Modeling Online Multicategory Purchase in Travel

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Manuscript date: Jun 14, 2009

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Modeling Online Browsing and Purchase of Airline Tickets

ABSTRACT

In this paper we investigate online purchase behavior at the basket level and model the multicategory purchases in the travel product category. While prior research in marketing has looked at browsing or individual category purchase decisions, we study consumers' online purchase of airline, car rental and hotel purchases together using a unique dataset of household-level dynamic click stream panel data. We use a two-stage model to study (i) the propensity of consumers to purchase a combination of products as a basket and (ii) the choice of the website where consumers will make those purchases. We then estimate the propensity of consumers to purchase a particular combination of products in their basket from different websites. This behavior constitutes a high dimensional system of multinomial equations which are then solved using a simulation-based econometric technique. We find significant effects of {dependent variables} in determining consumer multicategory purchase behavior. Our results can help managers identify the major determinants of multicategory purchase as well as provide insights into cross promoting as well as upselling other products to consumers who visit their website.

Key Words: airline, car rental, hotel, travel, multinomial choice, purchase, behavior, multi stage models

1. Introduction

Brand choice and store choice models have been extensively explored in depth by marketing researchers in the retail packaged goods context (for a brief review of an extended framework see Ben-Akiva et al 1999). This stream of literature has also spawned interest in multi-category or basket purchases (Harlem and Lodish 1995), retail chain level demand (Baltas 2005), store choice models, category characteristics and promotional elasticies (Narasimhan, Neslin and Sen 1996) and understanding purchase incidence at the grocery store in more detail (Manchanda, Ansari and Gupta 1999). Scant attention has been paid to category demand in prior literature, despite its importance for retailers. Only a small body of research has considered the effects of individual brands on category sales and there has been so far little work at the category level in understanding demand or consumer behavior especially in the online environment.

A recent extension of the online stream of literature into retail space has been furthering our understanding of shopping paths at the grocery store (Bradlow, Hui and Fader 2008). We believe this was to a large extent influenced by path analysis literature using clickstream data that became prevalent with the increasing dominance of the internet (Montgomery et al. 2004). In this paper we pursue this in the reverse direction and extend the work in multi-category and basket purchases in the retail space to online purchases thus contributing to the stream of literature on online basket purchases whilst drawing motivation from the past literature that exists in the retail packaged goods context.

In our work on basket purchases we steer clear of the concept of bundling (Chung and Rao 2003) as those constitute a class of travel products typically sold as vacation packages. We look at basket of travel purchases wherein the consumer makes multiple purchase transactions to constitute a single or combination of travel products.

2. Conceptual Development

We consider the consumer process of making a purchase comprising a basket of travel products in two stages. In the first stage the consumer decides on what combination of travel products to purchase and in the second stage embarks on making the purchase(s) from a particular travel portal or website. The first stage is assumed to be influenced by prior browsing

and purchase experience undertaken for travel trips while the second stage is assumed to be influenced by the first stage as well as browsing experience prior to making a purchase. In addition to prior shopping behavior we also take into account consumer demographic factors as they have also been shown to contribute in affecting consumer choices (Ainsle and Rossi 1998). It is also a common practice in research to assume various stages in the consumer decision making and purchase process (Olshavsky and Granbois 1979). Its also possible that consumers have a budget or internal reference point (Bell and Buklin 1999) for the various products in the category as part of their purchase decision.

2.1 Factors Affecting Basket Choice and Browsing

We expect consumer preferences to exhibit differences between choice of various basket combinations based on a few factors summarized below.

2.1.1 Basket preference

Consumers undertake travel for various reasons and depending on the travel needs that exist within the population its possible that there exists a base level of preference for various baskets or travel product combinations. We are especially interested in determining the base level preference for various combinations of travel products as no prior work has shed light on this. We believe that single product basket purchase would dominate the multiple product basket purchases as most travel is primarily driven by business or leisure trips from point A to point B or related to hotel stays in a particular geography being visited.

2.1.2 Consumer Demographics

We also investigate the impact of consumer demographics on basket purchases for travel products. We expect larger households to make basket purchases in order to avoid inconvenience when traveling. Its possible Older consumers would have less disposable income and could possible be less likely to make basket purchases. Also those who have broadband connections are less price sensitive and hence could be more prone to making basket purchases online.

2.1.3 Category Experience

We also investigate the impact of prior browsing history for various product combinations. Its possible consumers exhibit some state dependence in their browsing habits and we are keen to learn if consumers who browse more for a basket of products are likely to end up making a basket purchase or any purchase in general.

2.1.4 Prior Purchase

It is also possible that just like prior browsing experience that prior purchase of a basket of products could positively impact similar basket purchase or any purchase in general due to some state dependence or inertia effects.

2.1.5 Interaction Effects

Using interaction terms we are also interested in investigating the combined impact of demographic impact and prior browsing behavior on purchases. These interaction or combined effects could be very useful for managers to come up with a target profile of consumers who are more likely to make a purchase and tailor their media plans to effectively activate these target consumers. We also investigate the variance amongst consumer preference for various basket combinations but do not assume any expected relationship apriori.

2.2 Factors Affecting Site Choice and Purchase

The factors affecting basket purchase also have an impact on site choice and we investigate the impact of these factors further.

2.2.1 Site Preference

It is a known fact that consumers tend to frequent some stores as opposed to others and some of the factors impacting store choice have been documented in prior store choice literature. (Keng & Ehrenberg 1984, Rust & Donthu 1995). We expect similar behavior in the online space and investigate the base level preference for various sites and their combinations when it comes to a basket purchase. We intend to tease out this effect from the intercepts associated with each site choice combination and delineate the differences of making a basket purchase on one site or a combination of multiple sites. We are also interested in seeing if there is a preference to make a basket purchase on travel portals compared to other sites.

2.2.2 Consumer Demographics

We also investigate the impact of demographic factors on basket purchases, especially their role in predicting website choice while pursuing a basket transaction. Prior studies have indicated price sensitiveness to be lower amongst broadband consumers and higher amongst larger households (Nair, Chan, Cheema 2009 working paper).

2.2.3 Category Experience

We believe consumers who have a lot of prior browsing history on a particular site could exhibit state dependence and favor such sites more compared to others when making a basket

purchase. It is also possible for this prior experience to have a different influence depending on whether it's a travel portal or not. Overall we expect the impact of overall prior browsing history in travel to significantly and positively influence the likelihood of making a basket purchase from all site choice combinations.

2.2.4 Prior Purchase

We also believe prior purchase could result in purchase loyalty in subsequent purchases wherein consumers are more likely to make basket purchases from the same site.

2.2.5 Interaction Effects

The interaction effects of demographics with prior travel browsing history and prior purchase on same site combinations are also very interesting and worth investigating because it has targeting implications that manager's can act on to maximize likelihood of basket purchases. In addition to accommodating various interaction efforts we also account for site heterogeneity exhibited by consumers to better understand differences between sites when it comes to basket purchases

3. Data

We use the ComScore clickstream dataset available from the WRDS database for our analysis. This dataset comprises of surfing and transaction details of 100,000 households[1] that are a representative sample of the US population in 27 product categories. In this study we extend our earlier work by modeling purchases in three categories airlines, car rental and hotel, however, we restrict ourselves to modeling the purchase behavior of consumers and do not explicitly model the browsing behavior. A total of 8937 households in the travel category fit the criteria required for our analysis. To ensure that a household's browsing is only related to a specific observed purchase we use the following three conditions: (1) we only focus on the household's browsing seven days prior to a purchase (the browsing period which captures 96% of all search that consumers indulge in); (2) we only study the household's purchase in the travel category (travel portals, airline, car rental and hotel websites) during that seven day period; and

[1] Hereafter we will use "households" and "consumers" interchangeably with the same meaning.

(3) on top of that, we only choose households that have had no surfing on travel websites for seven days prior to the browsing period.

Travel category forms a significant portion of online purchases made by consumers with the mean being two out of ten purchases amongst the 27 product categories. As we are interested in studying purchase behavior that is related to a purchase across multiple categories we focus only on those travel websites that also provide an option for consumers to make such a purchase (airline, car rental or hotel). Specifically we investigate purchase behavior on travel portals (such as Expedia, Orbitz, and Hotwire) and category specific websites (like Southwest, Delta, and American for airlines; Hertz, Avis, Budget, Alamo and Enterprise for car rentals and Hilton, Hotels.com, Choicehotels.com, Sixcontinentshotels.com and Mariott for hotels) where consumers have an option to purchase the travel product online.[2]

We used the browsing and purchase behavior of households in the first three months of data (July 2002 – September 2002) as the household's prior experience on travel websites. We then use the transaction sessions for airline, car rental and hotel purchases in the last three months for model estimation.

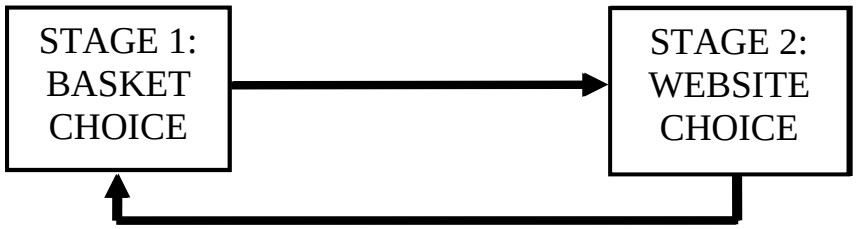
In this study we focus on purchase behavior for (i) airline tickets (ii) car rental and (iii) hotel purchases that are either bought alone or in conjunction with an airline purchase.

4. Model Specification and Estimation

We propose a two stage model of purchase behavior for travel products. In our model consumers choose the products at the basket level first followed by the choice of the website where they can buy the basket of products. Hence the two stages we model are (i) choice of products at the basket level and (ii) choice of purchase site. This framework is pictorially depicted in Figure 1.

Figure 1: Proposed two-stage model of basket level purchase behavior

[2] We excluded from the analysis those households that were very heavy users (whose purchases exceeded the 99.9th quantile both in terms of amount as well as number of transactions). We also excluded transactions on websites which were auction sites, search engines and payment gateways such as ebay.com, lycos.com, netbooker.com and authorize.net (these constituted less than 5% of the recorded travel purchases). Multiple purchases bought by a household were clubbed together if they occurred at the same time on a particular website (e.g. spouses buying airline tickets).



In the first part of this section we outline the model used to study the factors that predict basket composition. Initial data analysis revealed it is important to model choice of what products comprise the consumers' basket as that would considerably reduce the number of options that are available to the consumer in subsequent stages when it comes to choice of the purchase site. Understanding what factors affect the composition of products at the basket level would help us to also gain insights on the influence the basket composition has on which site consumers would finally end up making their purchase on. The different product combinations that comprise the basket level decision of the consumer are as summarized in Table 1.

Table 1: Basket level choices

Travel Category Purchases	Unique Households	Transactions (6 Mos)	Transactions (Last 3 Mos)	Transaction sets
Airline Only	6029	8074	3754	3754
Car Rental Only	1072	1578	734	734
Hotel Only	2921	4054	1799	1799
Car and Hotel	145	364	181	76
Air and Hotel				210
Air and Car Rental	856	2620	1233	158
Air, Car and Hotel				65
Total	8937	16690	7619	6796

In the second part of this section we model the website choice, in particular, we focus on the choice of purchasing from a particular travel portal. We focus on travel portals because most travel portals provide the opportunity of purchasing airline, hotel and car products on the same site though this has now also become more prevalent on airline websites too. The other compelling reason is that it adds to the parsimony of our model which can be easily extended to incorporate other websites too.

Table 2: Website choice

Website Type	Product Category		
	Airline	Car Rental	Hotel
Travel Portals		Expedia Orbitz Travelocity Hotwire Other Travel portals	
		Other sites*	
* Sampling of other sites (includes other travel portals and all other airline, car rental and hotel websites)	Southwest Delta American Jetblue US Airways	Avis Budget Hertz Alamo Enterprise	Hilton Sixcontinentshotels.com Hotels.com Choicehotels.com Mariott

4.1 Modeling Basket Level Choice

We study the basket level choice behavior of consumers prior to making a purchase by using a random coefficients approach of the traditional multinomial logit model (for example see Gudagni and Little 1983) which we explain in detail later. We treat each combination of the three major travel products airline, car rental and hotel bookings as a choice that the consumer makes to constitute the basket. As we are interested in what constitutes the basket and not the actual sequence of purchases we club airline purchases followed by a car rental purchase and car rental purchase followed by airline purchase together.

Let a discrete variable $B_{ict} = 1$ indicate that consumer i purchases combination c at time period t, and $B_{ict} = 0$ otherwise. For $B_{ict} = 1$, combination c has to exist in consumer i's consideration set (which includes all possible options) and then c has to dominate other combinations in this consideration set in terms of propensity to purchase that combination under cost-benefit evaluation. We assume that these are determined by a list of factors including customer demographics (age, income, connection speed) Z_{it}, prior category experience H_{it}, expected level of expenditure P_{it} and prior combination-specific browsing experience S_{ij}. Prior category experience H_{it} is measured as the proportion of combination specific c pages viewed to the total pages viewed in the first three months on all websites selling travel products, and prior combination-specific browsing S_{ij} is measured as average daily pages viewed on

combination specific websites c in the first three months. Furthermore, I_{ict} is an indicator variable that denotes whether or not consumer i's last purchase was a specific combination c. This variable may affect the probability of c being in i's consideration set and may create inertia such that i may be more likely to purchase the same combination during the next purchase cycle. Finally, basket level choice is also affected by i's preference for a particular combination c that is independent from the above factors as well as accounts for any marketing activities for a specific combination c which is not observed in our data. This is termed as "basket preference" which is individual-and-time-specific in our model.

We assume that there is a latent variable B^*_{ict} that generates the basket choice decisions. $B_{ict} = 1$ if and only if $B^*_{ict} \geq B^*_{idt}$, for all other combinations d. We specify the function of this latent variable as

$$B^*_{ict} = \alpha^f_{ict} + \beta^f Z_{it} + \tau^f_c H_{it} + \gamma^f S_{ic} + \rho^f I_{ict} \quad (1)$$

In the above equation the superscript "f" denotes the first stage of our two stage model. The variable α^f_{ict} represents the latent basket preference for a particular combination. We use a random effects approach to model this variable as the follows

$$\alpha^f_{ict} = \alpha^f_c + \xi^f_{ic} + \varepsilon^f_{ict} \quad (2)$$

where α^f_c represents the mean basket preference for a particular combination that will be estimated as parameters, ξ^f_{ic} represents the individual-specific but time-invariant random effect for a combination, and ε^f_{ict} is the individual-and-time-specific idiosyncratic shock that we assume to be i.i.d. type one extreme value distribution.

We assume that $\lambda^f_i = \lambda^f + \eta^f_i$, where η^f_i is a time-invariant and individual-specific random variable which captures the consumer heterogeneity in response to expected expenditure level.[3] We allow ξ^f_{ic} and η^f_i to be correlated among themselves.[4] As we will explain later, we however do not allow these random effects to be correlated with the random effects in the second stage of the model as we believe that the basket preferences are more intrinsic and are not that easily changed by marketing interventions on a particular website and hence can be modeled

[3] For simplicity we assume that only basket preference intercepts are heterogeneous across consumers.

[4] Such correlations can be identified though the panel structure in our data.

independent from the choice of the purchase site which we model in the second stage. Since we explicitly model all possible combinations for the choice of the websites on which the basket is purchased the dimensionality of parameters is very large and accounting for all the correlations across each stage adds to further complexity.

To ensure proper identification we normalize the latent variable value for all hotel and car purchases as $B^*_{i,HC,t} = 0 + \varepsilon^f_{i,HC,t}$.[5] In our estimation model we also incorporate the interactions of demographic variables Z_{it} with all other covariates H_{it}, S_{ic}, and I_{ict}. Let T_i be the total number of household i's purchases observed in data. Correspondingly there are T_i combination purchases and each combination of purchase is defined as a set. Under the type one extreme value distribution for ε^f_{ict} and conditional on the random effects ξ^f_{ic} and η_i^f, we can write down the probability that a household's basket preference for a particular combination in the whole sample period as below.

$$\begin{aligned}&\Pr(i\text{'s history of basket preference}) = \prod_{t=1}^{T_i} \Pr(B^*_{ict} \geq B^*_{idt}, \forall d) \\ &= \prod_{t=1}^{T_i} \frac{e^{\alpha^f_c + \xi^f_{ic} + \beta^f Z_{it} + \tau^f_c H_{it} + \gamma^f S_{ic} + \rho^f I_{ict}}}{1 + \sum_{c=1}^{C} e^{\alpha^f_d + \xi^f_{id} + \beta^f Z_{it} + \tau^f_d H_{it} + \gamma^f S_{id} + \rho^f I_{idt}}} \end{aligned} \quad (3)$$

4.2 Modeling Choice of Purchase Site

In the second stage of the model we model the choice of the purchase site for each combination in the basket level choice. We illustrate the methodology for a combination purchase of which pertains to buying airline tickets A and hotel bookings H. Consumer i can purchase both these products in his/her basket from the same website or from different websites. The different combinations of making these purchases from the same travel portal $\{j, j\}$ or different travel portals $\{j, k\}$ or from a travel portal and one of the other sites (other travel portal, airline, car rental and hotel sites) $\{j, other\}$ or make both purchases from one of the other sites $\{other, other\}$ can be expressed as below.

$\{j, j\}$: (6 options)

[5] Because of this normalization the coefficients corresponding to all of the variables in equation (1) have to be interpreted as the difference in probabilities that consumers prefer a combination relative to their preference for hotel and car combination purchase.

$\{ j, k \}$: (15 options)

Table 3: Utility function for a combination of Airline and Hotel purchase

Air \ Hotel	Travel Portal	Other Site
Travel Portal	$V_{j,t}^A + V_{j,t}^H + u_t + \varepsilon_{j,t}^A + \varepsilon_{j,t}^H$	$V_{j,t}^A + V_{o,t}^H + v_t + \varepsilon_{j,t}^A + \varepsilon_{o,t}^H$
Other Site	$V_{o,t}^A + V_{j,t}^H + v_t + \varepsilon_{o,t}^A + \varepsilon_{j,t}^H$	$V_{o,t}^A + V_{o,t}^H + u_t + \varepsilon_{o,t}^A + \varepsilon_{o,t}^H$

The utility for these 25 choice combinations can be summarized as in Table 3. In the above expression $V_{j,t}^A$ is the indirect utility from making the airline purchase from website j, $V_{j,t}^H$ the indirect utility from making a hotel purchase from website j and the utilities when an airline purchase and hotel purchase are made from one of the other sites they are expressed as $V_{o,t}^A$ and $V_{o,t}^H$. The probability of both airline and hotel purchase being on a travel portal can now be written as

$$\begin{aligned} \text{Prob[j,j]} &= \text{Prob [} V_{j,t}^A + V_{j,t}^H \geq \max(V_{j,t}^A + V_{o,t}^H, V_{o,t}^A + V_{j,t}^H, V_{o,t}^A + V_{o,t}^H)] \\ &= \text{Prob [} V_{j,t}^A + V_{j,t}^H \geq V_{j,t}^A + V_{o,t}^H \text{]} . \\ &\quad \text{Prob [} V_{j,t}^A + V_{j,t}^H \geq V_{o,t}^A + V_{j,t}^H \,/\, V_{j,t}^A + V_{j,t}^H \geq V_{j,t}^A + V_{o,t}^H \text{]} . \\ &\quad \text{Prob [} V_{j,t}^A + V_{j,t}^H \geq V_{o,t}^A + V_{o,t}^H \,/\, V_{j,t}^A + V_{j,t}^H \geq \max(V_{j,t}^A + V_{o,t}^H, V_{o,t}^A + V_{j,t}^H)] \end{aligned} \quad (4)$$

Since $\varepsilon_{j,t}^A$ and $\varepsilon_{j,t}^H$ are assumed to be independent hence the conditional term in the second part of the equation drops out and the above equation reduces to

$$\begin{aligned} \text{Prob[j,j]} &= \text{Prob [} \varepsilon_{j,t}^H \geq V_{o,t}^H + v_t + \varepsilon_{o,t}^H - V_{j,t}^H - u_t \text{]} . \\ &\quad \text{Prob [} \varepsilon_{j,t}^A \geq V_{o,t}^A + v_t + \varepsilon_{o,t}^A - V_{j,t}^A - u_t \text{]}. \\ &\quad \int 1 \text{ [} \varepsilon_{j,t}^A + \varepsilon_{j,t}^H \geq V_{o,t}^A + V_{o,t}^H + u_t + \varepsilon_{o,t}^A + \varepsilon_{o,t}^H - V_{j,t}^A - V_{j,t}^H - u_t \text{]} . \\ &\quad dF(\varepsilon_{j,t}^A \,/\, \varepsilon_{j,t}^A \geq V_{o,t}^A + v_t)] \, . dF(\varepsilon_{j,t}^H \,/\, \varepsilon_{j,t}^H \geq V_{o,t}^H + v_t)] \end{aligned} \quad (5)$$

Now let us consider the case where airline is bought from website m and hotel is bought on website n. Then the 25 choices that are available to purchase a combination of airline tickets and hotel booking are as depicted in Table 4.

Table 4: Possible website combinations for Airline and Hotel purchase

Airm \ Hotel n	1 Expedia	2 Traveolocity	3 Orbitz	4 Hotwire	5 Other TP	6 Other Site
1 Expedia	(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
2 Travelocity	(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
3 Orbitz	(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
4 Hotwire	(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
5 Other TP	(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
6 Other Site	(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

As before, now the probability of a consumer i purchasing airline and hotel from website m and website n respectively can be written as

Prob[m,n]=Prob [A] . Prob [B] . Prob [C]

where A is [$\varepsilon_{n,t}^{H} \geq \max_{k}(V_{k,t}^{H} + v_t + \varepsilon_{k,t}^{H}, \forall k \neq n) - V_{n,t}^{H} - u_t$]

B is [$\varepsilon_{m,t}^{A} \geq \max_{k}(V_{k,t}^{A} + v_t + \varepsilon_{k,t}^{A}, \forall k \neq m) - V_{m,t}^{A} - u_t$] and (6)

C is [$\varepsilon_{m,t}^{A} + \varepsilon_{n,t}^{H} \geq \max_{k,l}(V_{m,t}^{A} + V_{n,t}^{H} + u_t + \varepsilon_{o,t}^{A} + \varepsilon_{o,t}^{H}, \forall k \neq m, \forall k \neq n) - V_{m,t}^{A} - V_{n,t}^{H} - u_t$]

Note that in the above equations u_t is the component of utility that consumers derive from making both the airline and hotel purchase from the same website and is explicitly modeled as a function of loyalty and {other independent variables}.

$u_{mm,t} = \alpha_0 + \beta_1 loyalty_m + \beta_2 loyalty_j +$ other indep variables

$u_{mn,t} = \alpha_1 + \beta_2 loyalty_j +$ other indep variables (7)

note:

$loyalty_m$ is an indicator variable that takes value 1 if both purchases are on same website

$loyalty_j$ is an indicator variable that takes value 1 if both purchases are on a travel portal

The indirect utility functions for purchasing an airline $V_{j,t}^{A}$ or hotel $V_{j,t}^{H}$ from a particular website website j is also expressed as a function of {independent variables - including consumer demographics Z_{it}, prior browsing experience as the average daily pages viewed S_{ij} on different sites in the first three months, H_{it} as a proportion of pages viewed on website j to the total pages viewed on all travel websites that the customer visited in the first three months, and whether or not consumer i*'s* last purchase was at j, I_{ijt} }.

This concludes are discussion for just one combination AH out of the possible 7 combinations as tabulated in Table 1. The above expressions can easily be extended and similar equations obtained for each of the different combinations.

4.4 Model Estimation

The major difficulty in model estimation comes from dimensionality nd to simplify the model we assume that the random effects in each stage and the random effects for purchases in different categories (e.g. $\varepsilon_{j,t}^{A}$ and $\varepsilon_{j,t}^{H}$) are also independent of each other. We assume the random effects to be normally distributed, as

$$\begin{aligned} &\varepsilon_{m,t}^{A} \sim N(0,\sigma_A^2) \\ &\varepsilon_{n,t}^{H} \sim N(0,\sigma_H^2) \\ &\varepsilon_{m,t}^{A}+\varepsilon_{n,t}^{H} \sim N(0,\sigma_A^2+\sigma_H^2) \end{aligned} \tag{8}$$

To solve the second stage of the model we use the simulated maximum likelihood approach for estimation. Let $\Psi_i = \{\varepsilon_{j,t}^{A}, \varepsilon_{j,t}^{H}, \varepsilon_{j,t}^{C}; \forall j;\ u_t;\ v_t\}$ be the vector of random effects in the equation system with the assumed distribution $F(\Psi,\Omega)$, where Ω is the set of all parameters to be estimated. The unconditional likelihood can now be expressed as follows:

$$L_i = \int \left(\underbrace{\Pr(A|\Psi_i)}_{\text{equation (6)}} \cdot \underbrace{\Pr(B|\Psi_i)}_{\text{equation (6)}} \cdot \underbrace{\Pr(C|\Psi_i)}_{\text{equation (6)}} \right) dF(\Psi_i;\Omega) \tag{9}$$

We estimate this likelihood using the simulated maximum likelihood method. We draw Ψ_i^s, *s=1, …,ns,* where *ns* is the number of simulated draws, following the distribution of *F* (which we will explain later).

The algorithm used to estimate the second stage of the model is as shown below

Step 1: Take 1000 draws of ε_t^s (6x6) for each element of Table 4

Step 2: Evaluate A as $\frac{1}{1000}\sum_{s=1}^{1000} \text{Prob}(\varepsilon_{n,t}^{H} \geq \max_k (V_{k,t}^{H} + v_t + \varepsilon_{k,t}^{H}, \forall k \neq n) - V_{n,t}^{H} - u_t)$

Step 3: Similarly evaluate B as $\frac{1}{1000}\sum_{s=1}^{1000} \text{Prob}(\ \varepsilon_{m,t}^{A} \geq \max_k (V_{k,t}^{A} + v_t + \varepsilon_{k,t}^{A}, \forall k \neq m) - V_{m,t}^{A} - u_t)$

Step 4: Evaluate C for each ε_t^s,

$$\text{Prob(m,n)} = \frac{1}{1000}\sum_{s=1}^{1000} [\ \text{Prob}(A^s).\text{Prob}(B^s)\{\geq 1\} + \text{Prob}(C^s)\{<1\}]$$

The corresponding simulated version of (9) can be expressed as

$$\hat{L}_i = \frac{1}{ns}\sum_{s=1}^{ns}\left(\underbrace{\Pr(A|\Psi_i^s)}_{\text{equation (6)}}\cdot\underbrace{\Pr(B|\Psi_i^s)}_{\text{equation (6)}}\cdot\underbrace{\Pr(C|\Psi_i^s)}_{\text{equation (6)}}\right) \quad (10)$$

Note: The superscript s in the above expressions implies simulated values.

The Nelder-Mead simplex algorithm we use is very efficient in estimating these complex models though some sensitivity to starting values was observed.

5. Results and Discussion

In this section we discuss results for the first stage of the model identifying factors impacting basket choice followed by results from the second stage of the model which sheds more light on the website choice for the various basket combinations. Though our modeling and estimation methodology can be easily extended to a basket with more than two products we limit our estimation to a basket with two products as our model has 79 parameters to be estimated and there are very few observations (195) for basket transactions with all three travel products in our data

5.2 Factors Impacting Basket choice

We infer the preference of various basket combinations from the intercepts associated with each basket combination and find that on average most consumers tend to have a preference to purchase a single product and not a basket of travel products. This could be primarily driven by business or leisure airline trips from point A to point B or hotel stays in a particular geography being visited. Amongst the basket of travel products consumers tend to have a higher preference on average for a basket of products compared to just a car rental product. Amongst the basket of products the combination of all three i.e. air, hotel and car rental products has a higher base level preference compared to any two way combination of travel products. Note that since our model is conditional on a purchase being made the outside option is a basket of car rental and hotel product (see Table 5 first set of results). Though we find consumers who make basket purchases on average are more likely from a larger household, older, have a broadband connection, higher income and more likely to have a child in the family we don't find the demographic parameters to be significant (see Table 5 second set of results).

Table 5: Base level basket preference and demographic factors

	Parameters	Estimates
Base level preference for various Basket Combinations	Air and Hotel Combo	-0.155 (0.474)
	Air and Car rental Combo	-0.231 (0.396)
	Air, Hotel and Car rental Combo	-0.143 (0.347)*
	Airline Only	1.765 (0.305)*
	Hotel Only	0.781 (0.310)*
	Car rental Only	-0.288 (0.291)*
Demographic factors	Household Size	0.111 (0.474)
	Age	0.057 (0.396)
	Income	0.042 (0.347)
	Child Present	1.765 (0.305)
	Connection Speed	0.781 (0.310)

* indicates p < .05. Standard errors are in parentheses

We also investigate the impact of prior browsing history for various product combinations and find that on average consumers who browse more for a basket of products are likely to end up making a purchase, and this likelihood is more pronounced towards purchasing a single product as opposed to a basket of products. Though these inferences are directionally insightful we find that these results are significant only for Air and Car rental combo as well as airline and hotel only products (see Table 6 first set of results). We also find a positive impact of browsing within the travel category to positively impact purchase (see Table 6 second set of results) and this is consistent with our findings from an airline only model (see Nair, Chan and Cheema, 2009 working paper). Though not significant we find directional evidence that purchasing a basket of products in the past doesn't seem to increase the likelihood for repeat purchase of same product combo (see Table 6 third set of results).

Table 6: Prior purchase and browsing history (category and basket specific)

	Parameters	Estimates
Prior browsing history in basket	Air and Hotel Combo	0.002 (0.000)
	Air and Car rental Combo	0.002 (0.000)*
	Air, Hotel and Car rental Combo	0.002 (0.000)
	Airline Only	0.003 (0.000)*
	Hotel Only	0.004 (0.000)*
	Car rental Only	0.005 (0.000)
Prior browsing history in travel		0.288 (1.086)*
Prior purchase of same basket/combo		-0.039 (1.144)

* indicates p < .05. Standard errors are in parentheses

Based on the various interaction effects we incorporate in our modeling effort we find significant evidence that consumers who browse more and are either older or have higher incomes have a higher propensity to make a purchase(see Table 7 first set of results). It is also evident that consumers who made a prior purchase and were either older or have higher income were significantly predisposed to make a purchase (see Table 7 second set of results). The results for interaction of connection speed with prior browsing history and purchase were not significant. These insightful for managers to create a target profile of consumers who are more likely to make a purchase.

Table 7: Interaction Effects

	Interactions	Estimates
Prior Browsing history in travel	Age	0.585 (0.072)*
	Income	0.621 (0.175)*
	Connection Speed	-1.606 (0.921)
Prior Purchase of same basket/combo	Age	0.126 (0.082)*
	Income	0.094 (0.179)*
	Connection Speed	-0.228 (0.167)

* indicates $p < .05$. Standard errors are in parentheses

We find higher variance amongst consumer preference for Air & Car rental basket combination (0.2504), Car rental only (0.1274) and Air, Hotel and Car rental combination (0.0081) purchases in that order (see Table 8). This could primarily be driven by difference in preferences between leisure and business travelers and is something that needs to be investigated in future studies with richer data that distinguishes between these user types. We also find the covariance between Hotel only purchase (-0.0120) as well as Air & Hotel combo (-0.0007) purchase with Car rental only purchase to be negative indicating consumers could be considering these transactions as substitutes. This could be possibly due to the typical behavior exhibited by business travelers i.e. the consumer might be choosing to fly in and stay overnight at a hotel near final destination and use a cab to get to the work location or rent a car to drive to and out of the work location same day. We also find that the covariance of Hotel Only purchase with Air and Car rental only purchase to be higher and positive (0.0120) indicating they could be complementing each other and consumers might be using these separate purchases in lieu of a combination of Air, Hotel and Car rental combo purchase.

Table 8: Basket choice Variance-Covariance parameter estimates

Parameter	σ_{AH}	σ_{AC}	σ_{AHC}	σ_{A}	σ_{H}	σ_{C}
σ_{AH}	0.0009					
σ_{AC}	0.0010	0.2504				
σ_{AHC}	0.0003	0.0024	0.0081			
σ_{A}	0.0002	0.0005	0.0004	0.0003		
σ_{H}	-0.0007	0.0120	0.0003	0.0001	0.0024	
σ_{C}	0.0018	0.1100	0.0046	0.0026	-0.0120	0.1274

*** indicates p < .001, ** indicates p < .005, * indicates p < .01. Standard errors are in parentheses

5.2 Factors Impacting Website choice for various basket purchases

We infer the base level preference for various site choice combinations when it comes to a basket purchase from the intercepts associated with each site choice combination and find that on average most consumers tend to have a preference for purchasing a basket of travel products from different sites one of them being what we define as other site (mostly airline site).

This could be primarily driven by air travel being an important part of any travel plan as well as the loyalty connected with airline rewards programs. Amongst those consumers who choose to complete their basket of travel product purchases on the same portal we find the base level preference to be highest for Orbitz followed by Expedia, Other travel portal, Travelocity and Hotwire in that order (see Table 9). The base level preference is lowest for site combo of Expedia & Travelocity when it comes to making a basket of travel purchases. Note that since our model is conditional on a purchase being made the outside option is a basket purchase made on Other sites only.

Though we didn't find demographic factors to be significant and only directional when it came to basket purchases, we find them to be significant in predicting website choice while pursuing a basket transaction. A child's presence in the household positively influences basket purchases across all site choice combinations while consumers who have a larger household or are older or have higher income or broad band connections are less likely to complete basket purchases across all site choice combinations (see Table 10 first set of results). Consumers who have a prior browsing history on two specific combinations of sites (i) Orbitz and Other sites (mostly airline sites) and (ii) Orbitz and Other travel portals (not significant) exhibit a higher likelihood of making a basket purchase across all site choice combinations. Consumers who have prior browsing experience on Expedia and Orbitz (-10.074 see Table 10 second set of results)

being the least likely to make a basket purchase across all site choice combinations. Others who exhibit similar behavior worth noting (though not significant) are those with prior browsing experience on Other travel portals and Other sites(mostly airline), Travelocity and Other site (mostly airline) Expedia and Hotwire.

Table 9: Base level site choice preference for basket purchases

	Parameters	Estimates	
Base level site choice preference for basket purchases	Expedia only	-5.0318	(10.300)
	Expedia & Travelocity	-12.214	(0.254)*
	Travelocity only	-7.400	(0.782)*
	Expedia & Orbitz	-5.045	(0.054)*
	Travelocity & Orbitz	-5.864	(0.418)*
	Orbitz only	0.357	(70.08)
	Expedia & Hotwire	-8.077	(0.000)
	Travelocity & Hotwire	-7.169	(0.000)
	Orbitz & Hotwire	-7.148	(0.062)*
	Hotwire only	-7.798	(0.000)*
	Expedia & Other portal	-6.508	(0.000)
	Travelocity & Other portal	-7.194	(1.880)
	Orbitz & Other portal	-7.087	(0.826)
	Hotwire & Other portal	-9.547	(0.000)
	Other portal only	-5.888	(0.799)
	Expedia & Other site	0.989	(0.000)
	Travelocity & Other site	1.073	(0.113)*
	Orbitz & Other site	0.819	(0.022)*
	Hotwire & Other site	0.171	(0.000)
	Other portal & Other site	-0.432	(0.287)*

* indicates $p < .05$. Standard errors are in parentheses

We also find a significant impact of overall prior browsing history in travel to significantly and positively influence the likelihood of making a basket purchase from all site choice combinations. Note however that though there is a positive impact of prior purchase on the various site choice combinations on a basket purchase form the same site choice combinations this result is not significant (see Table 11 first set of results).

The interaction effects of demographics with prior travel browsing history and prior purchase on same site combinations were also investigated and the impact of connection speed though positive was not found to be significant. However older consumers or those with higher income had a significant difference in the way they influenced basket purchases across all site

combinations decreasing the likelihood when the prior browsing history was higher – learning impact; and increasing the likelihood when prior purchase history was higher – transaction impact (see Table 11 second set of results).

Table 10: Demographics and Prior browsing history (site specific)

	Parameters	Estimates
Demographic factors	Household Size	-0.753 (0.001)*
	Age	-0.309 (0.000)*
	Income	-0.579 (0.000)*
	Child Present	1.514 (0.024)*
	Connection Speed	-0.164 (0.023)*
Prior browsing history by site choice combinations	Expedia only	-0.621 (0.000)
	Expedia & Travelocity	-2.102 (0.002)*
	Travelocity only	-1.215 (0.003)*
	Expedia & Orbitz	-10.074 (0.000)*
	Travelocity & Orbitz	- 1.598 (0.000)
	Orbitz only	-4.701 (0.006)*
	Expedia & Hotwire	-5.290 (0.000)
	Travelocity & Hotwire	-1.173 (0.000)
	Orbitz & Hotwire	-0.488 (0.000)*
	Hotwire only	-4.970 (0.000)
	Expedia & Other portal	-1.429 (0.000)
	Travelocity & Other portal	-2.557 (0.000)
	Orbitz & Other portal	0.115 (0.000)
	Hotwire & Other portal	-0.626 (0.000)
	Other portal only	-0.061 (0.000)*
	Expedia & Other site	-0.817 (0.000)
	Travelocity & Other site	-6.604 (0.000)
	Orbitz & Other site	16.437 (0.000)*
	Hotwire & Other site	-0.516 (0.000)
	Other portal & Other site	-8.883 (0.000)

* indicates $p < .05$. Standard errors are in parentheses

In our models we also incorporate intercepts to measure the base level of preference (more like brand equity) to make a basket of purchases separately (i) from the same website and (ii) from travel portals to see if they have an impact collectively as a group. We also use an indicator variable to separate out the impact of loyalty of making the basket of purchases from (i) the same website (more like state dependence or stickiness) or (ii) from travel portals collectively as a group. This is an important nuance of our model the interpretation of which helps us understand the impact these factors have on influencing basket purchases for various

site combinations. We find that consumers have a base level preference to make basket purchases from the same website and the large significant coefficient on this suggests that the brand equity or rewards programs on various sites which could be causing this dominates most other factors including loyalty or state dependence effects arising from a basket purchase (see Table 12 first set of results). This could also be an outcome of consumers executing on their basket purchases based on the choices post a search on all other sites. We also find that consumers have a lower base level preference of purchasing their basket from travel portals collectively as a group. This could be because (i) travel portals might be attempting to extract more consumer surplus through bundling and (ii) consumers are successful in finding better deals on basket purchases directly from non-travel portals i.e. service providers like airline sites.

Table 11: Prior purchase, browsing history (category specific) and Interaction Effects

	Interactions	Estimates
Prior browsing history in travel		3.937 (1.560)*
Prior purchase from same choice combo		2.237 (0.861)
Prior Browsing history in travel	Age	-2.071 (0.028)*
	Income	-0.501 (0.080)*
	Connection Speed	7.847 (2.231)
Prior Purchase of same site combo	Age	10.333 (0.017)*
	Income	7.367 (0.024)*
	Connection Speed	4.638 (2.056)

* indicates $p < .05$. Standard errors are in parentheses

When it comes to loyalty we find that consumers have a loyalty or stickiness for making basket purchases on the same website as well as from a travel portal and both of these results are significant and positive however the collective impact of travel portals compared to non-travel portals is greater that the loyalty that is related to making basket purchases from the same website (see Table 12 second set of results). This could be because (i) non-travel portals don't have slightly lower number of alternatives to offer or (ii) the ease of use when it comes to making basket purchases on a travel portal as they are by design geared up to offer many alternatives from which a consumer could make a choice. Note during the period of study non-travel portal sites didn't have much options in this regard.

Table 12: Base level preference and loyalty effect of purchasing entire basket from same site or travel portal

	Parameter	Estimates
Base Level preference to make purchases from	Same Website	10.511 (0.000)*
	Travel Portal	-0.647 (0.000)
Loyalty	Same Website	0.285 (0.000)*
	Travel Portal	0.500 (2.056)*

* indicates p < .05. Standard errors are in parentheses

Due to the complexity of the model and the limited number of observations that were available we do not find the estimates of the variance covariance matrix to be significant (see Table 13 for a summary of these results). However we note that these estimates can be used directionally to make some inferences that could be worth diving deeper into when voluminous transaction data for online basket purchases becomes available. We find the greatest site choice heterogeneity for basket purchases associated with a single site to be on Expedia (24.791) indicating that either Expedia (i) attracts a diverse target audience or (ii) price discriminates amongst its audience better and makes the right basket offerings to the right consumer. The site choice heterogeneity was least pronounced for basket purchases on Orbitz (0.748) indicating profile of consumers making basket purchases on Orbitz to be very similar or those that knew exactly what to get and where on Orbitz. Other site combinations with large heterogeneity were Expedia and Travelocity (14.467) and Hotwire and Travelocity (27.685). Combinations with negative site heterogeneity that are worth mentioning are Expedia and Hotwire(-13.557) and Orbitz and Other travel portals (-15.838). Also note that the top three portals exhibit positive site heterogeneity amongst themselves while exhibiting a negative site heterogeneity with other travel portals indicating that the consumers on the top three portals and those on other travel portals exhibit completely different behavior and could have a different target/segment profile.

Table 13: Basket choice Variance-Covariance parameter estimates

Parameter	$\sigma_{Expedia}$	$\sigma_{Travelocity}$	σ_{Orbitz}	$\sigma_{Hotwire}$	$\sigma_{Other\ Portals}$	$\sigma_{All\ other\ sites}$
$\sigma_{Expedia}$	24.791					
$\sigma_{Travelocity}$	14.467	4.491				
σ_{Orbitz}	3.482	1.501	0.748			
$\sigma_{Hotwire}$	-13.557	27.685	10.859	18.358		
$\sigma_{Other\ Portals}$	-3.438	-6.649	-15.838	11.665	1.073	
$\sigma_{All\ other\ sites}$	4.104	-3.893	0.290	1.391	5.727	5.052

*** indicates p < .001, ** indicates p < .005, * indicates p < .01. Standard errors are in parentheses

6. Conclusions

In this paper we develop a two-stage model to study the category purchase propensities followed by propensity to purchase from a travel website. We model (i) the propensity to purchase a given basket by a consumer and, (ii) the choice of the website where consumers will make the purchases that constitute this basket and how these choices are inter related. We find significant effects of the {descriptive variables} in determining consumer purchase behavior. We also find that the choice of the first site to where consumer makes a purchase has a significant impact on choice of the purchase site for other products in the basket indicating multicategory efficiencies.

Managers can use these results to identify the major determinants of consumer online behavior for basket level purchases and make appropriate marketing interventions based on this understanding of how consumers approach buying multiple products at the same time from multiple or same website. The correlations between the various travel products provide unique insights into travel habits of consumers in addition to providing bundling opportunities for service providers to better serve consumer needs. In this paper we also tease out consumer preferences in making multiple travel product purchases on a travel portal as opposed to pursuing this on separate service provider websites. This model also provides unique insights on how travel portals such as Expedia and Orbitz can better satisfy consumer needs by providing a basket of complementary products which involve air tickets purchase, car rental and/or hotel bookings and also explain why many airline sites have moved towards selling car rental and hotel products to successfully compete with travel portals. Managers can also use the insights from our demographic indicators to create a profile of target consumers who are more likely to make a purchase. Availability of more detailed demographics in the Comscore data set could aid managers in fine turning their segmentation strategy and develop more detailed target profiles.

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