Tabulated decision aids and airfare pricing

Eran Rubin a, b *, Benny Mantin b

a Faculty of Technology Management, Holon Institute of Technology, Holon, Israel
b Department of Management Sciences, University of Waterloo, Waterloo, Canada N2L 3G1

A R T I C L E   I N F O

Article history:
Available online 21 December 2011

Keywords:
Airline industry
Dynamic pricing
Internet
Price dispersion

A B S T R A C T

When people shop for airline tickets, the effort-demanding cognitive process of assessing alternative travel dates may have significant effects on consumer decisions. With the advent of the Internet, consumers are gaining access to a growing number of alternative flights. Decision support tools can assist consumers in their search for travel dates and price combinations. Airline carriers have started offering such tools to support flexible travel-date searches on their websites. In this research, we analyze the economic effects of such tools. We hypothesize that these tools directly affect airline carriers’ pricing schemes. As airline carriers display more alternatives on a flexible date search, price variation and number of price changes are expected to decrease, and the average price is expected to increase. We empirically test our hypotheses using airfares from a wide range of US domestic routes. The results broadly support our hypotheses.

© 2011 Elsevier B.V. All rights reserved.

1. Introduction

The travel industry provides one of the most successful examples of online purchasing adoption. Travelers who purchase online account for 83% of all US online consumers (Henry 2007). Expenditures on online travel amounted to US$111 billion in 2008, and this figure is expected to increase to US$153 billion by 2013 (Harteveldt 2009). This is not surprising, and the reasons have been well studied in the literature. Generally, airline tickets are “low touch products,” which consumers do not need to feel, touch, smell, or try on, and thus do not require an offline presence prior to purchase (Chiang and Ruby 2003).

Airline tickets have another characteristic that may be highly important in digital purchase environments, their pricing mechanism, which usually prompts high variations in prices. Revenue management systems employed by airline carriers facilitate the pricing of airline tickets as a function of time and demand. While intuitively appealing to sellers, these systems complicate the purchase decision process for buyers: not only do they have to evaluate the product and its features, but they also must consider the timing of the purchase and the timing of consumption. It may very well be that products that differ only slightly on either consumption or purchase date would differ significantly in price.

Given the potential for significant price differences, searching, finding, and deciding on travel dates when purchasing airline tickets can be critical. The Internet provides consumers with enhanced product search capabilities, making this medium even more attractive for travel purchases. Online decision aids can reduce the cognitive effort required in employing some decision strategies, and therefore can affect decision processes and outcomes.

When useful information is effectively displayed by the decision aid, cognitive effort associated with obtaining information can be reduced, and improved decision strategies can be formulated and employed (Kennedy et al. 1998). Thus, different levels of information accessibility can result in different products purchased by consumers and hence may affect products’ prices (Granados et al. 2008). Specifically, in the context of airline ticket purchasing, different levels of access to information are imposed by the decision aid according to the number of alternative travel days displayed in a single table. When a decision aid provides better access to alternative dates, passengers can easily identify flights with lower airfares on alternative dates. Hence, they may purchase tickets that might have otherwise been left unnoticed. This suggests that different demand patterns are experienced according to the properties of the decision aid, and thus, the variance in decision aid properties is expected to affect the pricing of products.

In this research, we examine this relationship in the context of the airline industry. We look at the relationship between the decision aids that carriers provide to their customers, and the resulting pricing realizations. As carriers’ websites developed, airlines started offering consumers alternatives to their originally indicated travel dates. Date-flexible search options allow consumers to obtain a quick overview of fares on alternative travel dates, if they are willing to consider changing their trip plans for a lower fare on adjacent travel dates. These date-flexible options, which are commonly presented in a tabulated format, differ across airlines, while some provide lowest fares on 49 different travel date combinations (seven possible departure dates by seven possible return dates), others provide prices on 25 different travel date combinations, and some provide prices on only...
nine different date combinations. These differences provide a unique opportunity to examine economic outcomes resulting from variation in displaying information to support purchase decisions. We examine the extent to which varying levels of information accessibility provided by the decision aid, relate to the realized posted prices of airfares on the Internet. Ultimately, by controlling the information accessibility to their potential customers, airlines can possibly affect the decisions made by consumers.

With more date combinations presented at the time of purchase, consumers are more likely to find and purchase alternatives with lower prices. Improved visibility of low-demand alternatives could potentially smooth demand across flights, or at least divert some of the more elastic demand from busy itineraries to less congested ones, thereby reducing price variations across flights. We, therefore, hypothesize that enhanced information to consumers establishes a negative relationship with price fluctuations. Additionally, since this process is expected to increase the average fill rates of planes (as potential customers are not "rejected" due to full flights or high prices, and select, instead, cheaper alternatives from the same carrier), we hypothesize that higher average travel fares will be charged by carriers.

We test our hypotheses by analyzing a series of airfares for 54 different routes offered by carriers employing similar decision aids, but differing on the number of alternatives they present. Our results show that when the number of alternative dates displayed in a single table is larger, the variance of fares is smaller and the average price charged is higher.

This research has many interesting business implications. If a relationship between the accessibility of information provided to consumers on e-commerce sites and vendors' pricing exists, it is possible that sellers can foster decision processes that will help divert customers to purchase low demand products and, thus, increase their demand.¹

This paper is organized as follows. In Section 2, we review the literature. Section 3 develops the hypotheses. In Section 4, we describe the empirical test of our hypotheses. Section 5 explains the research settings. In Sections 6 and 7, we provide the empirical analysis and discuss the results. In Section 8, we conclude and suggest directions for future research.

2. Price dispersion in the airline industry

The US airline industry has gone through some significant changes in the past three decades. We first provide an overview of the US airline industry, and then we review the sources of price dispersion related to this industry.

2.1. Airline industry background

Under the historical conditions of airline regulation, the Civil Aeronautics Board (CAB) controlled prices in the US, and used a mileage-based formula to ensure equal prices for equal distances, ignoring all differences (even substantial) in the operating costs of the routes (Belobaba et al. 2009). The Airline Deregulation Act of 1978 signaled the prelude to an evolution of an entire industry, as this act eliminated the strict relationship between airline fares and distance traveled. Furthermore, with the deregulation, different origin-destination (O–D) markets can have prices that are not related to the distance traveled or even the airline’s operating costs, resulting in one of the most profound consequences of the deregulation, the emergence of low-cost carriers. The emergence

¹ When considering imposing decision processes that may affect consumers’ decision making, firms may need to further consider customer value. This trade-off is important, however, competition may, ultimately, force firms to adopt inferior choices.

of these low cost carriers induced major carriers to match the low-fares in order to maintain their market presence and their share of traffic.

Generally, all legacy carriers use similar revenue management pricing schemes based on the same set of factors. On top of the traditional distance based pricing, the newly-introduced factors include the presence of low-cost carriers and characteristics of the O–D market. Based on these factors, revenue management pricing combines three economic principles: cost-based pricing, demand-based pricing and service-based pricing (Simpson and Belobaba 1992).²

Cost-based pricing stems from the microeconomic practice of “marginal cost pricing,” in which the producer sets its prices equal to the marginal cost of producing an incremental unit of output. The marginal costs of carrying an incremental passenger are very low and airlines could not possibly cover their total operating costs under a strict marginal pricing scheme. Yet, some elements, such as distance traveled, will come into play under this principle (Belobaba et al. 2009).

Demand-based pricing gives rise to segmenting the consumers according to their willingness-to-pay. Elements contributing to these pricing schemes would include business travelers, compared to leisure travelers, as the former is typically willing to pay more than the later. This research is associated with price sensitive consumers and, in line with the mainstream literature on airfare pricing, is concerned with the lowest fares offered by the airline. By contrast, service-based pricing highlights the importance of the quality of the product, giving rise to product differentiation (e.g., first class versus coach). Since this research is concerned with the leisure traveler, the analysis is limited to coach seats.

The airline industry provides a wealth of data that has stimulated a rich empirical research stream which studies, among other topics, pricing and price dispersion. Traditional work has used transacted data (from the US Department of Transportation) such as the work by Borenstein and Rose (1994). Recent work has turned to online posted prices – a stream that studies aspects of pricing such as the behavior of prices over time, substitution, and dispersion. McAfee and te Velde (2007) studied, among other things, whether competition reduces variance of prices, and whether the prices of substitutes are correlated. Piga and Bachis (2007), find that volatility tends to increase in the last four weeks. The research, thus far, has not studied how the design of the websites and the level of information accessibility could potentially affect consumers’ decisions and, hence, the realized prices and their dispersion.

2.2. Sources of price dispersion

Price dispersion is inherent in many markets and, as Varian (1980) has stated, “the ‘law of one price’ is no law at all.” Several works (e.g., Borenstein and Rose 1994, Gerardi and Shapiro 2009, Liu and Serfes 2006) have explored the relationship between different variables and price dispersion using transacted ticket data from the US Department of Transportation’s Origin and Destination Survey database. Together, these studies have shown that price dispersion is associated with three major factors: market structure (e.g., competition intensity), route characteristics (population and distance), and competitors’ specifics (e.g., operations structure). With respect to search costs, a stream that explores online prices has revealed that while the Internet has reduced consumers’ search costs in general, the actual search employed by online consumers is, in fact, limited. Hann and Terwiesch (2003) have found that the number of steps consumers are willing to undertake in online environments is limited. Johnson et al. (2003) provide a model that suggests that ease of use and experience affect the willingness-to-search.

² The theory and practice of pricing and revenue management are provided in Talluri and van Ryzin (2004), Phillips (2005), and Boyd (2007).
Recently, Chellappa et al. (2011) provided further support to these findings, with evidence that price dispersion persists in online airfare markets even after controlling for the traditional sources of dispersion. Along this line of argument, we analyze whether the extent to which price information is easy to reach upon purchase decision as another source for price dispersion.

### 2.2.1. Airline focus

Tsikriktsis (2007) has identified two main carrier categories within the US domestic airline industry: full-service carriers (FSCs) and focused airlines. The FSCs consists of the major airline carriers, such as US Airways and American Airlines, which traditionally have employed the hub-and-spoke type of network, cover a large variety of airports, serve both domestic and international destinations, and rely on frequent flyer programs to lure customers.

The focused airlines, which consist primarily of low-cost carriers (LCCs), usually operate point-to-point networks and they serve mainly domestic destinations. As LCCs' service is limited (no meals, no advanced seat selection, no airport lounges), they can offer a very restricted product differentiation. LCCs' limited differentiation usually ends up with the adoption of the everyday low price (EDLP) strategy. Chellappa et al. (2011) have shown that the difference in the pricing strategy (EDLP by LCCs and non-EDLP by FSCs) is a source for price dispersion in this industry. Similarly, Mantin and Koo (2009) have demonstrated the impact of the presence of LCCs: faced with competition stemming from LCCs, FSCs adopt aggressive high-low pricing, which results in greater price dispersion.

### 2.2.2. Market structure

Competition intensity in a market can dramatically influence pricing decision by firms. While several studies find that price dispersion increases in competition intensity (e.g., Borenstein and Rose 1994, Hayes and Ross 1998, Stavins 2001), few others document the contrary—price dispersion decreases in competition (Evans et al. 1993, Gerardi and Shapiro 2009). Regardless of the direction of influence, however, there is a general agreement that the level of competition influences price dispersion.

### 2.2.3. Route characteristics

It has long been recognized that route characteristics can impact the level of prices and their dispersion. Importantly, the flight distance is a primary driver of the operational cost (Swan and Adler 2006). Another important route characteristic is related to population, which can be measured in a variety of ways. The population of the metropolitan area of both the origin and the destination airport is often included as an instrument (e.g., Gerardi and Shapiro 2009).

### 3. Information displayed on a decision aid and the purchase decision

Generally, decision aids have the potential to help users overcome their cognitive limitations; however, the design of a decision aid restricts the decision-maker to certain decision processes that are embedded into the system (Silver 1990). Behavioral decision-making literature (Payne et al. 1993) and a significant body of information systems (IS) research suggest that when a computerized decision aid is used, the decision process taken by the user is highly dependent on the amount of effort it requires. See Todd and Benbasat (1999) for a review. According to this literature, the objectives of a decision-maker are to both maximize the decision quality, and minimize the effort. As these objectives often conflict, trade-offs are made between the two. Empirical studies, simulations, and the conceptual literature have all indicated that effort is the more important factor influencing the processes taken (Todd and Benbasat 1999). Interestingly, this trade-off consideration seems to hold whether or not the user has an incentive to arrive at the optimal, or most accurate, decision (Beattie and Loomes 1997). Hence, according to the cost-benefit model, in the analysis of a decision aid, the effort required while using the decision aid should be given at least as much attention as that given to the potential functionality of the aid (Todd and Benbasat 1994).

Related to this, it has been shown that the easier it is for consumers to obtain price information, the higher the consumers’ intentions are to search for these prices (Su 2008). These findings are consistent with the cost-benefit model, and are based on information search theory (Telser 1973), according to which consumers search for information as long as the marginal gains from the search are higher than the marginal costs. Accordingly, a decision aid can help reduce search costs by enhancing information integration and information processing, thereby improving consumer decision-making process by providing the right information at the right time (Burke 2002).

To this end, decision makers tend to use a two-stage process in choosing from large sets of alternatives (Payne 1976). In the first stage decision makers prune the decision search space, and in the second stage they switch to a more demanding decision strategy, to choose from the alternatives. It has been shown that by moderating cognitive effort, web-based decision aids can affect both stages of the decision process. Specifically, Haubl and Trifts (2000) show two factors in a decision aid that can reduce cognitive effort: the decision aid’s ability to recommend viable alternatives, and the decision aid’s ability to assist in comparing alternatives using a comparison matrix. The former factor reduces cognitive effort when establishing the consideration set (i.e., the number of relevant alternatives to be considered). The latter factor reduces cognitive effort, and enables a more accurate decision when evaluating alternatives from the consideration set.

Since decision makers tends to use a decision strategy that requires the least amount of effort (Todd and Benbasat 1999), the number of date alternatives offered by an airline's decision aid can establish the size of the consideration set evaluated by the consumers; the specific attributes supported by the comparison matrix of the decision aids are more likely to be the core attributes considered by the consumers. Interestingly, as the number of available alternatives increases, decision makers tend to establish a smaller and more uniform consideration set (Parra and Ruiz 2009). With the comparison matrix, the airlines effectively impose the size of the consideration set, regardless of the users’ natural tendencies.

### 4. Theoretical integration

In this section we integrate our literature review with the state of affairs in the airline industry to derive the possible effects of the employed decision aids on the patterns of realized prices.

#### 4.1. Airline ticket purchasing

Choosing an itinerary for a city pair is not a trivial process. Consider two aspects of the purchasing process: loyalty and price. Loyalty, driven by frequent flyer programs (FFPs), can dramatically bias consumers’ choice towards a certain service provider. FFPs introduce a high switching cost for consumers (e.g., Carlson and Lüägren 2006), who are likely to remain loyal to their carrier of choice to collect miles. Within the boundaries of a carrier to which they are loyal, for many consumers, the price of the ticket is a dominant differentiating attribute. Therefore, our hypotheses concentrate on the lowest airfare offered by an airline on a route. Our focus on the lowest airfare offered is consistent with the mainstream literature that tracks posted airfares. See Button and Vega 2007 for a review.

As noted, carriers’ websites have gradually developed to offer consumers flexible date search modes. These search modes provide consumers with a tabular overview of an extensive number of
combinations of departure and return dates all at once. The tabular formats provide consumers with a quick reference to lower-priced tickets in the days immediately before and immediately after the requested departure and return dates. While all carriers provide this tabular format, the size of the table, or namely the number of combinations displayed on a single web page, differs between carriers. The more combinations displayed on a single web page, the more alternatives that can be easily incorporated into the consideration set at the first stage, and the less effort required when executing a price-based decision strategy on these alternatives in the second stage. Inclusion of an entire consideration set on a single web page reduces effort associated with its formation for two reasons: it reduces action-based effort and it reduces the time required for its formation. Action-based effort refers to the number of actions (e.g., scrolls, mouse movements, and navigations) associated with accessing consideration set information (Bettman et al. 1990, Hoque and Lohse 1999). Formation time is the time required to access the information instead of devoting it to the actual decision task (Dennis and Taylor 2006).

Hence, the more combinations displayed on a single table, the larger the consideration set imposed on the consumer, and, since the combinations are provided on a price-based comparison matrix, a more accurate price-based decision emerges. When information about different alternatives is not in a single table, the decision maker is either forced to rely on memory or invest more effort to keep track of previously accessed information. Therefore, the effects of providing a larger set of alternatives increases the probability of finding and purchasing a comparatively low-priced flight.

Fig. 1 illustrates two such decision aids, as were offered by Delta Air Lines and Northwest Airlines. In Northwest’s case, a large consideration set, including 49 alternative combinations, is easily established. Furthermore, notice that within this consideration set, the least expensive combination fare is listed at the bottom-left cell, while central adjacent cells do not present major decreases in prices. In fact, there is no directional search option for consideration set formation that would lead the consumer to the lowest available price. Northwest’s format provides a better platform for establishing a larger consideration set as it would require a Delta customer more than four navigation operations to obtain an equivalent coverage of alternative travel dates. Even more so, Northwest imposes a consideration of more alternatives. Additionally, at the second stage the customer must rely on memory when employing a decision strategy. That is, if the same number of alternatives is considered by a Delta customer, Northwest still makes it easier to examine all prices within the considered search space. A Delta customer would have to wait for web-pages to download and rely on memory for comparison of alternatives. Thus making a Delta customer’s price-based decision less accurate. Furthermore, Granados et al. (2010) show evidence that easy access to price information increases sensitivity to prices. Related to this, note that in Fig. 1 prices are emphasized by airlines, and thus price sensitivity is enhanced and a price based decision between alternatives is more appealing in terms of cognitive effort.

4.2. Hypotheses

4.2.1. Prices on the same day of purchase, for different days of travel

Fostering a larger consideration set and a more accurate price-based decision suggests important implications for demand differences across travel dates. The larger the consideration set, with support for an accurate price based-decision, the higher the probability that the low-priced flights would be noticed and purchased.

The attractiveness of diverting to alternative itinerary dates may differ from one consumer to another: some may be willing to adapt their plans as long as they save on the airfare; some may be willing to change to specific dates only after a certain saving threshold is met; others may be totally inflexible in their travel dates. Deviating to alternative travel dates thus depends on the magnitude of the price differences between the alternatives. The larger the price difference is, the greater the attractiveness is of the less expensive alternative. Still, as all legacy carriers have similar consumer bases (Ba et al. 2011), the probability that low-priced flights would be noticed and purchased increases as the visibility of these alternatives increases.

According to this, as a larger consideration set is imposed on the customer, price differences across travel dates for the same airport-pair are expected to be lower. Formally, our first hypothesis is:

**Hypothesis 1 (H1).** The more travel date alternatives displayed by a carrier on its website, the lower the variance of the lowest prices offered by the carrier for different travel dates on a specific airport-pair.

Since the expected monetary savings should be higher as the cognitive effort imposed in finding them increases (Hann and Terwiesch 2003), carriers with smaller comparison matrices may try to increase the visibility of tickets by further reducing their prices. In line with the Hypothesis 1 (H1), such actions will impose a high price variance on those carriers’ tickets. In contrast, since a larger comparison matrix increases demand through the decision aid properties rather than through increased price reductions, the average price of flights can remain high. In other words, easier access to prices of alternative travels is expected to balance demand across travel dates, while reducing the need for price reductions.

These effects on demand variability have important implications associated with the carriers’ ability to generate revenue. The effects of an increased flexible consumer base on the average price charged, have been numerically demonstrated in Borgs et al. (2011), and derive our next hypothesis:

**Hypothesis 2 (H2).** The more tabulated travel-date alternatives displayed by a carrier on its website, the higher the average of the lowest prices offered by the carrier for different travel dates on a specific airport-pair.

4.2.2. Prices for the same day of travel, on different days of purchase

Another measure of price variability is that of the cheapest flight as measured on different purchase dates. As time progresses, if realized demand does not meet the forecasts made, carriers may need to affect demand by modifying prices. As noted, with more tabulated alternatives presented on a single page, there is an increased probability that even small price variations will be detected by consumers, thereby facilitating easy diversion of consumers to alternative, low-priced, flights. In other words, with more tabulated alternatives, improved access to prices is expected to result in higher demand elasticity (Granados et al. 2010). 

**Hypothesis 3A (H3A).** The more tabulated alternatives displayed by a carrier on its website, the lower the variance of prices of the cheapest flights between an airport-pair on a specific travel date, on different dates of purchase.

---

3. In addition, such tables incorporate special visualization schemes, such as different color and font, that enable easy identification of the lowest available price alternatives.

4. That is, even if a customer had in mind establishing a consideration set of only one day difference, Northwest provides more alternatives to consider.

5. Stated differently, as the visibility of alternatives increases, consumers consider more remote alternatives and effectively become more flexible with travel dates. It has been shown in numerical models that as the number of time flexible consumers increases, the variance of prices is expected to decrease (Borgs et al. 2011).
Furthermore, when consumer demand is better managed, firms may have less need for frequent updating of prices to stimulate demand. Since price changes are disliked by consumers (Hall and Hitch 1939), perceived to be unfair (Kahneman et al. 1986) and may antagonize consumers (Blinder et al. 1998), companies would generally prefer to avoid price changes if other ways to generate the same revenue can be found (Feng and Gallego 1995). Therefore, price change frequency is a function of a firm’s attempts to increase unexpected low demand, and if demand is well forecasted, then the need for price changes is mitigated.

Since lower prices on alternative travel dates, when presented on a single webpage, shall improve fill rates and overall demand forecasting, the need to frequently adjust fares is expected to decrease.6 This notion is formalized in the next part of the hypothesis:

**Hypothesis 3B** (H3B). The more tabulated travel-date alternatives displayed by a carrier on its website, the lower the number of daily price changes in the lowest prices for travel on a specific airport-pair on a specific date.

---

Similar to the different measures of price variance, we also use another measure for price levels. The next measure we employ is the cheapest flight, as measured on different purchase dates. As noted with respect to Hypothesis 2, as more alternative travel dates are presented to travelers, demand is controlled without extensive reduction in prices. Hence, our next hypothesis:

**Hypothesis 4** (H4). The more tabulated travel-date alternatives displayed by a carrier on its website, the higher the average of the lowest price for flights between an airport-pair on a specific date, on different dates of purchase.

---

5. Testing the hypotheses

5.1. Data source

To test our hypotheses, we need to properly measure the variance of prices offered by the airlines, quantify the flexible search offered by the different carriers, and control for additional variables. Collection of information was conducted from a single source to ensure consistency in data across airlines, similar to McAfee and te Velde (2007) and Bilotkach (2006). Specifically, we have gathered data from ITA Software (matrix.itasoftware.com), a consolidator website that does not sell tickets and is associated with Google. While some online travel agencies provide only a subset of the offerings available (Clemons et al. 2002), ITA Software provides full

---

6. Indeed, with more consumers switching to lower priced airfares, prices might increase on the low demand days as the flight fills up faster than expected. A priori, it is hard to determine which effect will dominate. However, larger tabulated decision aids, are bound to help generate more accurate forecasts, as forecasts become increasingly based on general market demand rather than flight based demand. Improved accuracy in forecasts is expected to reduce the need to update flight rates. We thank the anonymous referee for raising this point.
access to all tickets offered by various carriers.\footnote{For example, on a simple PIT-MCO search, Expedia had only one flight option with American Airlines, compared with ten options provided by ITA Software.} We have collected the lowest one-way airfare data on a sample of 54 different US domestic routes for each of the airlines studied. In the construction of our sample, we included major airports as they represent the backbone of the US domestic airline network and are responsible for a major share of passenger transportation. We derived our sample from the index of major airports provided by the Federal Aviation Administration (www.fly.faa.gov), while excluding airports with direct competition from other nearby major airports (Chicago, the New York area, San Francisco, and Miami).\footnote{Airport competition may expose airfares to a variety of effects that have not been sufficiently studied. For example, McAfee and te Velde (2007) have noticed that travel dispersion than other carriers (Chellappa et al. 2011), therefore, captures the same aspect of price variability, we have collected data pertaining to the two weeks immediately preceding the flights. As well, by examining the impact of number of alternative flight dates on price variation in the final two weeks, we measure the cumulative impact of the comparison matrices on airfares over time.

It has been shown that US legacy carriers exhibit greater price dispersion than other carriers (Chellappa et al. 2011), therefore, our analysis focuses on those legacy carriers. Specifically, our empirical analysis includes all of the legacy carriers at the time of our data collection: American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, and US Airways. All of these legacy carriers offered tickets on the airport-pairs and routes that we included in our sample.

Hypotheses 1 and 2 are concerned with the product being purchased (i.e., a flight on a specific travel date), while hypotheses Hypotheses 3 and 4 deal with the timing of the purchase (i.e., time before the product expires). In other words, in the former two hypotheses we are concerned with the price of similar flights, varying only on departure date, while in the latter two hypotheses we allow the number of days prior to departure to vary. Different data sets are required to test these two sets of hypotheses.

Fig. 2 illustrates the data collection for these two samples. The first sample (to test Hypotheses 1 and 2), to which we refer as Sample 1, comprises the airfares offered by the airlines for flights taking place on different dates. On a fixed purchase day, the lowest available airfares for each of the ensuing 14 days were gathered for every airline for each airport-pair, yielding a total of 4531 price observations.\footnote{While our analysis presents the results collected on a single date, to confirm our results, data was also collected on other dates and for different time spans (up to one month), yielding similar results.} Data collection for this sample is depicted in Fig. 2a.

The second sample (to test Hypotheses 3 and 4), to which we refer as Sample 2, studies the behavior of prices as time progresses towards the departure date. To generate this sample, we fixed the departure date and collected airfare data on a daily basis starting at fourteen days out, and up to one day prior to the departure date. This data collection was repeated for 14 fixed departure dates. In total, 62,226 price observations were collected. Data collection for this sample is depicted in Fig. 2b.

Table 1 provides summary statistics on these samples’ data characteristics. The first batch of data provides statistics on Sample 1, the prices of flights departing on different dates, available on a fixed purchase date. The second batch of data provides statistics on Sample 2, the prices of flights for the same departure dates, offered on different dates of purchase. Table 1 shows that our sample incorporates a wide range of ticket prices. The top 5% price in this sample is approximately $785, while the bottom 5% prices are $135 and $115 for the first and second samples, respectively. Finally, the last batch of data refers to explanatory variables, which are discussed in the next subsection.

5.2. Model specification and variables

The dependant variable used for testing Hypotheses 1 and 3A is the coefficient of variation (CV), which normalizes all price variations according to a single scale, by measuring the standard deviation divided by the mean price of tickets provided by a carrier on a route. In testing Hypothesis 3B, we used the Number of Price Changes conducted by an airline on a route. Finally, the dependant variable for Hypotheses 2 and 4 is the Price Mean, an average of the lowest prices observed in the relevant sample.

The control variables used in our study are grounded in airfare pricing literature, described earlier. As discussed, variables affecting airfare prices can be classified into three broad groups: market structure variables, route characteristics, and carrier-specific variables (Cho et al. 2007).

Market structure variables try to encompass the competitive environment of the market. We use the Herfindahl–Hirschman Index (HHI), which quantifies market concentration (taken from Farecast.com’s market share values). This index takes values between 0 (perfect competition) and 1 (a monopoly). We also include an LCC (Low Cost Carrier) dummy, which equals 1 when an LCC competes on the non-stop route and 0 otherwise. This accounts for the potential drop in average prices on the route due to the presence of an LCC (Chellappa et al. 2011, Tretheway and Kincaid 2005).

With respect to route characteristics, the two main variables that are typically used are the distance between the airport pairs and the population of the metropolitan areas served by the airports. The Distance variable used in our analysis is based on a great circle route application and is measured in kilometers. Population values are extracted from the Census Bureau, in line with the method used by Gerardi and Shapiro (2009). Our Population variable corresponds to the arithmetic mean of the two area’s populations, in order to capture the projected volume of passengers on the route.

Carrier-specific variables consider the unique characteristics of the different airlines that are consistent across the different routes. Most of these characteristics are naturally controlled for in our analysis since our samples are based on legacy carriers only. These carriers share similar structural costs, operate similar networks, and offer similar product segmentation (i.e., class fares). However, since all of these carriers operate their flights in a hub-and-spoke type of network, the location of carriers’ hubs still needs to be controlled for. Having a hub at either end of the route offers the carrier much more versatile routing opportunities due to connecting flights. We account for such possible difference in our analysis by incorporating Hub on Route, a dummy variable that indicates the presence of a hub at either the origin or the destination for a given carrier (Gerardi and Shapiro 2009).

Finally, based on our analysis, in this paper we propose a new carrier-specific variable affecting price – the extent to which they make prices of alternative travels accessible. To quantify this proposed variable, we have analyzed the websites of the six major legacy airline carriers, and the number of alternatives provided when a consumer undertakes a flexible flight search. Table 2 summarizes our findings.

We quantify the differences between the legacy carriers from Table 2 using the variable Alternatives. This variable corresponds to the total number of alternatives offered by the carriers on a single flexible search. Our review of carrier websites revealed that all six legacy carriers provided a grid of options – except for American
Airlines, which separated departure and return choices during a flexible flight search. Still, this method provided seven options on a single screen.\(^{10}\) Hence, Alternatives is a scale variable that captures magnitude differences for the same aspect across airlines. Therefore, by definition, Alternatives is not expected to capture firm-specific effects with no relation across firms, and it is very different, for example, from firm dummy variables, which are used to capture firm-specific effects.

To summarize, we estimate the following regression equations to test the sign and significance of the Alternatives variable.

\[
\text{Dependent Variable} = \alpha_0 + \alpha_1 \cdot \text{Alternatives} + \alpha_2 \cdot \text{HHI} \\
+ \alpha_3 \cdot \text{Distance} + \alpha_4 \cdot \text{Population} \\
+ \alpha_5 \cdot \text{HubOnRoute} + \alpha_6 \cdot \text{LCCDummy},
\]

where Dependent Variable is: the coefficient of variation in Hypotheses 1 and 3A; the number of price changes in Hypothesis 3B; and the mean price of lowest fare in Hypotheses 2 and 4.

The bottom portion of Table 1 provides summary statistics for the different explanatory variables in our samples. It can be seen that the sampled routes connect densely populated areas, thus incorporating airports serving major metropolitan areas. Low cost carriers (LCCs) offer flights on 31 of the sampled routes, while on the remaining 23 routes, there are no LCC flights. The different routes exhibit different levels of competition, with the top 5% HHI parameter set at 0.73 and the bottom 5% set at 0.39. Finally, the distance traveled on each of the routes varies as well, with a median distance of 1459 km.

Table 3 provides the correlation matrix of the model variables. The correlation matrices of Sample 1 and Sample 2 are presented in Table 3a and b. These tables show that the correlations between the independent variables are weak, and that in most of the cases they are also statistically insignificant. Hence, it appears that no collinearity issues exist between our model variables.

6. Results

When airfares are analyzed, the possible correlation between errors must be accounted for. More specifically, the unique characteristics of each route may result in correlated price offerings by different carriers on the same route. Similarly, the pricing strategy of a carrier may result in correlated price offerings by the carrier on different routes. Failure to control for such clustering of errors can lead to massive under-estimated standard error and consequent over-rejection using the standard hypothesis test (Cameron et al. 2006). We therefore account for such possible correlations by analyzing our data using a two-way clustering method, that is, clustering errors both by routes and by carriers. Thus, by using two-way clustering, we control for error correlation that may result from any carrier specific pricing mechanisms, as well as any route specific pricing issues.\(^{11}\) To this end, the two-way clustering method

\(^{10}\) One may argue, though, that due to the differences in presentation formats, American Airlines cannot be measured on the same scale. However, even when American is eliminated from the analysis, none of the qualitative conclusions are altered.

\(^{11}\) Clustering method best controls for possible under estimation of standard errors (as, in simple terms, they effectively reduce the number of observations rather than merely control for different means across groups). All of our results hold to a higher level of significance when using dummy variables to control for carrier specific effects.
Descriptive statistics.

### Table 1

<table>
<thead>
<tr>
<th>No. of observations</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1: Prices of flights departing on different dates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>American Airlines</td>
<td>756</td>
<td>375</td>
</tr>
<tr>
<td>Continental Airlines</td>
<td>753</td>
<td>417.3</td>
</tr>
<tr>
<td>Delta Air Lines</td>
<td>756</td>
<td>337.5</td>
</tr>
<tr>
<td>Northwest Airlines</td>
<td>756</td>
<td>583.8</td>
</tr>
<tr>
<td>United Airlines</td>
<td>754</td>
<td>324.9</td>
</tr>
<tr>
<td>US Airways</td>
<td>756</td>
<td>282.3</td>
</tr>
<tr>
<td>Total</td>
<td>4531</td>
<td>390.2</td>
</tr>
</tbody>
</table>

### Table 2

| Differences in the number of alternatives among the carriers’ websites. |
|-----------------------------|-------------|------------------|
| Airline                     | Alternatives presentation | # of alternative dates on a single screen |
| American Airlines           | Only columns: ±3           | 7                |
| Continental Airlines        | Grid: ±3                 | 49               |
| Delta Air Lines             | Grid: ±1                 | 9                |
| Northwest Airlines          | Grid: ±3                 | 49               |
| United Airlines             | Grid: ±2                 | 25               |
| US Airways                  | Grid: ±1                 | 9                |

Our first hypothesis is that the number of alternatives is negatively correlated with the variance in the lowest prices exhibited by a carrier, for flights on the same airport-pair, offered on different dates. Table 4 presents regression results where the dependent variable is the coefficient of variance. Quite profoundly, we find that, even after controlling for price dependencies within each airline and within each route, the number of alternatives presented by the decision aid affects price variation. The coefficient of variance is significant at the 1% level and negatively correlated with alternatives. As can be expected, the competition level on a route, represented by HHI, is also significant at the 5% level.

It is important to note that the Alternatives parameter represents the marginal effect of a single additional travel date. That is, the marginal reduction of variance is approximately 0.36% with each additional alternative displayed. This implies that, when comparing tabulated matrices of 3 × 3, to those of 5 × 5, the difference is of 16 cells (an increase from 9 cells to 25 cells), and thus the reduction in variance is of 16 × 0.36% = 5.76%. Similarly, when comparing tabulated matrices of 5 × 5 to 7 × 7, the decrease in variance amounts to 8.64%.

Table 5 shows the results of regression specifications pertaining to hypotheses Hypothesis 3A and 3B. In these specifications, the dependent variable is the variance of the lowest prices offered by a carrier on different purchase dates, for a flight on a specific travel date on the same airport-pairs. The results confirm that the extent to which a website provides alternative dates is negatively correlated with the variance of the lowest available airfares on the airport pair. The Alternatives parameter is negative and significant at the 1% level when explaining the coefficient of variance.

### Table 3

Correlation matrices of model variables.

#### 3a: The correlation matrix of Sample 1

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>HHI</th>
<th>Distance</th>
<th>Hub on route</th>
<th>LCC (dummy)</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternatives</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHI</td>
<td>0 (p = 1)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td>0 (p = 1)</td>
<td>-0.15 (p = 0.0004)</td>
<td>0.02 (p = 0.22)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hub on route</td>
<td>-0.06 (p = 0.0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LCC (dummy)</td>
<td>0 (p = 1)</td>
<td>-0.55 (p = 0.0001)</td>
<td>-0.02 (p = 0.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0 (p = 1)</td>
<td>0.27 (p = 0.0)</td>
<td>0.2 (p = 0.0)</td>
<td>0.01 (p = 0.56)</td>
<td>-0.48 (p = 0.0)</td>
</tr>
</tbody>
</table>

#### 3b: The correlation matrix of Sample 2

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>HHI</th>
<th>Distance</th>
<th>Hub on route</th>
<th>LCC (dummy)</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternatives</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHI</td>
<td>0 (p = 1)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td>0 (p = 1)</td>
<td>-0.15 (p = 0.0)</td>
<td>0.02 (p = 0.74)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hub on route</td>
<td>-0.06 (p = 0.24)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LCC (dummy)</td>
<td>0 (p = 1)</td>
<td>-0.55 (p = 0.0)</td>
<td>-0.02 (p = 0.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0 (p = 1)</td>
<td>0.27 (p = 0.0)</td>
<td>0.2 (p = 0.0002)</td>
<td>0.008 (p = 0.85)</td>
<td>-0.48 (p = 0.0)</td>
</tr>
</tbody>
</table>
Table 4
Testing hypothesis H1. This regression uses Sample 1—prices of flights departing on different dates, available on a fixed purchase date. The sample includes lowest fare price data for 6 airline carriers over 54 routes. The dependent variable is coefficient of variation. *Alternatives* is the number of alternative flight dates offered by the airline on flexible fare search. Hub on route is a dummy parameter indicating whether the carrier has a hub at either end of the route. Population is the mean population (in millions) of the city pair pertaining to a route. Distance is the total distance between the two cities connected by the route (in thousands of kilometers). LCC is a dummy variable indicating whether a low cost carrier offers flights on the route. HHI is the Herfindahl–Hirschman Index of the route. N is the number of route-carrier pairs accumulated.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Coefficient of variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternatives</td>
<td>-0.0036 (−3.63)**</td>
</tr>
<tr>
<td>HHI</td>
<td>-0.0203 (−2.28)*</td>
</tr>
<tr>
<td>Distance</td>
<td>-0.013 (−0.77)</td>
</tr>
<tr>
<td>Population</td>
<td>0.0112 (0.9)</td>
</tr>
<tr>
<td>Hub on route</td>
<td>0.007 (0.4)</td>
</tr>
<tr>
<td>LCC (dummy)</td>
<td>-0.0046 (−0.11)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.4216 (4.7)</td>
</tr>
<tr>
<td>N</td>
<td>324</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1485</td>
</tr>
</tbody>
</table>

Two-way clustering regressions (by airline and by route); t-statistic in parentheses; * significant at 10%. ** Significant at 5%. *** Significant at 1%.

respect to the number of changes in airfares for specific travel dates on a specific airport pair, the number of alternatives displayed also appears to be highly correlated. In this regression specification, we also find a positive correlation between price changes and distance. Nonetheless, Alternatives is most significantly correlated with price changes, suggesting that the Alternatives parameter is an important contributor to an airline’s frequency and magnitude of price changes. Further, the negative correlation is consistent with the idea that when the search costs are low, demand can be controlled for by providing suitable alternatives that are easy to find. On the other hand, when search costs are high, demand is influenced mainly through price changes. The marginal reduction in the number of price changes being made on the lowest fare flight offered for a specific travel date is about 0.02 per additional alternative.

With supporting evidence for variability reduction, we next examine whether the supported pricing mechanisms enable an increase in the average lowest available airfare (Hypotheses 2 and 4). Table 6 shows the results of regression specifications in which the dependent variable is the lowest fare, at the route level, averaged either across departing dates or across purchasing dates: in the first specification, the dependent variable is the fare averaged across different departure dates. We test Hypothesis 2 using Sample 1. In the second specification, the dependent variable is the fare averaged across different dates of purchase. Thus, we test Hypothesis 4 using Sample 2.

In both specifications, the Alternatives variable is positive and significant at the 1% level. Not surprisingly, other variables are found to be highly significant as well. Specifically, consistent with the literature, it appears that when a low-cost carrier operates on a route, the lowest price offered by other carriers on the same route is significantly reduced. As well, the more populated the two serviced cities of the route, the lower the average fare offered. Finally, as expected, we also find that as the distance between the airport-pairs increases, the average nominal airfare increases accordingly.

Hence, the results of our tests support our main hypotheses that as the number of date-wise alternatives offered to the potential passengers increases, the relative variance of the lowest prices decreases, the number of price changes decreases, and that, at the same time the average low price increases.

7. Robustness

A possible concern that we have not addressed thus far is that of endogeneity, as a reverse causality argumentation may be suggested. Under reverse causality, the number of alternatives displayed is derived from the variance of prices rather than the other way around. In this respect, we note that since the size of the matrix exposed by an airline is fixed, in order for the variance to affect the matrix size, the magnitude of price variations exposed by airlines should be fixed as well. It has been shown that the variance of prices varies over time (Chellappa et al. 2011); hence,
a reverse causality argument does not appear to hold. Nonetheless, statistical evidence underlying reverse causality is still desired.

Our analysis is based on a variable that has not been looked at previously, and therefore it is hard to suggest instrumental variables associated with it. On the other hand, as discussed in the previous sections, previous research suggested variables that help in explaining price variance. We therefore employ instrumental variables to model the coefficient of variation of prices, and check for the significance of the reverse causality argumentation by employing a two-stage least squares (2SLS) regression. We apply the following structural model:

Stage 1: \[ CV = f(\text{Low Cost Carrier}, \text{Route on hub}, \text{HHI}, \text{Distance}, \text{Population}) \]

Stage 2: \[ \text{Alternatives} = f(\text{Predicted CV Route on hub, HHI, Distance, Population}) \]

In this model, \( CV \) is the dependent variable in Stage 1, and its measure serves as an independent variable in Stage 2, jointly with the Route on Hub, HHI, Distance, and Population variables. Hence, the specification employs Low Cost Carrier as an instrument variable, and allows us to test for statistical evidence suggesting that the coefficient of variation of prices derives the number of alternatives.

The results of Table 7 show that the reverse causality argument yields an insignificant relationship between the variables. Importantly, the correlation between coefficient of variation and the number of alternatives is negative and insignificant. Thus, as suggested, the results do not support a reverse causality theory.

We further examine the processes that lead to price variance reduction. Our hypotheses were derived from the notion that as more alternatives are displayed, even small price differences will be noticed (by consumers) and attract purchases. In contrast, when fewer alternatives are displayed, purchasing will be induced through large price differences. Therefore, the effect of the number of alternatives displayed should be robust and hold across time as the departure date approaches.

We further examine whether the increased price variation has the same effect as easier access to information does (or whether low priced tickets are still not noticed and purchased when access is limited). If increased access to price information has a stronger effect on purchasing low demand tickets than increased price variance, then as time progresses towards departure date, price variance may further decrease, with a more significant effect for an airline that provides a larger matrix of prices.\(^{12}\)

To test for these effects we use Sample 2 and take the 3-day coefficient of variation derived from the prices of departure on the 1st, 2nd and 3rd departure dates sampled,\(^{13}\) the dates for which we have the most observations over time. (See Fig. 2b.) A three-day coefficient of variance means that for each day we compute the variance of prices for three days: the day itself, and the two days preceding it (i.e., it can be perceived as a moving average calculation of the variance). We also devised an additional explanatory variable to capture the interaction of time until departure and the size of the matrix. Namely, we define the variable \( \text{SizeTime} \) as follows:

\[ \text{SizeTime} = \text{Alternatives} \cdot \text{TimeToDeparture} \]

In the regression we include the main effects of both Alternatives and TimeToDeparture.

Table 8 shows the regression results in which the dependent variable is the three- (four-, or five-) day coefficient of variation experienced on a route by an airline. It can be seen that the effect of Alternatives is robust, as Alternatives is negative and significant at the 1% level in all regressions. We further see that the interaction effect captured through SizeTime is somewhat ambiguous. A negative and significant coefficient of SizeTime would suggest that the coefficient of variation of prices decreases faster as the matrix size increases. However, it is hard to conclude from the results whether an interaction effect holds since SizeTime is only significant (and negative) in one of the three regression specifications. These results suggest that the effect of diversion of customers to lower demand flights, through increased access to information, is similar or possibly stronger than the effect of increased price differences.

8. Conclusion

We have argued that accessibility of information on the decision aid deployed on a vendor’s website can affect consumers’ decisions and thereby influence vendors’ pricing. We also have analyzed the airline industry and claimed that by reducing the cognitive effort involved in the search process of alternative goods, airlines effectively encourage consumers to consider a wider range of alternatives prior to purchase, thus allowing them to reach better decisions. This process, which permits consumers to self-select appropriate products, balances demand across goods. These aspects directly relate to airlines’ pricing strategies.

We have tapped into a unique opportunity to analyze differences in decision aids provided in the airline industry. Studying legacy carriers in the US domestic airline industry, we have observed that the selected carriers offered results for date-flexible searches to different extents. While some carriers facilitated a search incorporating only the immediate days before and after the requested departure and return dates, others facilitated the incorporation of a whole week of departure and return combinations.

Hence, according to consumer decision making literature, the cognitive effort involved in a decision process for finding a low priced ticket differs between carriers’ site. Accordingly, we have raised several hypotheses with regard to the behavior of prices as affected by the decision aids. Our primary hypotheses state that, in general, extended information reach decreases the variation of
prices over time, decreases the number of price changes, and increases the average price charged. We have examined variation of prices in a number of ways: (1) variation in the prices of flights on the same route, departing on different dates; (2) variation in the prices of flights on the same route and departure date, offered on different dates of purchase; and (3) number of price changes. Lower variation of prices across travel dates suggests that with extended information reach, smaller possible monetary gains can yield to the purchase of a lower demand product. In line with Hann and Terwiesch (2003), these findings support the idea that the cognitive effort involved in finding the products is reduced. Lower variation of prices across time, and a smaller number of price changes, suggests that forecasting is improved and the need to change prices to increase demand is reduced.

Similarly we have examined the average price of the lowest fare in two ways: (1) the average of the lowest airfare of flights on the same route, departing on different dates, and (2) the average of the lowest fare of flights on the same route and departure date, offered on different dates of purchase. In both measures, a higher average suggests that carriers are able to increase demand on products without necessarily reducing price, and thus maximize profit. These hypotheses were validated using our sampled data collected on a daily basis on a variety of US domestic routes. The results of our analysis strongly support the idea that the number of alternative travel dates offered by an airline on its website is directly related to the realized variance of prices, the number of price updates, and the mean price.

Our hypotheses are derived from previous work done in the information systems literature. The effect of decision support tools on decision processes and outcomes has been well studied in IS for almost two decades. Such research provides significant evidence for the relevance of a cost benefit model when analyzing decision support tools. However, previous IS work that empirically evaluated decision support tools, has predominantly employed laboratory-based empirical designs. This work incorporates an empirical design based on industry data. We believe the work presented in this research provides an important step towards further validating previous work and understanding its implications in different industry settings. We showed that the analysis of the airline industry provides fruitful grounds to conduct such experiments.

The results we derived have important implications. It appears that, while consumers may intuitively patronize their preferred carriers to incorporate decision support tools with an extended number of alternatives presented, easing access to information may actually not be in the consumers’ favor. With easier access to alternative itineraries, consumers appear to have fewer opportunities to find variance in price offerings. Hence, consumers willing to invest time and effort in search will have fewer opportunities to reduce their monetary costs. In contrast to that, this research raises interesting opportunities for businesses to generate revenue. Often businesses invest significant amounts of money in the advertising and promotion of products. According to the results presented in this paper, another way to divert demand is through the level of information presented by the decision support tool.

It should be noted that we do not measure cognitive effort directly. Rather, we use the number of alternative trip dates presented by an airline as a proxy for the effort required in accessing and evaluating date/price combinations. As suggested in this paper, in order to consider the same number of options, users who access a website that displays a limited number of alternative travel dates, need to conduct more searches than users who access a website with a larger number of alternatives. Thus, the former group of users needs to apply more effort, which, according to the cost-benefit model, they are reluctant to do.

This research raises some interesting questions associated with the design of corporate websites. In our case, if more alternative itineraries facilitate superior pricing mechanisms, why are not all of the carriers using this format? Many explanations can be proposed. One explanation could be that fewer alternatives impose advantages not relevant to pricing (perhaps technological considerations – better system maintenance, easier updates of data, etc.). An equally appealing explanation is that some (or all) of the carriers are not aware of the pricing impacts the number of tabulated alternatives impose – the flexible flight search format is supported only to provide similar functionality to the one available on competitor’s sites.

We believe this research has many practical implications as it takes a step forward on work done in previous studies. Previous studies have provided unilateral evidence for the effect of decision aid design on consumer’s cognitive effort and choice processes. We utilize this knowledge and examine the possible economic effect of these differences. In essence the number of alternatives presented, captures the ease with which customers can find alternative low-priced flights provided by the carrier. In the future, perhaps additional innovative ways for providing online consumers with alternatives, at no cost, can be suggested. Additional directions for future work can be derived from this research by raising questions
such as, what types of online search options are more attractive to consumers, and, therefore, how will this affect the popularity of websites? To what extent does the number of alternatives affect pricing of other consumer products, not necessarily subject to revenue management pricing? As we noted, airline tickets fall under the category of low-touch products, which are frequently bought online. An interesting topic for future research would be to examine whether our findings hold also for high-touch products, and if so, whether the magnitude of the effects differs between these two types of products. Another interesting research question would be to look at the effect of the decision aid on the timing of a purchase. As noted, customers have a choice not only on which product to purchase but also on when to purchase it. This research examined the product choice; many possibilities for future research can be suggested with respect to timing decisions. These are only a few of the research directions that can build on our research and improve understanding of the processes originating from the interaction between online purchase decisions and pricing mechanisms.

Acknowledgments

The authors would like to thank the Editor and the three anonymous referees whose input has led to a significantly improved exposition of our results. This research was partially supported by a Natural Sciences and Engineering Research Council of Canada (NSERC) grant.

References