DEMAND AND REVENUE IMPACTS OF THE OPAQUE CHANNEL: EMPIRICAL EVIDENCE FROM THE AIRLINE INDUSTRY

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ABSTRACT

Opaque selling is a mechanism whereby a seller conceals product or price information from buyers prior to purchase. Over time opaque intermediaries, such as Hotwire and Priceline.com, have emerged as an established distribution channel for the travel industry. The opaque channel has two countervailing effects: it can increase sales by attracting price-sensitive travelers who may otherwise not purchase, but it may also cannibalize sales from the transparent online channel (e.g., Orbitz, Expedia) or the offline channel (e.g., traditional travel agencies). While the extant analytical literature has examined these two effects, there is a paucity of empirical research that investigates the net impact of these effects and the overall viability of the opaque channel. We use a market response model and a massive dataset of economy class reservations from a major U.S. airline to empirically examine the demand generation and cannibalization effects of the opaque channel. We find that:

1) The opaque channel cannibalizes the online transparent channel but not the offline channel. This cannibalization occurs mainly in the discounted segment, but not in the full-fare and super-discounted segments. We find significant cannibalization in low-, but not high-competition markets.

2) The opaque channel is viable in high-competition markets, where it increases total sales volume and does not cannibalize the transparent channel.

Furthermore, we develop an empirical model to estimate the impact of prices across different channels on revenue, and we apply it to the opaque channel. The results suggest that the airline can substantially increase its revenues by reducing opaque fares in high-competition markets and by raising them in low-competition markets and during the low season.

Keywords: Cannibalization, channel strategy, market expansion, opaque selling, pricing, revenue management.

1. INTRODUCTION

The travel industry has been using opaque selling since Priceline.com's *Name-Your-Own-Price* (NYOP) patented mechanism emerged in 1998. NYOP selling is opaque because both the price and key characteristics of the product are concealed until a bid is accepted by the seller (Hann and Terwiesch, 2003; Terwiesch, et al., 2005). For airline tickets, Priceline.com conceals itinerary information and the identity of the airline carrier. Hotwire was launched by major U.S. airlines a few years later to compete in the opaque segment. Its opaque mechanism is a variation of Priceline.com in that it is not a bidding mechanism. Rather, a price is posted for an offer that conceals key itinerary information and airline identity. Other opaque sites have since appeared in other international travel markets.

Opaque intermediaries have become an established distribution channel for the travel industry. The potential benefits of opaque selling for travel suppliers are threefold. First, opaque selling can be used as a price discrimination mechanism (Jiang, 2006). Second, it can generate incremental sales from price-sensitive consumers who would otherwise be priced out of the market, in line with the literature on damaged goods (Deneckere and McAfee, 1996). Third, opaque selling can be used as a competitive lever. Offering low opaque prices is a way to "steal" customers from competitors, particularly those with low brand loyalty. In the presence of an opaque channel, a firm can lose revenue by choosing not to make opaque offers while competitors do (Huang and Sošić, 2010).

Despite years of research, there is still much controversy regarding the economic benefits of opaque selling. This is because introducing opaque offerings benefits a seller only if the incremental revenue from opaque sales—whether by generating new demand or by stealing market share from competitors—exceeds the revenue loss from the cannibalization of customers who are willing to pay for a regular product, but end up purchasing an opaque one. This is particularly relevant in the online channel, where it takes little effort for customers to search for opaque offerings. Much of the existing work to assess this trade-off has been based on analytical modeling. This line of research shows that the impact of opaque selling depends on many factors, including demand characteristics (Jerath et al., 2010; Fay and Xie, 2008; Granados et al., 2008), product characteristics (Jiang, 2006), consumer loyalty (Fay, 2008), industry structure (Fay, 2008; Huang and Sošić, 2010), and competition (Jerath et al., 2010; Shapiro and Shi, 2008). Because of the presence of many contributing factors with countervailing effects, the net impact of introducing an opaque channel is fundamentally an empirical question. However, related empirical evidence is scarce, in line with the reality of the revenue management literature.

As pointed out by Jerath et al. (2009, p. 281), "although numerous studies have modeled airline revenue management decisions, there have been very few attempts to verify these findings empirically." There have been some recent attempts to empirically validate revenue management theories (see, for example, Puller et al., 2008), but empirical studies on the revenue impacts of opaque selling are particularly scarce. We are only aware of the studies by Granados et al. (2008, 2010), who compare price elasticities of the offline, online transparent, and opaque channels. They find that the opaque channel has a high price elasticity and suggest that opaque offers need to be significantly discounted in order to attract demand. These findings underscore the importance of understanding the net revenue impact of the opaque channel. A significant discount in opaque offerings may indeed lead to demand generation, but the risk of cannibalization is also higher.

Our overall objective is to investigate whether and under what circumstances introducing an opaque channel is desirable from a seller's perspective. To this end, we analyze the sales generation and cannibalization effects of the opaque channel, and examine the factors that moderate these effects. We provide what we believe to be the first empirical evidence of the impact of opaque selling for sellers, in relation to market expansion (i.e., sales generation), cannibalization, and overall revenue. In particular, our research addresses the following questions:

- What are the market expansion and cannibalization effects of the opaque channel? What factors moderate these effects?
- What is the impact of opaque offerings on revenue? What are the implications for revenue management and channel strategy?

We use a massive dataset of economy class bookings from a major U.S. airline, which includes sales via the *offline* channel (e.g., traditional travel agencies), the *online transparent* channel (e.g., Travelocity, Expedia), and the *opaque* channel (e.g., Priceline.com, Hotwire). We employ a market response model introduced by Carpenter and Hanssens (1994) to estimate market expansion and cannibalization effects. In line with this methodology, we break down the economy class bookings into *full fare*, *discounted*, and *super-discounted* segments, but we extend the application of the model to a multi-channel context.

We look at two aspects of the demand impact of the opaque channel: (1) whether the opaque channel increases total passenger volume; and (2) how the opaque channel changes the market share of the other channels (i.e., cannibalization effects). Surprisingly, we find no significant effect of the opaque channel on total passenger volume when we estimate it for the full sample. This finding is at odds with the popular assumption in the analytical literature that the opaque channel increases total demand. However, a split-sample analysis by degree of competition shows that the opaque channel does increase total passenger volume in high-, but not low-competition markets. This result supports the analytical finding by Huang and Sošić (2010), who argue that a monopolist can enjoy higher revenue by avoiding the NYOP channel, but a seller in a competitive market should adopt the NYOP channel when competitors do.

In terms of the impact on the shares of the other channels, we find that the opaque channel cannibalizes the online transparent channel but not the offline channel. This result can be explained by the fact that most travelers are single-channel shoppers (Granados et al., 2011). We also find that cannibalization occurs in the discounted segment, but not in the super-discounted segment. One would assume that price-sensitive travelers from the super-discounted segment are a good target for opaque offerings, but the close proximity between super-discounted and opaque prices may explain the low cannibalization of the super-discounted segment that we observe. This is consistent with a normative model in which travelers are modeled as rational economic agents, and also in line with the results of Granados et al. (2008). Further analysis reveals that, while the opaque channel cannibalizes online transparent sales in both the high- and low-demand seasons, the effect is much larger in magnitude during the low-demand season. Our results also show that cannibalization occurs only in low-competition markets.

We extend the Carpenter and Hanssens (1994) model to estimate the *revenue elasticity* of each channel, or the change in revenue due to a change in a channel's price. We show that the revenue elasticity of a channel can decompose into three components: 1) revenue impact due to a change in the total passenger volume; 2) the channel's own fare impact on revenue; 3) and revenue impacts due to changes in channel shares. An analysis based on this revenue elasticity model shows that the airline can increase revenues by reducing opaque fares in high-competition markets and by increasing opaque fares in low-competition markets and during the low season. We estimate the annual revenue potential of these opaque fare changes to be in the range of $4-8 million. Based on these results, we offer specific recommendations for pricing and revenue management of the opaque channel. Our results also underscore the importance of tactical controls of inventory for opaque sales, emphasizing the role that revenue managers can play to ensure the viability of the channel.

This paper is organized as follows. In the next section, we review related studies that inform our subsequent empirical analysis. In section 3, we develop the empirical models. In section 4, we describe the data and methodology. In sections 5 and 6, we present and discuss the findings. We conclude in Section 7 with a summary of contributions and implications for revenue management and multi-channel strategy.

2. REVIEW OF CONCEPTS AND ANALYTICAL RESULTS

Our research is closely related to the literature on opaque selling, and more broadly to the revenue management literature in which opaque selling is often viewed as a recent innovation for marketing and price discrimination. Furthermore, market expansion and cannibalization are driven by the channel and product choices of individual consumers, whose behavior has been the topic of intensive study in the information systems, marketing, economics, and operations management literature. For a thorough review of the relevant literature on opaque selling, please refer to Jerath et al. (2009).

2.1. Conceptualization of Opaque Selling

Opaque selling is an example of innovative mechanisms for marketing and price discrimination (Talluri and van Ryzin, 2004). Fay and Xie (2008) introduce the concept of *probabilistic selling* wherein one seller offers multiple products, which can be seen as a broad category under which opaque selling falls. They show that offering probabilistic goods can reduce the seller's information disadvantage, which lessens the negative effect of demand uncertainty on profit, and can solve the mismatch between capacity and demand, thereby enhancing efficiency. Opaque products can also be viewed as a particular form of *flexible products* (Gallego and Phillips, 2004). A seller offering a flexible product promises to deliver one of several horizontally differentiated products to a customer upon purchase, and has the flexibility to assign one of the pre-specified products to the customer after purchase. Opaque selling is a particular instance whereby customers are informed about the product assignment immediately after purchase. Opaque products are also often offered as a form of *last-minute selling* (Jerath et al., 2010). In direct last-minute selling, a seller offers unsold inventory at discounted prices when the product is about to perish.

2.2. Cannibalization and Market Expansion of the Opaque Channel

The effectiveness of a selling mechanism is often affected by consumer search costs for product offerings. While the online channel has offered firms the possibility to innovate with opaque selling mechanisms, it also enables travelers to search more easily for transparent and opaque offers, and therefore reduce consumer search costs (Bakos, 1997). One exception is the online NYOP mechanism. Using data from a German NYOP retailer, Hann and Terwiesch (2003) find that consumers' frictional costs of submitting multiple bids are high. Lower search costs for online travel offers can increase overall demand, but they can also increase cannibalization because it takes little effort for high-valuation customers to check low-end offers.

The current work on price discrimination, market expansion, and cannibalization by the opaque channel is dominated by analytical modeling. Overall, this body of literature suggests that the opaque channel can benefit sellers because it can be used to price-discriminate between high- and low-valuation customers (Fay, 2008; Granados et al., 2008; Jiang, 2006; Shapiro and Shi, 2008; Wang, 2009). However, the findings on the net effect of market expansion and cannibalization are mixed, depending mainly on assumptions about the degree of competition, capacity constraints, and the level of demand.

Degree of Competition

Analytical studies on the impact of the opaque channel exist in both monopoly and competitive settings. Jiang (2006) considers a situation in which a monopolist offers two horizontally differentiated products. The products can either be offered in the transparent or opaque channel. She finds that when consumer valuations for transparent and opaque offers are close, it is optimal for the seller to use the opaque channel because the increase in market size will offset the negative cannibalization effect. However, Granados et al. (2008) empirically show that consumer valuations of transparent and opaque fares can differ substantially, which may violate the conditions required for the opaque channel to be viable in Jiang's model. This is consistent with Huang and Sošić (2010), who find that a monopolist may earn higher revenues in the absence of an NYOP channel.

In contrast, other studies suggest that the opaque channel may benefit sellers in a competitive setting where two or more sellers offer products in both transparent and opaque channels. Fay (2008) studies two sellers that offer opaque products through an intermediary in a market with loyal and non-loyal customers. He shows that opaque goods may allow finer market segmentation and price discrimination, which will cause market expansion, in part, by serving the full segment of non-loyal customers. Furthermore, the opaque channel will be profitable when there is a high level of brand loyalty in the market, but it can increase price rivalry and decrease total industry profit when brand loyalty is low. Shapiro and Shi (2008) introduce a modified Hotelling model of horizontal differentiation in order to examine price discrimination by the opaque channel, and they consider cannibalization, but not market expansion. They show that opaque selling intensifies competition in the price-sensitive segment, but can alleviate competition in the premium segment, thus leading to higher overall profits for a particular range of parameter values.

In sum, the analytical literature suggests that the opaque channel may be more viable for a seller in a competitive setting, compared to a monopolistic setting. In this study, we empirically validate this by examining the impact of the opaque channel in markets with different levels of competition.

Capacity Constraints and Demand Level

Jerath et al. (2010) study the conditions under which duopolistic sellers prefer opaque selling over direct last-minute selling without opaque features. Their results indicate that opaque selling is preferred as the probability of having high demand increases, challenging the usual notion that opaque selling is purely a mechanism to dispose of unused capacity. The rationale is that high demand leads to low seat inventory allocated to opaque offers close to departure, which in turn, induces early bookings at higher prices and consequent higher overall profits. This result is in line with Wang et al. (2009), who show that contracting with an NYOP retailer is less desirable as the seller adds more capacity. Their rationale is that what makes the opaque channel viable is the uncertainty of demand, and not the expectation of excess capacity. Similarly, in a study on the role of an NYOP channel in a market with competitive sellers and capacity constraints, Huang and Sošić (2010) show that the existence of an NYOP channel may lower seller profits because it tends to intensify competition, and this competition exacerbates as capacity increases.

Overall, these studies suggest that it may be best to offer opaque products in high-demand seasons when there are seat capacity constraints. In order to verify this analytical result, we compare the impact of the opaque channel in high- and low-demand seasons.

Summary

Our review of the literature so far suggests that, depending on factors such as demand characteristics, product characteristics, brand loyalty, and industry structure, the opaque channel may or may not lead to higher revenues. These mixed results mirror the debate in the travel industry over the long-term viability of the opaque channel. In air travel, while many new and innovative online pricing strategies have emerged (Klein and Loebbecke, 2003), opaque selling still remains a niche segment, and there are instances in which airlines have avoided offering opaque products because of concerns about cannibalization (Shapiro and Shi, 2008). Also, most competitive moves in air travel have been toward higher levels of transparency, and even Hotwire and Priceline.com have introduced their own transparent retail mechanisms to compete in this direction (Granados et al., 2010). We contribute to this discussion by providing what we believe to be the first empirical evidence of the net effect on revenues of the opaque channel, accounting for both market expansion and cannibalization.

3. EMPIRICAL FRAMEWORK

A Market Response Model

Market response models have been widely used for marketing decision-making in a wide variety of industries (Hanssens, Parsons, and Schultz, 2003). In particular, different types of market response models have been developed and used to examine the relationship between marketing mix variables and performance measures, such as sales or market share. In order to examine the market expansion and cannibalization effects across channels (i.e., offline, online transparent, and opaque), we employ a market response model introduced by Carpenter and Hanssens (1994). Their model has been used to estimate market expansion and cannibalization effects across different airline fare segments. We adapt the model to estimate cross-channel effects. The adapted model has several properties that are important for our analysis. First, it allows us to estimate the impact of a channel's price change on total passenger volume. This is important because we want to examine whether or not opaque selling contributes to market expansion. Second, it allows us to estimate asymmetric cannibalization (or expansion) effects across channels. Because we believe that the extent to which offline sales and online transparent sales are affected by opaque fares may be different, this feature of the model is important for our analysis. Third, the demand impacts of a price change can be expressed in terms of own-channel price elasticity and cross-channel price elasticities, thereby facilitating our subsequent analysis.

Adapting the model from Carpenter and Hanssens (1994), we use the response model consisting of the following set of log-linear equations:

$$Q_t = \exp\left(A_0 + \sum_j A_j p_{jt}\right), \quad j \in \{offline, transparent, opaque\}, \tag{1}$$

$$m_{it} = \exp\left(B_0 + \sum_j B_{ij} p_{jt}\right), \quad i, j \in \{offline, transparent, opaque\}, \tag{2}$$

where Q_t is the total passenger volume on a given origin-destination (OD) city-pair on departure date t; m_{it} is the "channel share" or the share of passengers who purchased a ticket via channel i on departure date t; p_{jt} is the average ticket price for channel j on departure date t; and A_j and B_{ij} are response parameters. A_j is the estimate of the impact of each channel on the overall market size (i.e., total passenger volume). B_{ij} is the cross-channel cannibalization (or expansion) effect, which can be asymmetric (i.e., $B_{ij} \neq B_{ji}$ for $i \neq j$). In the remainder of the paper, we often drop the time index t for simplicity and ease of exposition.

One advantage of this model is that the cannibalization and market expansion effects can be easily expressed in terms of elasticities, i.e., the percentage change in demand associated with a percentage change in a channel's price. The elasticity of total passenger volume (or simply volume elasticity) with respect to the price of channel j is $D_{jt} = A_j p_{jt}$, so the prices of different channels can have different impacts on market size, depending on the price level and the response parameter A_j. The volume elasticity is analogous to the price elasticity of demand in economics. The share elasticity of channel i with respect to the price in channel j is $E_{ijt} = B_{ij} p_{jt}$, which will vary, depending on the price level of channel j and the response parameter B_{ij}.

Revenue Elasticity Model

In order to examine the net effect of the opaque channel, we extend Carpenter and Hanssens' model to estimate the marginal revenue effects of price changes in the opaque channel.

We model the marginal revenue effects in terms of *revenue elasticity*. We define revenue elasticity with respect to the price of channel k as

$$R_k = \frac{\partial Rev / Rev}{\partial p_k / p_k}, \tag{3}$$

where $Rev = Q\sum_i m_i p_i$ is the total revenue of the airline, and $i \in \{opaque, transparent, offline\}$.

Substituting equation (1) for Q and equation (2) for m_i in equation (3), and taking the partial derivative with respect to p_k leads to

$$\frac{\partial Rev}{\partial p_k} = A_k Q \sum_i m_i p_i + Q m_k + Q \sum_i m_i p_i B_{ik}. \tag{4}$$

Plugging equation (4) into (3) and simplifying, we obtain

$$R_k = \frac{\partial Q / Q}{\partial p_k / p_k} + \frac{\partial \left(\sum_i m_i p_i\right) / \left(\sum_i m_i p_i\right)}{\partial p_k / p_k}. \tag{5}$$

Equation (5) provides a parsimonious breakdown of the marginal effect of a channel's price change on total revenue. The first term is the volume elasticity with respect to the price of channel k. To understand the second term, note that $\sum_i m_i p_i = Rev / Q$ is the average revenue per ticket. Hence, the second term can be interpreted as the elasticity of average revenue per ticket with respect to p_k. We can further break down the elasticity of average revenue per ticket into own elasticity and cross-channel elasticity by rewriting equation (5) as

$$R_k = \frac{\partial Q / Q}{\partial p_k / p_k} + \frac{m_k p_k (1 + p_k B_{kk})}{\sum_i m_i p_i} + \frac{\sum_{i \neq k} p_k B_{ik} m_i p_i}{\sum_i m_i p_i}. \tag{6}$$

Given that channel share elasticity is defined as $\frac{\partial m_i / m_i}{\partial p_k / p_k} = B_{ik} p_k$, we can rearrange terms in equation (6) to obtain

$$R_k = \frac{\partial Q / Q}{\partial p_k / p_k} + \frac{m_k p_k}{\sum_i m_i p_i} + \sum_i \frac{m_i p_i}{\sum_j m_j p_j} \left(\frac{\partial m_i / m_i}{\partial p_k / p_k} \right). \tag{7}$$

The second term on the right-hand side of equation (7) is the revenue share of channel k, which measures the marginal revenue increase from a price increase in channel k. We call this the *own-channel fare impact* on revenue. The third term is the sum of three terms, each denoting the revenue share of a channel multiplied by the channel share elasticity with respect to the price in channel k. In other words, this term captures the revenue impact of channel share changes associated with a price change in channel k. Therefore, we call this the *channel share impact* on revenue. Once the parameters of the market response model are estimated, we can estimate the revenue elasticity of the opaque channel by calculating each term in equation (7) based on the parameter values and the averages of the total passenger volume, prices, and channel shares.

4. DATA AND METHODS

Data and Variables

We use a massive dataset of economy class reservations from a major U.S. airline (hereafter referred to as the Airline) with a non-disclosure agreement. The dataset contains detailed reservation data for 5 months of departure dates from January to May, 2005 and consists of more than 800,000 records. Each record has reservation details including origin city, destination city, ticket price, departure date, ticket issue date, advance purchase (in terms of the number of days prior to departure), and booking agency.

Based on the booking agency, we categorized the reservation records into three channels: o*ffline*, *online transparent*, and *opaque*. The *offline* sales consist of reservations made through traditional offline travel agencies. *Online transparent* sales include bookings from online travel agencies, such as Orbitz, Travelocity, and Expedia. *Opaque* sales include bookings made through agencies that conceal product information until after purchase.

An examination of the reservation data reveals that there is significant variation in passenger volume across weekdays. To deal with this issue, we aggregated our data at the weekly level so that Q is the weekly total passenger volume, m_i is the weekly average channel share, and p_i is the weekly average price in channel i on a given city-pair. We measure *channel share* (the passenger share of each channel) for a given city-pair as the ratio between weekly passenger volume in each channel and the total weekly passenger volume. For *channel price*, we calculate the average weekly price of tickets sold through each channel for a given city-pair.

We include several control variables that can influence the total passenger volume and channel shares. One control variable is *market concentration*. We use the Herfindahl-Hirschman index (*HHI*), which is defined as $HHI_i = \sum_{k=1}^{n_i} s_{ki}^2$, where s_{ki} is the market share of carrier k and n_i is the number of carriers in city-pair i. *HHI* has been widely used as an inverse proxy of competition across disciplines (Derfus et al., 2008; Edwards, 1977; Granados et al., 2011). Because the presence of low-cost carriers can influence customers' purchase decisions, we also control for *low-cost carriers' market share* (hereafter *LCC*), which is measured as the sum of the market shares of low-cost carriers, such as Southwest, Frontier, Airtran, ATA, and Spirit Airlines. The Airline's market power can also influence the response to price changes; hence, we control for the *Airline's market share* (hereafter *MS*). To construct these control variables, we use 2004 data on each carrier's market share for each city-pair using the DB1A database of the U.S. Department of Transportation.

To control for any unobserved market-specific effects that may influence demand, we include dummy variables for *origin cities*. Also, customers' purchase behavior (e.g., purchase channel, price sensitivity) may change, depending on whether the trip is for leisure or business. Because we do not explicitly observe the purpose of the trips, we classified destinations into *leisure* and *business* and included a dummy variable. Certain weeks may experience greater passenger volume than others. To control for any unobserved time-specific effects (e.g., seasonality), we included dummy variables for departure weeks. Table 1 presents the summary statistics.

Table 1. Summary Statistics (*n* = 799)

Variable	Mean	Std. Dev.	Min.	Max.
Total Passenger Volume (Q)	755.04	1,050.41	11	6,600
Offline Share (m_{off})	.645	.174	.208	.928
Online Transparent Share (m_{tran})	.325	.161	.063	.750
Opaque Share (m_{opa})	.030	.053	.0003	.586
Offline Fare (p_{off})	132.46	61.74	24.41	524.56
Online Transparent Fare (p_{tran})	107.74	59.06	56.91	450.11
Opaque Fare (p_{opa})	66.77	45.30	8.07	392.14
Market Concentration (*HHI*)	.369	.140	.131	.885
Low-Cost Carriers' Market Share (*LCC*)	.257	.236	0	.991
The Airline's Market Share (*MS*)	.274	.247	.002	.939

Table 2 shows pair-wise correlations. There is a correlation of 0.75 between the fares of the transparent and offline channels. While this is expected because airlines tend to price across channels homogeneously via computer reservation systems, it raises concern of multicollinearity for each response function. To address this concern, we checked for multicollinearity among our independent variables using variance inflation factors (VIFs). The mean VIF was 1.56, with a maximum of 2.47. This suggests that multicollinearity is not an issue in our estimations.

Table 2. Correlations among Variables

	Q	m_{off}	m_{tran}	m_{opa}	p_{off}	p_{tran}	p_{opa}	HHI	LCC	MS
Q	1.00									
m_{off}	.39*	1.00								
m_{tran}	-.32*	-.95*	1.00							
m_{opa}	-.31*	-.39*	.09*	1.00						
p_{off}	-.37*	-.01	-.07*	.26*	1.00					
p_{tran}	-.38*	.10*	-.21*	.29*	.75*	1.00				
p_{opa}	-.22*	.004	.03	-.10*	.36*	.35*	1.00			
HHI	.07	.10*	-.11*	-.01	-.11*	-.07*	-.12*	1.00		
LCC	.24*	-.15*	.20*	-.13*	-.39*	-.42*	-.20*	-.20	1.00	
MS	.50*	.72*	-.66*	-.33*	.06	0.001	.002	.24*	-.27*	1.00

Note: * $p < 0.05$

Estimation Procedures

Based on the variables defined above, we estimate the following set of equations:[1,2]

$$\ln Q = \alpha_0 + \alpha_1 p_{off} + \alpha_2 p_{tra} + \alpha_3 p_{opa} + \text{controls}, \tag{8}$$

$$\ln m_{off} = \beta_{10} + \beta_{11} p_{off} + \beta_{12} p_{tra} + \beta_{13} p_{opa} + \text{controls}, \tag{9}$$

$$\ln m_{tra} = \beta_{20} + \beta_{21} p_{off} + \beta_{22} p_{tra} + \beta_{23} p_{opa} + \text{controls}, \tag{10}$$

$$\ln m_{opa} = \beta_{30} + \beta_{31} p_{off} + \beta_{32} p_{tra} + \beta_{33} p_{opa} + \text{controls}. \tag{11}$$

These equations are interrelated because *channel share* (m_i) is a function of total passenger volume (Q) and the sum of the channel shares is equal to one, by definition. Not surprisingly, there is a very high correlation of -0.95 between the market shares of the online transparent and offline channels. In general, in a situation where multiple equations are not independent of one another, seemingly unrelated regression (SURE) is more efficient than ordinary least squares (OLS) regression (Zellner, 1962). However, when the equations have identical independent

[1] We have suppressed the time subscript t for ease of exposition.
[2] Similarly, in order to examine cross-segment effects (full-fare, discounted, super-discounted, and opaque), we estimate five equations. See the Findings section for details.

variables as in our case, OLS is as efficient as SURE (Greene, 2000). Due to the cross-sectional and time-series nature of our data, heteroskedasticity (i.e., unequal variance of errors across city pairs) and autocorrelation (i.e., correlated error terms across time periods) may be present in our data. If errors are heteroskedastic and/or serially correlated, using ordinary least squares (OLS) estimation can be problematic because estimates will not be efficient, and standard errors will be incorrect (Greene, 2000). Using the Breusch-Pagan test, we checked for heteroskedasticity in equations (8) – (11), and found that heteroskedasticity is present ($p < 0.1$) in two out of four equations for the cross-channel effects model, and in three out of five equations for the cross-segment effects model. The Wooldridge (2002) test for autocorrelation indicates the presence of first-order autocorrelation (AR1) in eight out of nine equations we estimate. Therefore, we use feasible generalized least squares (FGLS) (Wooldridge, 2002), which can apply appropriate corrections for heteroskedasticity and autocorrelation, to estimate the equations separately.[3]

One potential issue in our estimation is endogeneity of the independent variables (i.e., prices). For example, if there is an exogenous shock (e.g., economic downturn due to recession), airlines may reduce prices if they expect lower demand. Even without exogenous shocks, airlines typically use demand as an input to set prices and inventory allocations. In these cases, the price variable may be endogenous, which may bias the estimation results. We tested for endogeneity of our price variables. Using the one- and two-week lagged values of prices as instruments, we checked for the endogeneity of the price variables based on Hansen's J and the C statistic tests for exogeneity (Baum, Schaffer, and Stillman, 2003). We ran these tests for the three price variables, both independently and jointly. All of the tests indicate that we cannot reject the null hypothesis that prices are exogenous ($p > 0.1$), so we conclude that endogeneity is not a concern.

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[3] For each equation, we made adjustments for heteroskedasticity and autocorrelation only when they are present. When neither issue is present, FGLS becomes equivalent to OLS.

5. FINDINGS

Market Expansion and Cannibalization Effects of Opaque Sales

Table 3 presents the results of estimating equations (8) – (11) for the full sample. We find that the total passenger volume responds to offline and online transparent prices, but does not respond to opaque prices (α_0 = -0.0001, $p > 0.1$). Thus, we do not find a significant market expansion effect from the opaque channel. We also find that opaque fares cannibalize online transparent sales (β_{32} = 0.0004, $p < 0.05$), but not offline sales (β_{31} = 0.0001, $p > 0.1$). We observe asymmetric cannibalization across channels. Both offline and online transparent fares cannibalize the opaque channel (β_{13} = 0.0048, $p < 0.01$; β_{23} = 0.0032, $p < 0.01$), while only online transparent fares cannibalize offline sales (β_{21} = 0.0018, $p < 0.1$). In summary, we observe that the opaque channel cannibalizes online transparent sales, but we find no significant impact of the opaque channel on the total passenger volume (i.e., no overall market expansion effect). This result does not support the assumption in the analytical literature that opaque selling can expand the market. A split-sample analysis below will qualify this broad finding.

Table 3. Market Expansion and Cross-Channel Effects

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Offline	-.0039*** (.0004)	-0.51	-.0012*** (.0001)	-0.16	.0012*** (.0002)	0.16	.0048*** (.0008)	0.64
Online Transparent	-.0025*** (.0004)	-0.27	.0018*** (.0001)	0.19	-.0044*** (.0002)	-0.47	.0032*** (.0008)	0.35
Opaque	-.0001 (.0004)	-	.0001 (.0001)	-	.0004** (.0002)	0.03	-.0088*** (.0007)	-0.59
N	737		737		737		737	

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, *= $p < 0.1$. Standard errors are in parentheses. Elas. = Price elasticity, only shown for significant coefficients. Control variables: departure week, origin city, leisure destination, HHI, low-cost carriers' market share, and the Airline's market share.

Effects of Opaque Sales on Different Fare Segments

To gain further insight into cannibalization by the opaque channel, we grouped fares in the offline and online transparent channels into three segments: *full-fare*, *discounted*, and *super-discounted*. Appendix A provides details on the categorization of fare classes into different segments. By treating opaque fares as a separate fare segment, we estimated market expansion and cannibalization effects across the four segments (see Table 4).

Table 4. Market Expansion and Cross-Segment Effects

	Total Passenger Volume	Fare Category Share			
		Full-Fare	Discounted	Super-Discounted	Opaque
Full-Fare	-.0007*** (.0001)	-.0011*** (.0003)	.0002 (.0002)	.0001 (.0001)	.0018*** (.0003)
Discounted	-.0030*** (.0003)	.0022*** (.0006)	-.0046*** (.0004)	.0015*** (.0002)	.0019*** (.0005)
Super-Discounted	-.0078*** (.0007)	.0061*** (.0012)	.0045*** (.0010)	-.0047*** (.0003)	.0067*** (.0011)
Opaque	.00002 (.0002)	.0007 (.0005)	.0007* (.0004)	-.0001 (.0001)	-.0087*** (.0005)
Observations	737	737	737	737	737

Note: Significance: $^{***} = p < 0.01$, $^{**} = p < 0.05$, $^{*} = p < 0.1$. Standard errors are in parentheses. Control variables: departure week, origin city, leisure destination, HHI, low-cost carriers' market share, and the Airline's market share.

Table 4 shows that the opaque channel cannibalizes the discounted fare segment, but has no impact on the full-fare or super-discounted segments. This result is consistent with existing models based on individual consumer rationality. Fay and Xie (2008) point out that probabilistic selling allows sellers to introduce buyer uncertainty through product assignment. When deciding on their channel choices, customers need to make a trade-off between a higher fare in the transparent channel and a lower fare offer with less product information (and thus more valuation uncertainty) in the opaque channel. Our results imply that the buyer uncertainty imposed through opacity is significant enough to create a segmentation barrier so that full-fare travelers choose to avoid opaque offerings.

On the other hand, there has to be a fare difference significant enough to justify the information disadvantage of an opaque product. Our results suggest that the difference between discounted and opaque fares tends to be high enough, while the difference between super-discounted fares and opaque fares is not. We elaborate on this further in our discussion section.

Split-Sample Analysis: High- vs. Low-Demand Season

The analytical results from Huang and Sošić (2010), Jerath et al. (2010), and Wang et al. (2009) suggest that the opaque channel is preferred in periods of high demand, in part due to capacity constraints that induce customers to purchase early at higher prices. We examine this conjecture by comparing market expansion and cannibalization effects in the high- and low-demand seasons. Also, during high-demand periods, opaque demand may be truncated by lack of inventory, which may explain our observation of no significant market expansion effect. Empirically, this argument would be indirectly supported if we observed market expansion in the low-, but not high-demand season. To examine differences in market expansion across seasons, we split the departure weeks into high- and low-demand seasons, based on average weekly revenue, and separately estimated the models for the subsamples (see Table 5).

Table 5. Opaque Channel Effects by Season

	Total Passenger Volume		Channel Share: Offline		Channel Share: Online Transp.		Channel Share: Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
High Season (n = 452)	. -.0001 (.0005)	-	.00003 (.0001)	-	. 0007*** (.0003)	0.05	-.0104*** (.0009)	-0.73
Low Season (n = 327)	.0001 (.0001)	-	.0001 (.0001)	-	.0018*** (.0003)	0.11	-.0066*** (.0013)	-0.41

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Standard errors are in parentheses. Elas. = Price elasticity, only shown for significant coefficients. Control variables: origin city, leisure destination, HHI, low-cost carriers' market share, and the Airline's market share. First and last weeks of departures were excluded due to truncation.

As shown in Table 5, cannibalization of the online transparent channel exists for both seasons, and it is greater in the low- (β_{32} = 0.0018, $p < 0.1$) versus high-demand season (β_{32} =

0.0007, $p < 0.01$), which lends indirect support for analytical studies suggesting that the opaque channel is more viable in periods of high demand. The market expansion effect of the opaque channel is not significant in either season (high season: α_0 = -0.0001, $p > 0.1$; low season: α_0 = 0.0001, $p > 0.1$). This finding eases our concern that inventory constraints may be affecting our results. If that were the case, one would observe market expansion in low-, but not high-demand seasons.

Split-Sample Analysis: High- vs. Low-Competition

Another important factor that can affect our results is the level of competition in each city-pair. In order to examine whether or how competition moderates cross-channel effects, we used the median value of HHI to split the sample into high-competition (low HHI) and low-competition (high HHI) city-pairs, and we estimated the models separately (see Table 6).

Table 6. Opaque Channel Effects by Level of Competition

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
High Competition (n = 394)	-.0019*** (.0007)	-0.13	.0003 (.0002)	-	.0003 (.0004)	-	-.0066*** (.0006)	-0.47
Low Competition (n = 405)	.0003 (.0006)	-	-.0001 (.0001)	-	.0010*** (.0003)	0.06	-.0106*** (.0011)	-0.71

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Standard errors are in parentheses. Elas. = Price elasticity, only shown for significant coefficients. Control variables: departure week, origin city, leisure destination, low-cost carriers' market share, and the Airline's market share.

Cannibalization by opaque fares is found only in low-competition city pairs. Opaque fares cannibalize the online transparent channel in city-pairs with low levels of competition (β_{32} = 0.001, $p < 0.01$), but not in city-pairs with high levels of competition (β_{32} = 0.0003, $p >$ 0.1). We also find that opaque fares increase total passenger volume in city-pairs with high levels of competition, but have no impact on the total passenger volume in city-pairs with low competition. We discuss these findings further in the next section.

Revenue Impacts of Opaque Sales

Table 7 summarizes the revenue elasticity and its components for each channel. We report only those effects that are statistically significant per our econometric results. For the opaque channel, the revenue elasticity is 0.02. This revenue elasticity value suggests that there is an opportunity to increase the revenue contribution of the opaque channel by increasing its price on average. Regarding the breakdown of revenue impacts, the volume elasticity of the opaque channel is zero because there is no significant market expansion effect. The own-channel fare impact of the opaque channel is 0.02. The channel share impacts of the opaque channel on the online transparent and opaque channels are 0.01 and -0.01, respectively. This means that a 1% increase in opaque fares will lead to a 0.01% increase in online transparent revenues (due to less cannibalization by the opaque channel), and a net 0.02% increase in revenue.

Table 7. Revenue Elasticity Values by Channel

				Channel Share Impacts		
	Revenue Elasticity	Volume Elasticity	Own-Channel Fare Impact	Offline	Online Transparent	Opaque
Offline Fare	0.13	-0.51	0.69	-0.11	0.04	0.02
Online Transparent	0.02	-0.27	0.28	0.13	-0.13	0.01
Opaque	0.02	-	0.02	-	0.01	-0.01

The table also shows that the revenue elasticity of the offline channel is 0.13. Thus, it appears that from a revenue management perspective, a large revenue opportunity exists by increasing offline fares. This is, in part, because the large share of the offline channel magnifies the effect of a price change. There is a relatively high own-channel fare impact (0.69), which is partially offset by a negative volume elasticity (-0.51) and a negative channel share elasticity (-0.05).

As Table 8 shows, when we compare different fare segments, opaque fares have a positive revenue elasticity, which implies that the Airline can increase its revenue by raising opaque fares. An increase in opaque fares has a positive channel-share impact on the discounted segment

(0.01) and a negative channel-share impact on the opaque segment (-0.01), which cancel each other out. The increase in revenue from customers already buying from the opaque channel (i.e., own-channel fare impact) leads to an overall positive revenue elasticity. In contrast, the negative revenue elasticities for the full-fare, discounted, and super-discounted segments suggest that these fares should go down, on average, to maximize revenue.

Table 8. Revenue Elasticity Values by Fare Segment

	Revenue Elasticity	Volume Elasticity	Own-Channel Fare Impact	Channel Share Impacts			
				Full Fare	Discounted	Super-Discounted	Opaque
Full Fare	-0.06	-0.24	0.25	-0.09	-	-	0.01
Discounted	-0.19	-0.46	0.25	0.09	-0.18	0.11	0.01
Super-Discounted	-0.03	-0.55	0.48	0.11	0.08	-0.16	0.01
Opaque	0.02	-	0.02	-	0.01	-	-0.01

Table 9 shows revenue elasticity estimates for high- and low-demand seasons. The revenue elasticity of the opaque fares is positive in both seasons. However, it is higher during the low-demand season due to the higher revenue share (0.04 vs. 0.02 in the high-demand season) and the higher cannibalization of the online transparent channel (0.04 vs. 0.01 in the high-demand season). Therefore, although increasing opaque fares will lead to a revenue increase in both the high- and low-demand seasons, the impact is higher in the low-demand season.

Table 9. Revenue Elasticity Values by Season

	Revenue Elasticity	Volume Elasticity	Own-Channel Fare Impact	Channel Share Impacts		
				Offline	Online Transparent	Opaque
High-Demand Season (*n*=452)	0.02	-	0.02	-	0.01	-0.01
Low-Demand Season (*n*=327)	0.05	-	0.04	-	0.04	-0.02

As shown in Table 10, the impact of the opaque fares depends on the level of competition in a given market. The revenue elasticity is negative in high-competition markets, but positive in low-competition markets. In low-competition markets, the opaque channel represents a significantly higher revenue share and hence, has a higher own-channel fare impact on revenue (0.06) than in high-competition markets (0.01). On the other hand, in high-competition markets, offering lower opaque fares will increase revenue mainly due to the large impact on total passenger volume (volume elasticity = -0.14). In low-competition markets, offering higher opaque fares will lead to an overall increase in revenue because the own-channel fare impact on revenue (0.06) and lower cannibalization of the online transparent channel (0.03) more than offset the negative channel share impact (-0.05). Overall, this revenue elasticity result by degree of competition suggests that the Airline can calibrate its fares across city-pairs by giving more weight to opaque sales in high-competition markets, in line with the analytical finding that the opaque channel is more viable in markets with high competition (Fay, 2008; Jerath et al., 2010, Shapiro and Shi, 2008). Instead, in markets with low competition, such as in monopoly markets, the presence of the opaque channel should be curtailed (in this case, by raising fares) so as to minimize cannibalization of the online transparent channel.

Table 10. Revenue Elasticity Values by Level of Competition

				Channel Share Impacts		
	Revenue Elasticity	Volume Elasticity	Own-Channel Fare Impact	Offline	Online Transparent	Opaque
High Competition (*n*=394)	-0.13	-0.14	0.01	-	-	-0.003
Low Competition (*n*=405)	0.04	-	0.06	-	0.03	-0.05

6. DISCUSSION AND REVENUE IMPLICATIONS

Market Expansion Effects

Our findings provide novel insights into the viability of the opaque channel, particularly for the travel industry. Our first broad finding is that the opaque channel does not increase the

Airline's total sales volume. This result is somewhat surprising, as the majority of the analytical literature assumes that the biggest advantage of opaque selling is its ability to tap into the segment of customers who are price-sensitive and who would be priced out at high-retail fare levels (e.g., Fay, 2008; Granados et al., 2011). This finding raises concerns about the viability of the opaque channel, because when the market expansion effect is not significant, any positive price-discrimination effect may not be enough to offset the negative revenue impact from cannibalization. This broad result lends support to the negative analytical results regarding the viability of the opaque channel (e.g., Huang and Sošić, 2010; Wang et al., 2009).

Our split-sample analysis, based on the level of competition, provides further insights into the market expansion effects of the opaque channel. For concentrated (low-competition) markets, we find that the opaque channel does not increase total passenger volume. This further feeds skepticism about the viability of the opaque channel. If there is any significant cannibalization by the opaque channel, since it is typically at the bottom of the fare hierarchy, an airline with a monopolistic position may be better off not offering opaque fares. This finding is consistent with the analytical result of Jiang (2006) in that an airline in a monopolistic setting may be better off offering only the transparent product if customers are heterogeneous in their willingness-to-pay.

One alternative explanation for not observing a market expansion effect is that inventory constraints may be leading to an artificially lower measure of total demand for the opaque channel. Yet when looking at the split-sample by season, we find that in both high- and low-demand seasons, there is no market expansion by the opaque channel. Thus, even during the low-demand season, when inventory constraints are likely to be less severe, we still do not find a significant market expansion effect. Therefore, this result mitigates the concern that inventory constraints may lead to underestimation of market expansion effects, although we cannot completely rule it out. Even if that were the case, the literature suggests that airlines may prefer to ration opaque inventory to induce early bookings at higher prices (Jerath et al., 2010; Wang et al., 2009). Therefore, any revenue loss from lost opaque sales due to inventory constraints may be offset by revenue gains of driving travelers to book at higher fares.

On the other hand, we find that there is an expansion effect by the opaque channel in city-pairs with high levels of competition. There are two possible explanations for this result. First, due to a battle for market share, the introduction of opaque fares by an airline may trigger opaque offers by other airlines, and the overall effect of these actions is that the opaque channel increases total industry demand in that market. Alternatively, the Airline may be effectively stealing market share from other airlines in a market with a stable total industry demand. Either way, this finding suggests that, despite the cannibalization effect, the opaque channel may be viable in markets with high levels of competition. The result that the opaque channel increases demand in competitive markets is consistent with the analysis of Fay (2008), who shows that the opaque channel can be an effective price discrimination mechanism, enabling sellers to capture the low-end segment of the market with low prices, without diluting the revenue of the high-end segment of the market. It is also consistent with Shapiro and Shi (2008), who show that even without considering market expansion effects, price-discrimination made possible by the opaque channel may lead to higher revenues.

Cannibalization Effects

Cannibalization across Channels. We find that the opaque channel cannibalizes the online transparent channel but not the offline channel. This is consistent with the fact that most travelers are single-channel shoppers (Granados et al., 2011). Price changes in the opaque channel are likely to impact the sales of transparent OTAs, but not offline channel sales. This finding provides face validity to the assumption that the opaque channel is a niche segment because it appeals only to a certain portion of online customers. This is good news for airlines because if the offline and opaque channels have separable demand sets, there should be less concern about cannibalization by the opaque channel. On the other hand, opaque intermediaries should recognize that opaque products require a niche strategy, so there is a limit to the potential demand they can generate. This may explain why in recent years, perhaps recognizing the limit for growth of their opaque mechanisms, intermediaries such as Priceline.com and Hotwire have introduced transparent mechanisms.

Cannibalization across Fare Segments. We find that the opaque channel cannibalizes the discounted, but not the super-discounted segment, which is the most price-sensitive segment of all. A possible explanation for this is that the difference between opaque and the super-discounted fares is not high enough to justify the information disadvantage of opaque products. We find support for this explanation in our data. The average fare for the discounted segment is $150.55, significantly above the average fare for the opaque channel of $66.77. On the other hand, the average fare for the super-discounted segment is $67.05; thus, it is close enough to the opaque channel to make opaque offers unattractive to customers in that segment. This finding is also consistent with Granados et al. (2008), who found that it is optimal for airlines to offer opaque products at a significant enough discount in order to offset the loss in transparency for consumers.

Cannibalization by Season. We find that the cannibalization of online transparent sales by the opaque channel is significant in both the high- and low-demand seasons. However, cannibalization is larger in magnitude during low-demand seasons. This result can be explained by the *rationing risk* considered in the analytical literature (Liu and van Ryzin, 2008); customers may not be able to find opaque fares at low prices if demand is high; therefore, they are more likely to purchase early in the transparent channel. This result also highlights the importance of the tactical revenue management principle to control the inventory availability of different fare products, even when there is ample capacity to satisfy demand. That is, even if an airline can fill all of its empty seats with opaque sales, it should ration inventory for opaque seats to avoid excessive cannibalization.

Moderating Effect of Competition. Based on a split-sample analysis between city-pairs with high and low levels of competition, we find that the cannibalization of the online transparent channel by the opaque channel exists in markets with low levels of competition. However, in markets with high levels of competition, no significant cannibalization effects by the opaque channel are found. One possible explanation is offered by Shapiro and Shi (2008), who find that introducing the opaque channel in a market results in effective price discrimination, which lessens competition in the transparent channel, leading to higher overall profits. Therefore, even without considering market expansion effects, it is possible for price discrimination by the opaque channel in competitive markets to make airlines better off because they have less incentive to lower transparent prices to compete for the low-end segment of the market. Rather, they can use the opaque channel to capture price-sensitive customers without diluting the revenue of the high-end segment.

Revenue Impact

The results of the revenue elasticity analyses suggest that overall, opaque fares are not optimal (i.e., revenue maximizing); thus, the Airline can increase its revenue by adjusting them. The average revenue elasticity of 0.02 indicates that an average 1% increase in opaque fares across markets and seasons will lead to a 0.02% increase in overall revenue, mainly due to less cannibalization of the online transparent channel. For major U.S. airlines, which had revenues between \$10-\$20 billion in 2009[4], this simple calibration of opaque prices to minimize cannibalization can represent revenue improvements of \$2-\$4 million.

However, the breakdown of the revenue elasticity analysis suggests that the revenue opportunity may be larger if the Airline adjusts opaque fares more surgically across seasons and markets. That is, the average revenue elasticity of 0.02 assumes an opaque fare increase across the board, but a more granular approach is warranted. Indeed, significant positive revenue elasticities exist for the high-demand season (0.02), the low-demand season (0.05), and low-competition markets (0.04). Therefore, increasing opaque fares accordingly is bound to increase revenues, in part because it will mitigate the cannibalization of online transparent sales. However, a much larger opportunity to increase revenues exists by reducing opaque fares in high-competition markets, where we estimated a revenue elasticity of -0.13. Decreasing opaque fares by 1% on average in high-competition markets will lead to a 0.13% increase in revenues. We estimate that these refined adjustments for the opaque channel can lead to a yearly revenue improvement of \$8-\$16 million for a major U.S. airline.

Table 11 summarizes the impacts of the opaque channel in our split-sample analyses, based on season and degree of competition. By only looking at the results by season, one might be concerned about offering opaque fares. Because there is no market expansion, there is a risk that price-discrimination effects may not be sufficient to offset cannibalization effects. The revenue elasticity analysis suggests that one strategy to improve revenues and make the opaque channel more viable is to increase opaque fares overall to reduce cannibalization.

The results, based on the degree of competition, portray further insights on how to calibrate prices across channels. Although it would be better for the Airline to raise opaque fares in low-

[4] Source: U.S. airline 2009 income statements.

competition markets, the Airline can further increase its revenue by lowering opaque fares in high-competition markets. As opaque fares go down in these competitive markets, new sales can be generated, but at the same time, cannibalization of the online transparent channel will tend to increase. The revenue impact is positive for the Airline, as long as the revenue increase due to sales generation is greater than the revenue decrease due to cannibalization.

Table 11. Summary of the Impacts of the Opaque Channel

Factor		Market Expansion	Cannibalization (Online Transp.)	Revenue Elasticity
Season	**High**	No	Yes	Positive
	Low	No	Yes	Positive
Competition	**High**	Yes	No	Negative
	Low	No	Yes	Positive

7. CONCLUSIONS

Implications

We conclude from our empirical study that the opaque channel increases revenue, as long as revenue managers are selective about the markets and seasons in which they offer opaque fares and about the fare levels. Our market expansion and cannibalization estimations suggest that opaque fares should be offered judiciously, mainly in markets with high levels of competition. The revenue elasticity analysis suggests that one way to increase revenues effectively is by increasing opaque fares when the main effect observed is cannibalization, and to decrease opaque fares when the main effect observed is market expansion. For example, because cannibalization of the online transparent channel is very strong during the low-demand season, the Airline should raise opaque fares to reduce this cannibalization. In contrast, for high-competition markets, where the market expansion effect was found to be significant, the Airline should decrease opaque prices in order to increase sales.

This research has broader implications for multi-channel strategies. The results suggest that cannibalization matters when a product with two quality levels is offered online, if one views an opaque product as being of lower quality. Contrary to the existing evidence that used books do not significantly cannibalize online sales of new books (Ghose et al., 2006), and contrary to the assumption that the online channel imposes higher switching costs and lock-in effects (Viswanathan, 2005), our findings are consistent with the notion that in many situations, it is easy to switch to lower-quality offerings in the online channel due to the plethora of sources that are available for consumers to search for goods and services online. On the other hand, we find that for the particular case of the airline industry, the cannibalization of offline sales by opaque offerings is not significant. However, we suspect that this separability of demand between the offline and opaque channels may not transfer to other industries. More research across industries and product categories is warranted in order to develop robust guidelines for multi-channel strategies.

Contributions

This is the first empirical study of the market expansion and cannibalization effects of the opaque channel. To date, much of the related literature has relied on analytical modeling, in which the results vary, depending on the modeling assumptions and the parameters considered. Our findings suggest that the opaque channel is viable only when cannibalization effects on other channels can be carefully managed, and therefore underscore the importance of tactical revenue management decisions. We have considered multiple controls and moderating factors to examine the demand and revenue impacts of opaque offerings. As a result, our work complements the analytical literature by offering new insights into the net impact of the opaque channel on sales and revenues.

We offer the revenue elasticity model developed in this paper as a methodology to break down the impact on revenue of a channel in terms of market expansion and cannibalization of sales in other channels. The model establishes clear links between these demand effects and revenue impacts. The Carpenter-Hanssens methodology, used to estimate market expansion and cannibalization, provides just the demand side of the story. Our revenue elasticity methodology provides a strong complementary perspective for revenue managers to implement fare adjustments effectively in order to maximize market expansion and minimize cannibalization across channels. The methodology can help identify whether or not the price differentials across channels are optimal, and what pricing actions can be taken to adjust these differentials in order to increase revenues.

The methodology adopted in this paper to estimate market expansion, cannibalization, and revenue impacts is applicable not only across channels, but also across other dimensions. We also believe that this methodology can be applied to other industries, as long as the demand function has a good fit with the Carpenter-Hanssens model. It will be interesting to see other applications of this model in the airline industry, as well as in other industries.

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Appendix A: Categorization of fare-classes into different segments

Fare class code	**Fare class code**
Full-fare	Top four fare classes in the fare hierarchy
Discounted	Four middle fare classes in the fare hierarchy
Super-discounted	Three bottom fare classes in the fare hierarchy
Note: Bookings for frequent flyer award tickets were removed from the dataset.	