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

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ABSTRACT

Over time, opaque intermediaries, such as Hotwire and Priceline.com, have become an established distribution channel for the travel industry. We use a market response model and a dataset of economy class reservations from a major international airline to empirically examine the demand and cannibalization effects of the opaque channel. We find that: (1) the impact of the opaque channel on total demand is positive and significant in markets with high levels of competition; and (2) overall, the opaque channel cannibalizes the online transparent channel, but not the offline channel nor the full-fare segment. However, we find that cannibalization of the offline channel moderately increases as markets become more concentrated. These results together suggest that airlines can benefit from opaque offerings mainly in markets with high levels of competition. Further, we develop a methodology to assess the revenue impacts of the opaque channel and show how it can be used by managers to develop and implement pricing tactics to increase demand and decrease cannibalization.

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

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1. INTRODUCTION

Opaque selling is a mechanism whereby a seller conceals product or price information from buyers prior to purchase. 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 posts discounted prices so it is not a bidding mechanism.

The potential benefits of opaque selling for travel suppliers are threefold. First, opaque selling can be used as a price discrimination mechanism (Jiang, 2006), where price-sensitive customers sacrifice transparency to get a lower price, while premium customers prefer the high quality, transparent fares. This price discrimination may also allow sellers to charge higher prices in the high-quality segment (Shapiro and Shi, 2008). 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. On the other hand, in the presence of an opaque intermediary, a firm can lose revenue by choosing not to make opaque offers while competitors do (Huang *et al.*, 2017).

Despite years of research, there is still much controversy regarding the economic benefits of opaque selling. This is because opaque offerings benefit a seller only if the incremental revenue from opaque sales—whether by increasing demand for the seller or benefiting from price discrimination—exceeds the revenue loss from the cannibalization of customers who are willing to pay for a regular product, but end up purchasing an opaque product at a discount. This is particularly relevant in the digital era, where it takes little effort for customers to search and find discounts on the Internet and on mobile devices, including opaque offers.

Much of the existing work to assess this trade-off has been based on analytical modeling. This line of research shows that the presence of opaque selling can increase or decrease seller revenues depending on 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 *et al.*, 2017), and competition (Jerath et al., 2010; Shapiro and Shi, 2008). These mixed results mirror the debate in the travel industry over the overall effects 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 of the higher priced, transparent offers (Shapiro and Shi, 2008). Also, most competitive moves after the advent of opaque sites have been toward higher levels of transparency; even Hotwire and Priceline.com eventually introduced their own transparent retail mechanisms (Granados et al., 2010).

Because of the presence of many contributing factors with countervailing effects, the net effect of the opaque channel is fundamentally an empirical question. However, related empirical evidence is quite limited. 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." Empirical studies that have directly examined the impacts of opaque selling are particularly scarce.

We provide what we believe to be the first empirical evidence of the impact of opaque selling in relation to demand, cannibalization, and revenue, based on a dataset of economy class bookings from a major international 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).[1] We employ a market response model (Carpenter and Hanssens 1994) and adapt it to our multi-channel context to examine demand and cannibalization effects across channels.

We look at two aspects of the impact on demand of the opaque channel for the airline sponsor of this study: (1) whether a lower price in the opaque channel increases total passenger volume, as evidence of the effect on total demand; and (2) how the opaque channel affects the market share of the other channels, as evidence of cannibalization effects. We find that both effects are present, although we find that the total demand effect is present only in markets with high levels of competition. This result is consistent with the notion that opaque fares are best leveraged in markets where airlines can effectively steal market share.

In terms of cannibalization effects, we find that the opaque channel cannibalizes the online transparent channel, but not the offline channel nor the full-fare segment. This is consistent with the strategy that airlines employ to sell discounted seats using opaque offerings to minimize the cannibalization of passengers with high willingness-to-pay.

The findings on demand and cannibalization effects of the opaque channel help us

[1] During the periods covered by our dataset, Hotwire and Priceline.com were offering transparent fares as well as opaque fares. We only considered their opaque offerings as opaque fares in our analyses while including the transparent offerings as online transparent fares.

understand the demand impacts, but not the revenue impacts. In order to examine the revenue impacts of the opaque channel, we extend the Carpenter and Hanssens (1994) model to estimate the *revenue elasticity*, the change in revenue in response to a change in a channel's price. Based on this new model, we offer specific recommendations for pricing and revenue management of the opaque channel.

2. THEORETICAL BACKGROUND AND HYPOTHESES

Background: Conceptualization of Opaque Selling

Fay and Xie (2008) introduce the concept of *probabilistic selling* wherein one seller offers multiple products as probabilistic goods, and opaque selling can be seen as falling within this broad category. They show that offering probabilistic goods can reduce the seller's information disadvantage, which reduces the negative effect on profit from demand uncertainty and 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 of flexible products promises to deliver one of several horizontally differentiated goods to a customer upon purchase, and gets to choose which one to deliver. Opaque selling is a particular instance of a flexible product, where only certain features that apply to all goods are revealed in advance. Opaque offers are often used as a form of *last-minute selling*, where a seller offers unsold inventory at a discounted price when the product is about to perish (Jerath et al., 2010).

The effectiveness of a selling mechanism depends in part on the search costs that consumers incur. While the Internet allows travel suppliers to widen their market reach, it also enables travelers to search more easily for transparent and opaque offers, and therefore consumer search costs have decreased significantly (Bakos, 1997). These lower search costs can lead to an increase in overall demand, but they can also increase cannibalization because it takes little effort for high-valuation customers to find low-end offers.

Impact of Opaque Offers on Total Demand

One potential positive effect of opaque fare offerings is an increase in total demand, which can potentially counter the negative effect of cannibalization. Fay (2008) studied 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, leading to higher demand, in part, by serving the full segment of non-loyal customers. Opaque fares are typically lower than the regular fares offered through transparent channels, so they can attract price-sensitive customer segments that would otherwise be priced out of the market. This rationale does not imply that only high-end customers will buy high-end products; it simply suggests that any cannibalization of higher-end customers due to an opaque fare reduction will be at least partially offset by an increase in demand for the opaque offer.

Also, some airlines may be reluctant to offer opaque fares, which may provide the opportunity for opaque sellers to steal market share and increase their own demand. This was the case of Germanwings, which offered opaque tickets with blind European destinations, and competitors did not match (Post and Spann, 2012). It is particularly difficult for airlines to match opaque fare offerings, since they would have to purchase competitors' opaque tickets to monitor opaque prices.

In summary, a discounted opaque fare may not be spotted by competitors, which can lead to an increase in demand for the airline. But even if competitors match the offer, the industry may experience an increase in demand as otherwise priced-out consumers enter the market. Hence, we propose:

__Hypothesis 1__: The lower the opaque price, the higher the total demand for the airline will be.

Cross-Channel Cannibalization by the Opaque Channel

Cannibalization occurs when travelers who would normally purchase from the online transparent or offline channels at a higher price end up purchasing in the opaque channel at a lower price. We hypothesize that cannibalization may be stronger in the online channel, compared to offline channel. First, because of the lower search costs on the Internet, a consumer searching online can more easily find an opaque offer than a consumer searching offline.

Second, online travelers may be inherently more price-sensitive and less averse to uncertainty. Offline consumers who purchase through traditional travel agencies are often business travelers who are less price-sensitive. In fact, there is a higher percentage of business travelers that book offline, while there is a higher percentage of leisure travelers that book online (Granados et al. 2012). Due to the schedule rigidity of business travelers, they also tend to be averse to the uncertainty resulting from product opacity (e.g., uncertainty about the itinerary). In contrast, leisure travelers tend to be less averse to such uncertainty because their travel plans are more flexible. Applied to our context, this implies that stronger cannibalization will occur in the online channel, where proportionally more leisure travelers book. Therefore, we propose:

> *__Hypothesis 2__: The cannibalization effect of the opaque channel is stronger for the online transparent channel than for the offline channel.*

Cross-Segment Cannibalization by the Opaque Channel

While the opaque channel is intended to serve a segment of highly price-sensitive travelers with relatively low willingness-to-pay, it may lead to cannibalization of the market segments with higher willingness-to-pay, such as business travelers or high-end leisure travelers. However, business travelers value their own time highly, and are willing to pay for the itinerary that best fits their needs. Likewise, high-end leisure travelers can afford to pay for convenience and efficient travel, so they will demand information about the most convenient itinerary. Therefore, we hypothesize that the high-end segments of the market will not be cannibalized by the opaque channel. Rather, the opaque channel will cannibalize the price-sensitive segments that do not typically pay a full fare. Therefore, we propose:

Hypothesis 3a*: The opaque channel does not cannibalize the full-fare segment.*

Hypothesis 3b*: The opaque channel cannibalizes the price-sensitive segments.*

3. EMPIRICAL FRAMEWORK

A Market Response Model

Market response models have been widely used in a variety of industries (Hanssens *et. al.*, 2003). Different types of market response models have been developed to examine the relationship between marketing mix variables and performance measures (e.g., sales, market share). The objective of market response models is to estimate the coefficients or *response parameters* of independent variables to see how a dependent variable responds to them.

In order to examine demand effects and cannibalization across channels, we employ a market response model introduced by Carpenter and Hanssens (1994). This model has been used to estimate demand effects and cannibalization across different airline fare segments. We adapt their model to estimate cross-channel effects using the following log-linear equations:

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

$$m_{it} = \exp\left(B_{i0} + \sum\nolimits_j B_{ij} p_{jt}\right), \quad i, j \in \{offline, transparent, opaque\}, \tag{2}$$

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. The coefficient A_j is the estimate of the impact of each channel on total demand (i.e., total passenger volume in our empirical analysis). The coefficient B_{ij} is the cross-channel cannibalization (or enhancement) effect, which can be asymmetric (i.e., in general, $B_{ij} \neq B_{ji}$ for $i \neq j$). In the remainder of the paper, we drop the time index t for notational simplicity and ease of exposition.

Price elasticity is the percentage change in demand associated with a percentage change in a channel's price. In our empirical model, the elasticity of total passenger volume (or simply *volume elasticity*) with respect to the price of channel j is $D_{jt} = A_j p_{jt}$. Cannibalization effects across channels are measured by *channel share elasticity*. The channel share elasticity of channel i with respect to the price in channel j is $E_{ijt} = B_{ij} p_{jt}$.

This adapted model is a good fit for our study for several reasons. First, through the estimation of the parameters A_j , we can measure the impact of a channel's price change on total passenger volume. This is important because we want to examine whether or not a price change of opaque offerings lead to higher total demand. Second, by estimating the parameters B_{ij}, we can measure asymmetric cannibalization effects across channels. Given that the extent to which offline and online transparent sales are affected by opaque fares may not be identical, 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 intuition to the results.

Revenue Elasticity Model

In order to examine the revenue impact of the opaque channel, we extend the model of Carpenter and Hanssens to estimate the marginal revenue effects of price changes in each channel. We model the marginal revenue effects in terms of *revenue elasticity*, or the change in revenue due to a change in a channel's price level. We define *revenue elasticity* w.r.t. 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 $i \in \{opaque, transparent, offline\}$.

Taking partial derivative of Rev with respect to p_k, we have

$$\frac{\partial Rev}{\partial p_k} = \frac{\partial Q}{\partial p_k}\sum_i m_i p_i + Q\sum_i \left(m_i \frac{\partial p_i}{\partial p_k} + \frac{\partial m_i}{\partial p_k} p_i\right). \tag{4}$$

Using (1), we have $\frac{\partial Q}{\partial p_k} = A_k Q$. Using (2), we have $\frac{\partial m_i}{\partial p_k} = m_i B_{ik}$. We also have $\frac{\partial p_i}{\partial p_k} = 1$ for $i = k$ and 0 otherwise. Replacing these in equation (4) yields

$$\frac{\partial Rev}{\partial p_k} = A_k Q \sum_i m_i p_i + Q m_k + Q \sum_i m_i p_i B_{ik}. \tag{5}$$

Plugging equation (5) into (3) and simplifying, we obtain

$$R_k = \frac{\partial Q / Q}{\partial p_k / p_k} + \frac{\partial\left(\sum_i m_i p_i\right) / \left(\sum_i m_i p_i\right)}{\partial p_k / p_k}. \tag{6}$$

Equation (6) 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 (6) as

$$R_k = \frac{\partial Q / Q}{\partial p_k / p_k} + \frac{m_k p_k (1 + p_k B_{kk})}{\sum_i m_i p_i} + \frac{\sum_{i \neq k} p_k B_{ik} m_i p_i}{\sum_i m_i p_i}. \tag{7}$$

Channel share elasticity is defined as $\frac{\partial m_i / m_i}{\partial p_k / p_k} = B_{ik} p_k$. By rearranging terms in (7), we obtain

$$R_k = \frac{\partial Q / Q}{\partial p_k \,/\, p_k} + \frac{m_k p_k}{\sum_i m_i p_i} + \sum_i \frac{m_i p_i}{\sum_j m_j p_j} \left(\frac{\partial m_i \,/\, m_i}{\partial p_k \,/\, p_k} \right). \tag{8}$$

The second term on the right-hand side of equation (8) is the revenue share of channel *k*, which captures the marginal revenue increase purely from increasing channel *k*'s price. Therefore, we call this term 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 change in the price of channel *k*. Therefore, we call this the *channel share impact* on revenue.

For our study, this revenue modeling extension allows us to use the estimates of the market response model to calculate a revenue response to changes in opaque fares, online transparent fares, or offline fares. Also, the intuitive break-down of the revenue elasticity allows us to provide practical recommendations for pricing and inventory managers to maximize revenue.

4. DATA AND METHODS

Data and Variables

We use a dataset of economy class reservations from a major international airline (hereafter, the Airline). Each record has reservation details for the outbound portion of a ticket, including origin city, destination city, average one-way prorated ticket price, departure date, booking date, advance purchase day (in terms of the number of days prior to departure), and booking agency. Note that we do not have individual bookings data. Each record in our dataset includes several bookings made on the same date with the same departure date, the same origin and destination, and the same booking agency; the ticket price is the average price of the individual bookings in the record.

Our data covers a five-month period from January 1 to May 31, 2005 with 21 full departure weeks.[2] There are 33 origin cities, 35 destination cities, and 712 unique origin-destination pairs.[3] Our data captures bookings with up to 237 advance purchase days prior to departure. Due to the sparseness of the opaque bookings, we aggregated bookings for the same departure date across all advance purchase days; then, we also aggregated bookings by departure week.[4] This resulted in 11,739 weekly records, each with a unique combination of origin-destination and departure week.

Based on the booking agency, we categorized the reservation records into three channels: o*ffline*, *online transparent*, and *opaque*. *Offline* reservations are made through traditional offline travel agencies. *Online transparent* reservations are made through online travel agencies without opaque features, such as Orbitz and Expedia. *Opaque* reservations are made through online agencies with opaque features, such as Hotwire and Priceline.com. Note that Hotwire and Priceline were offering both opaque and transparent fares during our sample period; therefore, we categorized their bookings accordingly in our dataset.

Due to the small number of opaque offerings, there are a large number of records with zero opaque sales (and therefore no price information) in our data. Because zero sales can occur due to relatively high fares, simply dropping these records may bias our results.[5] In order to address this issue, we have made two adjustments to our data. First, as mentioned above, we aggregated our data to the departure-week level because zero sales are much less likely to occur during an

[2] Note that we had 23 weeks, but dropped the first and last weeks because we did not have data for the full week.
[3] We do not include the full list of origin and destination cities to conceal the identity of our airline sponsor.
[4] This aggregation alleviates the concern about the misspecification of the model due to inter-temporal purchase behavior across booking dates and departure dates (e.g., customers wait for better fares and purchase in a future period, or they change their travel date to a day of week with a lower fare). We thank an anonymous reviewer for this important point.
[5] We thank an anonymous reviewer and the SE for pointing out this important issue.

entire week, compared to during a given travel day. This aggregation substantially reduced the number of records with zero sales.

Second, we imputed prices for records with zero sales using the prices from the week before and the week after. For example, when a record at departure week *t* for a given city-pair has zero opaque sales, we used the opaque fares from weeks *t-1* (e.g., $90) and *t+1* (e.g., $110) for the same city-pair. When opaque fares are available from both periods, we used the average value from the two periods; when an opaque fare is available in only one of the two periods, we used the opaque fare from the period having opaque fares; and when neither adjacent period has opaque fare information, we did not impute a price.

There are good theoretical justifications for our imputation approach. In the airline revenue management literature, it is shown that the optimal prices form a martingale (Ata and Akan, 2015); this means that the expected (or average) price for a particular route is constant throughout the booking horizon. Therefore, even though prices can swing up and down substantially, on average they stay constant. Since the fares used in our estimation are averages across weekly sales, they in general will not swing wildly from week to week. This imputation strategy significantly reduced the number of records with zero sales. Our final dataset includes 4,388 city-pair-week observations.

Based on this dataset, we estimate the following set of equations:

$$\ln Q = \alpha_0 + \alpha_1 p_{off} + \alpha_2 p_{tra} + \alpha_3 p_{opa} + \text{controls}, \tag{9}$$

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

$$\ln m_{tra} = \beta_{20} + \beta_{21} p_{off} + \beta_{22} p_{tra} + \beta_{23} p_{opa} + \text{controls}, \tag{11}$$

$$\ln m_{opa} = \beta_{30} + \beta_{31} p_{off} + \beta_{32} p_{tra} + \beta_{33} p_{opa} + \text{controls}. \tag{12}$$

where Q is the weekly total passenger volume for a given city-pair. m_i denotes the weekly average channel share, measured by the ratio of weekly bookings for channel i and weekly total passenger volume. p_i is the weekly average channel price, measured by the average weekly price of tickets sold through channel *i* for a given city-pair.

Control Variables

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*), defined as $HHI_i = \sum_{k=1}^{n_i} s_{ki}^2$, where s_{ki} is the market share of carrier *k* in city-pair *i* and n_i is the number of carriers in city-pair *i*. *HHI* has been widely used as an inverse proxy of competition (Derfus et al., 2008; Edwards, 1977; Granados et al. 2012). 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 used the DB1A U.S. D.O.T. data on airline market shares for the period of the study.

We introduce a variable to account for capacity constraints that may restrict sales for a given city pair. We cannot use flight seat capacity because a city-pair can have multiple one-stop and two-stop itineraries and often a dozen or more flights involved. Instead, we use the Airline's minimum daily price (hereafter *MIN*) in offline and online transparent channels for a given departure date and city-pair. This minimum daily price is an approximation of the opportunity cost of selling a seat in the market, or the minimum fare at which the system is willing to accept an origin-destination passenger in order to maximize network revenue, also known in revenue management as the *bid-price* (Talluri and van Ryzin, 1998). In fact, as Li et al. (2014) note, a proxy for bid price by origin-destination is actually a better approximation of the inventory available than seats available by flight, because modern revenue management systems allocate inventory for different fares based on the bid-price for a particular city-pair and itinerary request.

To control for any unobserved market-specific factors, such as regional income and local competitive dynamics, we include dummy variables for *origin cities*. Also, given that customers' purchase behavior (e.g., purchase channel, price sensitivity) may change depending on the destination, we also include dummy variables for *destination cities*. To control for any unobserved time-specific effects, we included dummy variables for each departure week.

Table 1 presents descriptive statistics, some of which are noteworthy. First, the opaque channel's share of the Airline's sales is 8.9%. Although it is smaller than the shares of the offline (58.1%) and online transparent (32.9%) channels, it accounts for a considerable portion of total sales. Second, the average opaque fare is $89.36, which is significantly lower than the average online transparent fare ($142.97) and about half of the average offline fare ($176.58). Therefore, a traveler gets a substantial discount by purchasing an opaque ticket. Third, the mean HHI is 0.419, which implies that the markets under study are quite competitive. Indeed, low-cost carriers enjoy sizable market shares, with an average of 20.2%. Finally, the Airline has an average market share of 14%.

Table 1. Summary Statistics (*n* =4,388)

Variable	Mean	Std. Dev.	Min.	Max.
Variables of Interest				
Total Passenger Volume (Q)	211.28	582.12	1	6,600
Offline Share (m_{off})	.581	.233	0	1.000
Online Transparent Share (m_{tran})	.329	.211	0	1.000
Opaque Share (m_{opa})	.089	.171	0	1.000
Offline Fare (p_{off})	176.58	85.08	41.39	1149.55
Online Transparent Fare (p_{tran})	142.97	83.95	20.79	1837.48
Opaque Fare (p_{opa})	89.36	45.12	35.97	478.64
Control Variables (excluding dummies)				
Market Concentration (HHI)	.419	.188	0.131	.969
The Airline's Market Share (MS)	.140	.196	0	.939
The Airline's Minimum Daily Price (MIN)	67.79	42.88	0.59	1143.78

Model Diagnostics and Selection of Econometric Estimation Method

To estimate equations (9)-(12), we use ordinary least square (OLS) regression with clustered robust standard errors. We made this choice based on the model diagnostics described below.

Multicollinearity. Table 2 shows pairwise correlations. The highest correlations in our data are those between the market shares of the different channels, which is expected. We checked for multicollinearity using variance inflation factors (VIFs). The mean VIF was 1.43, with a maximum of 2.30. This suggests that multicollinearity is not an issue.

Table 2. Correlations among Variables

	Q	m_{off}	m_{tran}	m_{opa}	p_{off}	p_{tran}	p_{opa}	HHI	MS	MIN
Q	1.00									
m_{off}	.24*	1.00								
m_{tran}	-.13*	-.71*	1.00							
m_{opa}	-.17*	-.49*	-.27*	1.00						
p_{off}	-.08*	.11*	-.14*	.02	1.00					
p_{tran}	-.06*	.14*	-.16*	.004	.42*	1.00				
p_{opa}	.01	.08*	.01	-.13*	.38*	.36*	1.00			
HHI	-.06*	-.21*	.07*	.20*	-.12*	-.17*	-.19*	1.00		
MS	.50*	.41*	-.27*	-.22*	.12*	.13*	.14*	-.11*	1.00	
MIN	-.21*	.07*	-.05*	.03*	.43*	.32*	.28*	-.04*	-.10*	1.00

Note: * $p < 0.05$

Heteroskedasticity and autocorrelation. Due to the cross-sectional and time-series nature of our data, heteroskedasticity and autocorrelation may be present in our data. We used the Breusch-Pagan test for heteroskedasticity and found that heteroskedasticity is present ($p < 0.01$) in our dataset. Also, the Wooldridge (2002) test for autocorrelation indicates the presence of first-order autocorrelation (AR1) ($p < 0.01$). To account for heteroskedasticity and autocorrelation, we use ordinary least square (OLS) with clustered robust standard errors (clustered at the city-pair level). Although we have multiple equations, we estimate each equation separately because doing so is as efficient as seemingly unrelated regression (SURE) when the equations have identical independent variables as in our case (Greene, 2000).

Endogeneity. Another potential issue in our estimation is endogeneity of price as an independent variable. To address this important issue, we employ two-stage least squares (2SLS) regression with instrumental variables in addition to OLS. In particular, we use the following instrumental variables (IVs): *Stage length, Hub, and Low-cost carriers' market share (LCC)*. *Stage length* and *Hub* are cost-side IVs and have been shown to be appropriate to address endogeneity in demand models because they influence prices but not the demand (Berry et al. 1995; Granados et al. 2012). *Stage length* is an often-used predictor of price and captures a city-pair's trip distance in air travel miles (Duliba et al. 2001). *Hub* indicates whether the city-pair origins and destinations are hubs of the Airline. Hub operations have been associated with higher prices and this variable can also control for the impact of multi-market competition on price.

LCC, our third IV, was chosen as a proxy for the level of competition because *HHI* is included as a control variable in the model. *LCC* has desirable characteristics as an IV because it is significantly correlated with all three price variables, but is uncorrelated with our dependent variables (Q, m_{off}, m_{tran}, and m_{opa}). In addition, we also use *one-week lagged price* as an additional IV. One-week lagged price satisfies the conditions for being a good IV – it is significantly correlated with current price, but not with the dependent variables. (Q, m_{off}, m_{tran}, and m_{opa}).

In the first stage of 2SLS regression, we regress prices on these IVs and all the other control variables.[6] In the second stage, the predicted prices are used as independent variables in the main equations. In order to satisfy exclusion restrictions, we did not include the IVs in the second

[6] Note that we instrument using the channel's own lagged price only (not the other channels' lagged prices). For example, to instrument opaque price, we use stage length, hub, LCC and one-week lagged opaque price. By doing this, we can effectively address endogeneity while preserving the relative prices across channels. As shown in Table A in Appendix, indeed, the pairwise correlations among the three prices remain similar (although slightly higher) after instrumenting.

stage equations (Greene 2000). In the next section, we present the results from OLS and 2SLS regressions.[7]

5. RESULTS: DEMAND AND REVENUE EFFECTS

Full-Sample Analysis across Channels

Table 3 presents the results of estimating equations (9) – (12) for the full sample, with both OLS and 2SLS estimations. Because the results are quite consistent between OLS and 2SLS, we only report findings from the 2SLS model for the remainder of the paper.

As expected, we find that the total passenger volume responds to the prices of the offline and online transparent channels, with the coefficients being negative and significant. That is, for these two channels, total passenger volume responds positively to a decrease in price. Surprisingly, the coefficient is not significant for the opaque channel at this broad level. Therefore, we do not find broad support for Hypothesis 1, that the airline's demand has a negative relationship with opaque prices across all markets, although we do find evidence in competitive markets as we describe below. We also find that opaque fares cannibalize online transparent sales (2SLS: 0.0013, $p < 0.01$) but not offline sales (2SLS: 0.0006, $p > 0.1$). Hence, we find support for Hypothesis 2, consistent with the notion that opaque offers should appeal to price-sensitive segments but not to the less price-sensitive offline segment.

One interesting result is that there is asymmetry in market response between the opaque and offline channels: the opaque channel does not cannibalize the offline channel, but the offline channel cannibalizes the opaque channel. The intuition is that many business travelers who book

[7] In order to further demonstrate the validity of our instruments, we report the results of weak identification tests and overidentification tests. As shown in Table B in the Appendix, the results of first-stage F-tests of weak identification indicate that our endogenous regressors are not weakly identified (i.e., our instruments are not weak). Also, the results of Sargan tests of overidentification indicate that our instruments are valid.

offline are not willing to purchase opaque fares even at heavily discounted prices, because of the flexibility and transparency requirements for business travel. But some price-sensitive leisure customers who purchase opaque fares are willing to upgrade to a full-fare at the right price.

Table 4 summarizes the revenue elasticity for each channel. For the opaque channel, the revenue elasticity is 0.08, which means that a 1% increase in opaque fares will lead to a 0.08% increase in total revenue. This revenue elasticity value suggests that there is an opportunity to increase the revenue contribution of the opaque channel by increasing its price. That is, on average, opaque fares for the Airline should be higher in order to mitigate the cannibalization effect of the online transparent channel.

Table 3. Full Sample Demand and Cross-Channel Effects

Panel A. OLS

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Offline	-.0008*** (.0003)	-.14	.0002 (.0002)	0	-.0007** (.0003)	-.13	.0015*** (.0003)	.26
Online Transparent	-.0005** (.0003)	-.07	.0003 (.0002)	0	-.0009*** (.0003)	-.13	.0008** (.0004)	.12
Opaque	**-.0003 (.001)**	**0**	**.0003 (.0003)**	**0**	**.0015*** (.0004)**	**.14**	**-.0018*** (.0005)**	**-.16**
N	4,388		4,388		4,388		4,388	
R-squared	.795		.197		.203		.277	
Adj. R-squared	.791		.182		.189		.264	

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, *= $p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, low-cost carriers' market share, the Airline's market share, and minimum weekly price.

Panel B. 2SLS

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Offline	-.0008*** (.0002)	-.14	.0002 (.0003)	0	-.0007** (.0003)	-0.11	.0012*** (.0004)	.22
Online Transparent	-.0006*** (.0002)	-.09	.0003 (.0003)	0	-.001*** (.0003)	-.1	.0009** (.0004)	.14
Opaque	**.0001 (.0007)**	**0**	**.0006 (.0004)**	**0**	**.0013** (.0006)**	**.12**	**-.0013* (.0008)**	**-.12**

N	4,388	4,388	4,388	4,388
R-squared	.792	.193	.200	.291
Adj. R-squared	.788	.179	.186	.278

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, the Airline's market share, and minimum weekly price.

Table 4. Revenue Elasticity Values by Channel (Based on 2SLS Results)

				Channel Share Impacts		
	Revenue Elasticity	Volume Elasticity	Own-Channel Fare Impact	Offline	Online Transparent	Opaque
Offline Fare	.49	-.14	.65	0	-.03	.01
Online Transparent	.17	-.09	.30	0	-.04	.01
Opaque	.08	0	.05	0	.04	-.01

These revenue elasticity results also suggest that there is an opportunity to increase revenue by raising the offline and online transparent fares. The revenue elasticity of the offline channel is 0.49, so a 1% increase in offline fares will lead to a 0.49% increase in revenues. Similarly, the revenue elasticity of the online transparent channel is 0.17. This is, in part, because the large revenue share of these channels magnifies the effect of a price change in terms of the own-channel fare impact (0.65 and 0.30, respectively), relative to the cannibalization effects. A retrospective look at the big losses airlines were incurring during the period of our study provides face validity to these results, because according to our revenue analysis, airline fares were sub-optimal. We expand on this in the Discussion section.

Effects of Opaque Sales on Different Fare Segments

To examine cannibalization of the opaque channel across different fare segments, we grouped fares in the offline and online transparent channels into three segments: *full-fare*, *discounted*, and *super-discounted*. By treating opaque fares as a separate fare segment, we estimated demand and cannibalization effects across the four segments (see Table 5).

Table 5 shows that the opaque channel cannibalizes the discounted segment (0.0036; $p < 0.01$), but not the full fare segment. This is consistent with our previous finding that the opaque channel cannibalizes the online transparent channel, which is mainly composed of discounted leisure fares, while it does not cannibalize the offline channel, which is often used to book full fare tickets by business travelers. Therefore, we find support for Hypothesis 3a, that the opaque channel does not cannibalize the full fare segment.

Our results also lend partial support for Hypothesis 3b, that the opaque channel cannibalizes price-sensitive segments. We find that the opaque channel cannibalizes the discounted segment, but not the super-discounted segment. A plausible and intuitive explanation for this is that super-discounted fares are offered at a price that is low enough so that most travelers prefer the value of the transparent super-discounted offers, compared to the opaque (and slightly lower) fare.

Table 5. Demand and Cross-Segment Effects (2SLS)

	Total Passenger Volume	Fare Category Share			
		Full-Fare	Discounted	Super-Discounted	Opaque
Full-Fare	-.0004** (.0002)	-.0002 (.0002)	.0002 (.0002)	-.0001 (.0001)	.0002 (.0002)
Discounted	-.0002 (.0003)	.0004 (.0004)	-.0013*** (.0004)	.001*** (.0003)	.0002 (.0004)
Super-Discounted	-.0031*** (.0011)	.0043*** (.0009)	.0013 (.0011)	-.0012 (.0009)	.0043*** (.001)
Opaque	**-.0006 (.0014)**	**.0011 (.0008)**	**.0036*** (.0009)**	**.0003 (.0006)**	**-.0016** (.0008)**
N	3,924	3,924	3,924	3,924	3,924
R-squared	.804	.203	.161	.286	.303
Adj. R-squared	.799	.184	.14	.269	.286

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, low-cost carriers' market share, the Airline's market share, and minimum weekly price.

Moderating Effects of Competition, Demand (Season) and Booking Period

We next refine and extend the main demand and cannibalization effects above, by examining several factors that can moderate the effects of the opaque channel. This additional analysis determines the conditions under which the airline is better or worse off by offering opaque fares, and whether the broad demand and cannibalization effects we observe using our full sample persist when we drill-down across different dimensions.

Our review of prior analytical studies reveals that the demand and cannibalization effects of the opaque channel depend on assumptions about various factors. Among others, *the degree of competition* (e.g., Shapiro and Shi, 2008) and *the level of demand* or season (Jerath et al, 2010; Huang *et al.*, 2017) have been frequently used. Thus, we examine the moderating effects of these two factors. In addition, in order to verify the common assumption in the literature that opaque fares are offered close to departure, we also examine the impacts of the opaque channel across different *booking periods*.

Degree of Competition. Prior literature suggests that competition is an important dimension to consider when assessing the impact of opaque offerings. For example, an opaque channel can increase seller revenues when two or more sellers compete in both transparent and opaque channels. Shapiro and Shi (2008) introduce a modified Hotelling model of horizontal differentiation to examine price discrimination by the opaque channel. 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 order to examine the moderating effect of competition, we interacted *HHI* with all the price variables including the opaque fare, and re-estimated the models (see Table 6). We find that the effect on total passenger volume is positive and significant in markets with high levels of competition (i.e., low HHI) but not in markets with low competition. Thus, we find partial support for Hypothesis 1, that a lower price for the opaque channel leads to higher demand in markets with high competition. We also find that the level of competition influences the extent to which the opaque channel cannibalizes the offline and online transparent channels. That is, the coefficient on the interaction with *HHI* is significant for both offline (0.0046, $p < 0.05$) and online transparent (0.0053, $p < 0.1$) fares. This implies that cannibalization by the opaque channel is more severe in less competitive markets. Interestingly, the cannibalization of the offline channel by the opaque channel becomes significant as the level of competition decreases.

Due to the smaller interaction effect on offline share (0.0046, $p < 0.05$) compared to that on online transparent share (0.0053, $p < 0.1$), we continue to find support for Hypothesis 2 – that the cannibalization effect of the opaque fare is greater on online transparent channel than on the offline channel – across different levels of competition.

Table 6. Opaque Fare Demand Effects by Level of Competition (*Higher HHI = Lower Competition*) (2SLS)

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Main effect of opaque fare	.0008 (.0007)	0	.0009* (.0005)	0.08	.0017*** (.0006)	.16	-.0018** (.0008)	-.17
Interaction effect (*HHI × Opaque Fare*)	**.009*** (.002)**	**-**	**.0046** (.002)**	**-**	**.0053* (.0028)**	**-**	**-.007* (.004)**	**-**
R-squared	.793		.194		.201		.292	
Adj. R-squared	.789		.179		.186		.279	

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, the Airline's market share, and minimum weekly price.

Level of Demand (Season). There are competing theories as to whether opaque fares are preferable in high or low demand seasons. Jerath et al. (2010), Wang et al. (2009), and Huang *et al.* (2017) show that opaque fares may be preferred under constrained capacity or high demand, while others argue that opaque offers are better for selling unused inventory when demand is low and capacity is not constrained. To examine differences in demand effects across seasons, we first split the departure weeks into high- and low-demand seasons, based on average weekly revenue. High-demand season consists of 10 departure weeks and low-demand season includes 11 departure weeks. We then created a dummy variable for season (1 for high-demand; 0 for low-demand), interacted it with the price variables, and re-estimated the models with the interaction terms.

As shown in Table 7, the effects on total passenger volume are statistically the same in magnitude for high- and low-demand seasons (both main effect and interaction effect are not significant with $p > 0.1$). Also, the coefficients of the interaction effect of season on offline and online transparent channels are not significant, which suggests the relative demand level across seasons does not affect the degree of cannibalization by the opaque channel.

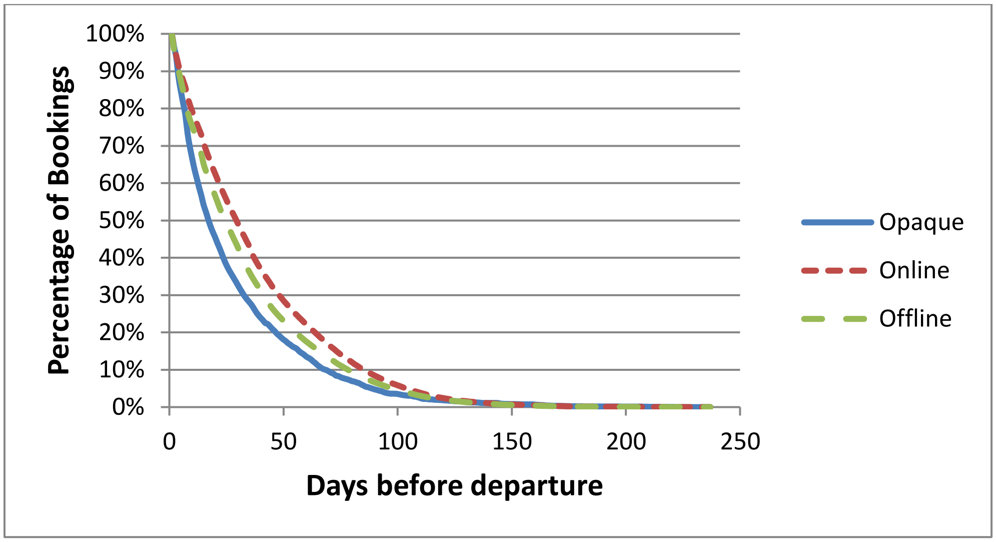
Table 7. Opaque Fare Demand Effects by Season (2SLS)

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Main effect of opaque fare	.0007 (.0002)	0	.001 (.0007)	0	.0014* (.0009)	.15	-.0013 (.0009)	-0
Interaction effect (*Season × Opaque Fare*)	**-.001 (.001)**	-	**-.0006 (.0005)**	-	**-.0003 (.0008)**	-	**-.0001 (.001)**	-
R-squared	.792		.194		.200		.291	
Adj. R-squared	.788		.178		.185		.278	

Note: Significance: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, the Airline's market share, and minimum weekly price.

Booking Period. An underlying assumption in much of the extant literature is that opaque selling is desirable for last-minute sales. That is, firms tend to offer opaque fares last-minute for seats that are forecasted to leave empty, thereby minimizing cannibalization of early bookers. To verify the assumption that most opaque bookings are made closer to departure date, we examined opaque booking patterns over the entire booking horizon. Figure 1 shows the cumulative percentage of bookings for opaque, online, and offline channels.

Figure 1. Cumulative Percentage of Bookings by Advance Purchase Period and Channel



Compared to online and offline bookings, relatively more opaque bookings are made closer to departure date. However, a significant portion of opaque bookings was made beyond 14 days before departure. Out of 11,094 opaque bookings in our dataset, the number of opaque bookings within 14 days to departure is 5,086 (45.84%), compared to 6,008 (54.16%) beyond 14 days. This is in contrast to the commonly held assumption that opaque bookings mainly occur close to departure date as a tool for last-minute sales to dispose of unused inventory (Jerath et al., 2010).

We also examined the impact of the opaque channel across booking periods, by means of a split-sample analysis of bookings made within 14 days before departure and beyond 14 days before departure (see Table 8). We used 14 days to split the sample because we observe a clear jump in prices when there are 14 days remaining prior to departure.

Table 8. Opaque Channel Effects by Advance Purchase Period (2SLS)

	Total Passenger Volume		Channel Share					
			Offline		Online Transp.		Opaque	
	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.	Coef. (SE)	Elas.
Within 14 Days (*n* = 2,725)	.0005 (.0011)	0	.0005 (.0005)	0	.0025*** (.0007)	.24	-.0013 (.001)	0
Adj. R-squared	.769		.206		.155		.287	
Beyond 14 Days	.0026 (.0018)	0	.0003 (.001)	0	.0022* (.0013)	.18	.0005 (.0014)	0

(n = 2,853)				
Adj. R-squared	.795	.199	.15	.229

Note: Significance: $^{***} = p < 0.01$, $^{**} = p < 0.05$, $^{*} = p < 0.1$. Clustered robust standard errors are in parentheses. Elas. = Volume or cross-channel elasticities. Control variables: departure week, origin city, destination city, HHI, the Airline's market share, and minimum weekly price.

Consistent with the results of the full sample analysis, we find that, in both booking periods, total demand effects of the opaque channel are not significant and the offline channel is not cannibalized by the opaque channel. Also, consistent with the full sample analysis, the opaque channel cannibalizes the online transparent channel, and the magnitude of the cannibalization is similar across booking periods (coefficients were 0.0025 with $p < 0.01$ and 0.0022 with $p < 0.1$ within and beyond 14 days, respectively.) Therefore, we find support for Hypothesis 2 across booking periods, that cannibalization is stronger for the online transparent channel.

6. DISCUSSION AND REVENUE IMPLICATIONS

Demand Effects

Our findings provide novel insights into the demand and revenue impacts of the opaque channel. Our first broad finding is that a decrease in the opaque channel price leads to higher total demand in markets with high levels of competition, in line with the notion that opaque offerings can help airlines steal market share from competitors or that it increases demand by bringing price-sensitive consumers into the market. In contrast, in markets that are highly concentrated, it may make sense to offer opaque fares at higher prices or not offer them at all, because cannibalization of otherwise higher paying customers may not be offset by an increase in total demand.

This finding can ease revenue managers' concern that the opaque channel inherently leads to lower revenues (e.g., Huang *et al.*, 2017; Wang et al., 2009), at least in highly competitive markets. In these markets, an optimal opaque fare can lead to higher total demand by tapping into the segment of non-loyal customers (Fay, 2008) or by stealing market share from competitors that are unaware of the airline's opaque offering or choose not to match it.

Cannibalization Effects

Cannibalization across Channels. We find that the opaque channel cannibalizes the online transparent channel but not the offline channel. This is in line with 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, without diluting the revenue of the high-end segment. This discrimination effect can happen for several reasons. First, many travelers are single-channel shoppers (Granados et al. 2012); thus, travelers who search online are more likely to shop within the online channel alone, rather than across both offline and online channels. Second, those who search online are more likely to find opaque offerings, compared to those who book offline. Third, more price-sensitive travelers tend to book online, and hence they are inherently more attracted to discounted opaque offerings.

The result that the opaque channel cannibalizes the online transparent channel is consistent across markets with different levels of competition, and across seasons and booking periods. This provides face validity to our methodology and results, and provides a compelling story for revenue managers on how to evaluate possible initiatives to fill seats with opaque offerings. The prescriptive guideline is to set the opaque fare at a high enough level to minimize cannibalization of the online transparent channel.

There should be less concern about cannibalization of the offline channel across seasons and booking periods. However, we did find a moderate increase in cannibalization of the offline channel as competition decreases, which reinforces that airlines needs to be judicious on how low to set opaque fares in highly concentrated markets.

Cannibalization across Fare Segments. We find that the opaque channel cannibalizes the discounted segment, but not the full-fare and super-discounted segments. This is in line with the finding that opaque offerings cannibalize the online transparent channel but not the offline channel. The intuition is that, since many full-fare passengers book via the offline channel, they are less likely to find opaque offerings. In contrast, many travelers search for discounted fares online, so they are naturally more prone to cannibalization as they also find opaque offerings.

In addition, full-fare passengers are not likely to sacrifice the transparency of a full-fare offer, because they have high willingness-to-pay for detailed information about the itinerary and the identity of the airline. This is typical of business travelers who are less price-sensitive and have specific departure and arrival schedule requirements.

The fact that the super-discounted segment is not cannibalized by the opaque channel suggests that at the right price, consumers are willing to upgrade from an opaque product to a transparent offer. In our dataset, the average one-way fare difference between the opaque and super-discounted fares is only $30; thus, based on the results, consumers' perceived value of the transparency about the itinerary and the Airline carrier appears to be at least this amount. Airlines typically introduce promotional low fares in an attempt to fill otherwise empty seats, but they do so in opaque form hoping that cannibalization will be minimized. It appears the Airline was able to mitigate cannibalization of the super-discounted segment by offering opaque fares that are high enough to discourage consumers from downgrading from a super-discounted offer to an opaque offer.

Opaque Bookings Across Advance Purchase Periods. We find that opaque sales occur not just close to departure; in fact, a larger percentage of the opaque sales occur relatively far from departure (i.e., beyond 14 days to departure). This finding challenges the assumption that opaque fares are mainly used for last-minute selling of otherwise empty seats.

Revenue Impacts

Our findings about the demand and cannibalization effects of the opaque channel indicate that airlines should carefully calibrate fares across channels to maximize total demand and minimize cannibalization. However, demand analysis alone is not enough to accomplish this, because the impact on revenues depends on the relative fare levels across channels. To this end, we offer the revenue elasticity analysis to complement the demand-based market response model. The results of this analysis suggest that overall, relative fares across channels are not optimal; the Airline can increase revenue with corresponding fare adjustments.

The average revenue elasticity of 0.08 for the opaque channel indicates that, other things being equal, an average 1% increase in opaque fares across markets and seasons will lead to a 0.08% increase in overall revenue. Similarly, the revenue elasticity for the offline and online transparent channels are 0.49 and 0.17, respectively.

These findings suggest that there is an opportunity for the Airline to raise fares across segments and channels. For a moderately large airline with $10 billion, this price calibration to maximize total demand and minimize cannibalization can represent an annual revenue increase of $74 million.[8] More generally, these findings are consistent with the fact that during the period of our study, airlines seemed to be caught in a prisoner's dilemma by pricing under cost, leading to billions of dollars in industry losses.

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[8] Since the sum of the revenue increase associated with 1% fare increase in each channel is 0.74% (0.08 + 0.49 + 0.17 = 0.74), the revenue impact is in the order of $74 million (10 billion * 0.74%).

A more surgical adjustment of the opaque fares may lead to higher revenues for the Airline. That is, the average revenue elasticity of 0.08 assumes a 1% opaque fare increase across the board to increase revenue, but a more granular approach is warranted, which may lead to even higher revenue gains. In particular, opaque fares should increase by at least 1% across markets on average, but the increases should be even higher in markets with low competition, where there is no significant demand elasticity by the opaque channel, and where opaque fares cannibalize the offline channel. These actions can also be made through inventory control of opaque fares. For example, the Airline can open the inventory of opaque fare seats disproportionately in markets with high competition.

7. CONCLUSIONS

Managerial Implications

We conclude that the opaque channel can be revenue positive if revenue managers set the right opaque fare levels in relation to those of other channels. In particular, one way to increase revenues is to increase opaque fares when the dominant effect observed is cannibalization, and to decrease opaque fares when the total demand effect is dominant. For example, for the Airline in this study, the total demand effect is higher in markets with high competition; therefore, offering lower opaque fares in these markets may be more appropriate, relative to markets with low competition.

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 the assumption that the online channel imposes higher switching costs and lock-in effects (Viswanathan, 2005), our findings show that in some situations, it is easy for consumers to switch to lower-quality offerings due to the plethora of sources that are available to search for goods and services online.

Contributions

To the best of our knowledge, this is the first empirical study of the demand 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 can be revenue-positive when total demand effects are maximized and cannibalization is minimized, thereby underscoring 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 revenue impacts of the opaque channel. Also, one novel insight we offer is that opaque offerings may have appeal beyond last-minute selling of distressed inventory.

Further, we offer the revenue elasticity model developed in this paper as a methodology to break down the impact on revenue of a channel based on total demand and cannibalization effects. The model establishes clear links between these demand effects and corresponding revenue impacts. While the Carpenter-Hanssens methodology provides the demand side of the story, our revenue elasticity methodology provides a complementary perspective for revenue managers to implement fare adjustments effectively in order to maximize total demand and minimize cannibalization. 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.

Limitations

Our study has some limitations and offers directions for further research. First, while our method of imputing prices for zero-sales weeks is theoretically justified, it is not perfect. In particular, our approach may introduce a downward bias to the impact of opaque prices on sales because zero opaque sales in a given week may be due to relatively high opaque prices. This means that the estimates we report may be conservative. Although we believe that correcting this bias will not affect our findings qualitatively, future research based on more "complete" data (i.e., with no need to impute opaque fares) will help estimate the "true" impact of opaque fares.

Second, we use minimum daily price to control for the effect of capacity. While minimum daily price is a good proxy for bid price that can approximate the inventory availability, future research should validate our findings using actual capacity and inventory data. However, acquiring inventory data will be challenging since airlines are reluctant to share such data.

Finally, because our data come from a single airline company, we were not able to examine the competitive effects of opaque fares. In particular, we find that a lower price for the opaque channel leads to higher demand in markets with high competition, and part of this demand effect may be attributed to stealing customers from competitors; however, our data do not allow us to separate share shift gains or losses from pure own-elasticity effects. Examining the competitive effects of opaque fares using data from multiple airlines will be an interesting avenue for future research.

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

APPENDIX

Table A. Correlations among Prices before and after Instrumenting

Correlations before Instrumenting				Correlations after Instrumenting			
	p_{off}	p_{tran}	p_{opa}		p_{off}	p_{tran}	p_{opa}
p_{off}	1.000			p_{off}	1.000		
p_{tran}	0.415	1.000		p_{tran}	0.442	1.000	
p_{opa}	0.378	0.364	1.000	p_{opa}	0.403	0.391	1.000

Table B. Results of Testing the Validity of Instrumental Variables

		Total Passenger Volume	Channel Share		
			Offline	Online Transp.	Opaque
First-stage F-test of weak identification	p_{off}	$F(4, 3572) = 98.09$ ($p < 0.0001$)			
	p_{tran}	$F(4, 3572) = 90.00$ ($p < 0.0001$)			
	p_{opa}	$F(4, 3572) = 830.16$ ($p < 0.0001$)			
Sargan test of overidentification		Chi-sq(1) = 0.445 ($p > 0.5$)	Chi-sq(1) = 0.270 ($p > 0.5$)	Chi-sq(1) = 0.025 ($p > 0.5$)	Chi-sq(1) = 0.422 ($p > 0.5$)

Note: In the first-stage F-test, the null hypothesis is that endogenous regressors are weakly identified. In Sargan test of overidentification, the joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term.