is observed in markets where EDLP airlines have high market power. Their prices in these markets exhibit more promotional characteristics than their HILO competitors in terms of relative price level. The former result suggests that EDLP airlines focus on building the "everyday low price" image in markets where they can afford to aggressively undercut competitors while maintaining stable prices at the same time; the latter suggests that these carriers may try to recover the loss in profit margins in markets where they can exercise discriminatory power and extract more premiums from consumers in those markets. These results not only offer the first evidence of category-specific price format adoption speculated in existing literature (Bell & Lattin,1998; Ho et al., 1998), but also suggest that the adoption of a "hybrid" strategy (EDLP in some markets, HILO in others) may be valuable particularly in online competition. Further, in reconciling the discrepancy in their image on price consistency, EDLP airlines adopt a strategy analogous to that of a "99cents" store and emphasize the stability of their low prices across different product markets.

The most notable difference between online EDLP pricing and that reported by literature in the offline context is that EDLP prices are *not* in general lower than HILO prices. While online EDLP prices are consistent with the expectations of low within-market variability, these results depart from findings of EDLP pricing in the offline markets in that temporal price variability EDLP airline is not significantly different compared to that of their HILO competitors online. In other words, the "within markets" characteristics of EDLP are more observable than the "across time" characteristics, suggesting a diminishing role of intertemporal price consistency in the practice of everyday low price in online markets. Part of this result can be attributed to the perishable nature of the product considered in this study; as consumers' reservation value increases when the departure date approaches, so does the price discriminatory power of the firms (Baye et al., 2004). An alternative explanation is that reduction in search costs in electronic markets has differential effects on consumers' price sensitivity along two dimensions. By making price information more accessible, consumers may focus on the comparison of "spot-prices" when they perform the search. However, due to the large number of prices available at the time of search, recall may be poor. As a result, electronic markets may increase consumers' price sensitivity at any given point in time when they perform price comparison but have a negative effect on consumers' *intertemporal price sensitivity;* hence, online sellers may find it profitable to engage in randomized pricing across time.

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Appendix

Determinants of Airline Pricing
Pricing of airline tickets are influenced by factors that fall into four broad categories: market power, competition, market structure, and cost.

Market Power – Market power of an airline determines its ability to mark up prices and create barrier to entry by competitors (Borenstein, 1989). It also plays an important role in the extent to which an airline enjoys economies of scale due to a large presence in particular airport(s) or route(s), the control over scarce resources such as the use of gates and runways (Berry, 1990), and the ability of the airline to price discriminate consumers based on their preferences (such as flying to/from congested airports during peak hours (Hayes & Ross, 1998)) and willingness to pay through restrictions imposed on tickets (Gale& Holmes, 1993; Dana, 1998; Stavins, 2001; Clemons et al., 2002).

Competition – The existence of competition limits the ability of an airline to exercise market power and mark up prices. It also reduces the possibility of collusion and domination by certain airlines, especially when there is intense competition among many airlines with small market shares in the market (Borenstein & Rose, 1994; Hayes & Ross, 1998; Stavins,2001).

Market Structure – Market structure has significant influence on pricing in the airline industry. For example, operating in or out of congested airports translates into higher opportunity cost for the airlines that may, at least partly, be carried over to consumers in terms of higher ticket prices (Berry et al., 1997; Stavins, 2001; Fournier & Zuehlke, 2004). Further, distance between origin and destination also affects the pricing of tickets. While lengthy flights allow more variability in a carrier’s choice of intermediate airports and greater economies of scale, variable costs also increase in proportion relative to the fixed costs of takeoff and landing (Borenstein, 1989; Berry et al., 1997; Hayes & Ross, 1998; Stavins, 2001).

Cost – The operational costs of airlines directly affect ticket prices and the ability of airline to pursue the low-price strategy. The higher the costs, the higher the prices need to be charged to cover the expenses of providing services in a given route (Borenstein, 1989). The costs of operating in a market are a function of the number of stops, flight distance, efficiency of aircraft utilization, and equipment size and variety. While large aircraft benefit from economies of scale on fuel in long-haul routes, smaller aircraft may be more cost-effective in short-haul markets due to high fixed costs of takeoffs and landings (Borenstein, 1989; Berry et al., 1997). Further, operating and maintaining a small variety of airplanes has been reported as important cost-saving measures by low-cost carriers such as Southwest (Neels, 2000).