

# ONLINE AND OFFLINE DEMAND AND PRICE ELASTICITIES: EVIDENCE FROM THE AIR TRAVEL INDUSTRY

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## ABSTRACT

The Internet has brought consumers increased access to information to make purchase decisions. As markets come closer to perfect information, one of the expected outcomes is an increase in competition. One of the consequences is an increase in the *price elasticity* of demand, or the percent change in demand due to a percent change in price, because consumers are better able to compare offerings from multiple suppliers. In this paper, we analyze the impact of the Internet on demand, by comparing the demand functions in the Internet and traditional air travel channels. We use a data set that contains information for millions of records or airline ticket sales in both offline and online channels. To our knowledge, this is the first study that uses massive sales data to compare consumer demand functions in the two channels. The results suggest that consumer demand in the Internet channel is more price-elastic for both transparent and opaque online travel agencies. We also find that the opaque OTAs are more price-elastic than the transparent OTAs. These results are after controlling for the different mix of business and leisure travelers across these travel agency types. We discuss the broader implications for multi-channel pricing strategy and for the transparency-based design of online selling mechanisms.

**Keywords:** Air travel industry, economics of IS, electronic markets, market transparency, mechanism design, multi-channel strategy, price elasticity, online travel agencies.

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## 1. INTRODUCTION

Classic economic theory suggests that higher availability of information brings markets closer to perfect competition and full market efficiency. In particular, with the proliferation of Internet-based markets, there is an expectation that *frictionless commerce* will emerge, where perfect information about product offers and prices online will lead to higher competition and a subsequent erosion of profits (Brynjolfsson and Smith, 2000). This outcome is likely to manifest itself in two ways:

- Suppliers will engage in price competition and lose their ability to price above marginal costs, leading to lower, less dispersed prices (Bakos, 1997; Brynjolfsson and Smith, 2000).
- Buyers enjoy lower search costs so they are able to make purchases that better fit their needs at a lower price (Bakos, 1997), further fueling competition among suppliers.

Since the advent of the Internet, academics have given a lot of attention to the former, by seeking to understand the impact of the Internet on market prices, and by taking advantage of the massive amounts of price information that can be found online. The results so far have been mixed. Some have found analytical and empirical support for lower prices in the Internet relative to traditional channels (Brown and Goolsbee, 2002; Brynjolfsson and Smith, 2000; Degeratu et al., 2000; Lee, 1998; Zettelmeyer, 2000; Zettelmeyer, et al., 2006). Others, in turn, have found higher prices on the Internet (Bailey, 1998; Lal and Sarvary, 1999) and the existence of price dispersion, which contradicts the *law of one price* expected in the presence of perfect competition (Baye, et al., 2004; Chellappa, et al., 2005; Clemons et al., 2002). Therefore, there is some evidence that, despite the potential loss of information advantages by suppliers and intermediaries, some of the frictions that mitigate head-on, price-based competition will remain.

On the other hand, there is still much research to be done on the latter to understand the demand drivers of changes in equilibrium prices. Market prices are the product of the tension between supply and demand, so understanding how the Internet impacts consumer demand will provide additional insights on the dynamics of competition in an environment where consumers enjoy better access to market informa-

tion. More broadly, there is a need for empirical verification of the impact of the Internet on the demand side.

One of the expected impacts of the Internet on demand is an increase in consumers' sensitivity to prices, due to the increased availability of information about competitive offerings (Lynch and Ariely, 2000; Smith, 2002; Smith, et al., 2001). If indeed there is a higher sensitivity to price changes online, competition will intensify, which may lead to lower margins in the long run. As Porter (2001) suggests, a paradox of the Internet is that as firms make market information widely available, they find it more difficult to capture the benefits in terms of profits. The higher is the price elasticity, the lower should be the optimal price. Not only is a lower price the economically rational decision, but also competitors will be more inclined (sometimes sub-optimally) to reduce prices because the reward in terms of incremental customers is likely to be higher. On the other hand, the winning firms will be ones that use information strategically to compete, by building internal digital systems to estimate the impact of information on consumer demand, and following through with the implications for the design of online selling mechanisms and pricing strategies (Granados, et al., 2008).

We contribute to this line of research by estimating and comparing the industry's demand functions in the offline and online channels, using a data set with information for millions of airline tickets sold in the U.S. market. In our dataset, the *offline channel* represents phone-based or face-to-face reservations via traditional travel agencies for leisure travel, and corporate travel departments and travel agencies, while the *online channel* is related to consumer-direct bookings via online travel agencies (OTAs) such as Expedia and Travelocity. The broad research questions that we examine are:

- What are the differences in price elasticity of demand between the offline and online channels?  
What factors drive these differences?
- What are the implications for pricing, multi-channel strategy, and IT strategy?

Our empirical results provide a new perspective on how the Internet channel leads to less friction by bringing markets closer to perfect information. This is one of the first studies that uses massive industry sales data to estimate price elasticities in the offline and online channels. We have used sales data to esti-

mate price elasticities, which is a more direct method than the multiple studies that estimate online price elasticity based on sales rank (e.g., Brynjolffson, et al., 2003; Chevalier and Goolsbee, 2003; Ellison and Ellison, 2007; Ghose, et al., 2006). We find broad support for the notion that the Internet as a distribution channel is more competitive, based on our findings that price elasticity is higher for *transparent online travel agencies* (OTAs) and *opaque* OTAs relative to the traditional or *offline* travel agency channel. We find these relationships even after controlling for the differences in the mix of travelers that book across these agency types. We were also able to tease out and separate the two major drivers of this higher elasticity online, namely the informational effects on consumers and the difference in the mix of segments that book online vs. offline.

We discuss the implications of these findings for competitive strategy and the link to the design of digital systems and electronic selling mechanisms. If the online channel is more price-elastic, digital systems to support price discrimination across channels are bound to emerge. For example, airlines can invest in inventory management techniques and systems to perform price discrimination across online and offline travel agencies. However, aside from cost-based price discrimination tactics such as charging a fee for offline bookings, air travel prices across channels are relatively homogeneous. Possible reasons are competitive inertia (Miller and Chen, 1994), fear of retaliation from competitors (Gimeno, 1999), or reluctance by airlines to penetrate the online channel lest a more transparent environment will create price pressures and erode profits.

Regarding the design of selling mechanisms, a more intense competitive environment will influence firm strategies as they use information to compete. For example, we find that opaque OTA demand is significantly more elastic than transparent OTA and offline demand, which suggests that the optimal price to be charged should be significantly discounted compared to the retail price (Granados, et al., 2008). This result also suggests that product attribute information can be an important dimension to be considered in the design of selling mechanism. From a broader perspective, firms must consider the impact on demand as they design electronic selling mechanisms and as they price their products across channels.

The rest of the paper is organized as follows. In §2, we provide the theoretical background, hypothe-

ses, and data. In §3, we present the econometric model of air travel demand, and the results of our analysis. In §4, we analyze and discuss our findings. §5 concludes with the implications for academics and practitioners, limitations of this research, and future research directions.

## **2. HYPOTHESES, DATA, AND MODELING PRELIMINARIES**

One of the tenets of frictionless markets suggests that *price elasticity*, the percent change in demand due to a percent change in price, will be higher online than offline, on the basis that the Internet allows consumers to search for information about competitive offerings at a lower cost (Smith, et al., 2001; Alba, et al, 1997) (henceforth referred to as the *frictionless markets hypothesis*). Upon review of the literature, we find that there are nuances that need to be considered in order to test the frictionless markets hypothesis. In this section, we first dissect the possible effects of increased availability of information on demand. Given the multiple possible effects of information on price elasticity, we categorize them as *direct* and *indirect* effects. Direct effects are related to a decrease in search costs for information. Indirect effects are related to the impact of market information on purchase decisions. We then develop hypotheses about the difference in price elasticities across channels and describe the data that was used to test the hypotheses, including some empirical modeling preliminaries.

### **A. Direct Effects**

The Internet reduces the cost of searching for alternative offerings prior to purchase. An example is the emergence of shopbots that perform searches across Internet sites to display, and compare product and price information from different suppliers (Smith, 2002). Indeed, travelers are able to construct larger consideration sets while searching online (Oorni, 2003). In addition, search engines such as Google play an increasingly important role in Internet shopping, serving as a core point of reference for travelers to engage in search.

Buyers are likely to benefit directly from this reduction in search costs, even if the amount of inquiries in the search increases (Bakos, 1997). There is some evidence that suggests consumers in the online travel sector “pocket” these search cost savings, which will in turn have a direct positive effect on de-

mand. Johnson et al. (2004) examined longitudinal click-stream data across leading e-commerce sites for books, compact disks, and air travel services, and found that the amount of online search was quite limited despite the reduction in search costs. In the travel sector, consumers on average make approximately three searches or queries online before purchasing an airline ticket, despite the numerous search sites available (comScore, 2006). Instead, there is some evidence that the lower search costs to search online can lead to reduced search as consumers stick to a search mechanism that has proven to be convenient. In a study unrelated to the travel sector, Lynch and Ariely (2000) performed experiments with an online wine store, and showed that the more transparent the mechanism, the higher was consumer retention. So a reduction in search costs is likely to have a direct positive impact on demand by generating customer satisfaction and repeat business.

## **B. Indirect Effects**

Once consumers have access to market information, they will in turn use it to the extent that it is a valuable input in the purchase process. The *indirect effects* on demand of better informed consumers can be broken down into the impact of information on the purchase decision and on channel selection. In this paper, we examine the impact of product and price information, since these are the main informational elements that differ across offline travel agencies and OTAs.

**Price Information.** Stigler (1961) suggests that in an environment of price dispersion, *information about market prices* allows consumers to find lower prices for a given product or horizontally-differentiated substitutes. For example, Brynjolfsson and Smith (2000) found that prices for books and CDs were lower in the Internet channel than through conventional retailers. This higher ability to effectively compare prices for similar product offers should increase price elasticity, because consumers have a larger consideration set to choose from, or a larger number of substitutes (Brons, et al., 2002).

This rationale implies that for highly differentiated markets, the impact of price comparison capability on price elasticity will not be as high as for commodity markets, because product attributes and brand dilute the weight of the price factor in the decision making process (Degeratu, et al., 2000). For example, in their experiments, Lynch and Ariely (2000) found that cross-store comparison had no effect on price sen-

sitivity for premium wines. Degeratu et al. (2000) compared the price sensitivity of consumers in grocery purchases and found that it was lower online.

**Product Information.** Increased *information about product characteristics and quality* allows consumers to ascertain their valuation of a product with higher precision and find a product that better fits their needs (Akerlof, 1970; Alba, et al., 1997). Other things being equal, product information is likely to lower price elasticity, as consumers focus their search on product characteristics and quality rather than on price. This assertion is founded on *information integration theory* (Degeratu, et al., 2000), which suggests that consumers assign importance weights and values to available search attributes and then add them to make a purchase decision. The weights assigned are relative to the information available. Weights will not be assigned to information that is not available, so to the extent that product and brand information is not available, more weight will be placed on the price factor. Likewise, if more product information is available, less weight will be placed on the price factor.

Product information is likely to reduce price elasticity more in markets with differentiated products, because as consumers are better able to identify products that fit their needs, they will discard other options, effectively limiting the consideration set to the one or few offerings that best fit their needs. Another theoretical argument for this assertion, based on information integration theory, is that when product attribute information is not available, in differentiated markets brand can act as a surrogate for these attributes so the weight on price will not be as high as in markets that are commoditized, where brand matters less (Degeratu, et al., 2000).

**Channel Selection.** The relative information availability about product offers, in addition to other service factors, will also influence *channel selection*. Different service features and information levels lead to partially-separable demand sets in the online and offline channels, or the existence of *offline-only shoppers* and *online-only shoppers*. Jupiter Media Matrix, then a leading Internet research firm, performed a survey of travelers in 2001, less than two years before the booking period in our study, and found that 42% of respondents were *offline-only* shoppers (Regan, 2001). Some travelers (e.g., business travelers) are locked into the offline channel because they place a high value on search time or simply

prefer the added value of an experienced travel agent. Others may not feel comfortable enough with computers to search for an airline ticket online. On the other hand, the same study found that 29% of the respondents were online-only shoppers.

PhoCusWright (2004), a travel consulting and research firm, performed a similar study a few years later—during the booking period of our study—and found that *online-only* shoppers had increased to 45%. Internet-savvy travelers prefer the convenience and availability of numerous offers online in order to make a purchase. Also, since lower search costs do not necessarily lead to more search (Johnson et al., 2004), some consumers may be locked-in to an online search process that has served them well in the past. This effect may be enhanced over time as travelers become more familiar and comfortable with their search options online.

The existence of single-channel shoppers can lead to a difference in the mix of customer segments across channels. Any difference in this mix of customers can at least partially explain differences in cross-channel price elasticities at the aggregate level. In the case of air travel, we can characterize this problem in terms of the mix of business and leisure travelers. Business travelers are less price-sensitive because they have less flexible and more complex travel needs than leisure travelers. Also, because they value time highly, some business travelers are more likely to delegate the search for an airline ticket to a travel agency or a corporate travel department. In contrast, leisure travelers are likely to embrace the benefits of the online channel for search, since they are more price-sensitive and have more flexible requirements to evaluate multiple offers (Clemons, et al., 2002). If leisure travelers are more price-sensitive and they gravitate to the online channel, then this channel selection effect will lead to a higher observed price elasticity of demand online.

**Summary.** Overall, the improvements in the availability of market information on the Internet channel lower search costs, which can lead to an overall increase in demand. In addition, there are three possible indirect effects on price elasticity of demand. Price comparison capabilities will increase price elasticity, product information will decrease price elasticity, and price-sensitive consumers will select a channel that offers easier comparison of product offerings and prices. The net change in price elasticity due to

price and product information will depend on the individual impacts and the degree of differentiation of the product. For highly differentiated products, the impact of product information may even lead to a decrease in price elasticity.

In this study, we examine the impact of these indirect effects through a cross-sectional analysis of price elasticities in the air travel industry. In this industry, the online channel allows fast search of airline offers to consumers, with detailed information on prices and product characteristics. Also, there has been a *channel self-selection effect*, as consumers gravitate either to the offline channel or to the online channel to make their purchase. We next hypothesize about the cross-channel elasticities in the air travel industry, taking into consideration these three effects of market information on the purchase decision.

## B. Hypotheses

We formally define *price elasticity* as  $\eta = \frac{\delta D}{\delta P} \cdot \frac{P}{D}$ , or the percent change in demand  $D$  due to a one percent change in price  $P$ . Demand decreases if price increases for normal goods such as travel, so  $\eta$  will be negative. If  $|\eta| > 1$ , demand is said to be elastic, because there is a higher proportional increase in demand due to a change in price. If  $|\eta| = 1$ , demand is unit-elastic. If  $|\eta| < 1$ , demand is inelastic. We define  $\eta_{TRANSPARENT}$  = price elasticity of transparent OTAs,  $\eta_{OFFLINE}$  = price elasticity of the offline channel, and  $\eta_{OPAQUE}$  = price elasticity of the opaque OTAs

**Offline vs. Transparent OTAs.** The OTA industry has increased the availability of both price and product information for travelers. Depending on the OTA, the number of priced itineraries for a search request can fluctuate, but in most cases the OTAs display multiple priced itineraries that travelers can choose from (Granados et al., 2007). In 2006, Travelocity, Expedia and Orbitz had approximately 80% market share among all OTAs in the U.S., and these sites typically provide at least 50 search results for a given search request.

These transparent OTAs offer information to consumers that used to be in the hands of airlines and travel agencies before the Internet became a viable distribution channel. The travel industry has legacy digital systems and electronic market platforms for the distribution of airline tickets. Travel agencies and

airlines use electronic reservation systems for phone-based and face-to-face interaction with travelers, which are integrated to sophisticated internal pricing and inventory management systems that airlines use to price each seat on a given flight. But transparent OTAs brought direct access to the information by creating new electronic selling mechanisms, consisting of a more user-friendly interface of the legacy distribution infrastructure. So rather than receiving just one or a handful of quotes from a travel agent or airline representative, travelers can browse through the numerous itineraries on their own. Travel agents and airline representatives do not necessarily have the capability or the incentives to bring full transparency, because it is not possible by phone to relay all the possible information about the options that are displayed via the CRSs. Also, they have incentives to minimize search costs to maximize sales, in addition to the need to satisfy a consumer's request.

Our theoretical review suggests that product and price information represent opposite forces on price elasticity of demand. First, price comparisons enabled by transparent OTAs such as Orbitz, Travelocity, and Expedia will lead to higher price elasticity relative to the offline channel. Second, product information will have a positive impact on demand by reducing price elasticity. The frictionless markets hypothesis suggests that the net effect will be a higher price elasticity, such that the effect of price information prevails. This leads to:

- **Hypothesis 1a (The Leisure Segment Transparent OTA Price Elasticity of Demand Hypothesis).** *In the leisure segment, air travel demand for transparent OTAs is more price-elastic than offline demand.*
- **Hypothesis 1b (The Business Segment Transparent OTA Price Elasticity of Demand Hypothesis.)** *In the business segment, air travel demand for transparent OTAs is more price-elastic than offline demand.*

Regarding channel selection, we find that there is a higher share of business travel offline than online. This makes sense because business travelers are more time-sensitive and likely to delegate the search task to an offline travel agency. In contrast, leisure travelers are more price-sensitive, so they are more likely to value and utilize online search capabilities. The higher share of leisure travelers in the online channel will lead to a higher price elasticity of demand.

Based on the expected larger impact of price comparison on price elasticity and the higher share of

leisure travelers online, we hypothesize that, overall, air travel demand for transparent OTAs will be more price-elastic than offline demand. This leads us to assert:

- **Hypothesis 1c (The Overall Offline vs. Online Transparent OTA Price Elasticity of Demand Hypothesis).** *Air travel demand for transparent OTAs is more price-elastic than offline demand, so that  $|\eta_{TRANSPARENT}| > |\eta_{OFFLINE}|$ .*

**Offline vs. Opaque OTAs.** As the OTA industry emerged, some players attempted niche strategies to differentiate themselves from the OTAs that simply translated reservation information from the consumers. Opaque OTAs such as Hotwire and Priceline.com developed an opaque strategy by providing no information on the airline name and itinerary in exchange for a discount on the price price.

Offline agencies typically provide one or two price quotes over the phone or face-to-face, similar to the single price offer of an opaque site like Hotwire. On the other hand, offline travel agencies provide the airline and itinerary while opaque sites conceal them. This difference in the product information is likely to drive the difference in price elasticity of demand between these two channels. In line with information integration theory, we hypothesize that the lack of information about the airline carrier and the itinerary details will lead to a higher price elasticity for the opaque OTAs relative to the offline channel, as consumers turn their attention to price comparison shopping (Degeertu, et al, 2000), and as they discount the value of an offer due to the lack of product information (Johnson and Levin, 1985). This leads to:

- **Hypothesis 2a (The Leisure Segment Opaque OTA Price Elasticity of Demand Hypothesis).** *In the leisure segment, air travel demand for opaque OTAs is more price-elastic than offline demand.*
- **Hypothesis 2b (The Business Segment Opaque OTA Price Elasticity of Demand Hypothesis).** *In the business segment, air travel demand for opaque OTAs is more price-elastic than offline demand.*

Regarding channel selection, a low percentage of time-sensitive business travelers will book on the opaque channel. Indeed, in our dataset we find that 4% of business travelers that book online purchased through opaque OTAs. The consequent higher share of leisure travelers booking in the opaque channel should lead to a higher price elasticity relative to the offline channel. The magnitude of the channel selection effect is likely to be high, because very few business travelers are willing to forego information about

a travel itinerary. We hypothesize that:

- **Hypothesis 2c (The Overall Offline vs. Online Opaque OTA Price Elasticity of Demand Hypothesis).** *Air travel demand for opaque OTAs is more price-elastic than offline demand, so that  $|\eta_{OPAQUE}| > |\eta_{OFFLINE}|$ .*

**Transparent vs. Opaque OTAs.** Opaque OTAs provide at most one or two priced offerings, with no information on product characteristics. Hotwire's opaque mechanism typically provides one priced offer with no details of airline name or itinerary. Priceline.com does not provide price or product information prior to purchase in its name-your-own price mechanism. Instead, transparent OTAs typically provide at least 50 priced offers with airline name and itinerary details. An inverse argument of the frictionless markets hypothesis, that less market information is likely to decrease price elasticity, suggests that the lack of information on competitive offerings will lead to a lower price elasticity for opaque OTAs. Therefore, we hypothesize that opaque OTA demand will be less price-elastic because they are concealing information about competitive offerings and substitute products will be concealed.

- **Hypothesis 3a (The Leisure Segment Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis).** *Leisure air travel demand for opaque OTAs is less price-elastic than that of transparent OTAs.*
- **Hypothesis 3b (The Business Segment Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis).** *Business air travel demand for opaque OTAs is less price-elastic than that of transparent OTAs.*

Regarding channel selection, there are very few business travelers in the opaque channel, and it is likely that the more price-sensitive leisure travelers are willing to use the opaque mechanisms. Therefore, price-sensitive travelers who self-select the opaque OTAs will increase the price elasticity of the opaque channel.

Based on the above analysis of informational impacts and channel selection, the net effect is not straightforward. The lack of competitive offers in the opaque channel is likely to drive down price elasticity, while the self-selection of price-sensitive online customers into the opaque channel should have the opposite effect. We hypothesize that the inverse of the *frictionless markets hypothesis* will prevail, so the net result is a reduction in price elasticity. This leads to:

- **Hypothesis 3c (The Overall Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis).** *Air travel demand for opaque OTAs is less price-elastic than that of transparent OTAs, so that  $|\eta_{OPAQUE}| < |\eta_{TRANSPARENT}|$ .*

### C. Data

We analyzed price elasticities in the online and offline channels at the industry level using a database of airline tickets sold by travel agencies through *global distribution systems* (GDSs) for travel between September 2003 and August 2004. The GDSs support electronic sales of airline tickets on the Internet, as well as sales via traditional travel agencies that provide the service through face-to-face or phone interactions. 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 47 U.S. origin-destination city pairs. We aggregated tickets by *city-pair* (i.e., origin city and destination city), channel, travel purpose, type of OTA, and time of purchase. Tickets were classified as *online* if they were sold by an OTA, and *offline* otherwise. The tickets were also classified based on whether the purpose of the trip was for business or leisure. Within the online channel, an OTA was classified as *transparent* if the search results for the OTA included the airline name and itinerary (e.g., Orbitz, Travelocity, and Expedia), and *opaque* if they did not (e.g., Priceline.com and Hotwire). At the time of the data collection, both Hotwire and Priceline.com had selling mechanisms that concealed both product and price information. Upon a search request, Hotwire provided a price quote with no airline name or itinerary. Priceline.com had the patented name-your-own-price mechanism where consumers bid for a ticket with no prior information on market prices or product offerings.

Data were available for a booking window of 20 weeks prior to departure. Our booking window for the data set spanned from March 2003 to August 2004. We further classified the tickets based on peak season (June, July, August, and December 15-January 15) or off-peak season. Because the number of peak season tickets sold reflect supply rather than demand patterns due to capacity constraints, we excluded peak season observations from this study. These exclusions reduced the sample to 5,160 records with aggregate information for 1.32 million tickets.

Table 1 presents descriptive statistics of the data set by trip purpose and channel. The average quantities are lower for leisure than for business, as expected based on the lower share of online sales at the time. The average prices were also lower for leisure than for business, as expected.

**Table 1. Descriptive Statistics**

VARIABLE	STATISTIC	LEISURE SEGMENT	BUSINESS SEGMENT
Quantity (passenger bookings)	Mean	392.68	121.42
	St. Dev.	1,318.67	679.08
	Range	1 – 35,810	1 – 10,499
Price (one-way, US\$)	Mean	142.16	262.34
	St. Dev.	69.90	211.25
	Range	15 – 409	88 – 1,863
<b>Notes:</b> For each segment, this table contains the average of quantity and price for all city-pairs and channels throughout the 20-week booking window. $N = 5,160$ . Sample is for the departure period September 2003 to August 2004.			

#### D. Demand Modeling Preliminaries

We consider the demand model  $DEMAND = f(Price, Channel, Controls)$ , where  $DEMAND$  is estimated in terms of quantity sold, and price is the average price in dollars of the tickets sold for a given city-pair, channel, segment, and season. (See Table 2.)

**Table 2. Air Travel Demand Model Variables**

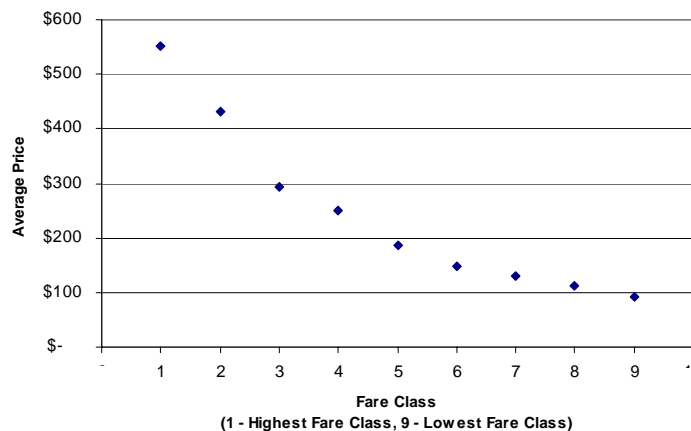
TYPE	VARIABLE	DEFINITION
Dependent	<i>QUANTITY</i>	Tickets sold, to represent $DEMAND$ .
Main effects	<i>PRICE</i>	Average price paid in dollars.
	<i>OFFLINE,</i> <i>TRANSPARENT,</i> <i>OPAQUE</i>	Dummy variables for offline, transparent, and opaque OTAs.
	<i>ADVPURCH</i>	Time of purchase in weeks before the flight's departure.
Control	<i>SEGMENT</i>	Business vs. leisure travel dummy.
	<i>CROSSPRICE</i>	Price of the alternative channel.
	<i>ORIGIN</i>	Origin city dummy variables for city-pairs.

#### Variables

**Price.** The variable  $PRICE$  captures market prices across channels, segments, and city-pairs. It also captures prices throughout the booking period of a flight, which can fluctuate due to airlines' dynamic pricing practices. The pricing structures in the airline industry are based on fare types that are tied to the

time of booking, such that the closer in time to departure, the higher is the price in the market. (See Figure 1.) In addition, inventory management systems selectively open and close fare types for sale based on demand forecasts (Talluri and van Ryzin, 2004). Ideally, these two are synchronized, such that seats for sale are allocated to travelers with a higher willingness-to-pay (e.g., business travelers) as the departure time approaches. However, forecasting systems are not perfect so sometimes low fare seats will be offered at a lower price for sale close to departure. This practice has increased over-time in response to macro-economic shocks like the 2001-2002 global economic crisis and to low-cost carriers' every-day low-price business models (Chellappa, et al., 2005). Low fare offers close to departure can be implemented through reductions in fares that are promoted and advertised, or simply by opening inventory for sale to lower fares. Both pricing structure and inventory management policies are reflected in our *PRICE* variable, because we capture prices for each week before departure. Prices in the dataset are by week(s) before departure, therefore, we explicitly capture the different prices that arise due to yield management practices for any given city-pair across the booking periods. This is a significant improvement compared to many airline demand studies that average out prices for the whole booking period (Brons, et al., 2001; Oum, et al., 1993).

**Figure 1. Average Price of Fare Classes**



**Note:** This figure shows the average fares for each fare class in the dataset of this study. The higher the fare class, the higher is the average price.

**Channel Dummy Variables.** We include dummy variables *TRANSPARENT* and *OPAQUE* for the transparent and opaque OTAs respectively, to account for their fixed effects relative to demand in the off-

line channel (*OFFLINE*). These fixed effects include service-related differences across channels and the maturity of the Internet as a distribution channel for travel services. To get a sense of what the net effect of these factors may be, we took into account the share of online sales in the travel industry during the period of our study. In 2004, the main period of flight departures in our data set, 27% of leisure air travel sales were made online (eMarketer, 2005), while the remaining 73% were made offline. Therefore, we should observe a negative fixed effect, which is in line with the lower share of online sales relative to the offline channel during that period.

**Advance Purchase.** A pervasive and well-recognized difference between consumers is the urgency of purchase (Stigler, 1964). This urgency of purchase and its impact on demand is captured in the variable *ADVPURCH*, which measures advanced purchase time in weeks before departure. This variable is not typically present in academic studies of air travel demand due to the difficulty in getting the detailed data, yet it is an important driver of demand variation. The closer to departure, the higher is the demand, as the sense of urgency increases. Therefore, we should see a negative relationship between *ADVPURCH* and demand.

**Segment.** We include a dummy variable for leisure vs. business travel, based on segmentation techniques by the corporate sponsor of this study. We expect lower demand for business travel relative to leisure, considering the distribution of seats that airlines assign to business and leisure travelers.

**Cross-Channel Prices.** The variable *CROSSPRICE* captures the price of the alternative channel. *CROSSPRICE* has an opposite effect on demand than price, so its relationship with demand is positive.

**Origin City Dummy Variables.** We assigned eight dummy variables for the origin cities in our sample, with the exception of New York, which we have assigned as the base case for comparison. They are: Boston, Denver, Detroit, Los Angeles, Memphis, Minneapolis, San Francisco, and Washington. These origin city dummies allow us to control for local demand drivers that are otherwise not included, such as income level effects, local travel preferences, regional competition, hub structure of the local airports, and the business activity in each local economy.

### 3. EMPIRICAL MODEL SPECIFICATION AND RESULTS

We now present our econometric model of air travel demand, together with correlation, endogeneity, and heteroskedasticity diagnostics. We then lay out and discuss the results of the estimated air travel demand model, and analyze the difference in price elasticity between the transparent OTAs, the opaque OTAs, and the offline channel.

#### A. The Log-Linear Air Travel Demand Model

Airline demand models in the transportation literature typically use the linear and log-linear specifications (e.g., Bhadra, 2003; Oum, et al., 1993; among others). With this in mind, we decided to employ a multiplicative specification, as follows:

$$QUANTITY = e^{\beta_1} \cdot PRICE^\eta \cdot TRANSPARENT^{\beta_2} \cdot OPAQUE^{\beta_3} \cdot ADVPURCH^{\beta_4} \cdot SEGMENT^{\beta_5} \cdot (1) \\ \cdot CROSSPRICE^{\beta_6} \cdot \prod_j ORIGIN_j^{\sigma_j} \cdot e^\varepsilon, \forall j \neq \text{New York}$$

In this model,  $\eta$  is the price elasticity of demand.  $ORIGIN_j$  represents dummy variables for each origin city  $j$  except the base case of New York. We also excluded the *OFFLINE* dummy variable in the estimation and used it as another base case for comparison. The elasticities for *ADVPURCH*, *SEGMENT*, and *CROSSPRICE* are represented by  $\beta_4$ ,  $\beta_5$ , and  $\beta_6$ . The log transformation of Equation 1 is:

$$\ln QUANTITY = \beta_1 + \eta \ln PRICE + \beta_2 \ln TRANSPARENT + \beta_3 \ln OPAQUE + \beta_4 \ln ADVPURCH \quad (2) \\ \beta_5 \ln SEGMENT + \beta_6 \ln CROSSPRICE + \sum_j \sigma_j \ln ORIGIN_j + \varepsilon, \forall j \neq \text{New York}$$

We estimated Equation 2 using ordinary least squares (OLS) regression. The log-linear model had an appropriate fit with an adjusted  $R^2 = 74.7\%$ , compared to the linear model OLS regression, which had an adjusted  $R^2 = 17.2\%$ . This result confirms the better fit of the log-linear model for air travel demand.

#### B. Model Diagnostics

**Multicollinearity.** See Table 3 for pair-wise correlations. There is one correlation of concern between two of the regressors, *PRICE* and *CROSSPRICE*, which is 0.82. This correlation is likely due to the common practice of airlines to price homogeneously across channels through wholesale distribution via GDSs (Chellappa and Kumar, 2005).

**Table 3. Pairwise Correlations for the Empirical Model Variables**

	1	2	3	4	5	6
1. <i>QUANTITY</i>						
2. <i>PRICE</i>	0.29***					
3. <i>ADVPURCH</i>	-0.45***	-0.10***				
4. <i>SEGMENT</i>	-0.51***	0.38***	0.00			
5. <i>CROSSPRICE</i>	0.05*	<b>0.82***</b>	-0.15***	0.00		
6. <i>TRAN</i>	0.17***	0.10***	-0.00	0.00	0.23***	
7. <i>OPAQ</i>	-0.49***	-0.46***	0.00	0.00	-0.21***	-0.47***

**Notes:** Significance: \* =  $p < 0.10$ ; \*\* =  $p < 0.05$ ; \*\*\* =  $p < 0.01$ . Correlations for *ORIGIN* dummy variables excluded for brevity; the highest correlation between *ORIGIN* dummies and any other variable was 0.37. The bold font points out the high (> 0.80) pair-wise correlation.

Further examination of this correlation led us to exclude the variable *CROSSPRICE* from the model for three reasons. First, when *CROSSPRICE* was included, the coefficient of  $\ln PRICE$  was positive and that of  $\ln CROSSPRICE$  negative, which would wrongly suggest an upward sloping demand curve. Therefore, the inclusion of this variable leads to inaccurate estimates of the variable of interest. Second, the variance inflation factor (VIF) of *CROSSPRICE* in the log-linear OLS regression was 22.03, which is above the threshold that is econometrically tolerable (Kennedy, 1998). Third, the correlation between *CROSSPRICE* and *QUANTITY* is low ( $\sigma = 0.05$ ,  $p = 0.07$ ), and the regression including *CROSSPRICE* only added 1.5% to the model fit  $R^2$  statistic, compared to the regression without it. The rationale for this lack of explanatory power of *CROSSPRICE* may be that travelers seldom engage in cross-channel shopping.<sup>1</sup> This is because the cross-channel prices are relatively homogeneous in the U.S. air travel market (Chelappa and Kumar, 2005; PhocusWright, 2004), so there is little incentive to engage in multi-channel shopping to find lower prices. Therefore, given the high risk of misspecification of the model and the low contribution of *CROSSPRICE* as an explanatory variable, we report results for a reduced model that excludes this variable in spite of its apparent *prima facie* relevance.

**Heteroskedasticity.** We performed a Breusch-Pagan (1979) Lagrange multiplier test for heteroskedasticity at the level of the model, against the fitted values of  $\ln QUANTITY$ . We rejected the hypothesis of

<sup>1</sup> A study by comScore-Yahoo! (comScore, 2006) provides face value to this claim. They found that only 12% of travelers search online and booked their tickets offline in 2006.

constant variance or homoskedasticity ( $\chi^2 = 177.47$ , d.f. = 1,  $p < .01$ ). We conclude that there is heteroskedasticity in the econometric model, although this test cannot diagnose exactly what its source is. One potential source of heteroskedasticity is *PRICE*. Demand in higher price ranges may exhibit higher variation due to the heterogeneity of consumers (both business and leisure travelers) at high prices. Based on the observation that *PRICE* might account for heteroskedasticity, we ran a second test by Goldfeld and Quandt (1965). We consider a known source of heteroskedasticity (i.e.,  $\text{var}[\varepsilon_i] = \sigma_i^2 = \sigma_i^2 z_i$ , with  $z_i = \text{PRICE}$ ). We were not able to reject the null hypothesis of homoskedasticity ( $p < .17$ ), however. To correct for other possible unknown sources of heteroskedasticity, we estimated the regressions using the Huber-White robust estimators for the standard error.

**Endogeneity.** In demand models, there is an inherent risk of endogenously-generated prices, which can lead to model misspecification due to a high correlation between prices and the residuals. This correlation between prices and the residuals can yield inconsistent estimators. In particular, in the air travel industry there is simultaneity in the determination of demand and prices, because airline pricing managers set prices based on existing bookings and historical sales, yet sales are affected by prices.<sup>2</sup> We addressed this potential problem of endogeneity by performing a two-stage least squares (2SLS) regression with instrumental variables for *PRICE*. We used the following instrumental variables:

- *STGLENGTH*: An often-used predictor of price is *stage length*, 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). The impact of stage length on prices is two-fold. First, it is directly related to variable costs such as fuel and crew expenses. Second, for shorter distances air travel prices will

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<sup>2</sup> The risk of misspecification due to endogeneity of prices is lower for log-linear demand specifications, based on the following rationale. Consider an airline monopolist in a market with marginal cost  $c$ , and  $\text{DEMAND} = f(\text{PRICE}, \varepsilon)$ . Assuming the firm can observe  $\varepsilon$ , with *linear demand*  $\beta_0 - \beta_1 \text{PRICE} + \varepsilon$ , it will set  $\text{PRICE}^* = \frac{\beta_0 + \beta_1 c + \varepsilon}{2\beta_1}$  (Villas-Boas and Winer, 1999). Notice that the optimal price is dependent on the error term, which illustrates the misspecification risk due to the correlation between the market price and the error term. With *log-linear demand*  $A \cdot \text{PRICE}^\eta \cdot \varepsilon$  though, the monopolist will set  $\text{PRICE}^* = \frac{\eta c}{\eta + 1}$ . In this case, the optimal price is not dependent on  $\varepsilon$ , only on the price elasticity of demand. So if the log-linear model is a good representation of air travel demand, there is less concern that endogenous prices will lead to biased estimation results.

be affected by prices in alternate modes of transportation such as trains and automobiles (Brons, et al., 2002).

- *MKT\_CONC*: The *degree of market concentration* in a specific city-pair influences market prices (Borenstein, 1992). We measured market concentration at the city-pair level using the Herfindahl index, or the sum of squares of the market shares of the different airlines.
- *HUB*: Hub operations have been associated with higher prices in the industry, so we incorporate a *HUB* variable to indicate whether the city-pair origins and destinations are hubs of an airline.

The *HUB* variable also controls for the effect on price of multi-market competition (Gimeno, 1999), where airlines set a foothold in a competitor's hub to retaliate and deter behavior in their own markets. This multi-market competition can have an effect on prices, as competitors are able to tacitly collude by retaliating against others that attempt to reduce prices in competitive hubs.

### **C. Results**

We re-ran the air travel demand model without *CROSSPRICE* to control for multicollinearity, and as a 2SLS regression with the instrumental variables for *PRICE* to control for endogenous prices. (See Table 4.) In addition, we report results with Huber-White robust standard errors to account for heteroskedasticity. To test for endogeneity, we performed a generalized Hausman test for the null hypothesis that the OLS estimator is consistent, and the hypothesis was rejected ( $\chi^2 = 162.67$ , d.f. = 14,  $p < 0.001$ ). Thus, we found that there is a risk of misspecification due to endogenously-generated prices, and going forward we report and interpret the results using the estimates of the 2SLS regression.

The reduced 2SLS model has an adjusted  $R^2 = 72.47\%$ . The magnitudes and signs of the coefficients are as expected. The results suggest that, overall, air travel demand is unit-elastic ( $\eta = -1.03$ , S.E. = 0.08,  $p < 0.01$ ). The estimate of  $\eta$  for the industry roughly coincides with the standard assumed value used by some airline pricing managers that we interviewed and which has been used traditionally as a criteria to make tactical pricing decisions, which provides face validity to our demand model.

**Table 4. Air Travel Demand Model: 2SLS and OLS Regressions**

VARIABLES	2SLS REDUCED MODEL			OLS REDUCED MODEL		
	COEFFICIENT (Robust SE)	<i>t</i>	<i>p</i>	COEFFICIENT (ROBUST SE)	<i>t</i>	<i>p</i>
• <i>Main Effects</i>						
$\eta$ ( <i>PRICE</i> )	-1.03***(0.08)	-12.67	0.001	-0.14***(0.04)	-3.40	0.001
$\beta_1$ ( <i>CONSTANT</i> )	14.11***(0.46)	30.91	0.001	9.3***(0.25)	36.96	0.001
$\beta_2$ ( <i>TRANSPARENT</i> )	-1.95***(0.06)	-34.76	0.001	-1.56***(0.05)	-34.35	0.001
$\beta_3$ ( <i>OPAQUE</i> )	-4.41***(0.09)	-48.57	0.001	-3.55***(0.06)	-59.40	0.001
• <i>Controls</i>						
$\beta_4$ ( <i>ADVPURCH</i> )	-1.47***(0.03)	-58.46	0.001	-1.36***(0.02)	-59.40	0.001
$\beta_5$ ( <i>SEGMENT</i> )	-2.05***(0.05)	-38.92	0.001	-2.47***(0.04)	-61.47	0.001
$\sigma_1$ ( <i>BOSTON</i> )	0.35***(0.11)	-3.34	0.001	-0.48***(0.10)	-4.73	0.001
$\sigma_2$ ( <i>DENVER</i> )	0.77** (0.12)	-6.43	0.001	-0.64***(0.11)	-5.53	0.001
$\sigma_3$ ( <i>DETROIT</i> )	-0.19** (0.09)	-2.05	0.040	-0.19** (0.09)	-2.19	0.029
$\sigma_4$ ( <i>LOS ANGELES</i> )	0.20* (0.11)	1.77	0.077	0.08 (0.11)	0.71	0.479
$\sigma_5$ ( <i>MEMPHIS</i> )	-0.75***(0.11)	-6.88	0.001	-0.78***(0.10)	-7.42	0.001
$\sigma_6$ ( <i>MINNEAPOLIS</i> )	0.07 (0.09)	-0.80	0.421	-0.18** (0.09)	-2.09	0.037
$\sigma_7$ ( <i>SANFRANCISCO</i> )	-0.04 (0.11)	-0.34	0.733	-0.07 (0.10)	-0.71	0.475
$\sigma_8$ ( <i>WASHINGTON</i> )	0.03 (0.11)	0.24	0.812	-0.07 (0.11)	-0.69	0.490
$R^2$ (Adj.- $R^2$ )	72.54% (72.47%)			74.72% (74.66% $\%$ )		
<b>Note:</b> N = 5,160. Models: OLS and 2SLS log-linear regressions with robust errors, to handle heteroskedasticity. Reduced model excludes <i>CROSSPRICE</i> . Significance: * = $p < .10$ , ** = $p < .05$ , *** = $p < .01$ .						

The dummy variables for the transparent and opaque OTAs are negative ( $\beta_2 = -1.95$ , S.E. = 0.06,  $p < 0.01$ ,  $\beta_3 = -4.41$ , S.E. = 0.09,  $p < 0.01$ ), which is in line with the actual lower share of online sales relative to offline sales during the 2003-2004 period. The advance purchase variable has a negative relationship with demand ( $\beta_4 = -1.47$ , S.E. = 0.03,  $p < 0.01$ ), so the farther in time from departure, the lower will be the demand. This makes sense since airline seats are a perishable commodity, and thus demand will be higher closer to departure. The *SEGMENT* variable has a negative coefficient ( $\beta_5 = -2.05$ , S.E. = 0.05,  $p < 0.01$ ), in line with the expectation that business demand is lower than leisure demand.

**Economy Class Price Elasticities: Business and Leisure Combined.** To estimate price elasticity differences across channels econometrically, recall that in the log-linear model, we set the power of *PRICE* ( $\eta$ ) as the price elasticity of demand. We used the following econometric specification, which breaks the power of price into the base elasticity for the transparent OTAs and its difference with respect to the elasticity of the offline travel agencies and opaque OTAs:

$$QUANTITY = e^{\beta_1} \cdot PRICE^{\eta_{TRANSPARENT} + \lambda_1 OFFLINE + \lambda_2 OPAQUE} \cdot ADVPURCH^{\beta_4} \cdot SEGMENT^{\beta_5} \cdot \prod_j ORIGIN_j^{\sigma_j} \cdot e^{\varepsilon},$$

$$\forall j \neq \text{New York} \quad (3)$$

In this model,  $\eta_{TRANSPARENT}$  is the price elasticity of the transparent OTAs, and it is the *base elasticity*. The parameter  $\lambda_1$  represents the difference between the price elasticity of the transparent OTAs and the offline channel. The parameter  $\lambda_2$  represents the difference between the price elasticity of the transparent OTAs and the opaque OTAs. Therefore, based on this specification, we can see that

$\eta_{OFFLINE} = \eta_{TRANSPARENT} + \lambda_1$  and  $\eta_{OPAQUE} = \eta_{TRANSPARENT} + \lambda_2$ . Taking the log-transformation of Equation 3 leads to:

$$\ln QUANTITY = \beta_1 + \eta_{TRANSPARENT} \ln PRICE + \lambda_1 \ln PRICE \cdot OFFLINE + \lambda_2 \ln PRICE \cdot OPAQUE + \beta_4 \ln ADVPURCH + \beta_5 \ln SEGMENT + \sum_j \sigma_j \ln ORIGIN_j + \varepsilon, \forall j \neq \text{New York} \quad (4)$$

To estimate this model we computed the new variables  $\ln PRICE \cdot TRANSPARENT$  and  $\ln PRICE \cdot OPAQUE$ , and included each one as a regressor in our estimations. The results are shown in Table 5. The 2SLS regression using this model has an adjusted- $R^2$  model fit of 72.69%.

**Table 5. Price Elasticities by Channel: Business and Leisure Combined**

VARIABLES	COEFFICIENT (Robust SE)	<i>t</i>	<i>p</i>
• <i>Main Effects</i>			
$\eta_{TRANSPARENT}$	-1.11***(0.08)	-13.39	0.001
$\lambda_1$ ( $\eta_{OFFLINE} - \eta_{TRANSPARENT}$ )	0.38***(0.01)	33.76	0.001
$\lambda_2$ ( $\eta_{OPAQUE} - \eta_{TRANSPARENT}$ )	-0.53***(0.01)	-40.92	0.001
$\beta_1$ (CONSTANT)	12.53***(0.43)	29.27	0.001
• <i>Controls</i>			
$\beta_2$ (ADVPURCH)	-1.46***(0.03)	-58.47	0.001
$\beta_3$ (SEGMENT)	-2.13***(0.05)	-41.25	0.001
$R^2$ (Adjusted- $R^2$ )	72.76% (72.69%)		
<b>Note:</b> N=5,160. 2SLS model estimation. Significance: * = $p < .10$ , ** = $p < .05$ , *** = $p < .01$ . Other control variables omitted for brevity.			

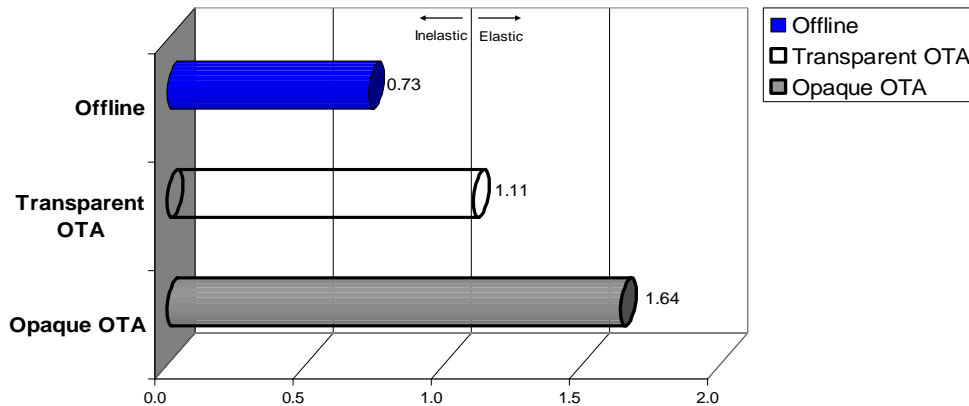
**Transparent-Offline Comparison.** The price elasticity for the transparent OTAs was found to be elastic at -1.11 ( $\eta_{TRANSPARENT} = -1.11$ , S.E. = 0.08,  $p < 0.01$ ). The estimate of  $\lambda_1$  is 0.38 ( $\lambda_1 = 0.38$ , S.E. =

0.01,  $p < 0.01$ ), so the price elasticity estimate of the offline channel is  $\eta_{OFFLINE} = \eta_{TRANSPARENT} + \lambda_1 = -0.73$ . We find support for the Overall Offline vs. Online Transparent OTA Price Elasticity of Demand Hypothesis (H1c). Demand for the transparent OTAs is more price-elastic than that of the offline channel.

**Opaque-Offline Comparison.** The estimate of  $\lambda_2$  or the difference between the price elasticity of the opaque OTAs channel and the transparent OTAs is  $-0.53$  ( $\lambda_2 = -0.53$ , S.E. = 0.01,  $p < 0.01$ ), so the price elasticity of the opaque channel is  $\eta_{OPAQUE} = \eta_{TRANSPARENT} + \lambda_2 = -1.64$ . The difference between the price elasticity of the opaque OTAs and the offline channel is  $\eta_{OPAQUE} - \eta_{OFFLINE} = \lambda_2 - \lambda_1 = -0.91$ . Therefore, we find support for H2c, that the price elasticity of opaque OTAs is higher than that of the offline OTAs.

**Transparent-Opaque Comparison.** Since  $\lambda_2 = -0.53$ , the price elasticity of the opaque OTAs is higher than that of the transparent OTAs, so we reject the Overall Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis (H3c). See Figure 1 for a graphical representation of the results.

**Figure 1. Price Elasticity Comparison across Channel: Economy Class**



**Note:** This graph depicts the relative price elasticities for the economy class cabin (business and leisure combined).

**Price Elasticities by Segment.** We performed price elasticity comparisons across channels by segment, by estimating price elasticities for the leisure and business segments separately. (See the results in Table 6.) These results allowed us to further understand the drivers of the price elasticity differences for the economy class cabin as a whole. The results suggest that the directional differences in price elasticity

across channels hold in relation to the Economy class cabin as a whole, with some nuances.

**Transparent-Offline Comparison.** We find support for the Leisure Segment Transparent OTA Price Elasticity of Demand Hypothesis (H1a) and the Business Segment Transparent OTA Price Elasticity of Demand Hypothesis (H1b). The price elasticity of the transparent OTAs is higher than that of the offline channel in both segments (Leisure  $\lambda_1 = 0.23$ , S.E. = 0.01,  $p < 0.01$ , and Business  $\lambda_1 = 0.55$ , S.E. = 0.01,  $p < 0.01$ ). The magnitude of this difference is found to be higher in the business channel, which is rather counter-intuitive. We discuss this result further in the next section.

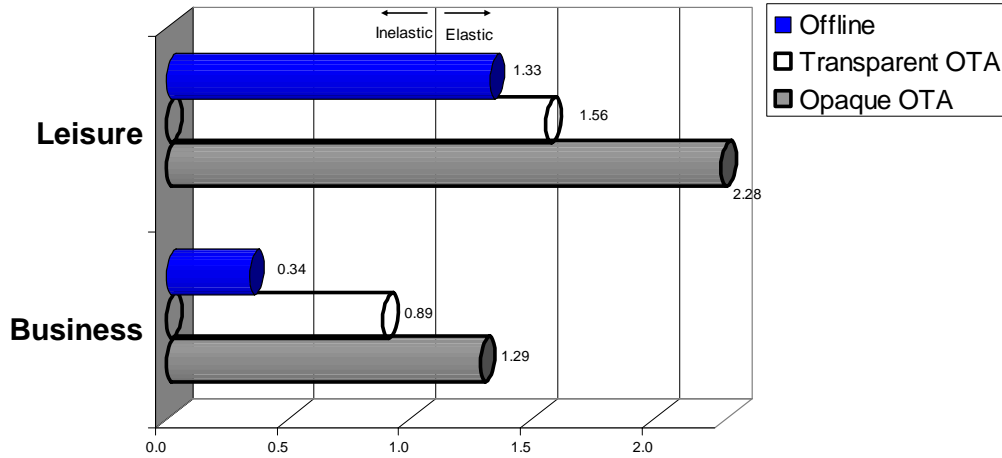
**Table 6. Price Elasticities Comparison by Channel by Segment**

VARIABLES	LEISURE			BUSINESS		
	COEFFICIENT (Robust SE)	<i>t</i>	<i>p</i>	COEFFICIENT (Robust SE)	<i>t</i>	<i>p</i>
$\eta_{TRAN}$	-1.56***(0.07)	-12.87	0.001	-0.89***(0.25)	-6.16	0.001
$\lambda_1$ ( $\eta_{OFFLINE} - \eta_{TRANSPARENT}$ )	0.23***(0.01)	21.78	0.001	0.55***(0.04)	15.03	0.001
$\lambda_2$ ( $\eta_{OPAQUE} - \eta_{TRANSPARENT}$ )	-0.72***(0.01)	-56.89	0.001	-0.40***(0.04)	-10.45	0.001
$\beta_1$ (CONSTANT)	11.26***(0.34)	32.63	0.001	13.24***(1.44)	9.17	0.001
$\beta_2$ (ADVPURCH)	-1.30***(0.04)	-35.04	0.001	-1.70***(0.07)	-23.87	0.001
<b>Note:</b> For each segment, N = 2,580. 2SLS model estimation. Significance: * = $p < .10$ , ** = $p < .05$ , *** = $p < .01$ . Other control variables omitted for brevity.						

**Opaque-Offline Comparison.** The difference between the price elasticity of the opaque OTAs and the offline channel in the leisure segment is  $\eta_{OPAQUE} - \eta_{OFFLINE} = \lambda_2 - \lambda_1 = -0.95$ . The analogous result for the business segment is  $\eta_{OPAQUE} - \eta_{OFFLINE} = -0.95$ . Therefore, we find support for the Leisure Segment Opaque OTA Price Elasticity of Demand Hypothesis (H2a) and the Business Segment Opaque OTA Price Elasticity of Demand Hypothesis (H2b). The demand for opaque OTAs is more price-elastic than that of the offline channel in both the leisure and business segments.

**Transparent-Opaque Comparison.** We find that the price elasticity of the opaque channel is higher than that of the transparent OTAs in both segments (Leisure  $\lambda_2 = -0.72$ , S.E. = 0.01,  $p < 0.01$ , and Business  $\lambda_2 = -0.40$ , S.E. = -10.45,  $p < 0.01$ ), so we reject the Leisure Segment Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis (H3a) and the Business Segment Opaque vs. Transparent OTA Price Elasticity of Demand Hypothesis (H3b). Figure 2 depicts these results.

**Figure 2. Price Elasticities by Channel and Segment**



#### 4. ANALYSIS AND DISCUSSION

In the previous section, we estimated the demand functions of the online and offline air travel channels. We found that the price elasticity is higher in the OTA channel than in the offline channel, for both transparent and opaque OTAs. Table 7 shows that online demand is more price-elastic than offline demand for both business and leisure segments. Within the online channel, opaque OTA demand is more price-elastic than that of transparent OTAs.

##### A. The Frictionless Markets Hypothesis

One of the tenets of perfect competition is that, from the demand side, consumers are more sensitive to price changes in markets with lower search costs. The finding that transparent OTA demand is more price-elastic than offline demand is consistent with the notion that less friction in the form of lower search costs will lead to higher price elasticity of demand and hence more intense competition. We find support for this hypothesis for both commoditized markets and differentiated markets, represented by leisure and business travel.

**Commodity Markets: The Leisure Segment.** In the leisure market, U.S. airlines struggle to stay profitable, one of the signs of the Bertrand-like pricing behavior that leads to marginal cost pricing. Compared to decades ago, domestic airlines have stripped their onboard economy class service of quality dif-

**Table 7. Summary of Results: Relative Price Elasticities across Channels and Segments**

SEGMENT	HYPOTHESES ON RELATIVE PRICE ELASTICITIES	THEORETICAL ARGUMENTS	EMPIRICAL RESULTS
Business and Leisure	H1a, H1b: $ \eta_{TRANSPARENT}  >  \eta_{OFFLINE} $	<i>Frictionless markets hypothesis</i> : More information leads to higher elasticity.	Supported for both business and leisure segments. $\lambda_1 =  \eta_{TRANSPARENT}  -  \eta_{OFFLINE}  > 0$
	H2a, H2b: $ \eta_{OPAQUE}  >  \eta_{OFFLINE} $	<i>Information integration theory</i> : Less product information leads to higher elasticity.	Supported for both business and leisure segments. $\lambda_2 - \lambda_1 =  \eta_{OPAQUE}  -  \eta_{OFFLINE}  > 0$
	H3a, H3b: $ \eta_{TRANSPARENT}  >  \eta_{OPAQUE} $	<i>Inverse of frictionless markets hypothesis</i> : Less information leads to a lower elasticity.	Rejected for both business and leisure segments. $\lambda_2 = \eta_{TRANSPARENT} - \eta_{OPAQUE} < 0$
Total – Economy Class	H1c: $ \eta_{TRANSPARENT}  >  \eta_{OFFLINE} $	<i>Frictionless market hypothesis</i> . <i>Channel Selection</i> : More price-sensitive travelers buy online.	Supported. $\lambda_1 =  \eta_{TRANSPARENT}  -  \eta_{OFFLINE}  > 0$
	H2c: $ \eta_{OPAQUE}  >  \eta_{OFFLINE} $	<i>Information integration theory</i> . <i>Channel Selection</i> : More price-sensitive travelers buy opaque.	Supported. $\lambda_2 - \lambda_1 =  \eta_{OPAQUE}  -  \eta_{OFFLINE}  > 0$
	H3c: $ \eta_{TRANSPARENT}  >  \eta_{OPAQUE} $	<i>Inverse of frictionless market hypothesis</i> . <i>Channel Selection</i> : More price-sensitive travelers buy opaque.	Rejected. $\lambda_2 =  \eta_{TRANSPARENT}  -  \eta_{OPAQUE}  < 0$

ferentiators such as premium meals and amenities – and most recently, even peanuts and crackers.

Our findings suggest that in such commodity markets, the net effect of the ability to compare offerings online will be an increase in price elasticity, which may in turn exacerbate the commoditization of the product. Not surprisingly, airlines have been reluctant to aggressively penetrate the online market, and it was only after several independent OTAs gained significant share in the late 1990s that they decided to reintermediate the online channel (Chircu and Kauffman, 2000; Granados, et al., 2006). Travelers, on the other hand, take advantage of the Internet channel to shop for low prices. A 2006 study by comScore (2006), an Internet research and consultancy firm, reported that in 2005 the OTA market reached over \$40 billion in revenues, and price was the number one reason for consumers to return to a site to book air travel.

**Differentiated Markets: The Business Segment.** In the business segment, we find that transparent OTA demand is more price-elastic than offline demand. Therefore, our results are consistent with the frictionless markets hypothesis not just for commodity products like leisure travel, but also for differentiated markets like business travel. The higher price elasticity that we find online for business travel is in contrast with Degeratu et al. (2000) and Lynch and Ariely (2000), who found that price sensitivity was lower online for groceries and premium wines.

These apparently contradictory findings can be reconciled in two ways. First, perhaps after years of shopping in the online channel, consumers have gained experience in searching, so they are able to better exploit the Internet to shop for lower prices, even when differentiation and brand matter. Therefore, the expected effect of the Internet on price elasticity may be gradually emerging, rather than emerging abruptly, particularly for differentiated markets. This gradual progression may help explain why this study finds higher price elasticities online but the others studies from previous years did not. Second, the emergence of meta-search engines for travel such as Kayak ([www.kayak.com](http://www.kayak.com)) and Sidestep ([www.sidestep.com](http://www.sidestep.com)) may be stripping air travel distributors of the possibility to obfuscate information with tactics to conceal prices. In contrast, in other industries where online price search engines are not as developed, firms are still in a position to conceal prices of competing alternatives. For example, Ellison and Ellison (2004) studied prices in an online search engine and found signs of obfuscation of consumer search by concealing shipping costs and forcing firm-by-firm product search. Oh and Lucas (2006) also found evidence that online vendors change pricing strategies frequently, making it difficult for consumers to learn their pricing strategies.

We also found that the elasticity differential of 0.55 between transparent OTAs and the offline channel in the business segment is higher in magnitude than the analogous 0.38 differential for the leisure segment. Yet the impact on price elasticity of the online channel should theoretically be lower in differentiated markets like business travel than in commoditized markets like leisure travel. Because price information is less important to business travelers, an increase in the ability to compare competitive offerings should have a lower impact on price elasticity for the business segment than for the leisure segment.

Moreover, business travelers are less concerned about booking the lowest price since the airline ticket is typically paid by the firm. Possible explanations for this counter-intuitive result are:

- Business travelers typically pay higher prices than leisure travelers, so some of them may be more sensitive to differences in price comparison capabilities across channels. That is, for the same improvement in availability of market information across segments, the impact on price elasticity may be higher at higher price points if there is a limited budget. Such may be the case particularly for business travelers with a cap on spending and for business executives of small and medium sized firms.
- Business travelers are less likely to search actively in the offline channel than the leisure traveler, because they would rather use the time for other more valuable tasks. In contrast, offline leisure travelers spend more time shopping for lower prices, and this search behavior is reflected in the offline price elasticity for the leisure segment. But if the online channel makes it easy to compare product offerings, the business traveler is in a better position to engage in efficient search.
- Corporate travel agencies and travel departments have dedicated resources and advanced search technologies to manage corporate travel arrangements. Included in their portfolio of tools are online search capabilities, so better resources and more experience may induce higher sensitivity to prices as corporate travel managers are better able to search for the best price for a given itinerary. Business travel is managed by expert staff that may have “tricks of the trade” than the leisure traveler to find lower prices.

### **B. The Inverse of the Frictionless Markets Hypothesis**

If lower search costs and higher price comparison capabilities lead to a higher price elasticity of demand, higher search costs and a lower ability to compare products and prices should lead to a lower price elasticity. Based on this inverse statement of the frictionless markets hypothesis, since opaque OTAs make search costs higher, the result should be a lower price elasticity of demand when controlling for the self-selection effect. Our results are not consistent with this argument, because we find that for both leisure and business segments, demand for opaque OTAs is more price-elastic than transparent OTAs. Pos-

sible explanations are:

- The lack of relevant information on product characteristics and quality can significantly increase price elasticity of demand, to the point where it undermines the effect of price information. That is, the impact of the lack of information on the itinerary and the airline carrier may have a higher impact than the lack of price information, for a net increase in price elasticity.
- There may be self-selection effect in the online channel not captured in our data. Consumer heterogeneity in the leisure segment can exist in the dimension of price sensitivity, and the more price-sensitive leisure travelers (e.g., college students) may gravitate towards the opaque OTAs.

### **C. Information Integration Theory**

*Information integration theory* suggests that more product information should decrease the importance that price or brand have on a purchase decision (Fazio, et al., 1989; Simonin and Ruth, 1998). Anderson (1968, 1971) originally stated this theory in general terms in social cognition literature. Likewise, less product information should lead to a higher focus on price comparison, which will increase price elasticity. The main difference between opaque OTAs and offline agencies is the lack of product information, so travelers using opaque mechanisms will be relatively more sensitive to price changes. Our finding that opaque OTA demand is more price-elastic than offline demand is consistent with this theoretical argument.

This result has implications for opaque OTAs and other market players. For opaque OTAs, the optimal market price should be significantly lower than the retail price, and they should match their level of opaqueness with their price levels. For OTAs and other online players, this result underscores the importance of designing online mechanisms that emphasize information on product attributes. Otherwise, the lack of information about product attributes is likely to compound the negative effect of price information, leading to highly price-elastic and competitive markets. For brick-and-mortar firms with an online presence, a sound multi-channel strategy will consider digital systems and the design of online selling mechanisms that make product attributes transparent to the customer, which will mitigate the negative impact on demand of price comparison capabilities. They should also collaborate with intermediaries in

the online channel to bring product attribute information to consumers in a transparent manner.

#### **D. Channel Selection**

Our results show that more price-sensitive customers will gravitate to channels with lower search costs and higher price comparison capabilities. Part of the reason why we observe a higher price elasticity online is the disproportionate set of leisure travelers that book online. In contrast, a high proportion of business travelers book offline, because they prefer the convenience of an assisted purchase that satisfies their complex needs and their value of time. This channel self-selection effect partially explains the higher price elasticity in the online channel for the economy class as a whole.

This finding highlights the importance of accounting for customer heterogeneity to estimate price elasticities (Bijmolt, et al., 2005). In our study, the channel selection effect increases the magnitude of the higher price elasticity observed online, due to the disproportionate share of leisure travelers who book online. To verify this claim, we compared the price elasticities for transparent OTAs and the offline channel with an aggregated dataset for economy class that *does not* separate business and leisure records. This is a common practice in studies where there is no information to induce customer heterogeneity, and for travel demand studies, the assumption is that economy class is representative of the leisure segment. The result based on this dataset is that the elasticity difference between transparent OTAs and offline is  $\lambda_1 = -0.49$ . In contrast, the result for the leisure segment in our analysis is  $\lambda_1 = -0.38$ . Therefore, the self-selection effect accounts for approximately 0.11 elasticity points or 22% of the difference in elasticity for the economy class, so the remaining 0.38 elasticity points or 78% of the difference can be attributed to the channel-specific differences including the product and price information provided.

### **5. CONCLUSIONS**

We conclude with implications of our findings for academics and practitioners. We note challenges and insights for competitive strategy. We also discuss our contributions, limitations and future research.

#### **A. Implications for Pricing, Multi-Channel Strategy, and IT Strategy**

The findings of this study represent both managerial challenges and opportunities. Our validation that

the online channel is more price-elastic than the offline channel justifies the reluctance of many established firms to compete aggressively in the online channel upon the risk of eroding profits as markets come closer to perfect information. One possible strategic implication is for firms in commoditized markets to retrench and avoid penetrating the online channel aggressively. Alternatively, they will continue to adopt the well-accepted multi-channel strategy to integrate the IT infrastructures across channels and create a seamless experience for the consumer. This approach of a seamless experience for the customer commonly includes setting homogeneous fares across online and offline channels.

**Competitive Inertia.** There is an opportunity to develop multi-channel strategies that capitalize on the heterogeneity of demand across channels. However, firms may be reluctant to deviate from a strategy that is focused on seamless experience for the customer. So despite the rational inclination to price-discriminate in online and offline channels given the higher price elasticity online, firms may be constrained by competitive inertia (Miller and Chen, 1994) and the fear of innovation in pricing strategies due to the risk of reciprocal threats from competitors (Gimeno, 1999). In the air travel industry, for example, given the established homogenous prices in the online and offline channels, it will take perhaps a growing conviction of the profit-enhancing benefits of cross-channel price-discrimination to fundamentally challenge the industry's *status quo*. Airlines are constrained by decades of pricing practices structured around distribution via reservation systems. In addition, they may be reluctant to implement reasonable yet transformational pricing practices that reflect the heterogeneity of consumers across channels, lest competitors may retaliate with severe punishment in their home market.

**Pricing Strategy.** A major challenge will be to strike a balance between the benefits of a homogeneous pricing structure and a seamless experience, and the benefits of price discrimination to take advantage of the heterogeneous cross-channel demand sets. One complication is that price-discrimination across channels can backfire because of discontent by offline customers that pay higher prices, once they become aware that others are paying lower prices online. Fortunately, the higher cost of offline sales has allowed some firms to effectively justify and perform this price discrimination. For example, U.S. airlines typically charge a fee if bookings are made by phone through their reservations offices, and the fee is

waived if the booking is made online. This is effectively a fixed-price premium that is charged for offline bookings due to the incremental costs of face-to-face and phone interactions, and it is conveniently in line with the discriminatory pricing that enhances revenues if price elasticities differ across channels. But there are probably many other unexplored opportunities. For example, airlines can innovate with inventory management techniques and systems to price-discriminate across channels.

**IT-Enabled Competitive Strategy.** There are other possible strategies that can be adopted in addition to pricing strategies. Firms can also develop transparency strategies online given the numerous options they have to display or conceal information. These strategies involve the coordination between pricing, the transparency-based design of selling mechanisms, and the consequent IT infrastructure requirements. Based on an analytical model of the impact of transparency on demand, Granados et al. (2008) suggest that it is revenue maximizing to align prices with the transparency level of each online selling mechanism. Alternatively, transparency levels can be adjusted if the firm lacks the market power to set prices; such is the case of OTAs, which are subject to the market power that airlines have to set prices.

In the context of multi-channel strategy, technology-enabled strategies can be adopted to confront the potential negative effects of higher price transparency. Suppliers and intermediaries can make IT investments to develop online selling mechanisms that increase product transparency and mitigate product uncertainty (Pavlou and Dimoka, 2008). For example, Orbitz, an OTA launched by major airlines in 2001, used state-of-the-art technology to develop a transparent selling mechanism based on a *matrix display* that highlights product characteristics in addition to simple sorting of travel options based on price. Since then, most online travel intermediaries have entered into heavy competition in the transparency space (Granados, et al., 2007), and even the opaque OTAs have implemented transparent selling mechanisms to compete in this dimension.

Similarly, Air Canada has developed a transparent pricing structure based on a customer-centric strategy, and it is investing on new and advanced Internet-based distribution platforms to implement an online à la carte interface that highlights the value of upgraded services. This is a bold move that is likely to offset the negative effect of price transparency on price elasticity with the positive effect of a customer cen-

tric, product-transparent pricing model. Air Canada so far implemented this strategy mostly in its portal, where it has the market power to do so. But it has been less successful in other channels like the OTAs and the offline channel, where there is more risk of retaliation and defection by competitors.

**Demand Analysis and Price Elasticity Estimates.** Another implication for managers is the need to track the demand functions by channel. Common practices in the airline industry are to set prices and perform inventory management based on the assumption that the same demand function applies across channels. We have introduced a practical and sound methodology to compare price elasticities across channels based on historical sales information. This methodology can potentially be used for comparisons across segments (e.g., business vs. leisure), market dimensions (e.g., regional comparisons, city-pair comparisons), or product attributes (e.g., price premium sensitivity for upgraded services). Based on these findings, we foresee the development of sophisticated digital systems that use sales data to estimate price elasticities in order to strategize accordingly.

## **B. Contributions, Limitations, and Future Research**

**Contributions.** The impact of the Internet on the efficiency of markets is determined by its influence on supply and demand. We have examined the impact of the Internet on consumer demand by comparing online and offline air travel demand functions. Our main methodological and theoretical contributions are:

- Much of the online vs. offline comparison in the literature is related to the topic of price dispersion due to the availability of pricing information. In this article, we capitalized on the use of a dataset that contains both sales and prices in online and offline channels, to go beyond the topic of price dispersion. The uniqueness of our sales data broken down by segment, agency type, and time of booking, allowed us to effectively compare price elasticities between the online and the offline channel. We find that both the transparent and opaque OTAs are more price-elastic than the offline channel, which suggests that both product and price information can influence price elasticity and the level of competition.

- We have used sales data to estimate price elasticities, which is a more direct method than the multiple studies that estimate online price elasticity based on sales rank (e.g., Brynjolffson, et al., 2003; Chevalier and Goolsbee, 2003; Ellison and Ellison, 2007; Ghose, et al., 2006).
- We are able to make contributions on how the Internet impacts elasticities in differentiated vs. commodity markets (i.e., business vs. leisure). Specifically, we found that, consistent with the theory, leisure travel demand is more price-elastic online than offline. But we also find, counter-intuitively, that price elasticity is also higher for business travel demand online relative to offline, and the magnitude of this difference is higher.
- We broke down the drivers of the price elasticity differential across channels, to provide evidence that both the mix of travelers and the channel-specific characteristics explain the differences.
- Our analysis of massive sales data is complementary to experimental methods to estimate price elasticities, as in Lynch and Ariely (2000). They performed experiments to induce demand with transparency level as the treatment variable, while our study uses actual sales to estimate the demand function and the price elasticities.
- The finding that price elasticity is higher online has direct implications for academic and practitioners. For practitioners, there are implications for the design of digital systems and electronic selling mechanisms to compete effectively.

**Limitations.** Nevertheless, we offer three limitations to this present study that also represent opportunities for future research. First, since we have not explicitly measured and tested the product and price information in the online and offline channels, we can only claim consistency of our findings with the tenets of the frictionless markets hypothesis and the information integration theory. We have controlled for other major factors that may account for this price elasticity differential across channels, including differences in the mix of customers segments. Further research is necessary to explicitly measure transparency levels across channels and online sites, and the corresponding impact on demand. Indeed, there is growing evidence that online markets are not completely frictionless, so there is a necessity beyond what

we have done in this study to examine instances where market information will lead to different outcomes. It will be interesting to revisit the issues that we have studied at a much more detailed level of granularity to understand the impacts of different kinds of information on consumers. For example, along the lines of Lynch and Ariely (2000), who studied the different effects of product and price transparency in an experimental setting, more experimental studies of the impacts of changes to the information provided on individual online sites or across sites can provide valuable insights. Also, price elasticity comparisons between OTAs that differ in their web design and information can bring new insights on this front.

Second, although we contend that the higher price elasticity online for air travel is likely to occur in other markets, more empirical studies in other contexts are necessary to verify this claim. Likewise, studies of other differentiated markets can be done to verify our findings and continue to reconcile our findings with other studies that have found lower price elasticity online.

Third, we recognize that the online travel industry is in a continuous state of flux, and the results we have found for the travel period of our study may not fairly represent all other time periods. Still, we believe the trend towards higher online price elasticity for the leisure segment will continue, as travelers become even savvier at searching online and as more price transparent selling mechanisms emerge, such as meta-search agents that scrape the Internet to provide a comprehensive set of search results. Future studies of air travel demand in the online channel will contribute to understand the long-term impact that the Internet will have in the industry, and lessons can be learned and applied to other industries where the online channel is maturing at a slower pace.

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