MARKET TRANSPARENCY AND MULTI-CHANNEL STRATEGY: MODELING AND EMPIRICAL ANALYSIS OF ONLINE TRAVEL AGENTS

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ABSTRACT
The Internet has transformed the nature of business-to-consumer transaction-making practices in many industries. Sellers now attract customers with innovative Internet-based selling mechanisms that can reveal or conceal market information. We define this market transparency in terms of the availability and accessibility of information about products and prices. Firms can influence market transparency either by designing and implementing their own Internet-based selling mechanism, or by offering their products through an existing electronic market or brick-and-mortar channel. We develop an economic model of a monopolist that can set heterogeneous transparency levels and price discriminate across distribution channels. The model provides normative guidelines for firms to set relative transparency levels and prices in order to maximize profits. We empirically evaluate pricing and market transparency strategy in the U.S. air travel industry to show the applicability of these guidelines. The evidence suggests that relative prices and transparency levels across the Internet and traditional air travel channels are sub-optimal.

Keywords and phrases: Economics of IS, econometrics, e-commerce, electronic markets, IT impacts, market transparency, multi-channel strategy, pricing, online travel agencies.

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I. INTRODUCTION

The Internet revolution brought about significant changes to market transparency in business-to-consumer (B2C) markets. To the benefit of consumers, it reduced the search costs of information about products and prices. In turn, sellers were able to attract customers with innovative market mechanisms that reveal or conceal market information. Transparency of products and prices in the digital economy is increasingly viewed strategically by firms as they consider the trade-off between attracting consumers with market information and the risk of losing information advantages (Tapscott and Ticoll, 2003). So today, organizations are faced with the paradox that the very benefit of the Internet—making information available to facilitate product marketing and distribution—also makes it difficult to capture profits (Porter, 2001).

Strategic questions arise for brick-and-mortar firms that also distribute their products in e-commerce channels such as the Internet. A representative case occurred in the air travel industry. In 2001 five major United States airlines introduced Orbitz (www.orbitz.com), an online travel agency (OTA) that displays a wide range of travel options based on combinations of airline carrier, flight schedules, travel dates, and price. Other OTAs have since changed their market mechanisms to try and match the level of transparency of Orbitz (Granados et al., 2006). However, not all strategies have been towards higher levels of market transparency. Major U.S. airlines also introduced Hotwire, an OTA with an opaque market mechanism that offers less information about the product and the carrier, albeit at discounted prices. (See Figure 1.) In the context of these design choices, traditional travel agencies continue to play a significant role in airline ticket sales.

The OTA industry example shows two impacts of e-commerce technologies on the practices of information disclosure. First, it has increased the overall ability of firms to disclose market
Figure 1. U.S. Airline Transparency Strategy: Transparent and Opaque Mechanisms

Note: This figure contains screenshots of two OTAs launched by major airlines. Orbitz was launched in 2001. It is a transparent selling mechanism that shows multiple options and prices from different airlines in the first screen, with the use of a matrix display. In addition, details about each offer are available by scrolling down. For this example, 168 travel options were offered. Hotwire was launched in 2000. It has an opaque market mechanism: one or two clearance fares, and the airline name and itinerary are only shown after a purchase is completed.

information, their transparency potential. Second, it has increased firms’ choices to conceal and distort product and price information. Some relevant questions to ask are: How does IT-enabled market transparency influence consumers’ economic behavior in B2C markets? How should firms strategize in a technological environment that enables multiple market transparency levels across distribution channels?

In this research, we develop an economic model of multi-channel transparency strategy, building on the work of existing marketing and IS research (Zettelmeyer, 2000; Riggins, 2004), which suggests that firms have an opportunity to strategize at the channel level to take advantage of consumer heterogeneity. In line with observations of real-world Internet-based strategies, we assume that firms innovate to attract consumers with novel selling mechanisms and that a market is in transition to equilibrium as firms seek differentiation in the presence of diverse information endowments and IT capabilities. So multiple channels may exist with different transparency levels. We model the impact of market transparency on consumers’ economic behavior in terms of demand shifts across channels and in terms of changes in the price elasticity of demand. The results broadly suggest that if the degree of information disclosure to consumers affects their economic behavior, relative prices should be adjusted accordingly. We then derive relative prices and transparency levels that a firm should adopt across channels to maximize profits.

One advantage of our modeling approach is that it can be used to empirically evaluate real-world multi-channel transparency strategies. We evaluate the multi-channel transparency strategy of U.S. airlines using a large set of airline ticket data. Our empirical analysis not only provides insights for managers in the airline industry, but it also illustrates how the model and its guidelines can be used for pricing and transparency strategy in other industries.

In the next section we provide a conceptualization of market transparency and multi-channel
strategy, and describe recent related developments in the air travel industry. In the third section, we present an analytical model of transparency strategy in B2C electronic commerce. In the fourth section we discuss the broader implications of the model for firm strategy. In the fifth section we analyze transparency strategies in the airline industry in both traditional channels and Internet-based travel agencies. Finally, we present conclusions and directions for future research.

II. MARKET TRANSPARENCY IN B2C ELECTRONIC MARKETS

To provide a foundation for a model of transparency strategy, we first conceptualize market transparency based on relevant finance, marketing and economics literature. We then summarize existing literature on multi-channel strategy. Finally, we characterize market transparency developments in the air travel industry since the advent of the Internet.

A. What is Market Transparency?

We define market transparency as the level of availability and accessibility of market information. In B2C electronic markets, market transparency is composed of several elements: price transparency, product transparency, supplier transparency, and availability transparency. We will focus on just two, product and price transparency. Price transparency exists when market prices and related information are made available, such as quotes and transaction prices. Product transparency (or product characteristics transparency) exists when the characteristics of the product are made available, including quality information. A more transparent market will result from greater transparency in one or both of these dimensions.

Price Transparency. Much of the literature on price transparency exists in the context of financial markets, where researchers have explored the extent to which greater transparency leads to higher market efficiency and liquidity. In this context, price transparency is typically

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1 Availability transparency refers to the extent to which inventory information on the seller’s side is available to potential buyers. Supplier transparency refers to the identity and description of the supplier.
modeled as an exogenous variable defined by a policy-maker or a central authority. This approach informs the ongoing policy debate about the appropriateness and breadth of the publication of transaction details to investors (Schwartz, 1995). In the financial market literature, price transparency takes multiple dimensions, such as order flow, transaction history, and price quotes (Biais, 1993; Lyons, 1994; Pagano and Roell, 1996).

Domowitz (1995) breaks down the impact of price transparency in financial markets into two categories: provision of liquidity and the price discovery process. **Liquidity** is the extent to which a buyer (seller) is able to find a seller (buyer) to complete a trading transaction in a reasonable amount of time at a reasonable transaction cost. In B2C electronic markets, while price transparency generally attracts consumers, it may deter sellers that may see their pricing strategies or cost structure exposed (Zhu, 2002). **Price discovery** is the process by which market prices are established. In B2C markets, price discovery enables consumers to ascertain their willingness-to-pay (WTP). Price transparency plays a role in this process by reducing uncertainty about trading prices.

**Product Transparency.** Marketing research offers valuable insights to conceptualize product transparency. Consumer behavior researchers have found evidence that consumers may view a product with suspicion upon the absence of information about a salient attribute. For example, Johnson and Levin (1985) observed lower product ratings when the appropriate product information was missing. Table 1 lists determinants of product transparency for consumers in B2C electronic markets.

Information about product features described in Table 1 determines product transparency and integrity, and minimizing cost and time. These features can be further broken down into two categories. **Digital product characteristics** are information-based features, such as programming
Table 1. Determinants of Product Transparency in E-Commerce

<table>
<thead>
<tr>
<th>PRODUCT CHARACTERISTICS</th>
<th>CONSUMER OBJECTIVES</th>
<th>Maximize</th>
<th>Minimize</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Quality</td>
<td>Comfort</td>
<td>Integrity</td>
</tr>
<tr>
<td>Digital</td>
<td>Features</td>
<td>Warranty</td>
<td>Privacy policy</td>
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<td></td>
<td>Market share</td>
<td>Flexibility</td>
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<td></td>
<td>Seller identity</td>
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<tr>
<td>Non-Digital</td>
<td>Features</td>
<td>Service quality</td>
<td>Reputation</td>
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<td>Service quality</td>
<td>Friendliness</td>
<td>Risk of use</td>
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<td></td>
<td>Congestion</td>
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Note: The consumer objective categorization and the content in each cell were adapted from Keeney (1999).

because it contributes to consumers’ economic objectives such as maximizing quality, comfort, code of a software product or the travel itinerary described by an airline ticket. The more digital are the characteristics of a product—up to the point where the product becomes a pure information good—the higher is the potential for product transparency in an electronic market setting. For example, airline tickets are information-based products that can be described electronically better than tangible goods, such as food or clothes, or intangible goods, such as tax consulting services or home repair services. Conversely, the greater the extent of non-digital characteristics such as intangible or experience-based features, the higher is the potential for transparency in traditional brick-and-mortar channels, where physical inspection or live demonstrations are possible.

Market Transparency and Willingness-to-Pay. The relationship between market transparency and consumers’ WTP is related to the type of information revealed or concealed. Stigler (1961) suggests that in an environment of price dispersion, information about market prices and purchase options may lead to lower prices, as consumers are able to find lower prices for a given product or horizontally-differentiated substitutes. Granados et al. (2005b) found empirical support for this proposition by examining demand and price elasticity by channel in the air travel industry. Brynjolfsson and Smith (2000) found that prices for books and CDs were
lower in the Internet channel than through conventional retailers.

On the other hand, product transparency may lead to higher WTP as consumers are able to ascertain their valuation of a product with higher precision, or as they are able to find a product that better fits their needs. Granados et al. (2005b) also found support for this proposition in their empirical analysis of the air travel industry.

B. Multi-channel Strategy and IT-Enabled Market Transparency

A single channel used to be how companies reached out to their customers. Today, thanks to e-commerce technologies, firms are increasingly using multiple distribution channels, including traditional brick-and-mortar channels and the Internet. The behavior of consumers in a multi-channel environment is diverse (Balasubramanian et al., 2005). *Single channel shoppers* either continue to use a conventional channel or shift completely to a new one, while *multi-channel shoppers* use multiple channels at one stage or at different stages of the purchase process. Firms are increasingly recognizing the need to have a presence in multiple channels to satisfy this diversity in shopping behavior by implementing *multi-channel strategies*.

There are technological factors that influence the ability of firms to implement an effective multi-channel strategy (Cappielo et al., 2003). But given the diversity of behavior by consumers in multi-channel purchases, there are different possible approaches. One approach is to serve multi-channel shoppers by making the shopping experience across channels as seamless and integrated as possible. Through this approach, a seller synchronizes product offerings and prices across channels and reengineers the organization for that purpose. In addition, an integrated systems architecture is necessary to effectively manage customer relationships (Sawhney, 2001). However, there is an emerging strategic perspective that suggests firms can profitably perform channel-based segmentation. Firms can take advantage of consumer heterogeneity to steer
customers to specific channels to the benefit of the firm (Myers et al., 2004). Riggins (2004) modeled consumer heterogeneity in terms of WTP and access to the online channel, and found that firms can differentiate products and price discriminate across channels to maximize profits. Zettelmeyer (2000) modeled a multi-channel scenario with low Internet penetration and found that firms will offer lower prices and provide more information to consumers in the online channel. We embrace the latter approach to examine the benefits for firms that strategically select the information to be disclosed by channel.

Prior to the advent of e-commerce technologies, sellers were restricted in their ability to disclose information to consumers, thus limiting their potential for transparency. Now, firms are not only faced with higher transparency potential, but they also have the possibility to position themselves at numerous points on or below that potential. For example, they can choose to conceal one or more determinants of product transparency. (See Table 1 again.) In particular, they can develop and implement electronic market mechanisms with a desired level of market transparency, or join existing ones. In other words, firms compete by selecting a market transparency tuple, [Product Information Available, Price Information Available] in the space of possible distribution alternatives. For example, U.S. airlines have adopted different combinations of product and price transparency by implementing IT-enabled, innovative selling mechanisms, by offering their tickets via existing electronic markets, and by maintaining distribution through offline channels (i.e., traditional travel agencies). (See Figure 2.)

At the high end of product and price transparency is Orbitz, (www.orbitz.com), an OTA launched in 2001 by six major airlines in the U.S., which claimed that it is the most transparent air travel Web site. Orbitz uses state-of-the-art technology to price and display more itineraries than other OTAs, and it uses preferred agreements with other airlines and travel agencies to offer
The lowest prices in the market (Granados et al., 2006). Airlines also offer tickets through other transparent OTAs such as Expedia (www.expedia.com) and Travelocity (www.travelocity.com). On the other hand, in 2000 U.S. airlines introduced an opaque market mechanism via a Web site called Hotwire (www.hotwire.com). Its selling mechanism targeted price-sensitive customers by concealing product information for one or two priced itineraries until the transaction has been completed. Airlines also participate in other opaque Web sites such as Priceline.com (www.priceline.com), which has a patented “name-your-own-price” mechanism. Through this mechanism, consumers electronically submit a contract-binding bid with no prior details on the airline, itinerary, and market price. Meanwhile, traditional travel agencies continue to play a significant role in the distribution of airline tickets, despite increased competition by OTAs. In this offline channel, although product information is readily available by phone or fax, there is a
limit to the number of priced itineraries that can be offered.

Although e-commerce technologies offer new opportunities for product distribution, they also add complexity to multi-channel distribution strategy. Suppliers such as airlines can sell products through channels with different levels of transparency. Multiple transparency levels across channels may have different effects on consumers’ economic behavior depending on the type of information disclosed or concealed, and on the degree of consumer heterogeneity. In the next section, we present an innovative way of modeling this problem that alleviates its inherent complexity. We then derive normative guidelines that firms can use to make decisions in a multi-channel environment with heterogeneous IT capabilities and transparency levels.

III. A MODEL OF MULTI-CHANNEL TRANSPARENCY STRATEGY

In this section, we present a model of transparency choice for sales distribution, where markets are in a state of flux as firms seek out differentiation strategies based on their information endowments and IT capabilities. This scenario, typical in the Internet era, arises in the presence of continuous technological innovation that leads to novel selling mechanisms, so there is no steady-state, market-wide level of transparency.

In economic and financial research, transparency is commonly viewed as exogenous, often imposed by a market operator or a government regulator. In this model, however, we assume that a seller has the technological ability to reveal or conceal information in conjunction with price-setting. This set of choices to establish prices and transparency levels by channel constitutes a *multi-channel transparency strategy*. We model the typical profit-maximizing and revenue-maximizing choices that a seller faces in a market where distribution channels with different transparency levels co-exist in a medium or short-term horizon.

In the context of this modeling effort, *channels* are distinguished based on their degree of
market transparency. For example, OTAs with different transparency levels such as Orbitz and Hotwire are considered different channels and OTAs with similar transparency levels such as Expedia and Travelocity are considered in the same channel.

A. Model Setup – Impact of Market Transparency on Consumer Demand

Consider a market with one monopolist that sells one good through two distribution channels, with total demand of the form \( x(p) = \lambda_0 - \lambda_1 p^\theta \), where \( \lambda_0, \lambda_1, \theta > 0 \). The parameters \( \lambda_0, \lambda_1, \) and \( \theta \) characterize the \( y \)-intercept, the steepness, and the curvature of the demand function, and \( p \) represents the price of the good, respectively. The \( y \)-intercept represents the base demand, or the total number of consumers that have a positive valuation for the good. The demand function is convex if \( 0 < \theta < 1 \), linear if \( \theta = 1 \), and concave if \( \theta > 1 \). With this functional form we seek a balance between simplicity, tractability, and generalizability of the results. The function would be linear if not for the power \( \theta \) of \( p \), so this modeling formulation offers to a certain extent the level of tractability and simplicity of linear demand models. On the other hand, by introducing a power \( \theta \) of \( p \), this demand function also includes the possibility of non-linearity. (See Figure 3.)

Figure 3. Market Transparency and Prices under Concave, Convex and Linear Demand

\[
x(p) = \lambda_0 - \lambda_1 p^\theta
\]

Note: This figure depicts three demand curves with different values of \( \theta \), which characterizes the curvature of the demand function \( x(p) = \lambda_0 - \lambda_1 p^\theta \). The function is concave if \( \theta > 1 \), linear if \( \theta = 1 \), and convex if \( \theta < 1 \).

Suppose the two channels exhibit different transparency levels. Transparent Channel \( T \) has a high-transparency mechanism to sell the good, while Opaque Channel \( O \) has a low-transparency
mechanism. If consumers value market transparency, on average WTP will differ by channel. We assume that the impact of market transparency on WTP pay is reflected in the base demand \( \lambda_0 \) or the price elasticity of demand, which is a function of \( \lambda_i \). Let the demand functions for channels \( O \) and \( T \) be:

\[
x_T(p_T) = \beta_0 - \beta_1 p_T^\theta \quad \text{and} \quad x_O(p_O) = \beta_2 - \beta_3 p_O^\theta,
\]

where aggregate market demand, \( x \), is the sum of the two individual demand functions, so \( x = x_O + x_T \). The base demand and steepness parameters \( \beta_0 \) and \( \beta_1 \) for Transparent Channel \( T \) can be expressed in terms of the respective parameters of Opaque Channel \( O \) as \( \beta_0 = \alpha_0 \beta_2 \) and \( \beta_1 = \beta_3 / \alpha_1 \). Substituting these into Equation 2 results in

\[
x_T(p_T) = \alpha_0 \beta_0 - \frac{\beta_1}{\alpha_1} p_T^\theta.
\]

Parameters \( \alpha_0 \) and \( \alpha_1 \) characterize the relative impact of market transparency on consumers’ WTP. If there is no impact, then \( \alpha_0 = 1 \) and \( \alpha_1 = 1 \). On the other hand, if market transparency decreases WTP, there are three possible scenarios for the Transparent Channel \( T \)’s demand relative to channel \( O \)’s: (1) base demand is lower, so \( \alpha_0 < 1 \), (2) price elasticity is higher, so \( \alpha_1 < 1 \), and (3) base demand is lower and price elasticity is higher, so \( \alpha_0 < 1 \) and \( \alpha_1 < 1 \). (See Figure 4). For the case where market transparency increases WTP, the sign of the inequality in each case is inverted.

**B. Profit Maximization**

Let the profit function be \( \pi(p_T, p_O, x_T, x_O, C) = p_T x_T(p_T) + p_O x_O(p_O) - C(x_T) - C(x_O), \) where \( C(x_i) \) is the cost function per channel. In a medium or short-term horizon, it is reasonable to assume that marginal selling costs are constant, so we denote \( C'(x_T) = c_T \), and \( C'(x_O) = c_O. \)
Figure 4. Characterization of Demand for Transparent and Opaque Channels

Note: In a market with heterogeneous transparency strategies across channels, if market transparency affects WTP, individual demand functions may differ. In particular, market transparency may affect the base demand, the price elasticity of demand, or both. This figure depicts the case where the base demand for the Transparent Channel $T(x_T)$ is lower than that of the Opaque Channel $O(x_O)$, while its price elasticity is higher.

To start, we assume that marginal selling costs are the same across channels, so $c_T = c_O$, which is reasonable if the key differentiation factor across channels is the revelation or concealment of existing market information. Under these assumptions, the firm should price discriminate across distribution channels as follows:

**Proposition 1 (The Transparency Strategy Proposition):** If market transparency decreases (increases) willingness-to-pay, the Transparent Channel $T$ should have a lower (higher) price than the Opaque Channel $O$ to maximize profits.

**Proof:** The profit maximizing prices for the two channels are given by

$$\alpha_0 \alpha_1 \beta_0 = \beta_1 p_T^* \beta \left[ 1 + \theta \left( 1 - c_T / p_T^* \right) \right]$$

and

$$\beta_0 = \beta_1 p_O^* \beta \left[ 1 + \theta \left( 1 - c_O / p_O^* \right) \right].$$

(See Mathematical Appendix).

Dividing the first equation by the second equation leads to

$$\alpha_0 \alpha_1 \beta_0 = \left( \frac{p_T^*}{p_O^*} \right)^{\theta} \frac{1 + \theta \left( 1 - c_T / p_T^* \right)}{1 + \theta \left( 1 - c_O / p_O^* \right)}. \quad (4)$$

Recall that if market transparency does not affect WTP, then $\alpha_0 = 1$ and $\alpha_1 = 1$. On the other hand, without loss of generality, if market transparency negatively affects WTP, then $\alpha_0 < 1$ or $\alpha_1 < 1$. Therefore, $\alpha_0 \alpha_1 < 1$. From Equation 4, it follows that $p_T^* < p_O^*$, so the transparent channel
should have a lower price relative to the opaque channel to maximize profits.

The Transparency Strategy Proposition suggests that if the degree of information disclosure to consumers affects their economic behavior, prices should be adjusted accordingly to maximize profits. This proposition is analogous to price discrimination in the presence of differentiated products, but in this case differentiation exists in the market transparency dimension rather than in the product characteristics.

The model’s assumption of homogeneous costs across channels applies to scenarios of channels with similar technological conditions. Such is the case across OTAs, which are typically powered by GDS technologies via the Internet. However, in other comparative scenarios, such as those of Internet vs. conventional channels, marginal costs in the transparent channel may be lower due to a higher level of automation (Riggins, 2004), or due to lower costs of facilitating consumer search (Zettelmeyer, 2000). In these scenarios, if market transparency has a negative effect on WTP, the Transparency Strategy Proposition also applies.

C. Revenue Maximization

If the goal is to maximize revenue, \( R \), the objective function can be represented by

\[
R(p_T, p_O, x_T, x_O) = p_T x_T(p_T) + p_O x_O(p_O).
\]

The revenue maximizing prices are given by:

\[
p_o^* = \left(\frac{\beta_0}{(\theta+1)\beta_1}\right)^{1/\theta} \quad \text{and} \quad p_T^* = \left(\frac{\alpha_0\alpha_1\beta_0}{(\theta+1)\beta_1}\right)^{1/\theta}.
\] (5), (6)

(See the Mathematical Appendix for additional information.) The ratio of these optimal prices is:

\[
P^* = \frac{p_T^*}{p_O^*} = \left(\frac{\alpha_0\alpha_1}{\beta_1}\right)^{1/\theta},
\] (7)

which we call the optimal price ratio equation.

Notice that this price ratio also results from substituting \( c_T = c_O = 0 \) in Equation 4. Therefore, this result from the revenue model characterizes the instance of the profit model where marginal
costs of production are close to zero. This applies to short-term decision scenarios with fixed production capacity, and to markets for information goods. Also, the optimal price ratio equation suggests that the price ratio depends on the demand function’s shape defined by the curvature parameter $\theta$. The lower is $\theta$ (i.e., the more convex or less concave is the demand function), the higher should be the price differential between the two channels to maximize revenue.

D. Practical Guidelines

The profit and revenue models so far provide a theoretical optimal relationship between transparency levels and prices across channels, other things being equal. However, the magnitude of the optimal price difference between channels is difficult to derive, because it depends on prior knowledge of the impact of market transparency on WTP, in terms of $\alpha_0$ and $\alpha_1$. In particular, an estimate or knowledge of the demand function for all channels would be necessary. We will next enhance the model by deriving optimal prices in terms of information about sales by channel, which is more commonly available.

To begin, let $S = x_r/x_o$ be the channel share ratio of the Transparent Channel $T$ and the Opaque Channel $O$. The representation of channel shares as a ratio has the advantage of measuring in a simple one-to-one context how one channel does versus the other. It also avoids the need to presume any a priori knowledge about the attributes that determine consumers’ choices (Batsell and Polking, 1985). The following proposition characterizes the optimal channel share ratio in terms of the relative transparency levels across channels:

**Proposition 2 (The Channel Share-Base Demand Proposition):** The optimal channel share ratio between two channels with heterogeneous transparency levels is equal to the base demand ratio, thus $S^* = \alpha_0$.

**Proof.** Substituting the demand Equations 1 and 3 for the two channels into $S = x_r/x_o$ yields the equality $\beta_0(\alpha,S - \alpha_0\alpha_1) - \beta_1(\alpha_0S^\theta_o - p_r^\theta) = 0$. By substituting the optimal prices $p^*_o$ and
\( p^*_T \) from Equations 5 and 6 into this equation, it follows that \( S^* = \alpha_0 \). (See Math Appendix.)

The Channel Share-Base Demand Proposition suggests that the effect of market transparency on the base demand can be observed in the historical sales across channels if the prices are optimal. On the other hand, if relative prices are not optimal, this equality will not hold. Given that \( S^* \) does not depend on \( \theta \), the proposition also shows that the optimal demands in the two channels are related by a factor equivalent to the impact of market transparency on the base demand, regardless of the degree of non-linearity. The intuition is that by selecting a position in the market transparency space, firms set the market potential or base demand for each channel. Through price competition, a supplier can pursue more market share than the one dictated by the base demand of its distribution channels, but this attempt will be sub-optimal.

The following corollary formally links channel shares to their respective prices.

**Corollary 2 (The Optimal Channel Share Ratio):** The optimal price ratio is a function of the channel share ratio.

**Proof.** Substituting \( S^* = \alpha_0 \) in Equation 7 results in

\[
0^* = \alpha = \frac{p^*_T}{p^*_O} = \left( S^* \alpha \right)^{\frac{1}{\theta}}.
\]  

The Optimal Channel Share Ratio corollary suggests that by tracking sales by channel, a supplier can determine whether the relative price and transparency levels across channels are optimal or whether they should be modified to maximize revenue.

Moreover, with knowledge about the impact of market transparency on WTP, more specific guidelines can be derived based on observed channel shares. We next characterize three possible scenarios for this revenue model. In one scenario, we assume transparency impacts the liquidity of market exchange. In the second scenario, we explore the impact of transparency on the price discovery process. Finally, the third scenario combines these two effects of market transparency. This scenario-based analysis leads to a methodology that firms can use to diagnose the impact of
market transparency on consumer demand and price elasticity, and to develop possible directional actions to improve revenues. At the outset, we caution that we do not necessarily expect to see a specific scenario in the real world. Rather, this scenario-based analysis is a stepwise analytical method to assess whether a multi-channel transparency strategy is optimal, and the corrective actions that can be taken otherwise.

**Case 1: The Base Demand Scenario**

By attracting or deterring consumers, market transparency may influence market liquidity. So an electronic mechanism that lowers search costs for promotional prices may cause a negative shift in the range of consumers’ reservation prices. This should lead to a lower base level of demand. (See Figure 5.)

**Figure 5. Characterization of Demand in the Base Demand Effect Scenario**

![Figure 5](image)

*Note: This figure depicts a scenario where market transparency affects the base demand but not the price elasticity of demand.*

The positions in the market transparency space of transparent OTAs such as Expedia and offline travel agencies provide an illustrative comparison. (See Figure 2 again.) Both channels provide similar levels of product transparency, but transparent OTAs provide many more priced offers per search request, to the direct benefit of all consumers. Under this scenario, the following proposition summarizes the implications for relative prices and channel shares.

**Proposition 3 (The Base Demand Effect Proposition):** If the seller sets prices by channel to maximize revenue, the channel share ratio will be equal to the $\theta^{th}$ power of
the price ratio, thus \( P_{\text{BaseDemand}}^\theta = S^* \)

**Proof.** Let \( P_{\text{BaseDemand}}^* \) be the optimal price ratio under the base demand effect. If market transparency only affects the base demand, \( \alpha = 1 \). Substituting \( \alpha = 1 \) in (10) leads to

\[
P_{\text{BaseDemand}}^\theta = S^*.
\]

In this base demand scenario, channel share information and an estimate of \( \theta \) will be sufficient for a seller to assess whether the relative prices and transparency strategies are optimal. For example, if the seller observes \( P^\theta > S \), then the multi-channel transparency strategy is sub-optimal and the seller should either decrease the transparency level of Transparent Channel \( T \), increase the transparency level of Opaque Channel \( O \), or increase the price differential between channels to maximize revenue.

Notice that for a linear demand function, \( \theta = 1 \), \( P_{\text{BaseDemand}}^* = S^* \). So the optimal price ratio and the optimal channel share ratio are equal. This result leads to the following corollary:

**Corollary 3 (The Linear Demand Channel Share Ratio):** In the presence of linear demand, the optimal price ratio will be equal to the optimal channel share ratio.

**Case 2: The Price Elasticity Scenario**

In some situations, market transparency may have an impact on the price discovery process, rather than on market liquidity. Innovative market mechanisms observed in Internet markets are a case in point. For example, both Hotwire and Priceline.com targeted price-conscious consumers through their opaque market mechanisms, which offer little information about the travel itinerary or the carrier (albeit at promotional prices). However, though Hotwire posts one or two low promotional prices, Priceline.com’s opaque market mechanism is based on a silent auction mechanism. One likely effect of their different transparency levels is that the relative price elasticities will differ, while the base demands will remain the same. (See Figure 6).
Note: This is a scenario where price transparency affects price elasticity of demand but not base demand.

In this scenario, the following proposition characterizes optimal prices and market shares:

**Proposition 4 (The Price Elasticity Effect Proposition):** If the seller sets prices by channel to maximize revenue, both channels will have an equal share of sales.

**Proof.** If market transparency only affects the relative price elasticities, \( \alpha_0 = 1 \). Recall that \( S* = \alpha_0 \). Therefore, \( S* = 1 \).

The *Price Elasticity Effect Proposition* suggests that the firm should price such that both channels have equal share of sales. For example, if the firm observes that *Transparent Channel T* has a lower share than *Opaque Channel O* such that \( S < 1 \), then it should decrease the transparency differential or increase the price differential between the two channels to maximize revenue. This may partially explain Priceline’s move to increase its overall transparency level by introducing a transparent selling mechanism.

**Case 3: The Mixed Effect Scenario**

If the relative transparency levels differ significantly between the two channels, the effect of market transparency is likely on both the base demand and the price elasticity of demand. (See Figure 4 again.) This mixed effect is illustrated by a comparison of opaque OTAs, such as Hotwire, and transparent OTAs, such as Orbitz. While transparent OTAs provide multiple offers for a traveler’s search request, Hotwire typically offers just a few priced options with little
product information, resulting in significantly different positions in the market transparency space in both price and product transparency dimensions. (See Figure 2 again.) The following proposition summarizes the implications for optimal prices and channel shares:

**Proposition 5 (The Mixed Effects Proposition):** If the seller sets prices by channel to maximize revenue, the price differential between channels will be higher compared to that of the base demand scenario.

**Proof.** Let $P^*_{\text{MixedEffects}}$ be the optimal price ratio under mixed effects. In this scenario, Equation 8 holds so $P^*_{\text{MixedEffects}} = S^* \alpha_1$. Recall that $P^*_{\text{BaseDemand}} = S^*$. Since market transparency decreases WTP, $\alpha_1 < 1$, so $P^*_{\text{MixedEffects}} < P^*_{\text{BaseDemand}}$.

The Mixed Effects Proposition suggests that the mixed effect of market transparency on base demand and price elasticity compounds the cross-channel price differential necessary to maximize revenue. Therefore, the guidelines from the base demand scenario should be applied, but to a larger extent. For example, if the seller observes $P^\theta > S$, then it should decrease the transparency differential or increase the price differential across channels to a level higher than it would in the base demand scenario. This may partially explain Hotwire’s effort to improve its overall transparency level by introducing a semi-opaque and a transparent selling mechanism.

**IV. DISCUSSION**

We have shown how sellers should strategize in the presence of IT-enabled distribution channels where transparency levels by channel are heterogeneous. Our core proposition, the Transparency Strategy Proposition, suggests that prices should be linked to the transparency level of each distribution channel. This proposition supports existing models of multi-channel strategy which suggest that firms can strategize across channels to their benefit by revealing or concealing market information in coordination with price-setting. The broad result that the more
transparent channel should be priced lower than the opaque channel is analogous to the finding of Zettelmeyer (2000) for the Internet vs. the conventional channel. However, a key contribution of our analysis is that, by modeling transparency impacts in terms of demand shifts or changes in the price elasticity of demand, we derive practical guidelines that firms can follow in order to implement multi-channel transparency strategy.

Next, we discuss these guidelines in more detail. The results suggest there are three factors that firms must consider as they adopt a multi-channel transparency strategy. (See Table 2.)

### Table 2. Multi-Channel Transparency Strategies

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Assumption or Condition</th>
<th>Key Results</th>
<th>Strategy Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit Model</td>
<td>Market transparency affects WTP. $c_T = c_O$</td>
<td>$\alpha_0 \alpha_1 = \left( \frac{p_T^<em>}{p_O^</em>} \right)^{\theta} \frac{1 + \theta(1 - c_T / p_T^<em>)}{1 + \theta(1 - c_O / p_O^</em>)}$</td>
<td>Price relative to the level of market transparency (this applies for all cases below).</td>
</tr>
<tr>
<td>Revenue Model</td>
<td>$c_T = c_O = 0$</td>
<td>$\left( \frac{p_T^<em>}{p_O^</em>} \right)^{\theta} = \alpha_0 \alpha_1$</td>
<td>Price and set transparency levels taking into account the convexity or concavity (i.e., $\theta$) of the demand function.</td>
</tr>
<tr>
<td>Revenue model with channel share-based guidelines</td>
<td>Base demand scenario: $\alpha_1 = 1$.</td>
<td>$\left( \frac{p_T^<em>}{p_O^</em>} \right)^{\theta} = \frac{x_T^<em>}{x_O^</em>}$</td>
<td>Price and set transparency levels such that the price ratio is equal to the $\theta^\alpha$ root of channel share ratio.</td>
</tr>
<tr>
<td></td>
<td>Linear demand: $\theta = 1$</td>
<td>$\frac{p_T^<em>}{p_O^</em>} = \frac{x_T^<em>}{x_O^</em>}$</td>
<td>Price and set transparency level such that the price ratio is equal to channel share ratio.</td>
</tr>
<tr>
<td></td>
<td>Price elasticity scenario: $\alpha_0 = 1$.</td>
<td>$\frac{x_T^<em>}{x_O^</em>} = 1$</td>
<td>Price and set transparency level such that channel shares equate.</td>
</tr>
<tr>
<td></td>
<td>Mixed effect scenario: $\alpha_0, \alpha_1 &lt; (&gt;) 1$</td>
<td>$\left( \frac{p_T^<em>}{p_O^</em>} \right)^{\theta} = \left( \frac{x_T^<em>}{x_O^</em>} \right) \alpha_1$</td>
<td>Set price differential to be higher (lower) or transparency differential to be lower (higher) than in the base demand scenario.</td>
</tr>
</tbody>
</table>

First, the domain-specific issues such as the economic objective, decision making process, and industry profile should be considered. The specific guidelines for multi-channel transparency strategy vary depending on whether the objective is to maximize profits or revenues. On the other hand, the results of the revenue model can be applied to tactical decisions of industries with
perishable goods or fixed capacity, where marginal production costs do not play a significant role in tactical pricing decisions. The revenue model also applies to information goods that have low costs of replication. More generally, if marginal costs $c_r$ and $c_o$ are negligible, the guidelines of the revenue model can be applied.

Second, knowledge about the demand function can lead to higher precision in the application of these guidelines. For example, knowledge of the curvature of the demand function in terms of the value of $\theta$ can help sellers to identify the optimal multi-channel transparency strategy. Third, knowledge about the impact of market transparency on WTP is important, because it determines whether the relationship between relative prices and transparency levels is positive or negative. Different determinants of market transparency may have different effects, and the more knowledge there is about these effects, the more effective the guidelines will be. Nevertheless, we propose a stepwise methodology that firms can use to assess revenue opportunities in the presence of heterogeneous transparency levels across channels. The resulting channel share-based guidelines are particularly useful because a firm can diagnose whether its multi-channel transparency strategy is sub-optimal, and the directional corrective actions that need to be taken.

In the next section, we apply these channel share-based guidelines to evaluate online vs. offline transparency strategy in the air travel industry, using a large data set of airline tickets.

V. ANALYSIS OF MULTI-CHANNEL TRANSPARENCY STRATEGY IN AIR TRAVEL

Since the Internet emerged in the 1990s, new transparency strategies have been employed in the U.S. air travel industry. Through sites such as Expedia, Travelocity, and Orbitz, consumers now are able to explore numerous options for travel, compared to just a few when searching by phone via traditional sales channels such as travel agencies and airline reservation offices. How should airlines price in online versus offline distribution channels, given their different levels of
In this section, we answer this question by analyzing a large sample of airline ticket sales. Based on our model, we expect to see different price levels in the online and offline channels. We use the revenue model to evaluate the relative price levels between these two channels. Tactical pricing decisions in air travel are usually based on an existing route plan, so in this context the main objective is to maximize revenue for a given fixed capacity.

A. Data and Modeling Preliminaries

We analyzed the multi-channel transparency strategy in the air travel industry using a database of airline tickets sold by travel agencies through global distribution systems (GDSs) for travel between September 2003 and August 2004. GDSs permit electronic sales of airline ticket on the Internet, as well as traditional sales via travel agencies. Excluded from this sample are airline direct sales including frequent flyer award tickets, which are usually transacted through airline portals or reservation offices. The database contains information for 2.21 million economy class tickets sold in 71 U.S. origin-destination city pairs. Tickets were aggregated by city pair, channel, and time of purchase. Tickets were classified as online if they were sold by an OTA, and offline otherwise. Data were available for a booking window of 25 weeks prior to departure. The tickets were further classified based on peak or off-peak season (peak season is June-August and December 15-January 15).

Because peak season tickets sold reflect supply rather than demand patterns due to capacity constraints, we excluded peak season observations from this study. Also, we excluded the opaque Web sites Priceline and Hotwire to focus on the comparison between the traditional travel agencies and the more transparent OTAs. These exclusions reduced the sample to 1.77 million tickets. The average one-way price of tickets sold offline was $197, compared to $150
for tickets sold online.

As the Transparency Strategy Proposition suggests, prices in the two channels should differ to account for the difference in their transparency levels. Next, we perform an analysis of the demand base scenario, the price elasticity scenario, and the mixed effect scenario using the data set of airline tickets to evaluate the relative prices and transparency levels across online and offline air travel channels is optimal.

We consider an air travel demand model of the form \( DEMAND = f(PRICE, \text{CONTROL VARIABLES}) \), where \( DEMAND \) represents air travel demand estimated in terms of quantity sold. (See Table 3.)

**Table 3. Air Travel Demand Model Variables**

<table>
<thead>
<tr>
<th>VARIABLE TYPE</th>
<th>VARIABLE</th>
<th>DEFINITION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent</td>
<td>QUANTITY</td>
<td>Tickets sold, to represent ( DEMAND )</td>
</tr>
<tr>
<td>Independent</td>
<td>PRICE</td>
<td>Average price paid</td>
</tr>
<tr>
<td>Control</td>
<td>INCOMEOD</td>
<td>Sum of gross product per capita of origin and destination cities.</td>
</tr>
<tr>
<td></td>
<td>ADVPURCH</td>
<td>Time of purchase in weeks before flight departure</td>
</tr>
<tr>
<td></td>
<td>STGLENGTH</td>
<td>City-pair trip distance in air miles</td>
</tr>
<tr>
<td></td>
<td>CROSSPRICE</td>
<td>Other channel’s price</td>
</tr>
</tbody>
</table>

**Note:** The data source for U.S. income per capita and population was the U.S. Bureau of Economic Analysis (BEA) Time-Series Data for Metropolitan Statistical Areas (www.bea.doc.gov).

**Control variables.** Income is a standard predictor in demand models (Brynjolfsson et al., 2003). In airline route planning, an airport’s catchment area is the area within which travelers commute to fly from the airport. (See Figure 7.) We are interested in estimating the income level of travelers in a city-pair’s catchment area.

The income per capita of an airport’s catchment area is estimated based on official 2003 gross product statistics of its corresponding city or metropolitan area. For U.S. airports the source is the Metropolitan Statistical Area (MSA) economic data from the Bureau of Economic
INCOMEOD is measured by adding the gross product of the MSA for the origin airport and destination airport and dividing this sum by the combined population.

Another relevant variable is the advanced purchase time prior to departure (ADVPURCH). A pervasive and well-recognized difference between consumers is the urgency of purchase (Stigler, 1964). In particular, demand may be significantly affected by consumers’ sense of urgency in markets with perishable products. Airlines have used this feature of the air travel product to price differentiate (Clemons et al., 2002). In this study, we incorporate time of advanced purchase measured in weeks before departure.

An often-used variable in air travel demand models is stage length (STGLENGTH). Stage length refers to a city-pair’s trip distance in air travel miles. This variable has been used in prior studies of airline performance, as noted by Duliba et al. (2001). Stage length can influence air travel demand in two ways. First, demand for short-haul trips will be influenced by alternate
modes of transportation, such as trains or automobiles. Second, short distance trips are more commodity-like than long distance trips, given the higher need for comfort and reliability.

Finally, we also control for the cross-channel price effect (CROSSPRICE). The cross-channel price effect is the impact on a channel’s base demand due to multi-channel shoppers that shift to or away from the channel based on price (Zettelmeyer, 2000).

B. Empirical Model for Base Demand Scenario Analysis

The guidelines of our model for multi-channel transparency strategy suggest that knowledge about \( \theta \) is needed to assess whether relative prices and transparency levels are optimal. Therefore, an econometric demand specification is required that resembles the non-linear demand function \( x(p) = \lambda_0 - \lambda_1 p^\theta \). Based on this requirement, we derived the following non-linear specification:

\[
QUANTITY = \beta_0 + \beta_1 * ONLINE - INCOMEOD^{\beta_2} * ADVPURCH^{\beta_3} * STGLENGTH^{\beta_4} * CROSSPRICE^{\beta_5} * PRICE^{\theta} + \varepsilon,
\]

where \( ONLINE \) is a dummy for online or offline sales (0 for offline and 1 for online) and \( \varepsilon \) is the error term. This model is like the demand function \( x(p) = \lambda_0 - \lambda_1 p^\theta \), where \( \beta_0 + \beta_1 * ONLINE \) is an estimate of the \( BASE DEMAND \) \( \lambda_0 \), and \( - INCOMEOD^{\beta_2} * ADVPURCH^{\beta_3} * STGLENGTH^{\beta_4} * CROSSPRICE^{\beta_5} \) \( * PRICE^{\theta} \) is an estimate of \( - \lambda_1 \). (See Table 4 for descriptive statistics on the data set.)

The average one-way price was $173 and the average number of tickets sold was 499.

We used STATA 8.0 (www.stata.com) to run iterative non-linear least squares (NLS) regressions until a converging best fit was found. To guide the iterations, we set base demand \( \beta_0 \) at 46,021, the maximum value of tickets sold in the sample. The model converged in the tenth iteration. The fit was appropriate (\( F = 464.47 \), adjusted-\( R^2 = 41\% \)) and all the variables were significant at \( p < .01 \). (See Table 5.)
Table 4. Descriptive Statistics

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>MEAN</th>
<th>STANDARD DEVIATION</th>
<th>MIN</th>
<th>MAX</th>
</tr>
</thead>
<tbody>
<tr>
<td>QUANTITY</td>
<td>498.80</td>
<td>1,840.48</td>
<td>1</td>
<td>46,021</td>
</tr>
<tr>
<td>ONLINE</td>
<td>0.50</td>
<td>0.50</td>
<td>1</td>
<td>2.72</td>
</tr>
<tr>
<td>STGLENGTH</td>
<td>1829.42</td>
<td>1405.92</td>
<td>227</td>
<td>5,566</td>
</tr>
<tr>
<td>INCOMEOD</td>
<td>$72,083</td>
<td>6.43</td>
<td>$60,930</td>
<td>$89,690</td>
</tr>
<tr>
<td>ADVPURCH</td>
<td>13</td>
<td>7.21</td>
<td>1</td>
<td>25</td>
</tr>
<tr>
<td>PRICE</td>
<td>$172.98</td>
<td>94.34</td>
<td>$34</td>
<td>$925.41</td>
</tr>
<tr>
<td>CROSSPRICE</td>
<td>$172.98</td>
<td>94.34</td>
<td>$34</td>
<td>$925.41</td>
</tr>
</tbody>
</table>


Table 5. Non-Linear Air Travel Demand Model Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>ESTIMATE</th>
<th>STD. ERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASE DEMAND ($\beta_0$)</td>
<td>46,021.00***</td>
<td>--</td>
</tr>
<tr>
<td>ONLINE ($\beta_1$)</td>
<td>-9,753.16***</td>
<td>310.67</td>
</tr>
<tr>
<td>INCOMEOD ($\beta_2$)</td>
<td>-2.01***</td>
<td>0.02</td>
</tr>
<tr>
<td>ADVPURCH ($\beta_3$)</td>
<td>0.32***</td>
<td>0.01</td>
</tr>
<tr>
<td>STGLENGTH ($\beta_4$)</td>
<td>-0.10***</td>
<td>0.01</td>
</tr>
<tr>
<td>CROSSPRICE ($\beta_5$)</td>
<td>-0.12***</td>
<td>0.01</td>
</tr>
<tr>
<td>PRICE ($\theta$)</td>
<td>0.46***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Note: N = 3,350. F(5, 3545) = 464.47, $R^2 = 41.52\%$; adjusted-$R^2=41.42\%$. The regression was run with a BASE DEMAND value of $\beta_0 = 46,021$, the maximum observed number of tickets sold. Significance levels for the estimates: * = $p$-value < 0.10, ** = $p$-value < 0.05, and *** = $p$-value < 0.01. The effect on demand of INCOMEOD, ADVPURCH, STGLENGTH, CROSSPRICE, and PRICE is the inverse of their estimated elasticities, because the sign of the term that incorporates these variables is negative.

Next, we provide some relevant regression diagnostics for non-linear least square regressions. The key assumptions for linear and non-linear least squares regression models are similar but they differ in some aspects (Greene, 2002). \(^2\) (Table 6 summarizes these differences.)

To ensure identification of model parameters in a non-linear model, it is not enough to diagnose multicollinearity, as it is in the linear regression model. Nevertheless, we report the pairwise

---

\(^2\) In linear demand functions, exogeneity of the regressors is required to ensure that there is no correlation between the disturbances and the conditional mean function. In non-linear models, the analogous condition is that the disturbances are uncorrelated with the derivatives of the conditional mean function with respect to the parameters (Greene, 2002). This condition will hold if disturbances are normally distributed. Normality plots of the disturbances in our models suggest that the disturbances are normally distributed, so this condition is satisfied.
correlations of the variables. (See Table 7.) Instead, the multiplication of each parameter by a constant should not lead to the same function. That is the case for our non-linear regression model. To ensure that there is a solution for the minimization of the least squares errors, the function must be continuous and twice differentiable. This condition ensures a local minimum.

Table 6. Regression Diagnostics in Linear Vs. Non-Linear Econometric Models

<table>
<thead>
<tr>
<th>ASSUMPTIONS</th>
<th>LINEAR MODEL</th>
<th>NON-LINEAR MODEL</th>
</tr>
</thead>
</table>
| Identifiability of model parameters              | • Check for full rank: No exact linear relation among variables or perfect multicollinearity  
                                                   • Diagnose multicollinearity via variance inflation factors                    | • Check to see if there is a non-zero parameter vector that equals the conditional mean function  
                                                   • Multiply parameters by same constant                                           |
| Error terms uncorrelated with conditional mean function | • Check for exogenous dependent variables                                    | • Determine if error terms and regressors are uncorrelated with derivatives of conditional mean function with respect to parameters  
                                                   • Determine if error terms and regressors uncorrelated                          | • Check for normality of disturbances                                             |

Source: Greene (2002)

Table 7. Pairwise Correlations for the Empirical Model Variables

<table>
<thead>
<tr>
<th></th>
<th>QUANTITY</th>
<th>ONLINE</th>
<th>STG-LENGTH</th>
<th>INCOME-OD</th>
<th>ADV-PURCH</th>
<th>PRICE</th>
<th>CROSSPRICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>QUANTITY</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ONLINE</td>
<td>-0.17</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STG-LENGTH</td>
<td>-0.09</td>
<td>-0.00</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INCOME-OD</td>
<td>0.09</td>
<td>-0.00</td>
<td>0.02</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADV-PURCH</td>
<td>-0.35</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE</td>
<td>0.12</td>
<td>-0.25</td>
<td>0.66</td>
<td>-0.21</td>
<td>-0.25</td>
<td>1</td>
<td>0.65</td>
</tr>
<tr>
<td>CROSSPRICE</td>
<td>-0.02</td>
<td>0.25</td>
<td>0.66</td>
<td>-0.21</td>
<td>-0.25</td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Note: The reader should note the pairwise correlations of 0.66 for PRICE and STG-LENGTH, and CROSSPRICE and STG-LENGTH. Also the correlation between PRICE and CROSSPRICE is similar at 0.65. The correlations are close to the criterion value of 0.80 that is often used to exclude highly correlated variables. We ran a Reduced Model also. This is the same model as is shown above, only omitting STG-LENGTH and CROSSPRICE, and obtained very similar results. This increases our comfort with the results.

C. Base Demand Analysis

The coefficient estimate of ONLINE, $\hat{\beta}_1$, is -9,753 (SE= 310.17, $p$-value < 0.01), which suggests that base demand for OTAs is lower than in the offline channel. However, this result
cannot be fully attributed to transparency, because ONLINE also incorporates all other channel-specific effects such as quality of service and channel maturity. Nevertheless, in the following analysis, we are able to use historical sales by channel and guidelines from the model to assess whether air travel transparency strategy is optimal across distribution channels. To begin, recall that knowledge of \( \theta \) is necessary to apply the guidelines from the revenue model. The estimate of \( \theta \) in the air travel demand model is 0.46 (SE = 0.03, \( p \)-value < 0.01), which suggests the air travel demand curve is convex.

To evaluate the relative price levels, let us assume initially that the base demand scenario applies, where market transparency decreases the base demand but does not affect price elasticity. Referring to the Base Demand Effect Proposition, if relative prices are optimal,  

\[
Pr^* = \left( \frac{P_{\text{online}}}{P_{\text{offline}}} \right)^\theta = S^*. 
\]

The observed price ratio was 0.80, and it was estimated by averaging the price ratios of each of the individual records. The mean estimate of \( P^\theta = (0.80)^{0.46} = 0.91 \), and the observed channel share ratio is \( S = 0.31 \), so \( P^\theta > S \). This inequality suggests that online vs. offline transparency strategy is sub-optimal, if it were not for the reasonable conjecture that the observed channel shares are affected by other factors such as the maturity of the Internet channel and structural differences in service quality and convenience. To address this issue, we adjusted the channel share ratio using the estimated channel effect, or the coefficient of ONLINE, which led to an adjusted \( S = 0.62 \). Since this observed channel effect includes the effect of market transparency, \( S \) is over-adjusted, yet the inequality \( P^\theta > S \) remains, so we conclude that airline multi-channel transparency strategy is sub-optimal and that there is revenue opportunity by attracting more customers to the online channel. From a pricing perspective, airlines can either raise offline prices, or lower online prices until the equality \( P^\theta = S \) holds. Alternatively, airlines
can decrease the transparency differential across channels.

D. Empirical Model for Price Elasticity Scenario Analysis

We performed an analysis to examine price elasticities by channel, and conclude that the OTA channel has a higher price elasticity compared to traditional travel agencies. We used a the log-linear econometric specification of air travel demand, which is commonly used to estimate air travel demand and which allows the estimation of a constant price elasticity along the demand curve. We included a parameter to define the difference in elasticities across the two channels:

\[
QUANTITY = \beta_0 \ast PRICE^{\eta + \gamma A} \ast INCOMEOD^{\beta_2} \ast ADVPURCH^{\beta_5} \ast STGLENGTH^{\beta_4} \ast CROSSPRICE^{\beta_6} \ast \prod_j \sigma_j ORIGIN_j \ast \varepsilon
\]  

(10)

In this model, \(A\) is a dummy variable for the two agency types (0 for OFFLINE and 1 for ONLINE). \(-\eta\) is the base price elasticity for OFFLINE and \(-\gamma A\) captures the price elasticity of ONLINE relative to OFFLINE. In addition, we include a dummy variable \(ORIGIN_j\) for each origin airport \(j\) in the sample. The base case origin city is New York, so its dummy variable is excluded from the regression. The \(\beta_i\)'s represent the elasticities for \(INCOMEOD, ADVPURCH, STGLENGTH,\) and \(CROSSPRICE\). The log-linear transformation of this function is:

\[
\ln(QUANTITY) = \ln(\beta_0) + \eta \ln(PRICE) + \gamma A \ln(PRICE) + \beta_2 \ln(INCOMEOD) + \beta_5 \ln(ADVPURCH) + \beta_4 \ln(STGLENGTH) + \beta_6 \ln(CROSSPRICE) + \sum_j \sigma_j \ln(ORIGIN_j) + \ln(\varepsilon)
\]  

(11)

See Table 7 again for pair-wise correlations of these variables. The highest observed correlations of 0.66 were between \(STGLENGTH\) and \(PRICE\), and also \(STGLENGTH\) and \(CROSSPRICE\). These correlations are expected because prices on long-haul trips tend to be higher than prices on short-haul trips. This is evident in our sample because it contains both domestic and international destinations, and prices tend to be higher for the latter. The correlation of 0.65 between \(PRICE\) and \(CROSSPRICE\) is second highest. This correlation is also
expected because channel prices fluctuate together following airlines’ posted prices. To assess whether these correlations are troubling, we estimated the variance inflation factors (VIFs) to test for multicollinearity. The highest VIF was 5.29 for $STGLength$, and the average VIF was 2.80. These VIF values suggest that multicollinearity is not inappropriately high (Kennedy, 1998). Nevertheless, in the analysis we included a Reduced Model that does not include $STGLength$ and $CROSSPRICE$, to evaluate the multicollinearity effects.

In demand models, there is an inherent risk of endogenously-generated prices, which can lead to model misspecification because of the potential correlation between prices and residuals (Villas Boas and Winer, 1999). In particular, in the air travel industry demand and prices may be simultaneously determined, as suppliers set prices based on existing bookings, and as the observed demand is affected by the set prices. We performed an analysis of the risk of endogeneity for the specific model specification in this study. Consider an airline monopolist in a market with demand function $DEMAND = A \cdot PRICE^n \cdot \epsilon$, and marginal cost $c$. Assuming that the monopolist maximizes profits, it will set $PRICE^* = \frac{nc}{\eta + 1}$. Notice that the optimal price is not dependent on $\epsilon$. Therefore, in this case there is less concern that simultaneity of price setting will lead to endogeneity problems in the econometric estimation. In contrast, that is not the case for linear demand specifications (Villas-Boas and Winer, 1999). To verify this, we performed a linear regression of $\ln(PRICE)$ on the residuals, and we found no significant correlation between $PRICE$ and the residuals. We conclude that the risk of misspecification of the model due to endogenously determined airline ticket prices is low.

The scatter plot of residuals against fitted values suggests that there is some degree of heteroskedasticity in both online and offline regressions. We performed a Breusch-Pagan (1979) Lagrange multiplier test for heteroskedasticity against the fitted values of $\ln(QUANTITY)$ at the
level of model. The hypothesis of constant variance or homoskedasticity was rejected ($\chi^2=69.16$, df=1, p-value <.01). We conclude that there is heteroskedasticity in the econometric estimation, although this test cannot diagnose exactly what its source is. One potential source of heteroskedasticity is $INCOMEOD$. Wealthy regions may exhibit a higher variance in sales than less wealthy regions. Based on the observation that $INCOMEOD$ might account for heteroskedasticity, we ran a second, less general test by Goldfeld and Quandt (1965). We consider a known source of heteroskedasticity (i.e., $\text{var}[\epsilon_i] = \sigma^2_i = \sigma^2_i z_i$ with $z_i = INCOMEOD$).

We were not able to reject the null hypothesis of homoskedasticity (p-value < .23). To correct for other possible unknown sources of heteroskedasticity, we performed the regressions using the robust estimators. (See Table 8.)

In the full model, the estimates of $\eta$ and $\gamma$ were negative and significant ($\eta =-0.62$, SE=0.08, p-value<0.01; and $\gamma=-0.27$, SE=0.01, p-value <0.01). (See Table 8.) The price elasticity differential in the reduced model is also significant and of a similar order of -0.30, so we conclude that price elasticity in the online channel is higher than in the offline channel.

E. Price Elasticity Analysis

The Price Elasticity Effect Proposition suggests that if market transparency only affects price elasticity of demand, then sales should be equal in both channels if prices are set optimally. However, the adjusted channel share ratio is $S = 0.62$. Therefore, analogous to the result in the base demand scenario, this analysis suggests that relative prices are not optimal, and there is revenue opportunity that can be obtained by raising offline prices, decreasing online prices, or decreasing the transparency differential between these two channels until their sales are equal.

F. Mixed Effects Analysis

Based on the base demand and price elasticity analysis, we conclude that transparent OTAs
have a lower base demand and a higher price elasticity than the offline channel. Given this mixed effect of transparency on consumers, the Mixed Effects Proposition suggests that airlines should decrease the transparency differential or increase the price differential between traditional and Internet channels to a larger extent than what the guidelines of the base demand and price elasticity scenarios suggest.

Table 8. **OFFLINE and ONLINE** Results: The Price Elasticity Differential

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>FULL MODEL</th>
<th></th>
<th></th>
<th>REDUCED MODEL</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COEFFICIENT (ROBUST SE)</td>
<td>t</td>
<td>SIGNIF.</td>
<td>COEFFICIENT (ROBUST SE)</td>
<td>t</td>
<td>SIGNIF.</td>
</tr>
<tr>
<td><strong>PRICE</strong></td>
<td>-0.62*** (0.08)</td>
<td>-7.42</td>
<td>0.00</td>
<td>-0.55*** (0.05)</td>
<td>-11.11</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>A</strong></td>
<td>-0.27*** (0.01)</td>
<td>-26.16</td>
<td>0.00</td>
<td>-0.30*** (0.01)</td>
<td>-38.31</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>CONSTANT (β₀)</strong></td>
<td>-0.50 (1.26)</td>
<td>-0.40</td>
<td>0.69</td>
<td>1.42 (1.26)</td>
<td>1.14</td>
<td>0.26</td>
</tr>
<tr>
<td>• Control Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>ADVPURCH</strong></td>
<td>-2.26*** (0.03)</td>
<td>-70.54</td>
<td>0.00</td>
<td>-2.12*** (0.03)</td>
<td>-71.51</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>INCOMEOD</strong></td>
<td>3.23*** (0.26)</td>
<td>12.22</td>
<td>0.00</td>
<td>2.67*** (0.26)</td>
<td>10.16</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>STLENGTH</strong></td>
<td>0.47*** (0.05)</td>
<td>9.34</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>CROSSPRICE</strong>(a)</td>
<td>-0.63*** (0.09)</td>
<td>-7.37</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Origin Dummy Variables (ORIGIN&lt;sub&gt;city&lt;/sub&gt;)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>BOSTON</strong></td>
<td>-1.18*** (0.11)</td>
<td>-10.73</td>
<td>0.00</td>
<td>-0.81*** (0.10)</td>
<td>-7.81</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>CHICAGO</strong></td>
<td>-0.85*** (0.14)</td>
<td>-6.63</td>
<td>0.00</td>
<td>-1.07*** (0.12)</td>
<td>-8.52</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>DENVER</strong></td>
<td>-0.99*** (0.14)</td>
<td>-7.28</td>
<td>0.00</td>
<td>-0.90*** (0.14)</td>
<td>-6.46</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>DETROIT</strong></td>
<td>-0.06 (0.08)</td>
<td>-0.79</td>
<td>0.43</td>
<td>0.03 (0.08)</td>
<td>0.43</td>
<td>0.67</td>
</tr>
<tr>
<td><strong>HOUSTON</strong></td>
<td>-1.37*** (0.12)</td>
<td>-11.45</td>
<td>0.00</td>
<td>-1.45*** (0.12)</td>
<td>-11.79</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>LOS ANGELES</strong></td>
<td>-0.35 (0.11)</td>
<td>-3.10</td>
<td>0.02</td>
<td>-0.05 (0.11)</td>
<td>-0.43</td>
<td>0.70</td>
</tr>
<tr>
<td><strong>MEMPHIS</strong></td>
<td>-1.08*** (0.09)</td>
<td>-12.41</td>
<td>0.00</td>
<td>-1.11*** (0.09)</td>
<td>-12.62</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>MINNEAPOLIS</strong></td>
<td>-0.03 (0.08)</td>
<td>-0.42</td>
<td>0.68</td>
<td>-0.00 (0.08)</td>
<td>-0.01</td>
<td>0.99</td>
</tr>
<tr>
<td><strong>SANFRANCISCO</strong></td>
<td>-0.66 (0.12)</td>
<td>-5.57</td>
<td>0.00</td>
<td>-0.20* (0.11)</td>
<td>-1.78</td>
<td>0.08</td>
</tr>
<tr>
<td><strong>WASHINGTON</strong></td>
<td>-0.44*** (0.11)</td>
<td>-4.00</td>
<td>0.00</td>
<td>-0.63*** (0.11)</td>
<td>-5.73</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>R² (Adjusted-R²)</strong></td>
<td>74.95% (74.84%)</td>
<td>73.70% (73.53%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** N = 3,550. Model: log-linear regression with robust errors, to handle heteroskedasticity. The significance levels are: * = p-value < .10, ** = p-value < .05, *** = p-value < .01. The Reduced Model excludes CROSSPRICE and STLENGTH. (a) The estimated coefficient of CROSSPRICE is contrary to intuition. We infer that this result is due to the correlation between CROSSPRICE and PRICE, so the elasticity estimate of CROSSPRICE may be capturing the effect of price elasticity, which is negative.

More generally, our results indicate that price discrimination may not be producing the managerially-desirable outcomes that are expected in air travel multi-channel strategy. The offline channel may be sub-optimally cannibalizing travelers from the online channel—if price and transparency alone are considered as the key strategy variables. Based on our analysis, we
encourage air travel managers to consider raising their offline prices, reducing their Internet prices, or decreasing the transparency level of the online channel in order to increase revenues.

VI. CONCLUSIONS

In the presence of advanced e-commerce technologies, sellers face strategic issues related to the development of technology that determine market presence, positioning, and information disclosure in multiple distribution channels.

A. Key Findings

Our analytical model supports these decisions by offering guidance to the economic soundness of multi-channel transparency strategy in B2C electronic commerce. The analytical approach is based on the relative rather than the absolute value that consumers place on different levels of market transparency, which alleviates the inherent complexity in assessing the impact of market transparency on consumers in order to develop an optimal multi-channel strategy. The resulting guidelines for managers are based on a diagnosis of historical sales information by channel, which is commonly available to firms.

This model is particularly useful for firms that have a captive market where the valuation of market transparency may differ among consumers. As sellers manipulate market information across channels, some consumers may switch to a different channel, and other consumers may not switch, although they may become more sensitive to prices. With the normative guidelines that we have derived, firms can make sound decisions when confronted with this problem in an environment where they can price-discriminate by channel, and where technological capabilities allow them to set transparency levels by channel.

Our modeling approach and empirical analysis echo the recent call for IS research that examines the role that IT plays in changing markets and that supports managerial decisions in
markets that are in perpetual transition to equilibrium (Clemons and Weber, 2002). The empirical analysis of the air travel industry shows how the guidelines can be used to assess whether a multi-channel transparency strategy is optimal, despite no prior knowledge of the impact of transparency is on demand.

B. Limitations and Future Research

Although our model provides normative guidelines based on an economic model of multi-channel strategy, due to the focus on developing a decision model with respect to transparency by channel, we assumed separability of demand between the transparent and opaque channels. This allowed us to develop theoretical results that are based on the sole effect of transparency but ignored the typical issues, such as income and cross-price elasticities. Including these factors in the analytical model would result in a transparency parameter, which may be appropriate in future research. But we believe that with real-world data it is possible to separate the impact of factors, such as income and cross-price elasticities, by using these as control variables. Thus, in our econometric model we controlled for the demand factors that we did not model analytically (e.g., income, cross-prices) to isolate the impact of channel-specific market transparency on demand.

In the analysis of air travel multi-channel strategy, we controlled for other channel-specific factors by adjusting the relative channel shares using the estimated coefficient for the channel dummy, which includes the transparency effect. Although we over-adjusted the relative channel shares, we were nevertheless able to derive interesting conclusions about strategic pricing and transparency levels across the online and offline in order to improve revenues. One possible enhancement to the econometric model would be to isolate market transparency impacts from other channel specific impacts by identifying and measuring channel-based characteristics that
impact demand, such as quality of service.

An interesting avenue for future research is to determine how different types of market information affect consumer demand and price elasticity. We have some empirical research underway to examine the impacts of product and price transparency on consumer demand (Granados, et al., 2005b). We can use the findings to further tailor the guidelines we have suggested for the multi-channel strategy model to the specific impacts of product and price information.

**REFERENCES**


**MATHEMATICAL APPENDIX**

We provide additional background on our profit and revenue maximization procedures, as well as a proof for the Optimal Channel Share Ratio Proposition.

**The Profit Maximization Procedure.** The profit function is
\[
\pi(p_T, p_O, x_T, x_O, C) = p_T x_T(p_T) + p_O x_O(p_O) - C(x_T) - C(x_O)
\]
\[
= p_T \alpha_0 \beta_0 - \frac{\beta_1}{\alpha_1} p_T^{(\theta+1)} + p_O \beta_0 - \frac{\beta_1}{\alpha_1} p_O^{(\theta+1)} - C(x_T) - C(x_O).
\]
Solving the optimal price for

**Transparent Channel** $T$ yields the following expression:
\[
0 = \alpha_0 \alpha_1 \beta_0 - \theta \beta_1 p_T^* - \beta_1 p_T^{*} + c_T \beta_1 p_T^* = \alpha_0 \alpha_1 \beta_0 - \beta_1 p_T^*\left(\theta + 1 - c_T / p_T^*\right).
\]
Rearranging terms leads to
\[
\alpha_0 \alpha_1 \beta_0 = \beta_1 p_T^* \left[1 + \theta \left(1 - c_T / p_T^*\right)\right].
\]
Similarly, for **Opaque Channel** $O$, $\beta_0 = \beta_1 p_O^* \left[1 + \theta \left(1 - c_O / p_O^*\right)\right]$.  

**The Revenue Maximization Procedure.** The revenue function is
\[
\pi(p_T, p_O, x_T, x_O) = p_T x_T(p_T) + p_O x_O(p_O) = p_T \alpha_0 \beta_0 - \frac{\beta_1}{\alpha_1} p_T^{(\theta+1)} + p_O \beta_0 - \frac{\beta_1}{\alpha_1} p_O^{(\theta+1)}.
\]
Solving for the optimal price of the **Transparent Channel** $T$ yields the following expression:
\[
0 = \alpha_0 \alpha_1 \beta_0 - \left(\theta + 1\right) \beta_1 p_T^* .
\]
Rearranging terms leads to the optimal price $p_T^* = \left(\frac{\alpha_0 \alpha_1 \beta_0}{\left(\theta + 1\right) \beta_1}\right)^{1/\theta}$.

Similarly, for **Opaque Channel** $O$, $p_O^* = \left(\frac{\beta_0}{\left(\theta + 1\right) \beta_1}\right)^{1/\theta}$.

**Proof of the Optimal Channel Share Ratio Proposition.** Let $S = x_T / x_O$ be the channel share ratio. Substituting the demand functions yields
\[
S = \frac{\alpha_0 \beta_0 - \frac{\beta_1}{\alpha_1} p_T^*}{\beta_0 - \beta_1 p_O^*}.
\]
Rearranging terms leads to
\[
\alpha_1 \beta_0 \left(S - \alpha_0\right) - \beta_1 \left(\alpha_1 S p_O^* - p_T^*\right) = 0.
\]
Substituting the optimal prices and rearranging terms results in
\[
\alpha_1 \beta_0 \left(S^* - \alpha_0\right) - \beta_1 \left(\alpha_1 S^* - \frac{\beta_0}{\left(\theta + 1\right) \beta_1} - \frac{\alpha_0 \alpha_1 \beta_0}{\left(\theta + 1\right) \beta_1}\right) = S^* - \alpha_0 - \frac{S^* - \alpha_0}{\theta + 1} = 0.
\]
Therefore, $S^* = \alpha_0$.  

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