Designing online selling mechanisms: Transparency levels and prices

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Abstract

Sellers increasingly compete with innovative Internet-based selling mechanisms, revealing or concealing market information. *Transparency strategy* involves design choices by firms that influence the availability and accessibility of information about products and prices. We develop decision support models for suppliers to set prices for online mechanisms with different transparency levels. We then empirically analyze the price levels set by airlines across transparent and opaque online travel agencies. Our results suggest that airlines can increase profit by increasing price differentials or influencing OTA transparency differences. We also discuss application generality and limitations of our results.
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1. Introduction

The Internet revolution has brought about significant changes in the ability of firms to compete for consumers with market information. It has reduced the costs of information search, offering consumers multiple purchasing channels and product options. Sellers are increasingly able to use advanced technologies to reveal, conceal, bias, or distort market information. Prior to the advent of the Internet, a firm's market presence was defined by its product offerings and respective prices. Now, a firm can also strategically design and implement different types of selling mech-

anisms or participate in existing electronic markets to influence *market transparency*, or the availability and accessibility of market information.

E-commerce technology advances are transforming the rules of market information disclosure. In the current technological environment, firms can increasingly manipulate the information they provide to consumers, so they are in a position to strategize in ways that were not possible in the past. The May 10, 2004 issue of *Business Week* magazine identified key industries where electronic commerce rewrote the rules for trading: books, music, travel, real estate, telecommunications, and jewelry. A common thread in these markets is that the Internet has caused a structural increase in the levels of market transparency.

Generally, Internet-enabled increases in market transparency benefit consumers because they are able to better discern the product that best fits their needs at a

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better price. On the other hand, the Internet provides sellers with flexibility to strategically determine the information they will provide to consumers via their selling mechanism. Some organizations have defined their competitive strategy around the design of mechanisms that challenge an existing market transparency regime. For example, in 2001 major U.S. airlines launched an online travel agency (OTA) called Orbitz, claiming that it was the most transparent travel Web site in the market. The Progressive Companies (www.progressive.com), a transportation vehicle insurance company, not only provides information about its insurance products online, but it also provides comparative prices and product characteristics of its competitors. Blue Nile (www.bluenile.com), a prominent cybermediary for jewelry, bases its strategy on educating consumers on the quality characteristics of diamonds. The innovative *transparency strategies* of these firms have allowed them to become leaders in their respective online markets.

We also observe the opposite strategy, where some firms strategically design and implement *opaque* selling mechanisms. For example, based on a niche strategy, Priceline.com (www.priceline.com) introduced a patented "name-your-own-price" mechanism that only reveals product and price information after the consumer has committed to purchase at a certain price. Hotwire, a similarly opaque mechanism, was launched by U.S. major airlines a few years later to compete in this niche market.

Sellers can also influence market transparency by selling their products in existing market exchanges. For example, if a firm decides to participate in an exchange that offers products from competitors, it is providing market transparency because consumers are able to compare the firm's prices with those of the competition. Such is the case of most major airlines, which post their travel offers and prices on multiple reservation systems and OTAs, so travel agencies and travelers can make product and price comparisons. In contrast, Southwest Airlines sells its tickets only through its own airline portal (www.southwest.com) or phone-based reservation service.

In this paper, we provide a decision support approach that firms can use to develop a *transparency strategy* based on mechanism design and price setting. We capitalize on earlier work that models the impact of market transparency on consumers to provide a stepwise methodology which can lead to effective transparency strategies [19]. This approach will allow managers to make joint strategic decisions regarding the transparency levels and prices with which they will compete. The rest of this paper is organized as follows. In the next section, we provide a theoretical argumentation about the need for a methodology that supports the design of selling mechanisms based on the impact of market transparency on consumers. In the third section, we present our decision support approach. In the fourth section, we provide an illustrative example of how this approach can be used to set transparency levels and prices, by empirically analyzing historical sales and prices of transparent and opaque OTAs. We discuss and interpret our primary findings in the fifth section, and then conclude with contributions, limitations and opportunities for future research.

2. Literature review

In this section, we conceptualize market transparency and its impact on consumers, based on existing literature in the IS, marketing, finance, and economics literature. Then we discuss the implications for the design of Internet-based selling mechanisms.

2.1. What is market transparency?

Market transparency is defined as the level of availability and accessibility of information about products and market prices. Firms influence the potential for market transparency by investing in technologies for product distribution and information revelation. Market transparency is influenced by the underlying technological infrastructure of online and offline distribution channels and the degree to which data are integrated across channels [10,38]. Market transparency may also depend on the digital versus non-digital attributes of the product. Generally, the higher the digital attributes, the higher is the potential for market transparency in the Internet channel [20].

Existing IS research on data and information quality assumes that information completeness and accuracy are desired outcomes [27]. If this assumption is valid, we should observe a homogeneous and high level of market transparency across online markets, as sellers exploit the transparency potential of the Internet. However, many firms capitalize on their ability to distort, bias, and conceal information in their favor [22]. Therefore, in this paper we assume that market transparency is not necessarily the desired outcome. Rather, depending on a firm's strategy, it will set a desired level of *accuracy*, *bias*, and *completeness* of information and design its online selling mechanisms accordingly. Therefore, we depart from the notion that higher market transparency is better, and instead we assume that firms consider the trade-offs of revealing and concealing different types of market information.

Market transparency can be broken down in terms of the type of information disclosed. We will focus on product and price information, which are important drivers of a consumer's purchase decision [3]. *Product transparency* is related to the revelation of product attributes and quality information, while *price transparency* is related to information about market prices, such as price quotes and historical transaction prices. A more transparent market for consumers will result from greater transparency in one or both of these dimensions. Next, we examine the possible impacts of product and price transparency based on existing theory and research.

2.1.1. 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 [5,36]. In this literature, price transparency takes multiple dimensions depending on the information disclosed, such as order flow, transaction history, and price quotes [4,32,35].

Price transparency is not only related to information about market prices, but also to information that may help buyers and sellers ascertain the price at which they are willing to trade [15]. For example, *order flow* in financial markets provides clues about the tension between demand and supply. Likewise, in air travel, information about available seats on a flight may provide similar clues. Therefore, we conceptualize price transparency in terms of information that allows market participants to discover the prices at which they are willing to trade.

For posted-price selling mechanisms, existing research suggests that it may not be in the firm's interest to fully inform consumers about market prices. By having more price information, consumers' sensitivity to prices may increase [21,31] and they may become aware of lower-priced alternatives [40], creating downward price pressures. In addition, firms will lose information advantages and the consequent ability to charge price premiums [3]. Therefore, there are trade-offs to be made, because while a price-transparent mechanism may attract more buyers, there is a potentially negative effect due to better informed consumers.

2.1.2. Product transparency

In the context of Internet-based sales, marketing studies have found that lower search costs for product information decrease consumers' sensitivity to prices, strengthen attitudes toward a retail Web site, and increase consumer retention [16,21,31]. In contrast,

Johnson and Levin [26] found that consumers may view a product with suspicion upon the absence of information about a salient attribute. These findings are in line with the economic rationale that information about product characteristics and quality can improve market efficiency [1], because buyers are better able to find the product that best meets their needs. However, there are trade-offs to be considered, as Lewis and Sappington [30, p. 310] suggest:

> "In deciding how much to allow potential buyers to learn about their tastes for a supplier's product, the supplier faces a fundamental trade-off. By endowing buyers with very precise knowledge of their tastes for a supplier's product, the supplier can create extra surplus by improving the match between buyers' preferences and their consumption patterns. Through price discrimination, the supplier can capture some of the surplus; but she will generally have to yield some of the surplus to the privately-informed buyers. On the other hand, if she provides little or no information to consumers about their idiosyncratic valuations for a product, a supplier may be able to extract nearly all the surplus of the 'average' buyer. But there is less surplus to extract when consumption patterns are not finely tailored to true preferences."

2.2. Implications for the design of online selling mechanisms

The literature review above suggests that most firms will benefit by displaying product information, while strategically distorting or concealing price information to their benefit. However, there are two practical constraints. First, while the Internet channel provides flexibility regarding the information that can be provided to consumers, the design decisions in the product and price transparency dimensions are not necessarily independent in practice. If a selling mechanism offers information about multiple products, consumers expect to see the corresponding prices in order to make a purchase decision. Moreover, unless the product is a commodity such that the lowest priced offer will be chosen, consumers will demand product information to effectively compare prices across competitors.

Second, different distribution channels may have different technological levels, which may limit the ability to integrate and homogenize information across channels. Therefore, in many market environments there may be different levels of market transparency at one

time. An Internet-based transparency strategy may require investments for technology innovation or upgrades to existing technologies to enable the desired levels of product and price transparency, or investments in distribution to exert control over structural market transparency levels.

The air travel industry provides a representative example [19,20]. In addition to the traditional travel agencies and airline-specific channels such as reservation offices and airline portals, the Internet allowed the emergence of the OTA channel in the 1990s, where incumbents and new participants capitalized on existing e-market technologies and reservation systems to distribute airline tickets online. Many players like Expedia (www.expedia.com) and Travelocity (www.travelocity.com) penetrated the market early by taking advantage of existing computer reservation systems (CRSs) and global distribution systems (GDSs) to sell tickets online. Their mechanisms provided much more product and price information to consumers than traditional offline channels. However, the use of legacy reservation systems technology to power their search engines structurally set the product and price transparency levels of their mechanisms, with limited flexibility to modify their Web site designs in the product and price transparency dimensions.

On the other hand, in 2001 five U.S. major airlines reintermediated the OTA market with Orbitz (www.orbitz.com), an OTA that bypassed the legacy reservation systems to offer more priced itineraries [12,22]. Thanks to advanced technologies for the construction of a travel itinerary, Orbitz introduced a matrix display which shows in one screen the lowest prices by airline and by number of stopovers. Since then, other OTAs have made significant investments to upgrade their mechanisms to match the transparency level provided by Orbitz.

Meanwhile, opaque mechanisms like Priceline.com (www.priceline.com) and Hotwire (www.hotwire.com) emerged, which concealed product and price information until the customer made a contract-blind bid to purchase the ticket. In exchange for this opaqueness, travelers are expected to bid at a lower price than the normal retail price level. Their opaqueness was a vertical differentiation strategy intended to provide these lower-priced tickets as inferior substitutes. In other words, they sought to differentiate price-sensitive leisure travelers from business travelers and others who care about arrival times and itinerary details. (Note: We thank an anonymous reviewer for the insights that helped us formulate transparency strategy as a form of differentiation based on the information disclosed to the consumer.) Since Orbitz introduced a new transparency regime in the industry, these opaque Web sites have recently shifted their strategies and entered the competition for higher transparency. In early 2005 Hotwire switched strategies to offer opaque, semi-opaque, and transparent search request results. Likewise, Priceline.com matched the matrix display of Orbitz, although consumers can still opt to make a bid through the opaque "name-your-own-price" mechanism. Most recently, meta-search engines such as Kayak (www.kayak.com) have emerged that display fares across multiple OTAs and airline portals to provide the most comprehensive set of priced itineraries, once again challenging existing market transparency levels.

The OTA industry example shows that due to industry conditions and existing technologies, market transparency will vary across online competitors, so suppliers are faced with the complex decisions to price and set transparency levels of their own selling mechanisms. The inherent complexity of these joint decisions may explain why up to this point there is little research and application of an integrated transparency strategy. But the problem is even more challenging for airlines in published pricing markets. In the U.S. market, for example, airlines are able to publish fares through the GDSs, effectively setting market prices and commissions. Travel agencies are mostly left with the intermediation task of distributing these prices to the consumers. Yet, the dynamic experimentation in market transparency by existing and new OTAs leaves the airlines with the overwhelming task of pricing strategically across mechanisms with different transparency levels. Individual airlines generally price homogeneously across transparent sites, including Orbitz, Expedia and Travelocity. They also occasionally sell distressed seat inventory at lower price levels via opaque mechanisms, such as Hotwire or Priceline.com. Based on our experience in the industry and through extensive conversations with pricing managers, it appears to us that these practices are based on sound intuition, at best, not models and theory.

Next, we provide a methodology to support decisions that suppliers face regarding price setting across online mechanisms with different transparency levels. We approached the complexity of the problem by seeking a robust yet practical methodology in three ways. First, we broke down the problem based on a supplier's need to price and set transparency levels of different mechanisms, and the need to consider this problem in a competitive context. Our analysis focuses on the former by modeling one supplier that distributes a product across two online mechanisms, and we leave the

latter as an opportunity for future research. Second, we conceptualized the impact of market transparency based on a *model of relative demand functions*, which allowed us to derive relative optimal prices and transparency levels across mechanisms, without having to derive the specific impacts on consumers of different levels of information. Third, we further broke down the problem of understanding the relationship between prices and transparency levels. To this end, our methodology first derives optimal relative prices across mechanisms with fixed transparency levels. We then show how these guidelines can also be used by suppliers to set or influence relative transparency levels across mechanisms given fixed price levels.

3. A decision support approach for online transparency strategy

Based on earlier work to model the impact of market transparency on consumer demand [19], we propose an approach for suppliers to set prices and influence transparency levels across mechanisms consisting of the following steps:

- **Step 1:** Estimate a demand function for the product.
- **Step 2:** Estimate the difference in the demand functions across two online selling mechanisms.
- **Step 3:** Set relative prices based on the difference in the demand functions. Alternatively, modify the transparency levels to influence the relative demand functions.

Next, we describe these steps in more detail.

3.1. Step 1: estimating a demand function for airline tickets

The first step is to specify a demand model to assess how demand may vary across online selling mechanisms with different transparency levels. For that purpose, suppliers can use historical sales and prices. The supplier should seek a demand model specification that best fits the data. This choice may vary depending on the industry or context where the decision tool is being applied. For air travel, there are well developed models of air travel demand that typically use either a linear or log-linear model [2,6,34,41]. According to the literature, linear and log-linear models work well in this applied context for the following reasons [33]. First, both the linear and log-linear models have been used extensively to model air travel demand and price elasticities, so they provide a nice benchmark for the

results in this study. Second, linear models have been used because they provide simple estimates with easily interpretable results, while log-linear models are capable of modeling non-linear air travel demand. And third, very few studies of air travel demand have tested more than one specification, yet different functional forms can lead to significantly different elasticity results. Thus, in order to test a few functional forms for demand, and in the interest of tractability and relevance of our methodology to the OTA industry case, as well as usability in practice, we use the linear and log-linear demand specifications.

3.2. Step 2: estimating differences in demand across selling mechanisms

3.2.1. Linear demand

In linear demand models, the impact of market transparency on demand can be expressed in terms of the impact on the base demand or on the price elasticity of demand. (See Fig. 1.) The *base demand* is defined as the demand at price $p=0$, or the set of consumers that has a positive valuation for the good. Consumers' decision to purchase from an online store may be influenced by its transparency level. The base demand for an online store will consist of consumers that are willing to buy the product based on the information provided. *Price elasticity of demand* is a measure of consumers' sensitivity to prices, and is defined as the percent change in demand due to a percent change in price.

Based on these possible impacts, we developed a model of the relative optimal transparency levels and prices that a firm should adopt to maximize profits and revenues, based on a linear demand model of the form $x(p)=\lambda_0-\lambda_1 p$, where λ_0, $\lambda_1>0$. The parameters λ_0 and λ_1 characterize the *y*-intercept or base demand and the steepness of the demand function, respectively; p represents the price of the good. We assume that market transparency impacts either the base demand λ_0 or the price elasticity of demand, which is a function of λ_1.

3.2.2. Non-linear demand model

We model the transparency strategy problem for a non-linear relationship between demand and price using the Cobb–Douglas or log-linear demand function $x(p,\mathbf{v})=Ap^{-\eta}\mathbf{v}^\kappa$, where A is a constant, $\eta>0$ represents the price elasticity of demand, and $\mathbf{v}$ is a vector of control variables, each to the power of their respective values in vector κ. In this model, the impact of market transparency is on the price elasticity of demand η. (See Fig. 2.)
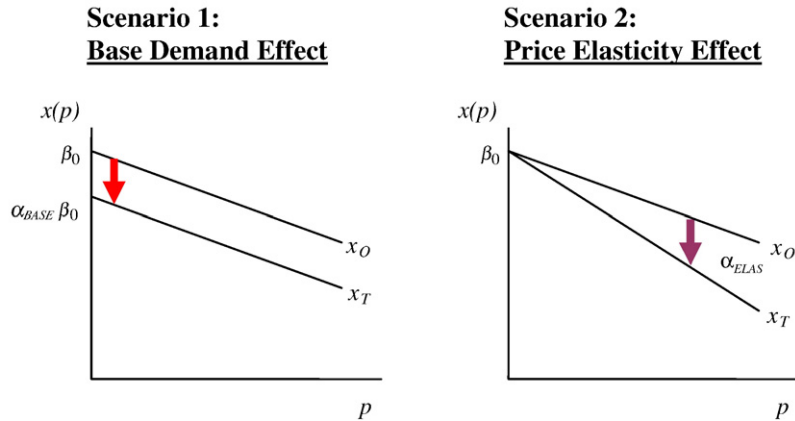
Fig. 1. Two selling mechanisms with different transparency levels: linear demand. Note: This figure illustrates the difference in the demand functions x_O and x_T of two selling mechanisms due to differences in their transparency levels. The impact can be on the base demand or on the price elasticity of demand, represented by the parameters α_{BASE} and α_{ELAS}.

3.3. Step 3: setting relative prices based on transparency levels

3.3.1. Modeling preliminaries and assumptions

We modeled the profit and revenue maximization problem in a scenario where a supplier distributes the product via two online mechanisms with different levels of market transparency. We assume that the supplier has the ability to price-discriminate across mechanisms. For example, in most market segments U.S. airlines have the power to set market fares, which are posted and distributed via GDSs to both online and offline travel agencies. Airlines also typically set the prices at which they will sell distressed inventory via opaque mechanisms such as Priceline.com and Hotwire.

Recall that a supplier can influence market transparency by setting the transparency level of its own selling mechanisms, by price-discriminating across mechanisms, or by participating in an existing market exchange. For simplicity, we model the firm's participation in an exchange in terms of price setting. If the price is infinite, there is no participation, and otherwise the price determines the supplier's presence in the channel or sales outlet. Our methodology first seeks to formulate optimal prices given fixed levels of transparency. We will then show how the supplier can use these results to evaluate and change the transparency levels of the selling mechanisms.

Since we consider two selling mechanisms in the online channel, we assume that there are no major differences in their distribution costs and technological levels. Therefore, we assume a marginal distribution cost c that is the same across mechanisms. In addition, we assume that the gross demand functions are the same

for the two mechanisms, except for any differences caused by the different transparency levels. This assumption is particularly applicable to the online retail environment and even more to the role of information brokerage of OTAs, where service quality is largely determined by the information provided and the extent to which it is presented in a user-friendly manner.

Finally, we assume that the quantities demanded across selling mechanisms are interdependent, that is, the quantity demanded through one mechanism is dependent not only on its own-price, but also on the price of the competing mechanism [29]. This assumption is necessary because, as opposed to product differentiated markets where independence may be a more reasonable assumption, in this case the product sold is the same and the only source of differentiation is the information provided about it. For example, in the OTA industry some consumers shop in both transparent
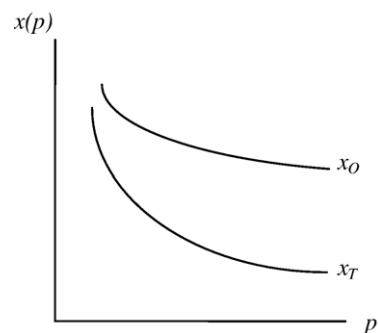

Fig. 2. Two selling mechanisms with different transparency levels: non-linear demand. Note: This figure illustrates the difference in price elasticity of non-linear demand between two online selling mechanisms with different transparency levels.

and opaque OTAs [14]. Therefore, it is likely that the degree of differentiation through information disclosed is not enough to warrant an assumption of independence. We accomplish this by setting an upper bound for total demand $\bar{X}$, such that a decrease in demand via one mechanism is picked up by the other one. Next, we provide the modeling results for the linear and log-linear demand models.

3.3.2. Linear demand and profit maximization

Suppose the two selling mechanisms exhibit different levels of market transparency. Mechanism T is transparent, while mechanism O is less transparent or *opaque*, with respective demand functions, $x_T(p_T) = \alpha_{BASE}\beta_0 - \frac{\beta_1}{\alpha_{ELAS}}p_T$ and $x_O(p_O)=\beta_0-\beta_1 p_O$. The boundary condition of total demand $\bar{X}=x_T+x_O$ models the interdependence of demand across the two mechanisms. This modeling choice is in contrast with Choi [13], who models interdependent demands with an additional term or cross-price effect in the linear demand function. In our case, this boundary condition is sufficient to model the cross-price effect of interdependent demands in terms of demand shifts, while reducing the modeling complexity that arises with an additional cross-elasticity term in the linear function. The limitation is that we assume total demand is fixed, but since we are interested in the relative prices and transparency levels, this is not a significant obstacle in our analysis. Parameters α_{BASE} and α_{ELAS} are the relative impacts of market transparency on demand. (See Fig. 1.) If market transparency has no impact on the base demand, $\alpha_{BASE}=1$, and if there is no impact on price elasticity then $\alpha_{ELAS}=1$, the demand functions are the same across mechanisms.

The case where $\alpha_{BASE}\neq 1$ and $\alpha_{ELAS}=1$ is analogous to *spatial horizontal product differentiation models under linear demand* [37], where a seller serves two markets and consumers' reserve prices have an identical uniform distribution based on heterogeneous tastes. Greenhut and Ohta [24] and Hoover [25] have modeled the transportation costs between two markets, such that the respective demand functions are linear and parallel. For two mechanisms with different transparency levels, the analogous *transportation cost differential* stems from the relative search costs for product or price information, and the consequent "utility distance" from the ideal product or the *purchase mismatch* that consumers will suffer upon purchase.

On the other hand, if $\alpha_{BASE}=1$ and $\alpha_{ELAS}\neq 1$, the effect of market transparency is on the elasticity of demand [16,21,31]. This case approximates a *vertical differentiation effect due to market transparency*, where base demands across mechanisms are independent but the elasticity of demand is either higher or lower for one mechanism at all price points in the demand curve. Also, since by construction α_{BASE} affects the coefficient of the own-price, this case is representative of well-behaved linear demand models of vertical product differentiation, where the impact of product differentiation is not only reflected in the cross-price effect, but also in the coefficient of the own-price [39].

The supplier's profit function is $\pi(p_T, p_O, x_T, x_O, C)= p_T x_T(p_T)+p_O x_O(p_O)-C(x_T, x_O)$, subject to $\bar{X}=x_T+x_O$, where $C(x_T,x_O)$ is a cost function and the marginal cost is $C'(x_T, x_O)=c$. The firm will select a price for each mechanism such that marginal revenues equal the marginal cost c [37]. Solving these profit-maximizing conditions under the total demand constraint leads to our first proposition:

Proposition 1. (The linear demand–profit maximization proposition)

Under linear demand, the profit-maximizing firm will set

$$p_o^* = \frac{\beta_O + c\beta_1}{2\beta_1} \tag{1}$$

and

$$p_T^* = \frac{\alpha_{BASE}\alpha_{ELAS}\beta_O + c\beta_1}{2\beta_1} \tag{2}$$

This proposition suggests that the supplier should price-discriminate across selling mechanisms if market transparency has an impact on either the base demand or on the slope of the demand curve. This general result is in line with the analogous models of price discrimination, but provides additional new insights on the effect of market transparency on consumer demand.

The combined effect of differences in product and price transparency across selling mechanisms may be multi-dimensional. For example, higher price transparency may have a positive effect on the base demand but a negative one on the price elasticity or slope of the demand curve. In addition, the design of the interface may influence specific dimensions of transparency, among them completeness, bias, and accuracy of information. Despite this inherent complexity, the results in the proposition suggest that it is the *net multiplicative effect* of transparency on the base demand and price elasticity that the firm should be concerned about. This net effect can be seen in Eq. (2), where the factor $\alpha_{BASE}\alpha_{ELAS}$ differentiates the two optimal prices. If the two effects are both negative (i.e., $\alpha_{BASE}<1$, $\alpha_{ELAS}<1$) or positive (i.e., $\alpha_{BASE}>1$, $\alpha_{ELAS}>1$), the price of the

transparent mechanism should be respectively lower or higher than the opaque mechanism. On the other hand, if the effects are not in the same direction (i.e., $\alpha_{BASE}<1$, $\alpha_{ELAS}>1$, or $\alpha_{BASE}>1$, $\alpha_{ELASE}<1$), such as in the scenario where a more price-transparent mechanism increases base demand but makes the demand curve steeper, the relative strength of these two effects will determine the sign of the differential between the two prices.

So far, this profit maximization model for linear demand provides a theoretically optimal relationship between transparency levels and prices across mechanisms. However, in practice this optimal relationship may still be difficult to derive: it depends on prior knowledge of transparency's impact in terms of α_{BASE} and α_{ELAS}. The estimation of these parameters will remain a challenge, as we will show in our empirical analysis. Yet, some firms may have enough information and analytical capability to develop demand function estimations, by market mechanism, while controlling for other site-specific effects. Even then, in an environment such as the air travel industry where OTA mechanisms experiment with the information they provide and in change the customer's interface, estimating these parameters may be a continuously moving target. We have observed this to be the case since 2001: each one of the major OTAs has made at least one significant change to their search result interface in a period of four years.

In the next section, we will provide some practical guidelines by deriving optimal prices and transparency levels based on historical sales. These practical guidelines are limited to the problem of *revenue maximization*, which is typical of capital-intensive industries with fixed capacities, such as the airline industry. The advantage of these managerial guidelines is that the derived optimal prices do not depend on the parameters α_{BASE} and α_{ELAS}.

3.3.3. Linear demand and revenue maximization

If the goal is to maximize revenue, the objective function is $R(p_T, p_O, x_T, x_O)=p_T x_T(p_T)p_O x_O(p_O)$. Solving the revenue maximization problem yields optimal prices, $p_O^* = \frac{\beta_0}{2\beta_1}$ and $p_T^* = \frac{\alpha_{BASE}\alpha_{ELAS}\beta_0}{2\beta_1}$. The ratio of these prices or *optimal price ratio* is

$$P^* = \frac{p_T^*}{p_O^*} = \alpha_{BASE}\alpha_{ELAS}. \tag{3}$$

Let $S=x_T/x_O$ be the *share ratio* or the relative share of sales between transparent and opaque mechanisms T and O.

Proposition 2. (The share-base demand proposition)

The optimal share ratio is equal to the base demand ratio, thus $S^*=\alpha_{BASE}$.

Proof. Substituting the demand functions for each mechanism and the respective optimal prices in $S=x_T/x_O$ leads to $S^*=\alpha_{BASE}$.

This proposition suggests that the effect of transparency on base demand can be observed in the share ratio *if* the prices are optimal. Therefore, if the relative transparency levels and prices are not optimal, the relative shares of the two selling mechanisms will not be optimal. In a sense, by selecting a transparency level for each selling mechanism, a revenue-maximizing firm indirectly sets the relative base demands, and any attempt to decrease the price of one mechanism to artificially increase sales will be sub-optimal. Next, we characterize this finding in terms of each possible scenario of the impact of market transparency on demand. (See Fig. 1.)

Case 1. base demand scenario

A possible scenario in which market transparency affects only the base demand is one where the difference in information provided affects the relative search costs. For example, providing easily accessible information on seat preferences for a flight makes it easier for travelers who care about seat preference, but possibly not others. Also, it is likely that this information will not influence the inherent distribution of reserve prices. The following proposition summarizes the implications for relative prices and shares if the impact of market transparency is on the base demand.

Proposition 3. (The linear base demand proposition)

If there is no impact of market transparency on price elasticity and the supplier price-discriminates across selling mechanisms to maximize revenue, the share ratio will be equal to the price ratio, thus $P^*=S^*$.

Proof. If there is no impact on price elasticity, then $\alpha_{ELAS}=1$. Substituting $S^*=\alpha_{BASE}$ and $\alpha_{ELAS}=1$ in Eq. (3) leads to $P^*=S^*$.

Here, information on sales for each mechanism will be sufficient for the firm to assess whether the relative prices and transparency levels are optimal. For example, if the firm observes $P>S$, it can modify the relative transparency levels or prices to improve revenues until the optimality condition $P^*=S^*$ applies.

Case 2. price elasticity scenario

In some situations, transparency may have an impact on sensitivity to prices. Assuming there is no impact on

the base demand, the following proposition characterizes optimal prices and channel shares:

Proposition 4. (The linear demand–price elasticity proposition)

If there is no impact of market transparency on base demand and the supplier price-discriminates across selling mechanisms to maximize revenue, the mechanisms will both have sales of $x_T^* = x_O^* = \frac{\beta_O}{2}$, so $S^* = 1$.

Proof. Recall from Proposition 2 that $S^* = \alpha_{BASE}$. Since for this scenario the demand base is not affected, then $\alpha_{BASE} = 1$, so it follows that $S^* = 1$. By replacing $\alpha_{BASE} = 1$ and $c = 0$ in Eq. (2), the resulting optimal prices $p_O^* = \frac{\beta_O}{2\beta_1}$ and $p_T^* = \frac{\alpha_{ELAS}\beta_O}{2\beta_1}$ lead to equal demands $x_T^* = x_O^* = \frac{\beta_O}{2}$.

The Linear Demand-Price Elasticity Proposition (P4) suggests that the firm should price such that each mechanism has equal sales volume. It also suggests that the sum of sales will be equal to the base demand of the opaque market. For example, if the firm observes that sales are lower for the transparent mechanism so that $S < 1$, then it should modify the relative transparency levels or prices across selling mechanisms until the optimality condition $S^* = 1$ holds.

3.3.4. Log-linear demand and profit maximization

If demand is of the form $x(p,\mathbf{v}) = Ap^{-\eta}\mathbf{v}^\kappa$, $x(p,\mathbf{v}) = Ap^{-\eta}\mathbf{v}^\kappa$, then the impact of market transparency can be captured in the price elasticity of demand η. As in the linear demand model, we use the boundary condition $\bar{X} = x_T + x_O$ to take into account the interdependence of demand across the two mechanisms, in contrast with the multiplicative term that captures the cross-price effect as in Choi [13]. Here again, since our focus is on analyzing the relative prices and transparency levels, it is reasonable to hold total demand constant in order to conveniently capture demand shifts rather than cross-price effects.

Let the demand for transparent mechanism T be $x(p_T,\mathbf{v}) = Ap_T^{-\eta+\alpha_{ELAS}}\mathbf{v}^\kappa$, and the demand for opaque mechanism O be $x(p_O,\mathbf{v}) = Ap_O^{-\eta}\mathbf{v}^\kappa$, where η is the price elasticity of demand for the opaque channel and α_{ELAS} represents the difference in price elasticity of demand between the two mechanisms. If $\alpha_{ELAS} < 0$, the net effect of market transparency is an increase in price elasticity, while if $\alpha_{ELAS} > 0$, the net effect is a decrease in price elasticity. With this setup, α_{ELAS} represents the combined impact on base demand (i.e., a shift upward or downward of the non-linear demand curve with respect to price), and a change in the slope of the demand curve

at any given price point, as illustrated in Fig. 2. The profit equation is

$$\pi(p_O, p_T) = Ap_T^{-\eta+\alpha_{ELAS}+1}\mathbf{v}^\kappa + Ap_O^{-\eta+1}\mathbf{v}^\kappa - cA\left[p_T^{-\eta+\alpha_{ELAS}}\mathbf{v}^\kappa + p_O^{-\eta}\mathbf{v}^\kappa\right] \tag{4}$$

subject to $\bar{X} = x_T + x_O$

In order to solve Eq. (4), we solve the profit-maximizing conditions of equating marginal revenues to marginal cost c, as motivated by Formby et al.'s [17] modeling structure for monopoly retailers. The resulting optimal prices are $p_T^* = \frac{c(-\eta+\alpha_{ELAS})}{-\eta+\alpha_{ELAS}+1}$ and $p_O^* = \frac{-c\eta}{-\eta+1}$. Hence, the *optimal price ratio* is

$$P^* = \frac{p_T^*}{p_O^*} = 1 + \frac{\alpha_{ELAS}}{-\eta(-\eta+1+\alpha_{ELAS})} \tag{5}$$

Eq. (5) shows that the optimal price ratio is a function of α_{ELAS}. In other words, the optimal relative prices are a function of the relative transparency levels and the consequent difference in price elasticity between the two mechanisms. From Eq. (5) we derive the following proposition:

Proposition 5. (The log-linear demand–price elasticity proposition)

The profit-maximizing prices for two selling mechanisms with log-linear demand and different transparency levels are:

i. *If market transparency increases (decreases) price elasticity and demand for the transparent selling mechanism is elastic, its price should be lower (higher) than that of the opaque mechanism.*
ii. *If market transparency increases (decreases) price elasticity and demand for the transparent selling mechanism is inelastic, then its price should be higher (lower) than that of the opaque selling mechanism.*

Proof. Demand for the transparent mechanism is elastic if $-\eta+\alpha_{ELAS} < -1$ and inelastic if $-\eta+\alpha_{ELAS} > -1$. If market transparency increases price elasticity, then $\alpha_{ELAS} < 0$. If $-\eta+\alpha_{ELAS} < -1$, then $P^* < 1$. Alternatively, if $-\eta+\alpha_{ELAS} > -1$, then $P^* > 1$. If market transparency decreases price elasticity, $\alpha_{ELAS} > 0$. If $-\eta+\alpha_{ELAS} < -1$, then $P^* > 1$. Alternatively, if $-\eta+\alpha_{ELAS} > -1$, then $P^* < 1$.

The Log-Linear Demand–Price Elasticity Proposition (P5) suggests that the optimal relative prices across selling mechanisms should be set not only based on the relative price elasticities, but also on the absolute value

of the price elasticity of the transparent mechanism. For example, if the price elasticity of the transparent mechanism is greater than that of the opaque mechanism ($-\eta+\alpha_{ELAS}<-\eta$) and its demand is elastic ($-\eta+\alpha_{ELAS}<-1$), then its price should be lower. If instead the demand of the transparent mechanism is inelastic, its price should be higher.

3.3.5. Summary

In this section, we have derived guidelines for a supplier to jointly set relative prices and transparency levels across two online selling mechanisms. We performed the analysis for linear and non-linear demand scenarios. The broad result is that if market transparency affects demand, the supplier should set prices accordingly. We offer specific guidelines for several scenarios: a linear demand scenario where market transparency affects the base demand, and linear and non-linear demand scenarios where market transparency affects price elasticity. In the next section, we apply this methodology to analyze prices and transparency levels in the OTA industry.

4. Application: the online air travel distribution channel

In this section, we use the decision support approach developed in the previous section to evaluate the relative transparency levels and prices across U.S. OTAs with different transparency levels. In this industry, airlines typically have the power to set prices across different channels, and they can influence transparency levels based on ownership stakes in OTAs (e.g., major U.S. airlines used to own Orbitz and Hotwire) or through negotiation of pricing agreements with the OTAs.

The data in this analysis is part of a large dataset of airline tickets sold for 46 city-pairs (e.g., Boston–Denver) during the period September 2003 to August 2004. The dataset contains tickets sold by all major airlines via OTAs, and it does not include tickets sold directly by airlines through their web portals. Each record contains information about tickets sold for a given origin–destination, date of travel, booking date, and inventory class. Tickets sold were further aggregated by OTA type, advance purchase time, and season. OTA types were *transparent* and *opaque*. The *transparent OTA type* included OTAs such as Travelocity and Expedia, which provide numerous priced tickets from multiple carriers for a given search request, including the airline name and the itinerary. The *opaque OTA type* included OTAs that return price and product details only after the purchase has been made, such as Priceline.com and Hotwire. These two agency types differ in both their product and price transparency levels.

The dataset contains the booking date for each ticket, which was subtracted from the travel date to derive the advance purchase time. *Advanced purchase time* is expressed in weeks before departure up to 20 weeks. The *seasons* were *peak* and *off-peak*; peak season tickets were sold for travel in June, July, August 2003 and December 15, 2003 to January 14, 2004. Based on this aggregation level, the dataset for this analysis contained 5160 records, but we excluded peak season records because they are more likely to incorporate supply constraints, so the final dataset contained 2580 records.

4.1. Objectives and rationale

Our goal in this analysis is to illustrate the applicability of the decision support approach proposed above. For that purpose the objectives are to estimate an air travel demand function, to estimate differences in the demand function across transparent and opaque OTAs, and to determine whether the observed relative prices and transparency levels are in line with the above propositions and guidelines. We perform this analysis by estimating industry-level demand functions for transparent and opaque OTAs.

The rationale for this level of analysis is twofold. First, we are interested in estimating with a reasonable level of accuracy the demand functions for the transparent or opaque mechanisms. An industry-level estimate of the difference in demand functions across OTA types seems plausible. Moreover, the industry-level analysis is likely to provide a comprehensive picture of how demand behaves across these two OTA types. On the other hand, information is not lost by using average industry-level prices because of the inherent price-matching behavior of airlines. At the level of detail of the dataset, for a given origin–destination, advance purchase date, travel date, and fare type, major airlines tend to match each other's prices. This price-matching behavior was also observed by Chellappa and Kumar [11], and is consistent with the collusive behavior that may arise in industries where electronic markets enable comparison of prices across suppliers [9].

This price-matching behavior in the airline industry also suggests that, as a whole, we can view the industry as one large single firm setting homogeneous prices for the same product but potentially price-discriminating across transparent and opaque OTAs. Therefore, this level of analysis is consistent with our modeling assumptions, where we consider a supplier that distributes its product via two mechanisms with different transparency levels.

Table 1
Air travel demand model variables

Variable type	Variable	Definition
Dependent	QUANTITY	Tickets sold
Independent	PRICE	Average price paid
Control	INCOME	Gross product per capita of origin cities
	ADVPURCH	Time of purchase in weeks before flight departure
	HUB	Dummy variable for hub operation at the origin city.
	OTATYPE	Dummy variable for OTA type (0 = Opaque, 1 = Transparent)

Note: The data source for U.S. income per capita was the U.S. Bureau of Economic Analysis (BEA) time-series data for metropolitan statistical areas (www.bea.doc.gov).

4.2. Estimating the air travel demand function

The proxy for demand is the amount of tickets sold, or QUANTITY. The independent and control variables are PRICE, INCOME, ADVPURCH, HUB and OTATYPE. (See Table 1.)

4.2.1. Control variables

Income is a standard predictor in demand models [8]. We estimated the variable INCOME based on the income per capita of the Metropolitan Statistical Area (MSA) of the origin city. The MSA is therefore a proxy for the origin city's *catchment area*, or the region populated by travelers that use the city's airport or airports. We hypothesize that INCOME has a positive impact on demand.

We also included the control variable ADVPURCH, which is a measure of the time of purchase in weeks before departure. This variable captures the dynamic changes in prices throughout the reservation period of a flight, which is a common practice in airline pricing. This practice is founded on the intensive use of revenue management systems to forecast demand and to make price adjustments accordingly. It is reasonable to assume that as a flight departure approaches, demand will be higher. Airlines typically price-discriminate by charging higher prices closer to departure. Therefore, we hypothesize that ADVPURCH has a negative relationship with demand. Hub operation in the origin city (HUB) may have a different impact, as travelers enjoy more non-stop service to many destinations. We hypothesize that HUB has a positive impact on demand. Finally, we include a dummy variable OTATYPE for each OTA type. This captures the effect of the difference in product and price transparency, and also other agency-specific effects on demand. Table 2 provides descriptive statistics of these variables.

Based on this demand model, we used econometric methods to estimate the linear model

$$QUANTITY = CONSTANT + \beta_1 PRICE \\ + \beta_2 INCOME + \beta_3 ADVPURCH \quad (6) \\ + \beta_4 HUB + \beta_5 OTATYPE + \varepsilon$$

and the log-linear model

$$QUANTITY = e^{CONSTANT} \cdot PRICE^{-\eta} \cdot INCOME^{\beta_2} \\ \times ADVPURCH^{\beta_3} \cdot e^{\beta_4 HUB} \cdot e^{\beta_5 OTATYPE} \quad (7) \\ \times e^{\varepsilon}$$

The results are shown in Table 3. The results suggest that the model with the best fit is the log-linear demand model, with an R^2 of 66%. In contrast the linear model had an R^2 of 28%. Thus, we selected the log-linear specification for the analysis. We next present regression diagnostics for multicollinearity, endogeneity, and heteroskedasticity.

4.2.2. Multicollinearity

Table 4 shows the correlation matrix of the variables in the model. No significant correlations were found between the independent variables. The mean VIF inflation factor was 1.19, and the highest VIF factor was 1.27, so we conclude that multicollinearity is not a concern.

4.2.3. Heteroskedasticity

The classic ordinary least squares (OLS) regression model assumes that the variances of the error terms are constant. We performed a Breusch–Pagan [7] test at the model level and the hypothesis of homoskedasticity or constant variance was rejected ($\chi^{2P} = 101.25$, $df = 1$, $p < 0.01$). One possible source of *heteroskedasticity*, or error term variance for different groups of observations, is the income level, since there may be a higher variance in demand for airline tickets as income per capita

Table 2
Descriptive statistics for model variables

Variables	Mean	Std. Dev.	Min	Max
QUANTITY	94.37	224.11	1	2662
PRICE	$141.65	$81.215	$27	$801
INCOME (000s)	$37.63	$4.12	$31	$47
ADVPURCH (weeks)	10.5	5.77	1	20
HUB (dummy)	0.82	0.38	0	1
OTATYPE (dummy)	0.71	0.45	0	1

Notes: N = 2580 records with aggregated information on tickets sold for 42 city-pairs.

Table 3
Air travel demand model: linear and log-linear regression results

Variables	Linear		Log-linear	
	Coeff.	Std. error	Coeff.	Std. error
Main effects				
PRICE	−0.50***	0.05	−1.13***	0.05
CONSTANT	157.24***	42.90	6.48***	0.83
Control variables				
INCOME	1.97**	1.00	0.86***	0.22
ADVPURCH	−1.52***	0.66	−1.49***	0.03
HUB	22.42**	10.74	0.07	0.06
OTATYPE	147.50***	8.82	2.58***	0.05
R^2 (Adj. R^2)	27.8% (27.7%)		65.8% (65.8%)	

Notes. Model: OLS. $N = 2580$. Signif: $* = p < 0.10$, $** = p < 0.05$, $*** = p < 0.01$.

increases. We performed a Goldfeld and Quandt [18] test for heteroskedasticity due to *INCOME*, and we could not reject the null hypothesis of homoskedasticity at a significance level of $p < 0.10$. But given that there is heteroskedasticity at the level of the model, going forward we report the results with White's [42] robust estimators of standard errors.

4.2.4. Endogeneity

In demand models, it is possible that prices are endogenously determined as a function of demand and other variables, which may result in misspecification of the model due to a correlation between *PRICE* and the residuals. This problem may be particularly apparent when comparing two OTAs that differ significantly in their market transparency levels, because airlines may intentionally price-discriminate to segment the market and avoid cannibalization across OTAs. In particular, airlines may be concerned about the revenue dilution that can occur if business travelers opt to search for fares in an opaque Web site which may be intended for more price-sensitive buyers.

To address this issue, we introduced two instrumental variables for *PRICE* to perform a *two-stage least squares* (2SLS) regression. The requirements for the instrumental variables are that they are correlated with the dependent variable and with the original independent variable for which they are substituted, but not highly correlated with the error terms [23]. These variables are:

- *STAGELENGTH*: We define this as the distance in air miles between two cities. Stage length influences the variable costs of airline operation, which in turn may influence price setting.
- *MKTCONC*: We measured the market concentration of each city-pair using the Herfindahl index, which is the sum of squares of the market shares of the

different airlines that serve a city-pair. This variable measures the ability of airlines to charge price premiums depending on their monopolistic or oligopolistic power in each city-pair.

We confirmed that these instrumental variables had desirable properties of correlation, as discussed earlier. Table 5 shows the results of the 2SLS log-linear regression with robust standard errors. Note that the 2SLS estimation procedure yields the instrumental variables estimator, *IV-ESTIMATOR*. We will use this model and approach in the next section to estimate the price elasticity for the transparent and opaque OTAs.

4.3. Estimating differences in demand across OTA types

Based on the decision support approach presented earlier, for the log-linear demand model we are interested in estimating the difference in price elasticity between the two OTAs. To estimate this difference, $QUANTITY = e^{CONSTANT} \cdot PRICE^{-\eta + \alpha_{ELAS}OTATYPE} \cdot INCOME^{\beta_1} \cdot ADVPURCH^{\beta_2} \cdot e^{\beta_3 HUB} \cdot e^{\varepsilon}$ was used, where η is the price elasticity of the opaque mechanism and α_{ELAS} is the price elasticity differential of the transparent OTA with respect to the opaque OTA. The log transformation of this equation is:

$$\begin{aligned} \ln QUANTITY = {} & CONSTANT - \eta \ln PRICE \\ & + \alpha_{ELAS}OTATYPE \cdot \ln PRICE \\ & \times \beta_1 \ln INCOME \\ & + \beta_2 \ln ADVPURCH \\ & + \beta_3 HUB + \varepsilon \end{aligned} \qquad (8)$$

Note that we have not included the cross-price effect between OTA types. In travel models, a common problem is that there is a high correlation between own and cross-prices [28]. In our case, we found a correlation of 0.85 between these variables in our data, which can be explained by the fact that airlines set fares across distribution channels, and the fares fluctuate in similar fashion across OTAs. However, since a price change in one OTA is typically reflected in a price change in other OTAs,

Table 4
Correlation matrix of logged variables

ln VARIABLE	QUANTITY	PRICE	INCOME	ADVPURCH	HUB
PRICE	0.09				
INCOME	0.04	0.07			
ADVPURCH	−0.57	−0.19	0.00		
HUB	−0.00	0.02	−0.41	0.00	
OTATYPE	0.51	0.41	0.02	−0.00	0.02

Table 5
2SLS log-linear regression results

Variables	Coefficient	Robust standard error
Main effects		
IV-ESTIMATOR	−1.21***	0.07
CONSTANT	6.77***	0.80
Control variables		
INCOME	0.89***	0.21
ADVPURCH	−1.49***	0.03
HUB	0.07	0.06
OTATYPE	2.61***	0.06
R^2 (Adj. R^2)	65.79% (65.72%)	

Notes. Model: 2SLS with White's robust estimation for error covariance matrix. $N = 2580$. The instrumental variables for *PRICE* are *STAGELENGTH* and *MKTCONC*, which meet the requirements we stipulated earlier for appropriate instrumental variables. 2SLS estimation yields an instrumental variables estimator, *IV-ESTIMATOR*. Its coefficient is an unbiased and consistent estimator of the price elasticity of demand. Signif: $* = p < 0.10$, $** = p < 0.05$, $*** = p < 0.01$.

the *PRICE* variable in our model captures the effect of price changes on industry demand, which is what we are intending to measure. Therefore, consistent with Kling [28], the omission of a cross-price effect is not a problem for our objective to determine the industry-level difference in demand across transparent and opaque OTAs.

Based on Eq. (8), the negative coefficient of ln *PRICE* in the econometric model is the price elasticity of the opaque OTAs or η, while the coefficient of $OTATYPE \cdot \ln$ *PRICE* is the estimate of the differential in price elasticity of the transparent OTAs with respect to the opaque ones, or α_{ELAS}. The estimation results are shown in Table 6. The estimate of the price elasticity of the opaque mechanism was positive and significant ($\eta = 1.63$, robust SE = 0.08, $p < 0.01$). In addition, the estimate of the price elasticity differential was positive and significant ($\alpha_{ELAS} = 0.55$, robust SE = 0.01, $p < 0.01$).

Because $\alpha_{ELAS} > 0$, we conclude that transparent OTAs have a lower price elasticity than opaque OTAs. Based on this result, it is likely that the effect of higher market transparency in the OTA market is a *decrease* in the price elasticity of demand. However, it is also possible that there are other factors that may affect the elasticity differential, so we cannot attribute all of the difference to market transparency.

4.4. Setting relative prices and transparency levels across OTA types

To jointly set transparency levels and prices based on the log-linear demand model, we need to apply the guidelines of the Log-Linear Demand-Price Elasticity Proposition (P5). Therefore, it is necessary to determine

whether the net difference in price elasticity between the transparent and opaque OTAs is positive or negative, and whether demand for the transparent OTA type is elastic. Regarding the former, we found that $\alpha_{ELAS} > 0$, so the net effect is a lower price elasticity. Regarding the latter, the estimate of $-\eta + \alpha_{ELAS} = -1.63 + 0.55 = -1.08$, which suggests that the price elasticity of the transparent OTAs is elastic. We performed a Wald test [23] for the null hypothesis $-\eta + \alpha_{ELAS} = -1$, and we rejected the null hypothesis ($F = 11.69$, $df = 1$, 2574, $p < 0.01$). So we conclude that the demand for the transparent OTAs is elastic. Therefore, based on the guidelines of the Log-Linear Demand-Price Elasticity Proposition (P5), the price of the transparent OTAs should be higher relative to the price of opaque OTAs.

5. Discussion

The observed average prices are \$98.70 for the opaque OTAs and \$159.04 for the transparent OTAs, resulting in an average 38% discount on the price of airline tickets sold through the opaque OTAs. These relative average prices by OTA type are in line with our finding that because the opaque OTAs have more elastic demand and demand for the transparent OTAs is elastic, the transparent OTAs should be priced higher. On the other hand, applying the estimated values of η and α_{ELAS} to the *optimal price ratio equation* (Eq. (5)), the resulting price ratio is $P^* = 5.22$. Therefore, based on the modeling guidelines, airlines can price-discriminate by offering discounted prices in the opaque OTAs by up to $1 - 1/P^* = 81\%$. Perhaps airlines can test price increases

Table 6
2SLS log-linear regression with price elasticity differential

Variables	Coefficient	Robust standard error
Main effects		
IV-ESTIMATOR	−1.63***	0.08
OTATYPE · ln PRICE	0.55***	0.01
CONSTANT	8.75***	0.86
Control variables		
INCOME	0.86***	0.22
ADVPURCH	−1.48***	0.03
HUB	0.06	0.06
R^2 (Adj. R^2)	64.36% (64.29%)	

Notes. Model: 2SLS with White's robust standard error (SE) estimation for error covariance matrix. $N = 2580$. The instrumental variables for *PRICE* are *STAGELENGTH* and *MKTCONC*, which meet the requirements we stipulated earlier for appropriate instrumental variables. 2SLS estimation yields an instrumental variables estimator, *IV-ESTIMATOR*. Its coefficient is an unbiased and consistent estimator of the price elasticity of demand. Significance: $* = p < 0.10$, $** = p < 0.05$, $*** = p < 0.01$.

in the transparent OTAs and monitor the cross-shopping behavior to see if positive net revenue is achieved.

Alternatively, the transparency levels of the OTAs can be modified to further search for revenue opportunities. In particular, there may be a revenue opportunity by reducing the transparency differential between transparent and opaque OTAs. This reduction in the transparency differential will lead to a lower optimal price ratio that is more in line with the current price differential between the two OTA types. Airlines can exert pressure for the transparency levels of OTAs to converge by setting and maintaining a price differential that forces OTAs to strategize effectively with their own transparency levels to compete.

From a broader perspective, the analysis of transparency levels and prices for transparent and opaque OTAs illustrates a key insight that the decision support approach provides for the case of log-linear demand: Relative prices between two online selling mechanisms depend not only on their transparency-driven price elasticity differential, but also on whether demand is elastic or inelastic. Just as firms will benefit from lowering prices in the presence of elastic demand, firms will also benefit from having a lower price for the selling mechanism with higher price elasticity, provided that its demand is elastic.

6. Conclusions

In this section, we conclude with our academic and practical contributions, and summarize limitations and future research directions.

6.1. Contributions to theoretical knowledge and managerial practice

In many electronic markets, firms are in a position to implement *transparency strategies* that capitalize on the potential to design their own electronic selling mechanisms, to participate in an existing electronic market, and to price-discriminate across channels based on the information provided to consumers. This research directly supports these kinds of efforts through its modeling and analysis, and the methodology that it offers to create effective pricing strategies. We have focused our analysis on scenarios where a supplier has the power to set online market prices, which is the case of airlines and the OTA industry.

Transparency strategies reflect the effort of firms to achieve differentiation based on the information disclosed. In turn, this differentiation should be accompanied by corresponding relative prices that reflect the differences in consumer tastes across mechanisms.

Based on our empirical analysis, we find that airlines can increase the price differential across mechanisms to increase revenues. We also showed that pressure OTAs have pressure to adjust transparency levels given the prices imposed by airlines. In particular, given that the price discount for opaque OTAs was lower than would be expected from our model, we conclude that opaque sites like Hotwire and Priceline.com were under pressure to approach the transparency levels of the major transparent OTAs Orbitz, Expedia, and Travelocity. Because opaque OTAs depend on the prices offered by airlines, they may be at a competitive disadvantage if the price differential relative to transparent OTAs is not enough to attract price-sensitive consumers. This finding is consistent with our observations of the behavior of Hotwire and Priceline.com, which have shifted their strategy to increase the transparency level of their selling mechanisms.

Our research also points out that since market transparency affects consumer demand, there is an increasing need for senior managers to establish a tighter organizational links among the IS, marketing, and sales departments of their firms. With better interdepartmental coordination, changes in Web site design can be considered in the context of its possible market impact. Perhaps an overarching effort with *transparency strategy* will facilitate these organizational links, such that there is a clear joint direction for functional and IT departments to follow. In this article, we derived some practical guidelines that managers can use to implement an effective and coordinated transparency strategy for Internet-based selling. We developed a decision support approach that managers can apply to set transparency levels and prices across online selling mechanisms. Our methodology provides specific directional actions that can be taken with relative price and transparency levels in order to maximize profits and revenues, with implications for the joint design of online selling mechanisms and price setting.

6.2. Limitations and future research

There are a number of ways that we can further enhance the methodology that we have offered in this research, which will further overcome some of its limitations. First, our methodology provides support for firms to derive optimal relative prices and transparency levels, but it does not incorporate potential competitive responses. This assumption was reasonable to analyze airline pricing at the industry level, but in future research we can relax the scenario of just one supplier to analyze more competitive market structures.

Second, the data that we have used are from 2003 and 2004, and it will be appropriate for us to continue to

work with updated data to see how airline pricing strategy and consumer sensitivity to channel and mechanism design have changed over time. The changes are likely to be subtle and interesting, and lead us to deeper insights into how the marketplace has been responding to strategic design differences in market transparency for airline tickets. As the manipulation of market transparency becomes more widespread and sophisticated, it is likely that we will begin to see additional design aspects begin to play a role, including further aggregation of airline tickets and fares for consolidated search via meta-search sites such as Kayak.com (www.kayak.com), Sidestep (www.sidestep.com), Farechase (www.farechase.com) and Mobissimo (www.mobissimo.com).

Third, by choosing a time period in which no major economic events or natural disasters occurred, we made a modest effort to control for significant events affecting air travel demand during the time that our data were collected. However, we did not control for industry-specific events such as announcements about the weakening of the finances of specific carriers, news of route-specific fare wars, destabilization of the typical price levels due to new entrants, and strikes affecting individual carriers which may have led to capacity changes for different routes.

Taken together, these observations of the limitations of our current approach and the opportunities for future research suggest that there is an unusually rich and important research agenda that can be pursued in this area. The work is made even more interesting due to the interest that some of the industry leading firms have in pursuing this kind of knowledge to inform their decisions about strategic pricing and transparency strategy.

Acknowledgments

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