Airline Passengers' Online Search and Purchase Behaviors: New Insights from an Interactive Pricing Response Model

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Abstract

This paper develops a model of airline customers' online search and purchase behaviors using page-by-page clickstream data collected from a web-based Interactive Pricing Response (IPR) system that was implemented by Freedom Air, a former low cost subsidiary of Air New Zealand. The IPR system represents a new business model designed to stimulate demand by dynamically offering discounts to highly time-flexible travelers in a way that does not trigger price responses from competitors. A new model based on Markov-methods that incorporates reference price effects is proposed to capture the dynamics of search and purchase behaviors of these highly time-flexible leisure travelers. Empirical results show that higher search intensities and purchase conversions occur as the relative discounts increase. In addition, while product attributes displayed on the previous screen are highly correlated with product attributes displayed on the current screen, fundamental customer choices related to whether to continue shopping, to purchase, or not to purchase are driven predominately by the relative discount level displayed on the current screen. Simulations are used to illustrate how these highly-predictable search and purchase behaviors can be integrated back into the IPR system, effectively enabling firms to control conversion rates and the relative discount rate ranges offered in the market, thereby maximizing incremental revenue generated by the IPR system.

Keywords: e-commerce, online search behavior, online purchasing conversion, buyer behavior, Markov chain models.

1 Introduction

The year 2008 is shaping up to be "the year of records" for the U.S. airline industry. Fuel prices have surged to all-time highs, an unprecedented number of carriers ceased operations within the short span of one week, and consolidation is clearly on the horizon as carriers cut back on U.S. capacity, legacy carriers progress through merger discussions, and low cost carriers contemplate new code share agreements (Kelly, 2008). Multiple factors have contributed to the current state of the U.S. airline industry including the emergence of online travel agencies (*e.g.*, Expedia, Orbitz, Travelocity, etc.) that facilitated the comparison of prices across airline competitors and the ever-increasing penetration of low cost carriers (LCCs) that employ very different pricing models than those used by legacy carriers. Specifically, the majority of LCCs in the U.S. use one-way pricing, which results in separate price quotes for the departing and returning portions of a trip. One-way pricing effectively eliminates the ability to segment business and leisure travelers based on a Saturday night stay requirement (*i.e.*, business travelers are less likely to have a trip that involves a Saturday night stay). Combine the use of one-way pricing with the fact that the internet has increased the transparency of prices for consumers and the result is that today, almost half of all air leisure travelers state that they purchase the lowest price they find when using online channels (Harteveldt, *et al.*, 2004).

In many ways, the internet has been both a blessing and a curse for carriers. On one hand, carriers have benefited from lower distribution costs and the ability to interact directly with consumers (versus relying on an intermediary travel agency). On the other hand, the internet has not only increased the transparency of prices for consumers, but for competitors as well. Monitoring competitive prices and seat availability (a measure of demand on competitors' flights) is becoming more common and viable at a large scale. The net result is a highly competitive market in which the ability to segment customers and price discriminate is becoming more difficult and price changes are quickly matched by competitors. In this environment, one may question whether it is possible for a carrier to leverage the strengths of the internet - and specifically the ability to interact directly with its consumers - to customize prices for individual consumers in ways that do not trigger price responses by the competition. Conceptually, the fundamental question of interest is to determine whether it is possible to stimulate new leisure demand by designing a product for highly time-flexible travelers that is sold via the internet.

In May of 2003, co-author David Post launched a web-based Interactive Pricing Response (IPR) system with Freedom Air International, a former low cost subsidiary of Air New Zealand, to explore these questions. This IPR system enables customers to individually generate prices based on their level of time-flexibility. The IPR system is designed to tap into a predominately unserved market of highly time-flexible people that would fly if they were able to offset some of their time-flexibility for a larger discount than is presently offered by the airlines. This allows airlines both the ability to generate incremental revenues, as well as the ability to better match supply and demand. Most important, given prices are customized to individual consumers and are dynamically generated based on the airline's current demands, competitors have no set price target on which to compete. In addition, data collected from the interaction with time-flexible travelers provides a unique opportunity to gain new insights into online customers' search and purchase behaviors, the primary research focus of this paper.

The first objective of this paper is to use the page-by-page clickstream data collected from the IPR system of Freedom Air to model the interaction between customer search and purchase behaviors and the firm's pricing policies. From a methodological perspective, a new model based on Markov-methods that incorporates reference price effects (or relative discount rates) is used to capture the depth and dynamics of customers' search and purchase behaviors. Results show that higher search intensities and purchase conversions occur as the relative discounts increase, particularly for discounts greater than 30%. Analysis of searching dynamics also suggests the presence of two customer segments: those who are less flexible and find discounts less than 30% have a distinct search behavior than those who are more flexible and receive discounts greater than 30%. In the latter case, these more flexible travelers are more willing to engage with the IPR system, perform more search queries, and purchase more often.

The second objective of this paper is to use the page-by-page clickstream data to gain new insights into customers' online search behavior. Results, based on Markov-methods, indicate that customers tend to change their search parameters linearly, one at a time, and cling to small search spaces. In addition, while there is a strong "stickiness factor" in the sense that the product attributes displayed on the previous screen are highly correlated with the product attributes displayed on the current screen, fundamental customer choices related to whether to continue shopping, purchase, or not purchase are driven predominately by the relative discount level on the screen. In this context, Markov-based models are found to be robust to predicting the search and purchase behaviors of these highly time-flexible leisure travelers.

The third objective of this paper is to develop a conceptual framework to illustrate how firms can integrate customers' search and purchase behaviors into the design of the IPR system. Specifically, simulations are used to demonstrate how two critical customer search parameters can be integrated into the IPR system, effectively resulting in the ability of firms to control conversion rates and the relative discount rate ranges offered in the market. It is our vision that the use of online interactive marketing to segment price-sensitive travelers into time-flexible and time-inflexible customers is a concept that can be applied across multiple industries. For example, automotive manufacturers may be able to use this model to smooth production of new deliveries by offering discounts to time-flexible customers who are willing to have their new vehicle delivered "anytime" within a wide delivery window. In turn, this can lead to decreased production costs (due to less peaking of demand) and increased revenue (due to additional vehicle sales). Similar applications of using flexible delivery windows for inventory management applications have been discussed extensively in the literature by other authors (*e.g.*, see Wang and Toktay, 2008, for an excellent review of the literature in this area).

Given an overview of the objectives of this study, the next section reviews the relevant literature and highlights how the main contributions of this study. This is followed by an overview of the IPR system and discussion of the unique data that it offers for modeling customers' search and purchase behaviors. Armed with an understanding of this system and data, the conceptual model used to investigate customers' search and purchase behaviors is described. This is followed by a discussion of the methodology, empirical results, and validation. Finally, key findings and directions for future research are summarized.

2 Literature Review and Main Contributions

Due to the ability to track customers and observe how they engage with the IPR system, the questions explored in this study are quite distinct from those reported in earlier work. While, in general, there has been some research related to the potential of uncertainty / flexible products, the concept of selling opaque products has been explored in a theoretical context by several authors (*e.g.*, see Fay, 2007; Fay, 2008; Gallego and Phillips, 2004; Gallego, *et al.*, 2004; Yabing, 2007). Here, an uncertainty / flexible product is one in which or more of the attributes are unknown (or opaque) to the customer at the time of purchase, thereby giving a level of "uncertainty" as to what the end product will be. These unknown attributes are revealed to the customer at a later stage. In contrast to some of the more well-known applications of opaque product sales that reveal the unknown product attributes at the time of purchase via reverse auction methods (*e.g.*, Priceline and Hotwire), this study is distinct in that it explicitly incorporates the time at which the customer knows these attributes as a variable that can be specified by the customer (*i.e.*, how many days in advance of the beginning of a trip the passenger needs to know the exact departure days and flights). Note that this is distinct from the business model used by some travel sites that allow individuals to search over a month's view of airline prices and chose the days that have the lowest fare (defined as the reference fare). In the IPR system, customers are offered a discount above and beyond this published reference fare in exchange for waiting until closer to the flight departure (when demands on flights are more certain) to know their exact travel itinerary.

Within the marketing literature, our work is most similar to that of Bucklin and Sismeiro (2003) and Montgomery, *et al.* (2004) in the sense that within-site analysis of consumer browsing behavior is explored using clickstream data. For example, Bucklin and Sismeiro (2003) investigate search depth (number of pages requested) and page-view-duration of online shoppers within a site. Our work is also similar in spirit to that of Johnson, *et al.* (2004), Moe and Fader (2004), and Park and Fader (2004) in the sense that conversion behavior and the depth and dynamics of online search behavior are examined. For example, Johnson, *et al.* (2004) study search depth (number of sites visited) of online shoppers, but their analysis is focused on visits to multiple sites. They use panel data that represents visits across multiple sites, while we use much more specific clickstream data that captures each individual's search activity within a site. Similarly, Moe and Fader (2004) investigate conversion (or purchasing) propensity of online shoppers across multiple sites. They decompose purchasing propensity in order to examine several effects - a baseline purchasing probability, visit effects (accumulated in each visit), and learning effects that evolve over time. Assuming that each effect is gamma distributed, they estimate the mean purchasing propensity. In contrast to this study, they also use visit-level data across multiple sites versus detailed clickstream data. Park and Fader (2004) also investigate conversion propensities of online shoppers across multiple sites by incorporating cross-site visit information and timing effects. Specifically, information from one site is to predict customer purchase behavior at another site using a multivariate timing mixture model.

It is important to note that fundamentally, the underlying motivations between these classic marketing studies and our work are quite distinct. Conceptually, the primary motivation for earlier studies has been to better understand customer search and purchase behaviors within a site or across competitor sites with the ultimate objective of personalizing product offerings and site designs to increase conversion rates. In contrast, our study starts with a website, namely the IPR system, which has already been designed with the intent of personalizing product offerings for a homogeneous population of time-flexible travelers. Consequently, the motivation for modeling customers' search and purchase behaviors within our business context is to determine if we can predict these behaviors as a function of relative discounts, thereby enabling managers to set conversion rates and relative discount rates offered in the market as a function of customers' searching parameters. Thus, while we can analyze questions typically explored as part of a study of online consumer behavior, we can analyze new questions as well.

Specifically, by modeling the dynamics of screen-to-screen transitions of discount rates, we can explore the interaction between customer searches and the firm's pricing policies and analyze questions typically explored as part of a study of online consumer behavior related to purchase conversions, search intensity, and search depth. A static or snapshot analysis of discount rates provides the ability to explore non-traditional questions related to whether customers searching for discounts explore the entire search space, or tend to cling to a small search space. In addition, based on the unique characteristics of our data from the IPR system, we can explore a range of new questions related to online customers' search behavior. A static or snapshot analysis of screen-to-screen transitions of customers' search behavior provides information on whether customers search along multiple parameters linearly or simultaneously. Additional insights can be gained with respect to whether individuals explore the entire search space, or cling to a small search space. Finally, a dynamic analysis of these customers' search transitions shows that customers' search behaviors are stable over time and exhibit stationary search spaces.

When viewed in the context of the existing literature, there are three primary contributions of this paper. First, we extend upon a business model described by Post, Mang, and Spann (2007) that leverages the strengths of the internet to interact with customers and customize prices for them in ways that do not trigger competitive price responses. To the best of our knowledge, this paper is one of the first to analyze data from this type of business model (which we may see occur more often in the travel industry in the near future) and one of the first to provide insights into its potential impacts. Second, from a methodological perspective, this work in quite distinct from that of earlier marketing papers that examined within-site or cross-site searching and purchase behaviors, due to the fact that the design of the IPR system itself resulted in the ability to target a relatively homogeneous population of time-flexible travelers. Consequently, in contrast to findings from earlier work, we find that relatively simplistic modeling techniques, namely first-order Markov chains, are quite powerful in predicting customers' search and purchase behaviors. Third, from a behavioral perspective, new insights into customers' search and purchase behaviors emerge from this study. Of particular interest is the fact that, consistent with prior research reported by Travelocity, the presence of two distinct customer segments is found: those individuals who view discounts below 30% are found to have distinct search and purchase behaviors than those who view discounts about 30%.

Given an understanding of how our work relates to the existing marketing literature, the next section describes the IPR system and data available for analysis.

3 Interactive Pricing Response (IPR) System

This section provides an overview of how customers interact with the interactive pricing response (IPR) system, how the underlying price response curves used in the IPR system are generated, and how revenue dilution is minimized through the product design. Summary characteristics of the data provided by the IPR system used to model customer search and purchase behaviors are also provided.

3.1 Overview

The potential to customize products to consumers based on interactive marketing has been noted my many authors (*e.g.*, see Montgomery, *et al.*, 2004, and references quoted there-in, namely Blattberg and Deighton, 1991; Hoffin and Novak, 1996; Alba, *et al.*, 1997; Pal and Rangaswamy, 2003; Ansari and Mela, 2003). However, in contrast to earlier ideas that customize product offerings shown to consumers based on demographic information, prior purchase history and/or how the customer arrived to the site, the IPR system can be described as a "needs based" marketing tool that segments the traveling market into individual products by allowing each person to effectively mass-customize their own travel product based on their degree of travel flexibility.

The IPR system used for this study was a user interface linked to the website of a small international airline, Freedom Air (which has since been merged into Air New Zealand). In 2003, the Freedom Air website was the third most frequented travel website in New Zealand, attracting approximately 170,000 visitors per month. The research instrument, branded Fare Choice (FC), was attached to the home page of the Freedom Air website. Once visitors activated the FC link, they were redirected to the FC user interface page where they entered their destination, group composition, how many nights at the destination, the earliest possible departure date, the latest possible return date, and how many days before the earliest departure date they want to be informed of the travel details (defined as prior notice, PN). The FC pricing page displayed the price calculated as a result of the parameters entered by the inquirer. At this stage, the inquirer could either revise the parameters or accept the price. Inquirers who decided to revise the parameters returned to the FC user interface page, where any or all of the inputs could be edited.

3.2 Pricing Response Curve

The price shown to the customer was generated by an underlying pricing curve that is a function of both inputs provided by the customer and an airline manager, as well as the amount of remaining capacity on those flights that could be used to satisfy the customer's travel criteria. The price that the FC customer paid for various degrees of uncertainty was created using a simple calculation. The algorithm attempted to make a compromise between what would seem to be reasonable for the customer and also what would make economic sense to the airline. The customer would expect that, with increasing uncertainty in travel dates, the price would decrease. On the other hand, the airline would want to reward customers that chose travel times in periods of low demand and discourage (with higher prices) customers from choosing travel windows where demand is high.

Formally, the shape of the pricing curve is given by δ, an uncertainty parameter defined as:

$$\delta = \left(1 - \frac{A}{A_{\max}}\right)^{\alpha} \left(\frac{PN}{PN_{\max}}\right)^{\beta}, \quad 0 < \delta < 1; \alpha > 0; \beta > 0$$

where the uncertainty parameter is used to calculate the price offered to the customer, or:

$$\text{Price offered} = \text{Bottom Price} + \delta(\text{Top Price} - \text{Bottom Price})$$

The top price (TP), bottom price (BP), α, and β are parameters set by an airline manager; TP and BP are used to bound the range of prices quoted to the customer, while α and β control the sensitivity of price to excess inventory and customer-specified prior notice, respectively. The ratios of A/A_{max} and PN/PN_{max} refer to measures of excess capacity and prior notice and conceptually capture information about whether passengers can travel in periods of low demand (reflected in A/A_{max}) and much uncertainty passengers are willing to accept (reflected in PN/PN_{max}). The formal calculations for these inputs are best understood using the graph shown in Figure 1.

The customer's time window (or window of flexibility) is defined as the set of possible travel dates given as the difference between the latest possible return date and the earliest possible departure date. When calculating a price, all possible flight combinations that fall within the customer's desired travel date range and length of stay are examined. A temporary booking is recorded for the

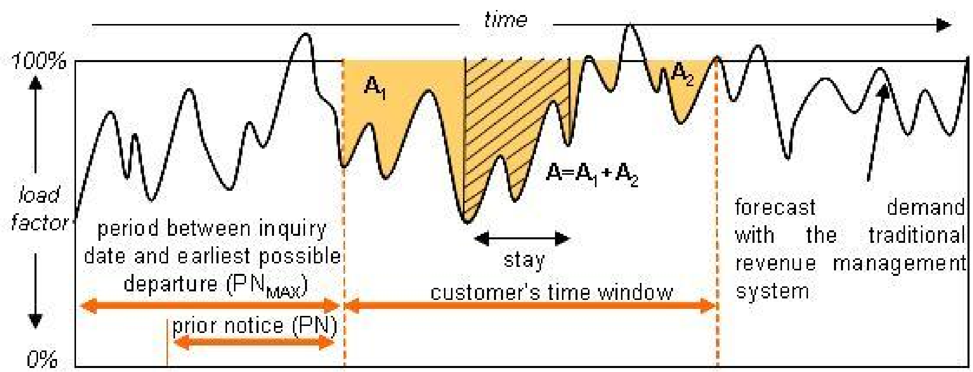

Figure 1: Graphical representation of inputs for the flexibility parameter (adapted from Post, Mang and Spann, 2007)

combination of departing and returning flights that result in the largest number of vacant seats.[1] Given information on which (departing) flight has the largest number of excess seats, the ratio of A/A_{max} is subsequently calculated.[2] Formally, A is the number of spare seats forecasted within the window of flexibility but does not include the spare seats on the dates during which the customer is expected to travel (this is based on the initial temporary booking dates). The area of $A_{\max}$ is given as the sum of the empty seats throughout the whole possible booking period (six months).

The ratio of PN/PN_{max} provides information on the customer's flexibility. Here, PN (prior notice) is defined as the minimum number of days prior to departure that the customer requires confirmation of their flight details and is defined as number of days between the date at which the customer is making an inquiry and the earliest possible departure date.

3.3 Additional Restrictions Placed on the Fare Choice Product

In order to help prevent revenue dilution from sales to only moderately time-flexible people at prices lower than their existing airfares, additional restrictions were associated with the FC product to ensure that a minimum level of flexibility was realized before a price would be displayed to an inquirer. This required level of time flexibility is called the "Limbo Bar" setting and was defined to be the ratio of the days the person wished to be at the destination divided by the number of days

[1] The actual flights booked are those that have the most empty seats based on the latest forecast data at the start of the customer's window of flexibility.

[2] Because Freedom Air used one-way pricing, pricing for the departing and returning flights were calculated separately. The extension of the formulas presented in this section to calculate price for each portion of the trip is straightforward, and omitted to maintain clarity of the discussion.

in the window of flexibility. The limbo bar setting was set at a minimum of 0.5 during the data collection phase. That meant a person that wished to go to a particular destination for seven days would have to be prepared to have a window of flexibility (*i.e.*, the time between the first possible departure date and the last possible return date) of at least 14 days in order to be displayed a price. Using a limbo bar less than or equal to 0.5 also ensures that the customer cannot guarantee being at the destination on a particular date (since the customer may be traveling on that day).

Conceptually, the FC product becomes more differentiated from the traditional fixed-date product (for the same length of stay at a destination) as the number of days in the flexibility window increase and/or the number of days of prior notice reduce. As analyzed extensively in Post, Mang, and Spann (2007), the design of the FC product resulted in little revenue dilution and was estimated to generate approximately 7% incremental revenue. The calculation of incremental revenue was based on an analysis of data from the IPR system and supplemented by customer surveys that were used to detect and account for revenue dilution due to cannibalization.[3]

3.4 Data Characteristics

The online clickstream data for this research was collected over a two-year period, from August 2004, to June 2006, and targeted to customers traveling on one of 21 routes between New Zealand, Australia, and/or Fiji. The majority of prices shown to customers were between NZ $300 and $500, where $500 was approximately equal to the lowest price offered on a traditional round trip Freedom Air itinerary.

Online clickstream data captures the sequence of web pages viewed by customers. We define four terms to describe how clickstream data was used for the analysis. A *search* is defined as the combination of two pages: the page in which a customer inputs search parameters and the page in which the price offered to the consumer is displayed. A *session* is defined as the sequence of page views occurring within a browser that is initiated by a search and followed by one or more consecutive searches. A *visit* is a series of pages in which a customer searches for a single

[3] Note that it is not possible to calculate incremental revenue exactly, as the number of people who purchased the flexible product, but would have paid more for the traditional product, is not known with certainty. This form of revenue dilution due to cannibalization was estimated by authors Post, Mang, and Spann (2007) based on customer surveys.

product (defined as an airline route). A *visit* may be comprised of one or more sessions. A *cookie* is used as a proxy for an individual consumer. As noted by Moe and Fader (2004), one limitation typically associated with clickstream data is that it is difficult to obtain characteristics that identify a particular user. In contrast to the U.S. where retailers are reticent to trace cookies stored in customers' computers due to privacy concerns, New Zealand retailers are much more open to tracking cookies. This provides us with the opportunity to use cookies to identify and track individual customers.

In order to clarify these definitions, Table 1 provides an example of the clickstream data used for this analysis. Each row represents a search that contains search parameters (route, time window, prior notice) and search results (price, purchase decision). The customer associated with cookie 1001 visits twice. During the first visit (denoted by "AA"), the customer searches for a ticket on route AKLOOL, while during the second visit (denoted by "BB"), the customer searches for a ticket on route BNEHLZ. Two sessions are associated with the first visit. During the first session (denoted by "abcd") the customer performs two search queries and closes the browser. The customer later returns for a second session (denoted by "abce") and purchases a ticket in a single search. Thus, the visit associated with the AKLOOL ticket is made after three searches that occur across two separate sessions. In this analysis, we associate customer search behavior with visits and study the sequence of searches within this visit in order to explore the dynamics of customer search and purchase decisions.

Date	Session	Visit	Cookie	Route	Window	Notice	Price	Purchase
08/25/2006 4:09:40 PM	abcd	AA	1001	AKLOOL	20	10	300	No
08/25/2006 4:10:10 PM	abcd	AA	1001	AKLOOL	25	10	280	No
08/25/2006 4:20:14 PM	abce	AA	1001	AKLOOL	30	10	275	Yes
08/26/2006 3:00:10 PM	bcde	BB	1001	BNEHLZ	30	15	200	No
08/25/2006 4:20:16 PM	klmn	KK	1002	BNEHLZ	120	30	150	No

Table 1: Example clickstream data

Table 2 presents summary statistics for the clickstream data used in this study. Note that most customers visit the site only once (*i.e.*, most visits contain a single session). On average, a customer searches three times. The purchase conversion rate per visit is approximately 3%. However, customers that ended up purchasing searched, on average, much more than three times.

Data View	Occurrences
Search	42,963
Session	19,546
Visit	14,352
Cookie	12,588
Purchase	474

Table 2: Summary statistics for clickstream data

4 Online Search and Conversion Behavior

Using data from the IPR system, different models of customers' search and purchase behaviors were developed. The conceptual model used to investigate search and purchase behaviors is shown in Figure 2.

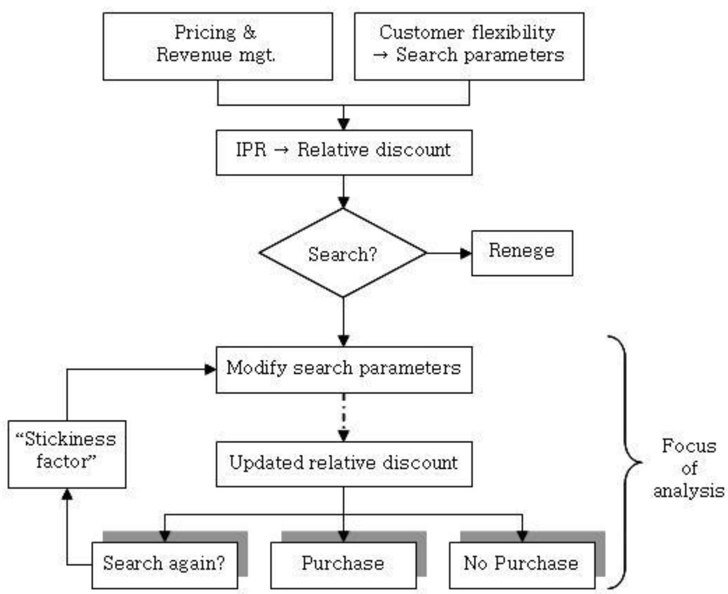

Figure 2: Conceptual model of airline customers' search and purchase behaviors

As discussed in the previous section, parameters linked to the underlying pricing and revenue management systems as well as parameters linked to the degree of uncertainty a customer is willing to accept are used to generate a price quote by the IPR system. Further, when the IPR system examines all possible flight combinations that fall within the customer's desired travel date range and length of stay, it records the lowest price associated with these standard products. This effectively enables one to calculate a relative discount, defined as the percentage discount that the customer receives for the FC product relative to the lowest price that is available on the traditional products over the specified window of flexibility. After seeing the first FC price quote (or being told the customer is not eligible for the FC product), the customer decides whether to continue searching or leave the site. Consistent with the rationale used in Bucklin and Sismeiro (2003), single site visits (such as those corresponding to the last two rows of Table 1) were excluded from analysis due to the fact they provide no information on searching behavior and, more importantly, are dominated by time-inflexible visitors who are not eligible for the FC product, and thus do not engage with the site. Also, note that due to the methodology used to define sessions, there are no instances in which a customer purchases upon viewing the first relative discount.

As shown by the shaded boxes in Figure 2, the focus of this analysis is on those customers who engage with the IPR system. These customers ultimately end in one of two state spaces: purchase or no purchase. From a modeling perspective, there are two key points of interest. First, the models allow for a "stickiness factor" in the sense that the product attributes displayed on the previous screen may be highly correlated with product attributes displayed on the current screen. Second, from the perspective of a firm that seeks to optimize incremental revenue and/or set a target conversion rate, it is ideal to model customer search and purchase behaviors as a direct function of the parameters used to determine the shape of the price response curve; however, as shown in Figure 2, the linkage between customer search parameters and the pricing response curve is "broken" as relevant revenue management and pricing information (namely A/A_{max}) was inadvertently not recorded. For these reasons, the relative discount level is used to predict customer search and purchase behaviors. Use of the relative discount level also provides the ability to more easily compare empirical results of this study to those reported from other studies.

These methodology used to explore these questions, along with corresponding empirical results are discussed in the following sections. First, static and dynamic analysis of screen-to-screen transitions of discount rates are presented. This is followed by static and dynamic analysis of screen-to-screen transitions for customer search parameters.

4.1 Conceptual Framework to Model Search and Conversion Behavior Using Discount Rates as States

In order to model and analyze online conversion behavior, we assume the following decision-making framework. Consumers input their travel flexibility parameters (time window, prior notice) and observe prices corresponding to these parameters. While searching for these flexible products, consumers have a lower reservation price below which they are willing to purchase and an upper reservation price above which they leave without purchasing. Hence, as soon as the price offered in the current search is out of these two boundaries, the consumer purchases or leaves the site without purchasing. Otherwise, if the price is between two boundaries, the consumer is ambivalent and does further searches by varying the travel flexibility parameters until the ambivalence is resolved.

We also assume that consumers are knowledgeable about the prices associated with the traditional product offering and use the lowest price offered on the traditional product as an anchoring reference price. Purchase decisions are made by assessing prices as discounts or surcharges relative to this reference price. We believe these assumptions are reasonable because: 1) the flexible FC product was a new product offering and thus, we expect customers to compare the flexible ticket prices to those of the traditional, non-flexible airline tickets; and, 2) the IPR system was accessed via the main page of the Freedom Air, which facilitated comparison between the flexible and non-flexible products. Most important, the use of a reference price for modeling purposes is convenient as we can control for market-specific effects (*e.g.*, departure/arrival airports, number of connections, length of connections, flight durations, etc.) as well as demand effects (*e.g.*, seasonality, holidays, etc.). The use of a reference price is also consistent with the methodology used by other researchers, most notably for Travelocity's "Good-Day-to-Buy" sales campaigns (Smith, *et al.*, 2007).

Another assumption is that purchasing decisions are primarily influenced by the price displayed from the current search. That is, we assume that the Markov property holds which implies, conditional on the present state of the system, its future and past states are independent. The validity of this assumption is shown as part of our empirical analysis.

4.1.1 Purchase Propensities

We start with snapshot analysis of purchase, no purchase, and search propensities. To distinguish between screen-to-screen and path-level behaviors, we define *propensity* as the screen-to-screen transition probability of moving from one state to another state. Thus, a *purchase propensity* is defined as the conditional probability of purchase given an individual is currently viewing discount rate d_n. We define *purchase probability* as the probability a search will eventually end in the purchase state. Formally, let d denote the discount rate of a flexible product relative to a reference (non-flexible) product. In addition, let $p(d)$ and $r(d)$ denote the corresponding purchase and no purchase propensities, respectively. For convenience, we discretize discount rates d into $d_1, ..., d_N$ and define $p_n = p(d_n)$ and $r_n = r(d_n)$ for $n = 1, ..., N$.

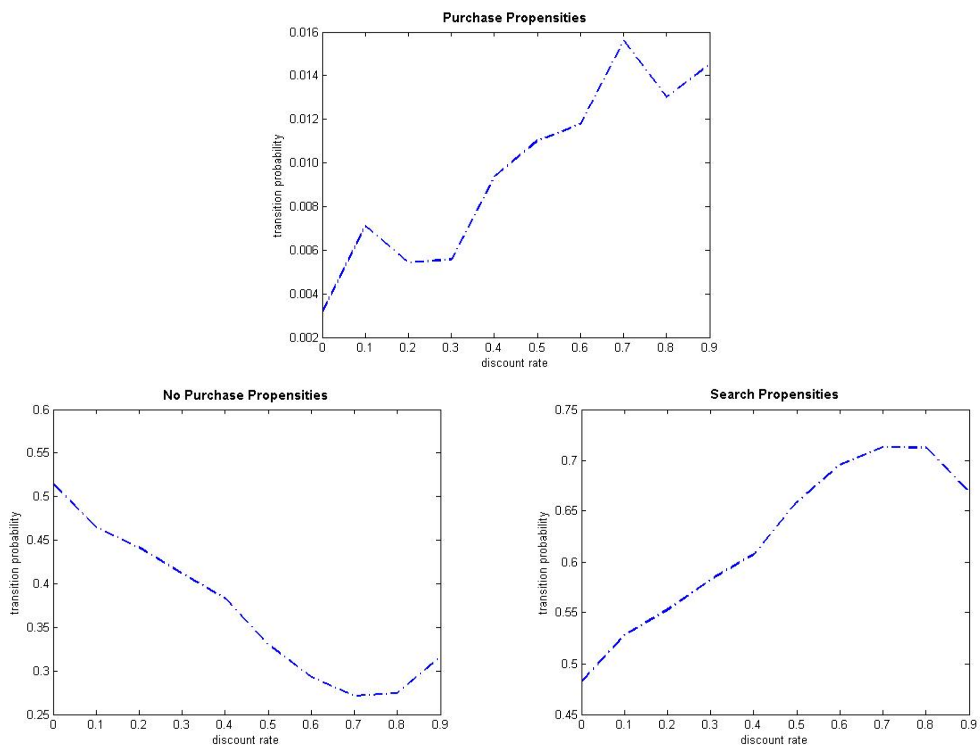

Figure 3: Purchase, no purchase, and search propensities

Figure 3 shows the average purchase propensities p_n and no purchase propensities r_n given discount rate d_n, which captures the conversion rates of a consumer in a single search (screen). It can be clearly seen that both the search intensity and purchasing propensities increase as the discount rate increases, particularly for discounts in the 30 - 70% range. From a behavioral perspective, the key finding is that purchase intensities really begin to increase at the 30% discount level. This rate is higher than that reported by Smith, *et al.* (2007) for Travelocity's "Good-Day-to-Buy" email marketing campaigns[4]. Intuitively, we expect the discount rate for the IPR system to be higher than that for the Travelocity, since the latter represents a traditional product with no product uncertainty. The pattern above 70% is heavily influenced by the IPR design (specifically, the bottom price setting), which led to few observations in which discount rates above 70% were offered to consumers. It is unclear what combinations of factors are causing the peak of purchase propensities at the 10% discount rate level. On one hand, this may be in influenced by the fact that when the IPR system was first implemented, a conservative pricing curve (*i.e.*, one that was less friendly to consumers) was used for the first nine months, which effectively resulted in the majority of consumers finding small discount levels. On the other hand, this peak may represent a distinct customer segment, namely one that is willing to sacrifice some travel flexibility (*e.g.*, willing to travel three days within a one week period) in exchange for a smaller discount.

4.1.2 Dynamics of Conversion Behavior

We model and analyze dynamics of consumer purchase decisions by incorporating the assumption that purchase decisions are driven by the discount rate associated with the current search results and are independent of past searches (*i.e.*, consumer conversion is independent of time and path). In other words, purchase conversions are driven by the discount rate that consumers currently see, regardless of how many pages they have been browsing and how they have been searching. Based on this assumption, the consumer decision process is modeled as a finite Markov chain which captures each search of a consumer. This methodology is consistent with that explored by Montgomery, *et al.* (2004) in the context of predicting user paths for an on-line bookseller. Formally, let $S = \{Purchase, No\ Purchase, d_1, ..., d_N\}$ denote the state space and $q_{ij} = \Pr\{\text{seeing } d_j \text{ in the next search given } d_i\}$ as the one-step transition probability. The transition matrix associated with the consumer decision process is thus given as:

[4] This was confirmed via e-mail communication with the authors, as the specific rate found in the Travelocity analysis is confidential and not explicitly reported in their paper.

$$
A = \begin{array}{ccccccc}
\text{purchase} & \text{no purchase} & d_1 & \dots & d_j & \dots & d_N \\
\end{array}
$$
$$
\begin{pmatrix}
1 & 0 & 0 & \dots & 0 & \dots & 0 \\
0 & 1 & 0 & \dots & 0 & \dots & 0 \\
p_1 & r_1 & q_{11} & \cdots & q_{1j} & \cdots & q_{1N} \\
\dots & & & & & & \\
p_i & r_i & q_{i1} & \cdots & q_{ij} & \cdots & q_{iN} \\
\dots & & & & & & \\
p_N & r_N & q_{N1} & \cdots & q_{Nj} & \cdots & q_{NN}
\end{pmatrix}
$$

In order to motivate further analysis, let $A_{i,j} = q_{ij}$ denote the transition probability from discount rate d_i to d_j. Also, let $A_{i,p} = p_i$ and $A_{i,r} = r_i$ denote purchase and no purchase probabilities, respectively. Figure 4 illustrates transition flows and probabilities among states. Note that the Purchase and No Purchase nodes represent recurrent states and $d_1, ..., d_N$ are transient states. Based on this purchase decision process, we investigate screen-to-screen analysis on how customers interact with IPR and how elastic consumer demand is to discount levels.

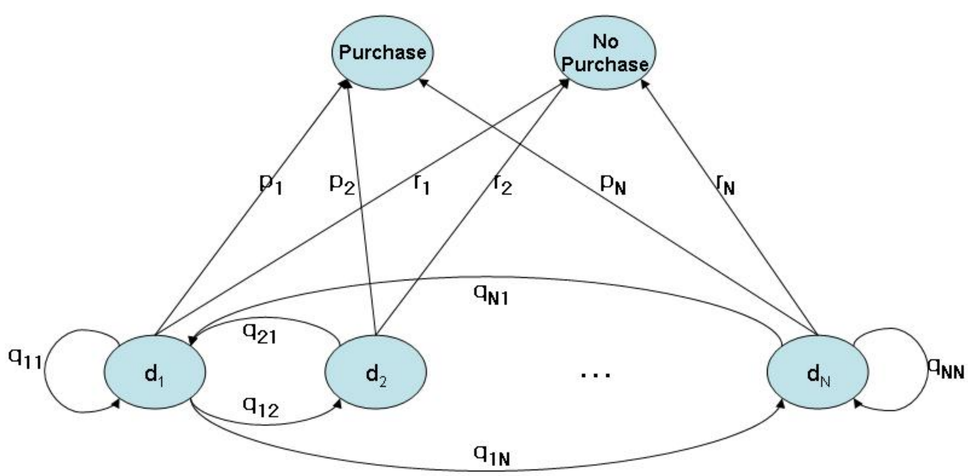

Figure 4: Transitions of states

Screen-to-screen Transition Behaviors and Evolution of Travel Flexibilities

Conceptually, the one-step transition matrix A captures screen-to-screen search patterns and allows us to explore how customers are interacting with the IPR system and searching for information. Figure 5 portrays the dynamics of customer search patterns as a function of the relative discount rate. *Stick* represents the probability that the new search parameters entered by the customer result in a discount level that is similar to that of the previous screen (*i.e.*, that the two discount rates fall within the same discretized discount range). In terms of the one-step transition matrix A, stick corresponds to the diagonal entries q_{ii} of matrix A and reveals that customers tend to cling to a small search space and are reticent to change their travel flexibility parameters. *Expand* and *Shrink* represent the probabilities that the new search parameters result in higher and lower discount rates, respectively. In terms of the one-step transition matrix A, expand corresponds to $q_{i,i+1} + ... + q_{iN}$ while shrink corresponds to $q_{1i} + ... + q_{i-1,i}$.

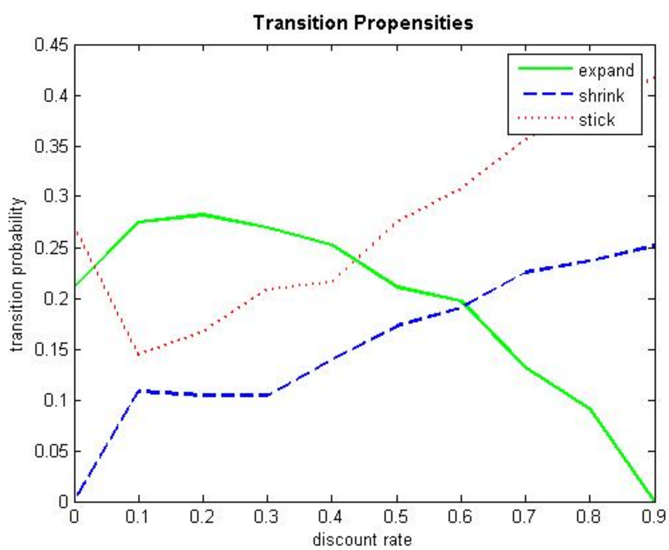

Figure 5: Screen-to-screen transition probabilities

The *stick*, *expand*, and *shrink* transition probabilities provide information on whether individuals tend to explore the entire search space, or cling to a small search space. As shown in Figure 5, customers tend to expand their search spaces and enter more flexible travel parameters until they reach a discount level of approximately 30% discount. For discount levels greater than 30%, customers are inclined to stick to their present search space or shrink the search space, *i.e.*, they are reticent to sacrifice additional travel flexibility for higher discounts. It is interesting to note that in the previous section, consumer purchase propensities doubled when they reached a 30% discount rate. The analysis of searching dynamics also suggests the presence of two customer segments: those who are less flexible and receive discounts less than 30% have distinct search behavior than those who are more flexible and receive discounts greater than 30%. In the latter case, these more flexible travelers are more willing to engage with the IPR system and explore how sensitive the discount levels are to changes in their travel flexibilities (*i.e.*, perform more search queries). These customers are also more likely to purchase, as shown in the next section.

Probability of Ending in Purchase State (Conversion Probabilities)

The use of a Markov chain to represent screen-to-screen transition behaviors is based on an assumption that the next state can be predicted based solely on information from the current state. Thus, given the initial search results of a customer, the entire search path (or states visited) can be predicted. This implies that we can predict the purchase propensity of a customer based on his/her initial search space or travel flexibility parameters. We can also compare forecasted and actual purchase propensities to verify that the Markov independence assumption is appropriate.

The entire search path can be predicted from one-step transition matrix. Formally, given the one-step transition probabilities A_{ij}, define A_{ij}^n as the n-step transition probabilities that an individual who starts in discount state d_i will be in state d_j after n additional transitions. Also, $A_{ij}^{\infty} = \lim_{n\to\infty} A_{ij}^n$ denotes the long-run transition probabilities that an individual who starts in discount state d_i will eventually end up in state d_j. Given Purchase and No Purchase are the only recurrent states, this implies that that regardless of the initial state (representing the first discount level seen by an individual), all customers will eventually end the session in a Purchase or No Purchase state. Thus, for all $i, j = 1, ..., N$,

$$\begin{aligned} A_{ij}^{\infty} &= 0 \\ A_{ip}^{\infty} &> 0 \\ A_{ir}^{\infty} &> 0. \end{aligned}$$

Purchase probabilities are given by A^{∞}_{ip}. The upper panel in Figure 6 compares the purchase probabilities computed from the one-step transition matrix A with actual purchase probabilities observed in the data. The probabilities estimated from the Markov model are very close to the actual probabilities, implying that the proposed Markov process is robust and effective in modeling and analyzing dynamics of purchase decisions. In addition, note that purchase propensities increase if the initial discount rate shown to the consumer is greater than 30%.

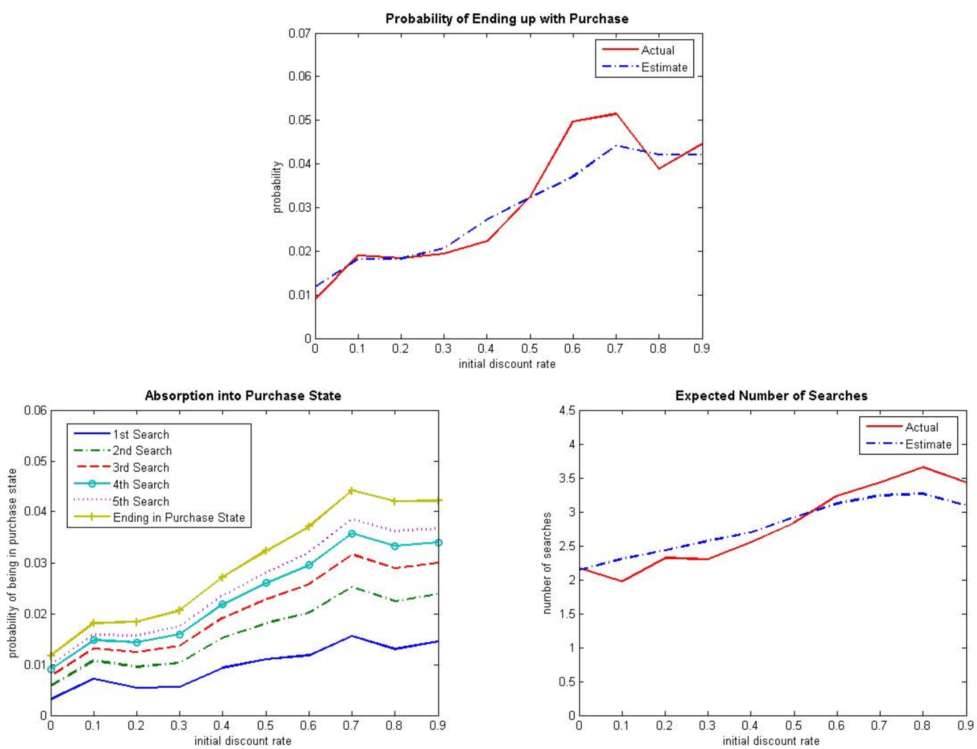

Figure 6: Purchase probabilities, search intensity, and search depth

Absorption into Purchase State (Search Intensity)

The n-step transition matrix, A^n, allows us to predict a customer's state in n steps (searches). By tracking A^n_{ij} over the search horizon, we can investigate how quickly the individual decides to purchase (or is absorbed into the purchase state), which is illustrated in the bottom left panel of Figure 6. Given any initial discount level, half of purchase conversions are made in the first two searches and the absorption rate decreases as further searches are going on. In addition, the discrepancies in purchase probability by initial discounts accelerate over searches. That is, additional searches facilitate purchase conversions even more in high discount rates, implying that customers with high discount rates tend to procrastinate and search more.

Search Depth

We can also explore how intensely a customer searches before making a decision to purchase or not purchase and investigate whether search depth is also predictable based on the customer's initial search parameters. Formally, starting in state d_i, a consumer makes a purchase decision and leaves the site with probability $p_i + r_i = A_{ip} + A_{ir}$. The probability the individual is in the Purchase or No Purchase states in period two is given as $A_{ip}^2 + A_{ip}^2$, which implies that the probability the individual leaves the site in period two is $(A_{ip}^2 + A_{ir}^2) - (A_{ip}^1 + A_{ir}^1)$. This leads to the following expected number of searches for a consumer who starts in state d_i:

$$(A_{i,p}^1 + A_{i,r}^1) + 2\big((A_{i,p}^2 + A_{i,r}^2) - (A_{i,p}^1 + A_{i,r}^1)\big) + 3\big((A_{i,p}^3 + A_{i,r}^3) - (A_{i,p}^2 + A_{i,r}^2)\big) + ...$$

As shown in the bottom right panel of Figure 6, the search intensity increases as the initial discount viewed by the customer increases, particularly for those discounts greater than 30%. Further, the predicted search depths estimated from the Markov model are very close to those observed in the data, which further supports the appropriateness of the Markov independence assumption.

4.2 Conceptual Framework to Model Online Search Behavior Using Search Parameters as States

Most customers search for more than one flexible ticket, changing their search parameters (time window and prior notice). While transitions of discount rates investigated in the previous section are a result of the interaction between customer searches and the firm's pricing policy, transitions of search parameters reveal customers' searching behaviors only. Thus, by analyzing the transitions of search parameters, we can understand general characteristics of online search activities.

We have already verified the Markov property, meaning that customer purchasing decisions are determined primarily by present search results, and are not heavily influenced by past searches. It is also natural to model customer searching process as a Markov chain. Let $S_B = \{(WD_k, PN_m), k = 1, ..., K \text{ and } m = 1, ..., M\}$ denote the set of search parameters that customers can choose, where WD and PN represent time window and prior notice, respectively. For a notational convenience, let us assume that SB is an ordered set, that is, $WD_1 < ... < WD_k < ... < WD_K$ and $PN_l < ... < PN_m < ... < PN_M$. Note that S_B contains only search parameters, not (Purchase, No Purchase) states, which implies that the Markov chain for searching behavior is conditional that a customer keeps searching. In addition, let us define one-step transition probability $P\{(WD_l, PN_n)|(WD_k, PN_m)\}$.

Before proceeding with further modeling, we first see if this two-dimensional Markov chain can collapse into one dimension. To do so, we investigate the independence of two search parameters, which is formally defined as follows:

$$P\{(WD_l, PN_n)|(WD_k, PN_m)\} = P\{WD_l|WD_k\}P\{PN_n|PN_m\}.$$

From the click stream data, we compute sample transition matrices - two-dimensional transition, time window transition, and prior notice transition - and verify the above independence equation holds, demonstrated in the following examples.

$$\begin{aligned} 0.6776 &= P\{0 < WD < 21, PN = 2|0 < WD < 21, PN = 2\} \\ &\sim P\{0 < WD < 21|0 < WD < 21\}P\{PN = 2|PN = 2\} = 0.6422 \\ 0.4354 &= P\{21WD < 30, PN = 3|21WD < 30, PN = 3\} \\ &\sim P\{21WD < 30|21WD < 30\}P\{PN = 3|PN = 3\} = 0.4289 \end{aligned}$$

We have observed $P\{(WD_l, PN_n)|(WD_k, PN_m)\}$ are close to $P\{WD_l|WD_k\}P\{PN_n|PN_m\}$. Also, we have observed that simultaneous changes of two parameters account for only 5.8% of total search activities, implying that customers are likely to search linearly. Based on the independence assumptions, we now model two Markov chains - one for time window and the other for prior notice, which are defined as the following transition matrices.

$$
B_W \quad = \quad \begin{array}{c} \begin{array}{ccccc} WD_1 & ... & WD_l & ... & WD_K \end{array} \\ \begin{pmatrix} w_{11} & ... & w_{1l} & ... & w_{1K} \\ ... & & & & \\ w_{k1} & ... & w_{kl} & ... & w_{kK} \\ ... & & & & \\ w_{K1} & ... & w_{Kl} & ... & w_{KK} \end{pmatrix} \end{array}
$$

$$
B_N \quad = \quad \begin{array}{c} \begin{array}{ccccc} PN_1 & ... & PN_n & ... & PN_M \end{array} \\ \begin{pmatrix} x_{11} & ... & x_{1n} & ... & x_{1M} \\ ... & & & & \\ x_{m1} & ... & x_{mn} & ... & x_{mM} \\ ... & & & & \\ x_{M1} & ... & x_{Mn} & ... & x_{MM} \end{pmatrix} \end{array}
$$

Stickiness Factor

A fundamental question about general searching behavior is whether individuals explore the entire search space, or they cling to a small search space. To answer the question, we measure the stickiness of searching transition, which corresponds the diagonal entries $\{w_{11}, ..., w_{kk}, ..., w_{KK}\}$ of B_W and $\{x_{11}, ..., x_{mm}, , x_{MM}\}$ of B_N. Figure 7 illustrates the stickiness of searching behaviors.

Notice that the probability of exploring in the same search space is, in general, high for both search parameters - implying that customers are unlikely to change their preserved search parameters. This result is consistent with that found earlier in the snapshot analysis of discount rate transitions. Also, the stickiness curves are U-shaped, which means that while customers with medium (moderate) travel flexibility are active in searching for more alternatives, customers with limited travel flexibility or high travel flexibility cling to their reserved search space. As an another measure for the stickiness of searching behavior, we compute correlation coefficients between two

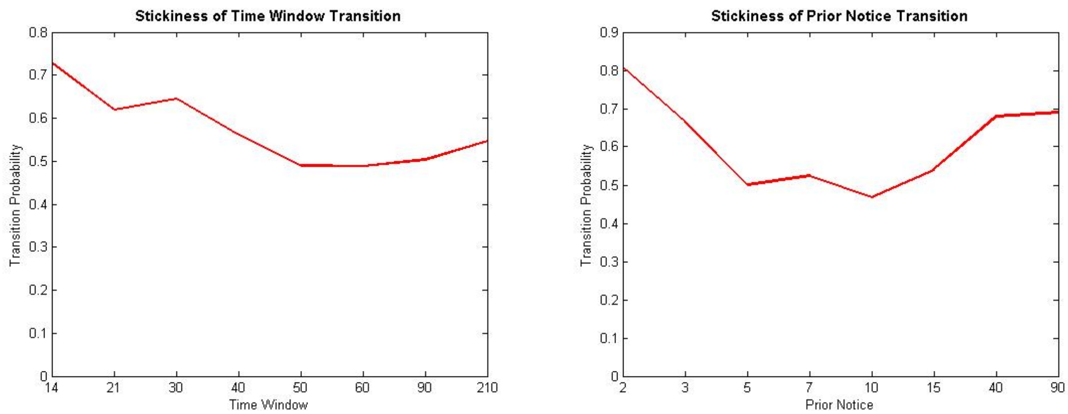

Figure 7: Stickiness of searching behaviors

consecutive search parameters, which is presented in Table 3. These high correlations support our conclusion on stickiness of customer searching behavior. Also, this trend is time-consistent, meaning the stickiness is almost constant over searches, as shown in Table 4.

Search Parameter	Correlation
Time Window	0.6904
Prior Notice	0.7563

Table 3: Correlation coefficients between two consecutive search parameters

Search Sequence	Time Window	Prior Notice
1st Search	0.724	0.712
2nd Search	0.697	0.724
3rd Search	0.687	0.709
4th Search	0.647	0.705
5th or More Searches	0.677	0.802

Table 4: Correlation coefficients over searches

Steady-state Search Distribution

In order to validate the appropriate of the Markov independence property in the context of searching behavior, we need to examine its long-run steady-state distribution. Earlier, we verified the appropriateness of this property in the context of long-run transition probabilities A_{ip}^{∞} and A_{ir}^{∞}, which provide information on the final state of the purchasing process (purchase, no purchase). Similarly, we can find the long-run transition probabilities of searching processes B_W^{∞} and B_N^{∞}. While the purchasing process has only two recurrent states, Purchase and No Purchase, searching processes have no transient states, since searching processes are conditioned on the fact that customers keep searching without leaving the site. Thus, the interpretation of long-run transition probabilities related to the searching processes is distinct from that related to the purchasing process. B_W^{∞} and B_N^{∞} characterize the steady-state distribution of search space, which explains how a customer explores the search space (conditional on the fact that the customer is still searching). Figure 8 compares the estimated steady-state distributions and actual distributions of search space. The estimated steady-state distributions are very close to the actual distributions of search space, which supports the appropriateness of using a first-order Markov model to represent customer search behavior.

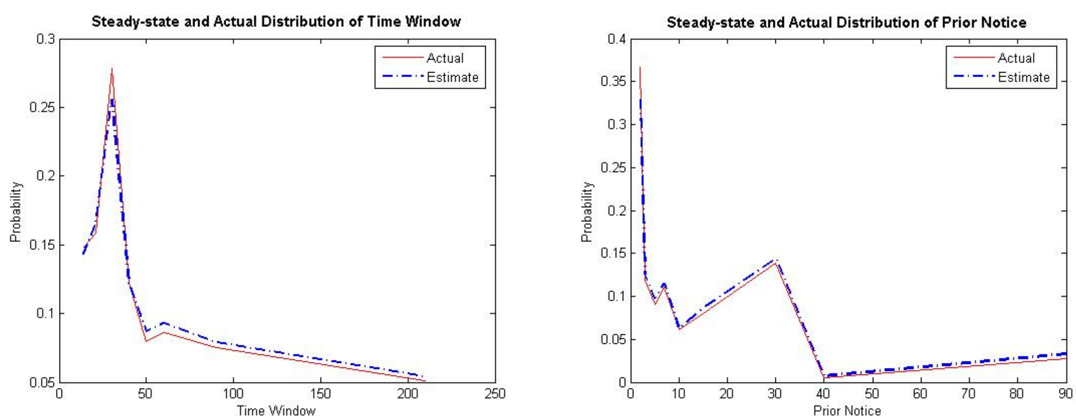

Figure 8: Steady-state distributions of search parameters

5 Integration of Customer Purchase Behaviors into Firm's Decision Making

From a behavioral perspective, this study has provided new insights into customers' online searching and purchasing behaviors for flexible travel products. From a firm's perspective, the primary question of interest is how to use these insights to better inform optimal pricing policies or design new flexible products. As noted earlier, due to data limitations, we cannot directly analyze the interaction between the firm's pricing policies and customer behavior. Nonetheless, we can demonstrate using simulation data how a firm can integrate customer behavior into pricing decisions and effectively show how the IPR system enables a firm to influence conversion rates and the relative discount levels offered in the market.

The simulation procedure involves three steps. The first step is to define the pricing policy. Recall that price of a flexible ticket is determined as follows:

$$\text{Price offered} = \text{Bottom Price} + \delta(\text{Top Price} - \text{Bottom Price})$$

$$\delta = \left(1 - \frac{A}{A_{\max}}\right)^{\alpha} \left(\frac{PN}{PN_{\max}}\right)^{\beta}, \quad 0 < \delta < 1; \alpha > 0; \beta > 0$$

Whereas customer search parameters are reflected in PN/PN_{max} and A/A_{max}, firms can control pricing of flexible products through α and β. As α and β increase, pricing become more sensitive to customers' search parameters - time window and prior notice - and results in higher discount rates. We analyze two scenarios for firms' pricing policy, based on actual parameters used by Freedom Air during the course of the data collection period: Scenario 1: $\alpha = 6$ and $\beta = 0.3$ and Scenario 2: $\alpha = 25$ and $\beta = 0.3$. Note that the pricing in Scenario 2 is more favorable to customers, leading to higher discount rates.

The second step of the simulation procedure captures customer search parameters from the clickstream data and simulates discount rates. These search parameters are input into the pricing equation associated with the firm's pricing scenario to compute the simulated prices and discounts that customers would have seen as they engaged with the IPR system. Figure 9 presents summary statistics of the simulated discount rates. As expected, discount rates in Scenario 2 are higher.

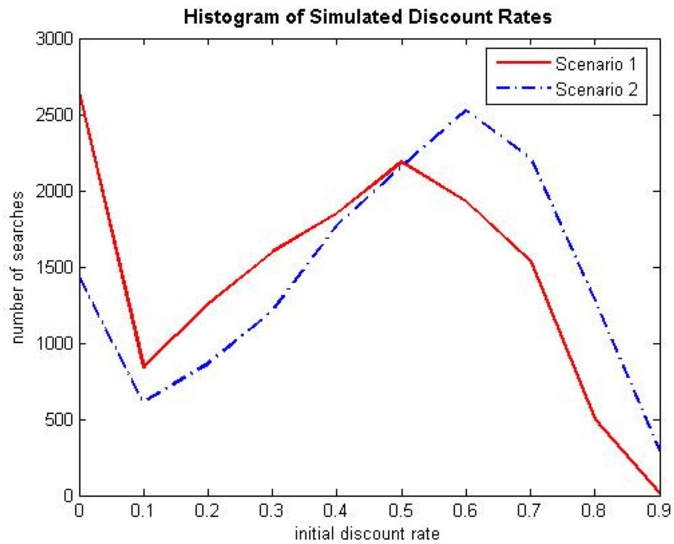

Figure 9: Simulated discount rates

The final step of the simulation procedure is to simulate eventual purchase probabilities given the simulated discount rates. Using the long-run purchase probabilities, A_{ip}^{∞}, the eventual purchase probabilities for each simulated discount rate can be computed. The average purchase probability in each scenario is given in Table 5.

	Scenario 1	Scenario 2	Actual
Purchase Probability	2.678%	3.095%	3.303%
Incremental Revenue	1.053%	5.369%	-

Table 5: Comparison of purchase probabilities for different pricing policies

We can compare the average purchase probability of scenario 2 (3.1%) to the actual purchase conversion rate per visit represented in the data (3.3%), since the actual pricing policy revealed in the data set is similar (but not exact) to that shown in scenario 2. We observe that these rates are similar. Also, the simulation exercise shows that purchases increase by 15.6% (from 2.678% to 3.095%) when a friendlier pricing curve is used. From the perspective of revenue, Scenario 1 results in 1.053% increase in total revenue while Scenario 2 results in 5.369% increase. Further, as noted earlier, this represents stimulated demand and incremental revenue, as the design of the FC product resulted in little revenue dilution (Post, Mang, and Spann 2007).

6 Discussion and Conclusions

6.1 Limitations

Before summarizing the main findings from this study, it is important to note that the standard limitations involved in any empirical study apply, *e.g.*, the results are limited in the sense that they represent the behavior of Freedom Air customers and may not be extendable to other airlines' customers. One of the most important modeling assumptions that may limit the ability to directly apply our methodology to other situations is related to the definition of a session. Specifically, in this study, we were able to use cookies to link multiple visits together to create a unique session. However, the ability to use cookies to track individuals (or households) may not be viable in all parts of the world. This is one way in which the methodology may need to be adapted for different situations.

6.2 Summary and Implications for Research

In summary, this paper has modeled online customers' search and purchase behaviors using data obtained from an Interactive Pricing Response (IPR) system. Within the airline industry, this product is quite unique in that it leveraged the strengths of the internet - particularly the ability of an airline to interact directly with consumers - to customize prices and offer steep discounts off of traditional products in a way that did not trigger price responses by the competition. In this context, Freedom Air was able to generate incremental revenues by *effectively making its discount levels opaque to competitors, despite the fact Fare Choice operated in an online distribution channel.* Fare Choice also enabled Freedom Air to "re-segment" the market and price discriminate based on the travelers' degree of time-flexibility. As the airline industry becomes even more competitive, and traditional product characteristics such as Saturday night stay, advance purchase, and other restrictions become obsolete, finding more innovative ways to price discriminate becomes even more crucial, particularly if fuel costs continue to rise to unprecedented high levels. While the original vision for Fare Choice was to provide a mechanism by which legacy airlines could better compete with low cost carriers without engaging in pricing wars, it is interesting to note that smaller, low cost airlines like Freedom Air have been the early adopters. Looking ahead, it will be interesting to see if the product is able to penetrate the market and, if so, which areas of the world will be most receptive to its implementation. To date, only two non-US applications have occurred (one with Freedom Air and a second, ongoing effort with an undisclosed European airline). More broadly, we believe that non-aviation industries can adapt the Fare Choice business model to target price-sensitive customers willing to delay purchases in exchange for discounts. This will allow firms to more effectively manage supply and demand (and increase profits) without making discount levels transparent to competitors.

The primary contribution of this article is related to the use of Markov-based models to investigate airline passengers' online search and purchase behaviors. In contrast to earlier studies of online customers' search and purchase behaviors, it is important to note that given the Fare Choice product was explicitly designed to target only highly time-flexible customers, Freedom Air was able to obtain detailed search and purchase data for a relatively homogeneous population of customers. We believe this is one of the primary reasons why, in this study, fairly simplistic Markov-based models could be used, with relatively high prediction accuracy, to model the depth and dynamics of customers' search and purchase behaviors. We believe the second primary reason why these simplistic Markov-based models were so powerful is that we were also able to incorporate reference price effects, *i.e.*, relative discount levels. The ability to assume independence across searches in this study is distinct from that of earlier studies such as that by Montgomery, *et al.* (2004) that find it is critical to incorporate the memory component of online path-analysis models to predict conversion rates for an bookseller, as paths represent heterogeneity in users' goals. Conceptually, this may point a new research opportunity in the sense that ability to *a priori* create products that target specific customers segments may present new opportunities to increase conversion rates while simultaneously collecting detailed information about these customers that is "uncontaminated" by the goals of other customer segments.

Finally, despite the ability to isolate a relatively homogeneous population of customers, the results of our study support the findings and opinions of other authors who stress the importance of modeling individual customer-level behavior in order to be able to accurately calculate aggregate online search and conversion behavior (*e.g.*, Johnson, *et al.*, 2004). Our study illustrates how, even among homogeneous time-flexible customers, there are two distinct customer groups. Specifically, empirical results show that higher search intensities and purchase conversions occur as the relative discounts increase, particulary for discounts above 30%. Failure to account for how relative discount rates influence customers' search and purchase propensities would lead to inaccurate aggregate estimates of customer search depth and conversion rates. However, by accounting for this relationship, predictions that are robust to the firm's current pricing policies (that may be influenced by seasonal demand fluctuations, flight capacity adjustments, etc.) are observed.

Thus, in conclusion, it is our hope that the description of the new Fare Choice product and corresponding analysis of online airline passengers' search and purchase behaviors will spur firms to consider new product designs that can help them better compete in highly-transparent online distribution channels. It is our opinion that this is one untapped area of research that has the potential to generate incremental revenue for firms.

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