# Choice-Menus for Mass Customization:
# An Experimental Approach for Analyzing Customer Demand
# With an Application to a Web-based Information Service

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## ABSTRACT

Customers are now active collaborators in creating value (Prahalad and Ramaswamy 2000). Companies are increasingly engaging themselves in mass customization (Pine 1999), and offering consumers a "choiceboard" (or a menu of choices) of various features and options for configuring their own products and services (Slywotzky, 2000). We discuss the use of experimental choice-menus for assessing customers' preferences and price-sensitivities for the variety of features and options that might be offered by a firm in its choiceboard. The proposed approach directly analyzes customers' portfolio of choices from each of several experimental menus, by estimating the utility for each menu item as a function of its characteristics, price, and other specific attributes such as multi-feature discounts. We accommodate customer heterogeneity in the utilities, allow for correlation of the utilities across items, and incorporate constraints in menu choices. Various technical issues and methodological contributions are discussed.

We illustrate the approach in a commercial application of a customized Web-based information service, typical of offerings in the information economy (Shapiro and Varian 1999). To assess predictive performance, we compare the proposed approach with alternative traditional approaches. We conclude with a discussion of the types of insights that can be obtained from our approach to menu choices, and their managerial implications.

# Choice-Menus for Mass Customization: An Experimental Approach for Analyzing Customer Demand With an Application to a Web-based Information Service

Rapid advances in information technology, operations flexibility, and the development of the World Wide Web are providing firms with unprecedented market opportunities. There has also been a parallel transformation of the role of customers, who are no longer passive audience but active players in co-creating value (Prahalad and Ramaswamy 2000; Prahalad, Ramaswamy, and Krishnan, 2000). Firms now offer customers a *choice-menu* of items (or “choiceboards”, Slywotzky 2000), and let them design their own products by choosing the items that are most appropriate to their needs. For instance, publishing companies on the Web allow customers to create their own customized publications by choosing from various sets of information categories and articles. News providers such as Reuters, Dow Jones, Bloomberg, and Pointcast provide packaged information services, and Web-portals like Yahoo offer customized services like MyYahoo. In the new information economy, companies such as information providers and publishers have exploited the Internet to mass customize their products and services (Shapiro and Varian 1999). Mass customization is intended to provide superior value to customers by meeting their unique needs for products and services (Pine 1999).

Mahajan and Wind (1999) recently called for new and richer market research models for new product assessment. Wind and Mahajan (1997) have noted that as firms develop capabilities to allow customers to *customize* their desired products, from a market research perspective the focus should be on the way consumers want to customize and their willingness to pay for customized features. Marketers familiar with conjoint analysis have long known the value of using experimentally-designed product or service descriptions to guide the definition of product and service concepts (see Green and Srinivasan, 1978, 1990 for exhaustive reviews; and Louviere, 1994 for a review of the behavioral foundations of conjoint analysis). By systematically manipulating product or service descriptions shown to a respondent with an experimental design, conjoint analysis allows decision-makers to understand customer preferences in an enormous range of potential market situations (see Cattin and Wittink, 1982; Wittink and Cattin, 1989; and Wittink, Vriens, and Burhenne, 1994 for surveys of industry usage of conjoint analysis). Conjoint analysis has evolved from asking customers to provide rankings or ratings of individual product profiles or descriptions, to have them make *choices* from several competing product and service profiles (cf. Cohen 1997; DeSarbo, Ramaswamy, and Cohen 1995; Louviere and Woodworth 1983; Lazari and Anderson 1994; Louviere 1994; Ramaswamy and Cohen 2000).

However, in situations where a firm has the capability to offer a myriad of features that customers can choose from to customize their own products, the strategic focus will typically be on *pricing optional features,* (rather than product lines) and *assessing feature demand* (rather than whole product demand). Consider, for instance, Dell Computer Corporation that has virtually reinvented the personal computer industry by offering product variety through mass customization (Magretta 1998). In an industry where the emphasis was on designing "whole" products and product lines for customers, the emphasis has shifted to designing feature portfolios that customers can choose from to design their *own* products. Customers can now configure their purchase of new personal computers by choosing from a menu of items pertaining to processor speed, memory, hard disk size, graphics cards, and so on, that are *individually priced*. Assessment of feature demand and customers' sensitivities to prices and discount structures can enable firms like Dell to leverage their internal resources and capabilities more effectively, and formulate more effective pricing, communication, and target marketing strategies that deliver customer value and maximize revenues or profitability.

### *Choice-Menu Experimentation*

The basic ideas of conjoint choice experimentation can be extended to present customers with several carefully designed *menu scenarios* of items or features available for customization, instead of the typical product profiles in conjoint analysis. Each menu scenario might vary the prices and availability of each feature, as well as other scenario-specific characteristics (e.g., discounts for choosing multiple features). Customers can then be allowed to choose the set of features that they find most appealing in each scenario. This "have it your way" approach to conjoint-type experimentation has been discussed by Ben-Akiva and Gershenfeld (1998), with additional comments by Louviere and Bunch (1998) and Cohen (1998).

Thus, in contrast to traditional conjoint analysis, menu-based experimental choice analysis mimics the consumer's real-world task in mass customized situations: choosing the desired level of product or service from a menu of potential options. While traditional conjoint analysis uses a fixed number of pre-designed product or service profiles, menu-based conjoint generates many different menu choices, far more than is ordinarily tested in traditional conjoint.

The *modeling challenge* lies in analyzing the menu choices of customers. In typical choice-based conjoint analysis, customers are asked to "pick one product profile with a total price" from many alternative profiles. In menu-based conjoint analysis, customers are asked to "pick several features from a menu of features that are individually priced". The responses therefore entail a binary vector of choices for each respondent, for each of the menu scenarios in the experiment. This represents a modeling challenge that is distinct from the traditional single choice analysis of data from choice-based conjoint experiments (e.g., using multinomial logit models, Louviere 1994; or multinomial probit models, Haaijer et al. 1998). Table 1 summarizes the key differences between choice-based conjoint and menu-based experimental analysis.

[Insert Table 1 here]

The recent literature on market basket analysis of scanner-based purchase behavior has attempted to model multiple choice data that arise in the context of analyzing baskets of frequently bought consumer products across shopping trips (e.g., Russell et al. 1997). These approaches attempt to understand choices of distinct stand-alone products, typically from different product categories, over time (e.g., Harlam and

Lodish 1995; Manchanda, Ansari, and Gupta 1999; Russell and Petersen 1997). There have also been approaches for the structural analysis of multivariate binary data (e.g., DeSarbo, Kim, and Fong 1999; DeSarbo et al. 1996; Erdem and Winer 1999).

Our focus, however, is on analyzing multiple choices of features for a given product, in a menu-based conjoint-like experimental setting where there may often be *constraints* on the choice of features, and the levels within a feature. For example, in purchasing a personal computer, there may be restrictions on choosing certain components (e.g., DVD drives, SCSI controller cards, graphics cards, etc.) that may be incompatible with each other. In other situations, certain premium features may simply not be made available by the provider if certain other features are not chosen. We discuss a Bayesian method of analysis that accommodates such *constrained menus.*

In the next section, we present the proposed Bayesian approach for menu-based conjoint analysis. We discuss the formulation and estimation of the empirical model and present the necessary technical details. We then illustrate the model in a commercial setting entailing a customized Web-based information service. We compare our approach with alternative methods, and subsequently discuss the results of our approach and its attendant managerial implications.

## THE PROPOSED APPROACH

Let:

i = 1, …, N customers;

j = 1, …, J features;

k = 1,…, K menu scenarios;

$y_{ijk}$ = binary variable indicating whether feature j was chosen by customer i in scenario k;

$z_{ijk}$ = customer i's latent utility for feature j for scenario k;

$X^{o}_{ijk}$ = feature-specific covariates (*e.g.* price sensitivity) for feature j in scenario k for customer i;

$X^{c}_{ijk}$ = cross-effect covariates (e.g., scenario-specific effects such as discount structures) for feature j in scenario k for customer i.

For each scenario k (such as in Figure 1), we can specify customer i's latent utility for feature j, $z_{ijk}$, as a function of the design variables (covariates) as follows:

$$z_{ijk} = \tilde{a}_{ij} + \tilde{b}_{ij} X^{o}_{ijk} + \tilde{g}'_{ij} X^{c}_{ijk} + e_{ijk}, \tag{1}$$

where $\tilde{a}_{ij}$ represents the intrinsic attractiveness of feature j to customer i, and $\tilde{b}_{ij}$ and $\tilde{g}'_{ij}$ represents sensitivities of customer i to the respective covariates. The density for $z_{ik}$, conditional on the model parameters and data, is given by:

$$f\left(z_{ik} \mid \Theta, X_{ik}\right) = \frac{\left|\Sigma\right|^{-\frac{1}{2}}}{\left(2p\right)^{\frac{J}{2}}} \exp\left\{-\frac{1}{2}\left(z_{ik} - m_{ik}\right)' \Sigma^{-1}\left(z_{ik} - m_{ik}\right)\right\}, \tag{2}$$

where $\Theta$ represents all of the model parameters, and

$$m_{ik} = \tilde{a}_{i} + \tilde{b}'_{i} X^{o}_{ik} + \tilde{g}_{i} X^{c}_{ik}, \tag{3}$$

where $\tilde{b}_i \mathrm{X}^o_{\mathrm{ik}} = \left(\tilde{b}'_{i1}\mathrm{X}^o_{\mathrm{i1k}},\ldots,\tilde{b}'_{iJ}\mathrm{X}^o_{\mathrm{iJk}}\right)'$, $\tilde{g}_i \mathrm{X}^c_{\mathrm{ik}} = \left(\tilde{g}'_{i1}\mathrm{X}^c_{\mathrm{i1k}},\ldots,\tilde{g}'_{iJ}\mathrm{X}^c_{\mathrm{iJk}}\right)'$, and $\mathrm{X}^{\mathrm{o}}_{\mathrm{ik}}$ and $X^c_{ik}$ contain the respective explanatory variables. We observe each customer i making a binary vector of portfolio choices $y_{ik} = \{ y_{i1k}, \ldots, y_{iJk}\}$. These multiple choices can be linked to the latent utilities as follows:

$$\mathrm{y}_{\mathrm{ijk}} = \mathrm{I}\left\{\mathrm{z}_{\mathrm{ijk}} > 0\right\}, \tag{4}$$

where $\mathrm{y}_{\mathrm{ik}}$, a J element vector, represents the collection of choices made on the k$^{th}$ menu scenario by the i$^{th}$ individual and where $\mathrm{I}\{\ \}$ is the indicator function. Expressions (1) through (4) constitute a multi*variate* probit model (e.g., Greene, 1997). It assumes that a collection of observed choices, recorded as a vector of binary variables y, depends on whether the elements of the vector of latent utilities, z, are greater or less than some threshold value (*e.g.* zero without loss of generality). If we assume that every customer has the same intrinsic attractiveness for each feature, as well as identical sensitivities to the covariates:

$$\tilde{a}_{\mathrm{i}} = \overline{a} \quad \text{and} \quad \tilde{b}_{\mathrm{i}} = \overline{b}_{\mathrm{i}}, \tag{5}$$

we obtain the *aggregate* multivariate probit model (Chib and Greenberg 1998).

Multivariate probit models are a generalization of the bivariate probit models presented by Ashford and Sowden (1970) and Amemiya (1985). The above specification of the multivariate probit model has the advantage of giving a natural structure for modeling *correlations* between item choices and for modeling relationships between covariates and choices. The correlations capture the cross dependencies in latent utilities across the items. In practice, the likelihood functions associated with multivariate probit models is difficult to evaluate, except under certain simplifying situations (see Ochi and Prentice 1984). As a result, such models have rarely been used, although recent classical simulation methods (Geweke, Keane, and Runkle 1994) could be utilized for estimation purposes. Recently, Chib and Greenberg (1998) introduced Bayesian methods for analyzing aggregate multivariate probit models that overcome many of the computational difficulties heretofore associated with estimating these models. They present a Markov Chain Monte Carlo (MCMC) algorithm that can be used to analyze an aggregate multivariate probit model. (The reader is referred to Gelfand and Smith (1990), Smith and Roberts (1993), Tierney (1994) for a discussion of Bayesian computation methods; and Allenby, Aurora, and Ginter (1995); Lenk et al (1996) for applications of Bayesian methods to conjoint analysis). Building upon the original work of Chib and Greenberg (1998), Manchanda, Ansari, and Gupta (1999) have recently discussed a multivariate probit model for examining consumers' purchase behavior of multiple categories of consumer packaged goods.

*A Constrained Random Effects Multivariate Probit Model*

We extend the aggregate multivariate probit model of Chib and Greenberg (1998) by incorporating *constraints* in menu choices, as well as *heterogeneity* in feature attractiveness, price sensitivities, and scenario-specific effects. There are often practical constraints on the menu choices due to design, production, operations, or delivery considerations on the part of the firm. Such menu constraints can be modeled by restricting the latent vector z in (2) to the appropriate subset of $\Re^J$. The density for $z_{ik}$, conditional on the model parameters and data, is now given by:

$$f\left(\mathrm{z}_{\mathrm{ik}} \mid \Theta, \mathrm{X}_{\mathrm{ik}}\right) \propto \frac{|\Sigma|^{-\frac{1}{2}}}{(2\pi)^{\frac{J}{2}}} \exp\left\{-\frac{1}{2}\left(\mathrm{z}_{\mathrm{ik}}-\mu_{ik}\right)^{\prime} \Sigma^{-1}\left(\mathrm{z}_{\mathrm{ik}}-\mu_{ik}\right)\right\} I\left\{z_{ik} \in \aleph\right\}, \tag{6}$$

where $\mathrm{I}\{\ \}$ is the indicator function and where $\aleph$ represents the set of possible feature combinations.

Given (2) and (6), it is easy to see that the full conditional density for $\mathrm{z}_{\mathrm{ik}}$ is a truncated multivariate normal density,

$$f\left(\mathrm{z}_{\mathrm{ik}} \mid \Theta, \mathrm{y}_{\mathrm{ik}}, \mathrm{X}\right) \propto \prod_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{I}\left\{\mathrm{z}_{\mathrm{ijk}}(-1)^{\mathrm{y}_{\mathrm{ijk}}}<0\right\} f\left(\mathrm{z}_{\mathrm{ik}} \mid \Theta, \mathrm{X}_{\mathrm{ik}}\right). \tag{7}$$

To accommodate customer heterogeneity in sensitivities to features and covariates, we specify the parameters $\tilde{\alpha}_{\mathrm{i}}$, $\tilde{\beta}_{\mathrm{i}}$ and $\tilde{\gamma}_{\mathrm{i}}$ as follows:

$$\tilde{\alpha}_{\mathrm{i}}=\bar{\alpha}+\alpha_{\mathrm{i}},\ \tilde{\beta}_{\mathrm{i}}=\bar{\beta}+\beta_{\mathrm{i}} \text{ and } \tilde{\gamma}_{\mathrm{i}}=\bar{\gamma}+\gamma_{\mathrm{i}}, \tag{8}$$

where $\alpha_{\mathrm{i}}$, $\beta_{\mathrm{ij}}$ and $\gamma_{\mathrm{i}}$ are random variables capturing individual differences in the parameters (cf. Gilks and Roberts 1996). A practical advantage of the above random effects formulation is that the aggregate model can be estimated first, by turning off the heterogeneous effects in the Bayesian computational procedure discussed below. This can facilitate fine-tuning the model for both specification and computational purposes. Individual differences in the parameters can then be estimated and different covariance structures for these parameters can be imposed as well.

*Bayesian Inference*

We impose the following prior densities on the model parameters:

$$\bar{\alpha} =_d N\left(0, I/\kappa_{\bar{\alpha}}\right),\ \bar{\beta}_j =_d N\left(0, I/\kappa_{\bar{\beta}_j}\right),\ \bar{\gamma} =_d N\left(0, I/\kappa_{\bar{\gamma}}\right), \tag{9}$$

$$a_i =_d N(0,\Lambda_a),\; b_i =_d N(0,\Lambda_b),\; g_{ij} =_d N(0,\mathrm{T}_j), \tag{10}$$

where $=_d$ means equal in distribution, the $k$ s are hyper-parameters, and $\mathrm{T}_j$ is a diagonal matrix with elements $t_{jc}$ on the diagonal. We use the conjugate prior for the covariance matrix $\Lambda$ and for the diagonal elements of $\mathrm{T}_j$,

$$\Lambda_a^{-1} =_d Wish(P_a, p_a),\; \Lambda_b^{-1} =_d Wish(P_b, p_b) \;\text{ and }\; t_{jc}^{-1} =_d \mathrm{Gamma}(\mathrm{b},\mathrm{a}). \tag{11}$$

In order to complete the model specification, we need to specify a prior distribution for the covariance matrix $\Sigma$. Following the approach of Barnard, McCulloch and Meng (1997), we define the covariance Matrix in terms of a diagonal matrix containing the standard deviations, S, and a correlation matrix, R, or $\Sigma = \mathrm{SRS}$. We avoid the identification problem, that arises when using a multivariate probit model, by requiring S to be an identity matrix. In addition, we assume, *a priori*, that R is uniformly distributed on the convex solid body in the hypercube $[-1,1]^J$ that leads to a symmetric, positive semi-definite matrix with diagonal elements equal to 1; see Rousseeuw and Molenberghs (1994) for a description of this convex solid body. Stated differently, the prior density for R is given by

$$R =_d U(\Im^J), \tag{12}$$

where $U(\cdot)$ is the uniform density and $\Im^J$ is the space of possible JxJ correlation matrices. To simplify notation, we will use $\Sigma$ for the correlation matrix.

Given this parameterization and prior density, the full conditional density for the correlation matrix $\Sigma$ is a constrained Inverted Wishart density,

$$f\left(\Sigma \mid \Theta, Z, \mathrm{X}\right) \propto \left|\Sigma\right|^{-\frac{1}{2}(NK)} \exp\left\{-\frac{1}{2} trace\left(\Sigma^{-1} B_{\Sigma}\right)\right\} I\left\{\Sigma \in \Im^{J}\right\}, \qquad (13)$$

where N is the number of customers, K is the number of times each customer makes a collection of choices and

$$B_{\Sigma} = \sum_{i,k}\left(\left(\mathrm{z}_{\mathrm{ik}} - m_{ik}\right)\left(\mathrm{z}_{\mathrm{ik}} - m_{ik}\right)^{/}\right). \qquad (14)$$

We estimate the posterior density of all the parameters, conditioned on the data, using a Markov Chain Monte Carlo (MCMC) algorithm; see Gilks, Richardson and Spiegelhalter (1996) for an overview of MCMC methods. In order to implement an MCMC algorithm, we need to specify the full conditional densities for each of the parameters in the model. These are summarized in an Appendix available from the authors.

The basic steps of the MCMC algorithm are given below.

1. Generate a random set of starting parameters, $\Theta^0$ and latent variables $\mathrm{z}_{\mathrm{ik}}^0$.

2. Generate new latent variables by drawing samples from (7). For each i and k,
$$\mathrm{z}_{\mathrm{ik}}^1 \sim f\left(\mathrm{z}_{\mathrm{ik}} \mid \Theta^0, \mathrm{y}_{\mathrm{ik}}, \mathrm{X}_{\mathrm{ik}}\right),$$
where $\sim$ means $\mathrm{z}_{\mathrm{ik}}^0$ is a random sample from f.

3. Generate a new correlation matrix $\Sigma$ by drawing samples from (13):
$$\Sigma^1 \sim f\left(\Sigma \mid \Theta_{-\Sigma}^0, Z^1, \mathrm{X}\right).$$

4. Generate new draws for the remaining parameters by sampling from their full conditional densities in the usual manner. This sampling will result in a new collection of parameters $\Theta^1$. Go to 2.

The above MCMC is straightforward to implement for the parameters where it is easy to sample from their full conditional densities. The computationally challenging part of implementing this algorithm comes in generating samples for parameters with *non-standard* densities, viz., a truncated multivariate normal density for the latent variable z, and sampling from an inverted Wishart density for $\Sigma$ constrained such that the random matrix is a correlation matrix. We discuss methods for overcoming these two major computational challenges that can prove useful to future Bayesian approaches in marketing applications. In particular, we utilize a Slice sampling algorithm (Damien, Wakefield, and Walker 1999; Krishnan, Ramaswamy, Meyer, and Damien 1999) to generate samples of z, and introduce a Metropolis Hastings (MH) algorithm (Chib and Greenberg 1995; Hastings 1970) based on the griddy Gibbs sampler (Ritter and Tanner 1992) that can be used to generate samples of $\Sigma$. These are discussed in the Appendix available from the authors.

## EMPIRICAL APPLICATION

As a means of conducting commerce, interest in the Internet and the World Wide Web has grown tremendously over the past few years. Along with this growth, customers have also become more demanding in their expectations. The Web offers customers a new and exciting means of searching for information and purchasing products and services (Hoffman and Novak 1997, 2000). Consider the case of content Web sites in which a service or product provider pays for placement in an organized listing. This is a well-known model in conventional media. To successfully implement a content site, like an Internet Yellow Pages (IYP), the firm must understand both the needs of paying advertisers and of the customers who will use the information.

Although the printed Yellow Pages provides guidance to the development of an IYP, the provider faces many potential advertisers, in this case small and mid-sized businesses, who are not computer or Internet savvy. With the Web being a relatively new advertising medium, pricing the paper-based Yellow Pages service does not provide help to a firm's Internet pricing strategy.

Thus, understanding potential advertisers' willingness-to-pay for additional services on content sites and searchable databases, like the IYP, will be crucial to the eventual success of these businesses. Such extra services include text, graphics, links to other sites, audio messages, and the like. Given the heterogeneity in the knowledge and abilities of individuals, companies, and organizations to develop a Web site or listing for themselves, it becomes even more important to understand which service options to offer, how to price them, and what the elasticity of demand might be.

We now discuss a specific commercial situation involving a leading information provider that has the ability to offer several mass customized services on the Internet. As the developer of an Internet Yellow Pages aimed at businesses in their service area, this firm could offer several customized features that would enhance the value of its product to advertisers. The company was thinking of offering a set of key features initially and had designed a pricing structure (including multiple feature discounts) and a contract commitment specification. Although the firm had developed this initial concept, it wished to probe the market before fully committing itself.

This firm basically wished to gauge advertisers' interest in *customizing* a free, standard IYP listing. In particular, how should the firm set its pricing structure for its service features so as to increase customer value and revenues? Several key pieces of information are required to implement a profitable business strategy, such as intrinsic advertiser preferences for the key features planned for the new service, the price sensitivity of advertisers to these features, the relationship between the pricing structure and advertisers' preferences for multiple features, and the influence of contract commitments and discounts on market demand.

As the customized enhancements are proprietary, we must present the key features (as well as some levels) in disguised form:

- Enhanced Listing (EL);
- Web Page Options (P1, P2, or P3);
- Enhanced Web Page (EP); and,
- Special Web Page (SP).

The Special Page incorporated the three Web Page Options while offering additional customized benefits. Hence, from the Enhanced Listing through the Special Page, these services are ordered in increasing customer benefits, complexity, and monthly fee. Note that within each service feature, the customer has flexibility to customize according to their own business needs, and can produce the listing in-house or work with the firm to produce it (for additional fees depending upon the extent of the design and programming work necessary). As part of the pricing structure, the firm wished to investigate different monthly price levels for each of the four key customized services, taking into account cost considerations and the potential value-added to its customers. The mean prices investigated for the various features were $25 for EL (three levels), $50 for P1 (three levels), $70 for P2 (nine levels), $90 for P3 (twelve levels), $50 for EP (three levels), and \$200 for SP (three levels). The firm was considering three types of advertising contracts (3, 6, or 12 months), and three types of discount options (none, x% if two features were chosen; and 2x% if three features were chosen).

Now, imagine a potential advertiser visiting the firm's Web site describing the firm's capabilities and in particular, its new IYP services. A new customer can get the standardized listing in exchange for information about their business that is provided to the firm. Since the firm is also a major telecommunications provider, the information provided can be used for targeting their other products and services. After registration, the customer may be given the opportunity to subscribe to its enhanced services. This has become a common strategy for information and communication services in the new economy.

Managers at small and mid-sized businesses in a major geographical region, who had responsibilities for their firm's advertising expenditures, were the targets for the interactive, customized, Web-based service. Businesses were called randomly and their advertising managers were pre-qualified with a five-minute telephone interview and invited to a nearby location to complete a self-administered interview. At the location, respondents completed the survey in small groups, with no more than eight in a group.

A sample menu scenario of customized services that could be offered to advertisers is shown in Figure 1. At the top of this particular menu scenario is the time commitment for signing up for the IYP service and the discount level that would apply if two services were ordered. The available customized services and their specific prices are shown below. From this menu respondents were instructed to choose the service(s) that would best meet their business' needs or to check the box that indicated that they would not enhance their free, basic IYP listing.

[Insert Figure 1 here]

In order to independently vary and test the effects of all service options, we designed the experiment as a fractional factorial design using a master design of 81 choice sets divided into nine sets of nine menus (Louviere and Woodworth 1983). The menus were rotated such that no two respondents in a room answered the same questionnaire. The firm was particularly interested in a potential service menu that defined the business case for the IYP. This menu was added to the nine menus from the design for each respondent. Each respondent thus provided choices from ten menus, nine of which were used to calibrate the statistical model, while the remaining menu served as a holdout scenario. In each menu scenario, the price of EP was greater than EL, the price of Page Option P3 > P2 > P1, and the price of SP > P3.

Each respondent first filled out a questionnaire with background information on their firm and its advertising spending for traditional Yellow Pages. IYP options were then explained so that the respondents were familiar with each of the alternatives, their benefits, and costs. After this explanation, an interviewing supervisor thoroughly explained how to fill out the menu-based conjoint task, so there were no questions about what they had to do. It took about 30-40 minutes for each interview to be completed and the respondent was paid $50 for their cooperation.

Table 2 summarizes the observed menu choices of features from the sample of 360 respondents, across all ten scenarios. Note that about 29% of respondents chose only the free basic IYP listing. The discount structure does not seem to have much of an effect on these respondents. About 53% of the sample chose an Enhanced Listing (of these respondents, about 12% chose EL only and the remainder chose EL in combination with other services). The x% discount increases the percent of people choosing any two features from about 29% (no discount) to about 38%. Similarly, the 2x% discount increases the percent of people choosing any three features from about 9% (no discount) to about 22%.

[Insert Table 2 here]

*Comparison with Alternative Approaches for Analysis*

The observed menu choices can be analyzed by converting the observed multiple choices into a single choice problem, that of choosing a single “array” combination from $2^N$ possible arrays. Given this view of the choice-menu data, standard multinomial choice modeling (software) can then be utilized to analyze the data. For example, Ben-Akiva and Gershenfeld (1998) turn the menu task into a single-choice modeling problem by exploding the choice set, and utilize a multinomial logit model (McFadden 1986) to estimate the utility of each of the bundles, and the characteristics of each bundle that influence its choice. Table 3 provides a conceptual comparison of this alternate approach with the proposed approach, for analyzing data from choice-menu experiments.

[Insert Table 3 here]

In the current application, each menu might thus be transformed as a simultaneous presentation all possible feature combinations with a total price that is the sum of the feature prices selected less appropriate discounts. When an individual selects a particular combination of features, that choice can then be treated *as if* she selected one combination from all of the possible combinations.[1] As there are six features, there are $2^6 = 64$ potential feature portfolios. Since the Special Page was a combination of the three Page Options, the respondent was instructed not to choose any Page Options if the Special Page were chosen, and not to choose the Special Page if any Page Options were chosen. Because of this restriction, the potential number of menu portfolios is reduced from sixty-four to twenty.

Because there are a wide range of possible choice models and specifications that could be compared, we utilize the utility specification as given in Ben-Akiva and Gershenfeld (1998), but adopt a multinomial probit (MNP) framework (e.g., Haaijer *et. al.* 1998). In the process, we overcome some of the limitations of the model proposed by Ben-Akiva and Gershenfeld (1998), e.g., they assume that customers are homogeneous in terms of their sensitivities to the various features and (total) price, which is a limiting assumption (Allenby and Rossi 1999; for a general discussion of the MNP model see Rossi, McCulloch, and Allenby 1996).

Hence, we empirically compare the proposed MVP approach with a random effects MNP model based on the utility specification of Ben-Akiva and Gershenfeld

[1] We thank (and agree with) an anonymous reviewer for pointing out that this distorts the behavioral underpinnings of a choiceboard task. However, given the prevalence of standard multinomial choice modeling software, and following another reviewer, we report an empirical comparison for the curious reader.

(1998). We denote this modified multinomial choice model for analyzing the 'converted' menu choices as the Modified MNP or MMNP approach. As summarized in Table 3, in contrast to the more traditional MMNP model, the MVP model specifies a *distinct utility for each feature* (as a function of its characteristics, price, and other scenario-specific attributes), which may be *correlated* with the utilities of other features. These correlations capture unobserved cross-dependencies in the items chosen and can thus *reveal* natural bundles.

For a fair comparison with the MVP model, we developed a Bayesian MCMC estimation algorithm for the MMNP model, similar to that of the proposed approach. Further, we empirically compare the MMNP with a simpler version of our multivariate probit (MVP) model (excluding the scenario-specific and cross effects in our model). The model specifications for the empirical comparisons have a unique intercept and price sensitivity for each feature. We now discuss the various models and then present the predictive performance of these models.

As noted earlier, in the empirical application, there are twenty different possible combinations of features. In the MMNP approach, we specify the utility of each possible combination as a latent random variable whose mean is a linear combination of appropriate covariates. Following Ben-Akiva and Gershenfeld (1998), we let the latent variable of each utility be a function of a set of dummy variable, which indicates the features that are present in each combination, and the total price of the combination of features, or

$$z_{ikb} = \tilde{b}_{i1} X_{1ikb} + ... + \tilde{b}_{i6} X_{6ikb} + \tilde{b}_{iP} X_{Pikb} + e_{ikb}, \tag{15}$$

where $z_{ikb}$ represents the latent utility of the b^th feature portfolio, where $X_{ikb1}$ is a dummy variable which indicates whether the first feature is included in the combination, and so on; $X_{ikbP}$ is the total price of the portfolio.

Given this general utility specification, we consider two different versions of the MMNP model, the first version is an aggregate version where the parameters for each individual are the same,

$$\tilde{b}_i = \left( \tilde{b}_{1i}, \ldots, \tilde{b}_{6i}, \tilde{b}_{Pi} \right) = \bar{b} \;. \tag{16}$$

The second version of this model that we consider is a random effects model where the different parameters are allowed to be correlated,

$$\tilde{b}_i = \bar{b} + b_i \text{ and } b_i =_d N\left(0, \Lambda\right). \tag{17}$$

To make the comparisons with the MVP model equitable, we consider a set of models that take advantage of the same information as used by the above MNP models, viz., the feature price information. For each MVP model we assume that the utility for a feature is a linear combination of an intercept and the price of that feature, or

$$z_{ikj} = \tilde{a}_{ij} + \tilde{b}_{ij} X_{ikj} + e_{ikj} \;, \tag{18}$$

where $z_{ikj}$ represents the latent utility of the j^th feature, where $X_{ikj}$ is the price of the feature and where

$$e_{ik} = \left(e_{ik1}, \ldots, e_{ik6}\right)' =_d N\left(0, \Sigma\right). \tag{19}$$

As with the MNP model we consider both an aggregate and a random effects version of this model. In addition, in order to investigate the advantage of modeling the correlation between the latent utilities, net of the intercept and price, we analyzed versions of these models where $\Sigma$ was forced to be equal to the identity matrix and where $\Sigma$ was a correlation matrix. Using this approach we are able to compare the predictive power between the MNP and the MVP models, between aggregate and random effects models and between MVP model without a correlation matrix and with a correlation matrix.

*Comparative Predictive Performance*

For purposes of our comparative study we divided the data set into a calibration data set and a hold-out data set by placing seven random observations per individual in the calibration data set and placing the remaining three observations per individual in the hold-out data set. Then for each model, we used the calibration data set to estimate the model parameters and then used these parameter estimates to determine how often the model accurately predicted the choice of each feature (marginal predictions) and the choice of combination of features (total predictions) for both the calibration and hold-out data sets.

When making any predictions of menu choices using the MVP, the restricted space of feature portfolios must be accommodated by restricting the latent vector z as shown in (6). In order to assess the predictive performance of the proposed MVP approach, we need to estimate the posterior probability that customer i in scenario k will choose the observed portfolio of features, $\mathrm{Prob}\left(\tilde{z}_{ik} \approx z_{ik} | X_{ik}, X, y\right)$, where $\approx$ means that both latent vectors represent the same portfolio (e.g. each element of both vectors have the same sign). These estimates can be obtained by calculating the ergodic average of the indicator function,

$$I\left\{\tilde{z}_{\text{ik}} \approx \text{z}_{\text{ik}}\right\}:\hat{\text{P}}\text{r}\,ob\left(\tilde{z}_{\text{ik}} \approx \text{z}_{\text{ik}} \mid \text{X}_{\text{ik}}, \text{X}, \text{y}\right) = \hat{E}_p\left[I\left\{\tilde{z}_{\text{ik}} \approx \text{z}_{\text{ik}}\right\} \mid \text{X}_{\text{ik}}, \text{X}, \text{y}\right] = \frac{1}{M}\sum_{m=1}^{M} I\left\{\tilde{z}_{ik}^{m} \approx \text{z}_{\text{ik}}\right\}, \quad (20)$$

where $\text{E}_p[\ ]$ represents the expectation under the target density, and $\tilde{\text{z}}_{\text{ik}}^{\text{m}}$ is drawn from an appropriate MCMC algorithm (see Roberts 1996), such as an algorithm similar to the Slice sampler algorithm, described in the Appendix available from the authors.

The resulting marginal and total predictions for the six comparative models are presented in Table 4. As discussed earlier, we compared two versions of the MMNP model, and four versions of the proposed MVP model. The first model is an aggregate MMNP model where the parameters were homogeneous across individuals. The second model is a random coefficients MMNP model with a covariance matrix. The third model is an aggregate MVP without correlations in the error terms (i.e., the correlation between the utilities of features, net of intrinsic attractiveness and price impact was forced to be 0). The fourth model extends this aggregate MVP model by accommodating consumer heterogeneity via a random effects MVP. The fifth model is the aggregate MVP that allows for correlations in latent utilities. The sixth model is the most general model entailing a random effects MVP and a correlational structure.

[Insert Table 4 here]

Note that the MVP model does significantly better than the competing models. While there is improvement in the marginal predictions of the proportion of respondents choosing a particular feature, there is a *dramatic* improvement in predicting portfolio compositions. Hence, the proposed approach is able to better capture the "complementarity" of feature choices in a portfolio. It is clear, at least for this data set, that the MVP model has far better predictive properties than the MNP model, especially in estimating the portfolio compositions.

Regarding consumer heterogeneity, it is not surprising that the random effects model performs much better than the aggregate model. However, note that even the aggregate MVP model performs marginally better than the random effects MMNP model. This drives home the importance of specifying the utility at the feature level, rather than the bundle level when modeling multiple choice data.

With regards to including a correlation structure in the MVP model, it is interesting to note that while the marginal predictions are very similar for the comparable model with and with out a correlation structure, in each case the correlation structure helps improve the model's ability to predict a combination of features. The impact of the correlation structure is obviously an empirical issue, which will vary across applications.[2]

## Discussion and Managerial Usefulness of Results

We now turn to a discussion of the specific insights obtained from examining the results from our complete model. Recall that the utility of each feature is modeled as a function of its intrinsic attractiveness, price, discount structure, minimum commitment,

[2] Note that if one wishes to make longer-term planning forecasts for a later point in time, one must extend the current model formulation to account for policy changes, e.g., by reparameterising the correlation structure as a function of the key policy variables. However, longer-term forecasting implications are somewhat irrelevant in

as well as the prices of the other features. After a burn-in period of 6,000 draws, we retained the last 2000 draws for summarizing the posterior distributions of the model parameters. Given a particular menu scenario $X_m$, we can calculate the posterior probability that customer i will choose a particular portfolio of features, $\text{Prob}\left(\tilde{z}_i \in \wp_\ell \mid X_m, X, y\right)$, where $\wp_\ell$ denotes a space that represents one of the possible feature combinations (e.g. the $\ell^{\text{th}}$ combination), in a manner similar to expression (20). It is then straightforward to calculate the posterior distribution of revenues.

*Menu Choice and Revenue Analysis*

As indicated earlier, the firm was interested in investigating a particular scenario that represented the business case for IYP. This scenario (henceforth referred to as the base case) entailed a menu of EP @ $25, P1 @ $50, P2 @ $70, P3 @$90, EP @ $50, and SP @$200, with a x% discount for two services and a 6 month contract commitment. Table 4 gives the estimated proportion of advertisers that include a particular feature in their menu choices, at the base case prices shown. Overall, the Enhanced Listing option is the most popular. The expected total revenue per month for the base case is $66.34.

Table 5 also shows the estimated feature choices for non-YP advertisers and heavy-YP advertisers, based on their reported spending on traditional Yellow Pages. The heavy-YP advertisers consist of those businesses that spend over $3000 a year on traditional yellow pages. In general, the heavy-YP advertisers appear to be more inclined to include the premium options, in addition to EL. The expected total monthly

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interactive environments like the current Web application, because the model parameters can simply be updated at sufficiently short intervals of time. We thank an anonymous reviewer for this point.

revenue from heavy-YP advertisers is higher at $77.56. It also appears that some of the non-YP advertisers may be very attracted to the Web as a new medium given the relatively higher proportion of this group (about 22%) choosing the Special Page.

[Insert Table 5 here]

We also calculated the expected total monthly revenue by varying the contract commitment and discount structure as shown in the table below.

| | *Contract Commitment* | | |
|---|---|---|---|
| *Discount Structure:* | *3 months* | *6 months* | *12 months* |
| No Discount | $59.12 | $62.32 | $64.89 |
| X% Discount | $65.63 | **$66.34** | $66.80 |
| 2X% Discount | $74.47 | $71.57 | **$75.53** |

The discount structure appears to have considerable impact on potential revenues. The type of contract commitment however does not appear to have much impact on revenues, possibly due to business advertisers often having annual budget cycles. The total base case revenue goes up from $66.34 to $75.53 for the 2x% discount, 12 month contract commitment scenario. Table 6 breaks down the expected revenue patterns under the different discount structures by the twenty feature portfolios, for the scenario with base case prices and a 12-month commitment.

[Insert Table 6 here]

Note that in going from no discount to x% discount, advertisers that choose a single service option appear to be inclined to add an optional service. The expected revenue for any single service drops from $23.99 to $19.49, but those for doubles increase from $27.63 to $31.90. In particular, monthly revenues from those choosing SP only and P3 only drop from a total of \$13.60 to \$9.45, while those for (SP, EP), (P3, EL), and (P3, EP) appear to increase. However, going from no discount to the larger 2x% discount brings in more revenue from customers who now choose more premium services. The revenues for singles are about the same but those for doubles increase from \$27.63 to \$34.26, and those for triples from \$13.27 to \$18.78. Hence, while the 2x% discount structure does not bring in more customers (see Table 2), it generates considerably more revenue for the firm, as customers migrate to the higher-end premium features.

The estimated correlation matrix $\Sigma$ (across features) is given in the table below.

| *Features:* | *EL* | *P1* | *P2* | *P3* | *EP* |
|---|---|---|---|---|---|
| *Page Option 1 (P1)* | -0.17 | | | | |
| *Page Option 2 (P2)* | **0.42** | -0.21 | | | |
| *Page Option 3 (P3)* | -0.28 | 0.23 | -0.24 | | |
| *Enhanced Page (EP)* | **0.35** | -0.22 | **0.32** | -0.31 | |
| *Special Page (SP)* | 0.09 | -0.27 | 0.16 | **-0.46** | 0.16 |

The EL, EP, and P2 options exhibit modest choice complementarities after taking into account the effect of the covariates. Note from Table 6 that the expected revenue from this triple is the lowest among all triples. The firm may wish to investigate bundling these three distinct options as a special package. The P3 option and the SP option are negatively correlated, implying that customers seeking premium options view these two as substitutes.

*Analysis of Different Pricing Structures*

We first systematically varied the price of each feature while holding the remaining features at base case prices. The marginal effects of these price changes are shown in Table 7 for the lowest and highest price levels for each feature. Note that overall, increasing the prices of the premium features brings in more revenues, especially from the heavy-YP advertisers. It appears that the firm may wish to experiment with setting its menu prices at the highest level, and target non-YP advertisers with special discount structures (e.g., 2x% for 2 services or more), and / or special packaged bundles. Table 8 illustrates some ten different menu scenarios and the expected revenues. The last two columns give the expected revenues and standard deviations with and without the menu constraints (i.e., restricted and unrestricted likelihoods). Note that using an unconstrained random-effects multivariate probit model results in over-estimation of the mean revenues with larger standard deviations. This underscores the importance of accommodating menu constraints in prediction of revenues.

Given the expected costs of delivering each service, the firm can also investigate scenarios that maximize profits. Further, in information service contexts, there are often features that can "lock-in" customers to the firm, which the firm may wish to price low, while varying the prices of other features. Focusing just on revenues, it appears from Table 8 that the maximum revenues occur at the highest price levels and a discount of

2x%. At base case prices, the mean preference, price effect, and total cross-price effects are given in the table below.

| *Feature Portfolios* | *Mean Preference* $\bar{\tilde{\alpha}}_{ij}$ | *Mean Price Effect* $\bar{\tilde{\beta}}_{ij}\bar{X}^{o}_{ijk}$ | *Mean Cross-Price Effects* $\bar{\tilde{\gamma}}_{ij}{}'\bar{X}^{c}_{ijk}$ |
|---|---|---|---|
| *Enhanced Listing (EL)* | 5.2 | -11.0 | 7.7 |
| *Page Option 1 (P1)* | -20.0 | -0.4 | -6.9 |
| *Page Option 2 (P2)* | -29.8 | -4.4 | 0.6 |
| *Page Option 3 (P3)* | -44.2 | -7.9 | 20.5 |
| *Enhanced Page (EP)* | -21.7 | -10.5 | 0.1 |
| *Special Page (SP)* | -27.4 | -9.3 | 5.8 |

Overall, advertisers appear to have a strong intrinsic preference for Enhanced Listing, as might be expected. It is interesting to note however that except for EL, the intrinsic preferences for the features appear to play a much larger role than the prices in determining the customers' utilities for the various features. This explains, in part, the reason for the increased revenues at the higher price points. For heavy-YP advertisers, the annual expense of choosing the premium options represents less than a third of their current spending on YP advertising.

Given the individual-level posterior estimates of the parameters, the firm can also undertake an analysis of "extreme" customers (Allenby and Ginter 1995). To illustrate, we isolated advertisers who had extreme sensitivity to the price of Enhanced Listing (the lowest quartile). The total revenue per customer was estimated to be $19.80 without any discount, $19.63 for x% discount, and $19.96 with 2x% discount (for base case prices and a 12 month commitment). From a strategy perspective, we would recommend that these customers need further inducement such as a free trial period. We also isolated customers who had high intrinsic attractiveness for EL (upper quartile). For these customers the 2x% discount structure had the highest impact on their inclusion of the EP option, followed by SP. This suggests a possible migration path via sequential promotions from EL to EP to SP. Other potential marketing scenarios could be investigated by means similar to these just discussed. We are unable to discuss other findings that emerged from profiling extreme customers, due to the proprietary nature of the commercial application.

## CONCLUSION

Given the ability of information providers or publishers to mass customize their portfolio of features or services, a major challenge for firms today is to set prices for their information products and services so as to increase customer value and revenues (Shapiro and Varian 1999). The Web allows firms to compete on the basis of benefits sought, effectively allowing the marketer to engage in value-based pricing. Shapiro and Varian (1999) note that while companies can attempt to develop and exploit information obtained from customer-provided profiles, online behavior and expensive marketing data, they could learn a great deal about their customers by offering them a *menu* of information products and seeing which ones they choose.

We discuss such a menu-based experimentation approach for the generation and utilization of market-based information of customers' price sensitivities and preferences, for the variety of customized options that a firm can potentially offer in the marketplace. The proposed Bayesian modeling approach, entailing a constrained random-effects multivariate probit model, provides an elegant means for obtaining such market-based information. From a methodological standpoint, we incorporate heterogeneity in feature attractiveness and effects of covariates, as well as any real-world constraints in menu choices. We also address computational challenges in estimating the model parameters, particularly the correlation matrix, and utilize two computationally efficient sampling methods (viz., the Slice sampler and the griddy Hastings Metropolis sampler).

The proposed approach enables firms to understand customers' choices of feature portfolios, price optional features, and assess feature demand, all to maximize customer value, revenues, profitability, and other strategic objectives of the firm. A detailed understanding of feature demand can enable firms to leverage their internal resources and capabilities more effectively, and engage in formulating successful mass customization strategies.

There has been considerable attention devoted to mass customization from a supply side perspective (Feitzinger and Lee 1996; Pine 1999). Information on the nature and extent of demand for the variety of products and services that can be offered through mass customization can help firms better manage their internal and external supply chains to keep costs down. Given the ability of the proposed approach to provide individual-level information, a firm engaged in offering mass customized services on the Web could potentially conduct menu-based conjoint experimentation with every potential customer visiting their Web site. Integrating the information obtained with the firm's databases can assist a firm in achieving the Holy Grail of mass customization, viz., manufacturing a product or delivering a service in response to a particular customer's needs, and doing it in a cost-effective way (Gilmore and Pine 1997; Pine, Peppers, and Rogers 1995). The illustrative commercial application demonstrates the kinds of analyses that can be conducted by a firm to better understand and fulfill the needs of increasingly heterogeneous customers.

Finally, as with any new approach, further research is necessary to evaluate, compare, and extend the promise it holds. Advances in Bayesian methods continue to enable richer representations of heterogeneity in demand and more efficient computation. These developments, coupled with increased flexibility in experimental designs and new channels of information exchange between firms and customers, provide numerous opportunities for researchers and managers alike in exploring and implementing new concepts for creating customer value.

**Table 1**
**Choice-based Conjoint vs. Menu-based Experimental Analysis**

| | *Choice-based Conjoint Analysis* | *Menu-based Experimental Analysis* |
|---|---|---|
| *Problem* | Understand and predict *consumers' (typically brand) choices of a single alternative* from competing alternatives in a product category. There is one total price for each alternative. | Understand and predict *consumers' customization of products and services, entailing the selection of as many features and options they desire* from a menu of (complementary) features and options, which are individually priced. |
| *Illustrative Applications* | Customer choosing a single brand of hotel (or any other "whole product") from competing brands of hotels. The product is pre-configured with a total price. | Customer choosing multiple features and options of Web-based information services, telecommunications services, and so on. There may be menu-specific characteristics such as discount structure, minimum commitment etc. |
| *Typical Data* | *Single choice* from *pre-configured whole products* with a total price in a choice set. There is a common alternative across all choice sets that scales the utility levels between choice sets. | *Multiple simultaneous choices of features and options* from each menu scenario. Each feature is individually priced. There may be firm (e.g., manufacturing) or consumer (e.g., budget) *constraints on choosing certain combinations of features*. |
| *Design of Models* | Given characteristics of alternatives, the model is designed to explain which *single brand* is chosen from a category | Given characteristics and prices of each feature, the model is designed to explain which *collection of features* is chosen. |
| *Theoretical Basis of Models* | Maximize utility of a *single alternative* from a set of competing alternatives yielding the classic *multinomial* (logit or probit) *choice* formulation. | If utility of each feature is above threshold, it is chosen; utility of all features are maximized simultaneously yielding *multiple chosen alternatives* in a *multivariate probit* formulation. |

**Table 2**
**Choice of Feature Portfolios (By Discount Structure)**

| *Feature Portfolios* | *Percent Choosing* | *No Discount* | *x% Discount (for two services)* | *2x% Discount (for three services)* |
|---|---|---|---|---|
| *Basic Listing Only* | 29.3% | 30.7% | 28.2% | 28.6% |
| *Marginals:* | | | | |
| Enhanced Listing (EL) | 53.2 | 49.7 | 54.9 | 56.1 |
| Page Option 1 (P1) | 19.0 | 18.3 | 19.5 | 19.4 |
| Page Option 2 (P2) | 9.4 | 8.7 | 9.6 | 10.3 |
| Page Option 3 (P3) | 14.3 | 14.0 | 14.4 | 14.4 |
| Enhanced Page (EP) | 18.9 | 13.6 | 18.3 | 26.7 |
| Special Page (SP) | 13.5 | 11.8 | 14.3 | 15.1 |
| *Singles:* | | | | |
| Any One Service | 26.5 | 31.5 | 22.9 | 23.4 |
| EL only | 12.1 | 14.4 | 10.5 | 10.7 |
| P1 only | 5.3 | 6.1 | 4.6 | 4.7 |
| P2 only | 2.1 | 2.7 | 1.4 | 2.1 |
| P3 only | 2.6 | 3.4 | 2.5 | 1.8 |
| EP only | 0.4 | 0.5 | 0.3 | 0.4 |
| SP only | 3.9 | 4.4 | 3.6 | 3.7 |
| *Doubles:* | | | | |
| Any Two Services | 30.6 | 28.8 | 38.4 | 25.4 |
| EL & P1 | 9.6 | 9.6 | 11.4 | 8.0 |
| EL & P2 | 4.7 | 4.2 | 5.5 | 4.5 |
| EL & P3 | 6.2 | 6.4 | 7.4 | 4.6 |
| EL & EP | 1.9 | 1.6 | 3.1 | 1.1 |
| EL & SP | 5.1 | 4.5 | 6.6 | 4.5 |
| EP & P1 | 0.5 | 0.2 | 1.1 | 0.3 |
| EP & P2 | 0.7 | 0.6 | 1.0 | 0.5 |
| EP & P3 | 1.1 | 1.0 | 1.1 | 1.1 |
| EP & SP | 0.8 | 0.6 | 1.2 | 0.7 |
| *Triples:* | | | | |
| Any Three Services | 13.5 | 9.0 | 10.5 | 22.6 |
| EL, EP, & P1 | 3.6 | 2.4 | 2.4 | 6.5 |
| EL, EP, & P2 | 1.9 | 1.2 | 1.8 | 3.1 |
| EL, EP, & P3 | 4.4 | 3.2 | 3.4 | 6.9 |
| EL, EP, & SP | 3.6 | 2.3 | 2.9 | 6.1 |

**Table 3**
**A Comparison of Alternate Approaches for Analyzing Data from Choice-Menu Experiments**

| | *The Traditional Single Choice Modeling ("pick one from many") Approach* | *Our Multiple Choice Modeling ("pick any from many") Approach* |
|---|---|---|
| *Analysis Setup* | Convert menu choices as a single choice of array from $2^N$ possible arrays | Preserve the individual menu choices. |
| *Modeling Approach and Theoretical Basis* | The classic multinomial choice approach can be used to model menu choice data by converting them to a "single choice from $2^N$ alternatives" data, as in Ben-Akiva and Gershenfeld (1998) who then posit a multinomial logit type specification. In the empirical comparison that we report in this paper, we actually enhance their choice model to accommodate heterogeneity and utility covariances using a random effects multinomial probit type specification (similar to Haaijer et al. 1998).<br><br>Most important, "utility" is conceptualized and thus specified at the level of an "array". The probability of choosing an array (from $2^N$ possible arrays) is specified as a function of its constituent features, prices etc. The objective is to maximize utility of a single array from a set of competing arrays by setting up a classic multinomial likelihood formulation. | A random effects multivariate probit (MVP) model that models the menu choices in terms of the probability of choosing a collection of features. There is a distinct latent utility specified for each feature (as a function of its characteristics, price, and other scenario-specific attributes), which may be correlated with the utilities of other features. These correlations capture unobserved cross-dependencies in the items chosen.<br><br>The likelihood is defined by the utility for that feature being greater than a certain threshold level. If utility of each feature is above threshold, it is chosen; the utility of all features are maximized simultaneously yielding multiple chosen alternatives in a multi*variate* probit formulation. |
| *Model Design* | Given characteristics of alternatives, the model is designed to predict which *single array* is chosen from all possible arrays. | Given characteristics and prices of each feature, the model is designed to predict which *collection of features* is chosen. |
| *Comments* | Gives the ability to evaluate "pre-determined bundles" easily.<br>However, as the number of features increases, the size of the exploded choice set becomes very large and unwieldy, and one must resort to 'sampling of alternatives'. For identification purposes, correlations between utilities of bundles, net of price and intrinsic effects, have to be set to a constant value—typically zero. | Reveals "natural bundles"; evaluation of pre-determined bundles requires extending basic model. One can assess the intrinsic worth of each feature and the price sensitivity of an individual to that feature. One can also model correlations between the utilities of these features, net of price and intrinsic effects.<br><br>However, our proposed approach requires additional computation to accommodate and preserve constraints in menu choices during estimation. |

**Table 4**
**Predictive Performance of Alternate Approaches for Analyzing the Menu-based Conjoint Data:**

| | *Model:* | *Aggregate MMNP* | *Random Effects MMNP* | *Aggregate MVP (Identity)* | *Random effects MVP (Identity)* | *Aggregate MVP (Correlations)* | *Random Effects MVP (Correlations)* |
|---|---|---|---|---|---|---|---|
| *Calibration Results:* | | | | | | | |
| | *Total** | 0.078 | **0.092** | 0.126 | **0.408** | 0.153 | **0.421** |
| | *Feature 1* | 0.50 | 0.50 | 0.51 | 0.74 | 0.50 | 0.74 |
| | *Feature 2* | 0.72 | 0.80 | 0.72 | 0.83 | 0.71 | 0.83 |
| | *Feature 3* | 0.86 | 0.91 | 0.86 | 0.91 | 0.86 | 0.91 |
| | *Feature 4* | 0.79 | 0.86 | 0.79 | 0.88 | 0.79 | 0.88 |
| | *Feature 5* | 0.67 | 0.48 | 0.68 | 0.84 | 0.71 | 0.84 |
| | *Feature 6* | 0.68 | 0.86 | 0.79 | 0.90 | 0.79 | 0.89 |
| *Hold-out Results:* | | | | | | | |
| | *Total** | 0.077 | **0.093** | 0.125 | **0.352** | 0.151 | **0.363** |
| | *Feature 1* | 0.50 | 0.50 | 0.51 | 0.69 | 0.50 | 0.70 |
| | *Feature 2* | 0.74 | 0.82 | 0.72 | 0.80 | 0.72 | 0.80 |
| | *Feature 3* | 0.85 | 0.90 | 0.85 | 0.89 | 0.85 | 0.89 |
| | *Feature 4* | 0.79 | 0.86 | 0.79 | 0.86 | 0.79 | 0.86 |
| | *Feature 5* | 0.66 | 0.48 | 0.69 | 0.82 | 0.71 | 0.82 |
| | *Feature 6* | 0.68 | 0.86 | 0.80 | 0.89 | 0.79 | 0.88 |

* Total represents the proportion of time that the model correctly predicted a combination of features.

*MMNP* = Multinomial Probit model (e.g., Haaijer et al 1998) modified according to the approach of Ben-Akiva and Gershenfeld (1998);
*MVP* = Multivariate Probit (Chib and Greenberg 1998);
Aggregate Model = All individuals have the same parameter values;
Random Effects = All individuals have different parameter values;
Identity = Correlation between feature specific utilities equal to 0.
Correlations = Correlation between feature specific utilities are estimated.

**Table 5**
**Estimated Marginal Feature Choices and Revenues for Base Case**[a]

| *Feature/Price Level* | *Percent Choosing Feature (X% Discount; 6 month contract)* | | |
|---|---|---|---|
| | *All Advertisers* (100%) | *Non-YP Advertisers* (22%) | *Heavy-YP Advertisers* (24%) |
| Enhanced Listing (EL): | | | |
| $ 25 | 0.508 (0.014) | 0.493 (0.024) | 0.546 (0.031) |
| Page Option 1 (P1) | | | |
| $ 50 | 0.162 (0.013) | 0.171 (0.030) | 0.126 (0.022) |
| Page Option 2 (P2) | | | |
| $ 70 | 0.082 (0.010) | 0.037 (0.017) | 0.162 (0.022) |
| Page Option 3 (P3) | | | |
| $ 90 | 0.133 (0.008) | 0.086 (0.016) | 0.189 (0.019) |
| Enhanced Page | | | |
| $ 50 | 0.140 (0.009) | 0.127 (0.017) | 0.224 (0.017) |
| Special Page | | | |
| $ 200 | 0.084 (0.010) | 0.106 (0.026) | 0.078 (0.015) |
| Total Monthly Revenues | $66.34 (3.10) | $57.06 (4.71) | $77.56 (2.79) |

[a] Estimated proportion of advertisers including feature in their menu choices (standard deviations in parentheses).

**Table 6**
**Revenue Patterns (at Base Case Prices, 12-months commitment)**

| *Feature Portfolios* | *No Discount* | *x% Discount (for two services)* | *2x% Discount (for three services)* |
|---|---|---|---|
| Total Revenue | **$ 64.89** | $ 66.80 | **$ 75.53** |
| | | | |
| *Singles:* | | | |
| Any One Service | **$ 23.99** | **$ 19.49** | $ 22.50 |
| EL only | $ 4.84 | $ 4.55 | $ 4.05 |
| P1 only | $ 3.41 | $ 3.21 | $ 2.23 |
| P2 only | $ 1.47 | $ 1.45 | $ 1.62 |
| P3 only | **$ 4.09** | **$ 2.78** | $ 2.71 |
| EP only | $ 0.67 | $ 0.83 | $ 1.17 |
| SP only | **$ 9.51** | **$ 6.67** | $ 10.72 |
| | | | |
| *Doubles:* | | | |
| Any Two Services | **$ 27.63** | **$ 31.90** | **$ 34.26** |
| EL & P1 | $ 5.67 | $ 5.56 | $ 5.49 |
| EL & P2 | $2.70 | $ 3.36 | $ 2.63 |
| EL & P3 | **$ 4.83** | **$ 5.81** | $ 4.63 |
| EL & EP | $ 1.75 | $ 1.74 | $ 3.89 |
| EL & SP | **$ 8.96** | $ 8.57 | **$ 12.22** |
| EP & P1 | $ 0.77 | $ 1.14 | $ 0.74 |
| EP & P2 | $ 0.69 | $ 0.46 | $ 0.42 |
| EP & P3 | **$ 0.71** | **$ 1.58** | $ 2.20 |
| EP & SP | **$ 1.55** | **$ 3.68** | $ 2.04 |
| | | | |
| *Triples:* | | | |
| Any Three Services | **$13.27** | **$15.40** | **$18.78** |
| EL, EP, & P1 | **$ 1.86** | $ 2.01 | **$ 4.44** |
| EL, EP, & P2 | $ 1.26 | $ 1.24 | $ 2.08 |
| EL, EP, & P3 | $ 4.82 | $ 5.26 | $ 5.03 |
| EL, EP, & SP | **$ 5.33** | $ 6.89 | **$ 7.23** |

**Table 7**
**Marginal Effects of Change in Feature Prices at Base Case Prices**
**(X% Discount, 6 month contract)**

| | *Base and Incremental Revenue* [a] | | |
|---|---|---|---|
| *Feature/Price Level* | *Total* | *Non-YP Advertisers* | *Heavy-YP Advertisers* |
| | Mean (Std) | Mean (Std) | Mean (Std) |
| Enhanced Listing (EL): | | | |
| $ 10 | 63.38 (2.77) | 54.27 (4.31) | 73.75 (3.12) |
| $ 40 | 74.83 (2.93) | 67.96 (5.60) | 85.82 (3.49) |
| Page Option 1 (P1) | | | |
| $ 25 | 66.04 (3.52) | 56.41 (5.44) | 77.87 (3.45) |
| $ 75 | 70.80 (2.63) | 62.88 (5.24) | 80.01 (3.45) |
| Page Option 2 | | | |
| $ 45 | 67.00 (2.65) | 57.70 (4.77) | 77.48 (3.23) |
| $ 95 | 73.60 (4.20) | 68.42 (4.91) | 82.45 (3.99) |
| Page Option 3 | | | |
| $ 55 | 66.73 (2.52) | 63.88 (3.77) | 77.94 (3.23) |
| $ 125 | 80.25 (3.71) | 69.44 (5.57) | 92.85 (4.69) |
| Enhanced Page | | | |
| $ 25 | 69.48 (4.56) | 58.83 (7.10) | 76.80 (4.42) |
| $ 75 | 76.70 (2.63) | 69.24 (3.99) | 89.42 (3.16) |
| Special Page | | | |
| $ 100 | 64.45 (2.52) | 58.22 (4.24) | 76.39 (3.24) |
| $ 300 | 83.43 (2.54) | 71.68 (5.05) | 90.98 (3.99) |

**Table 8**

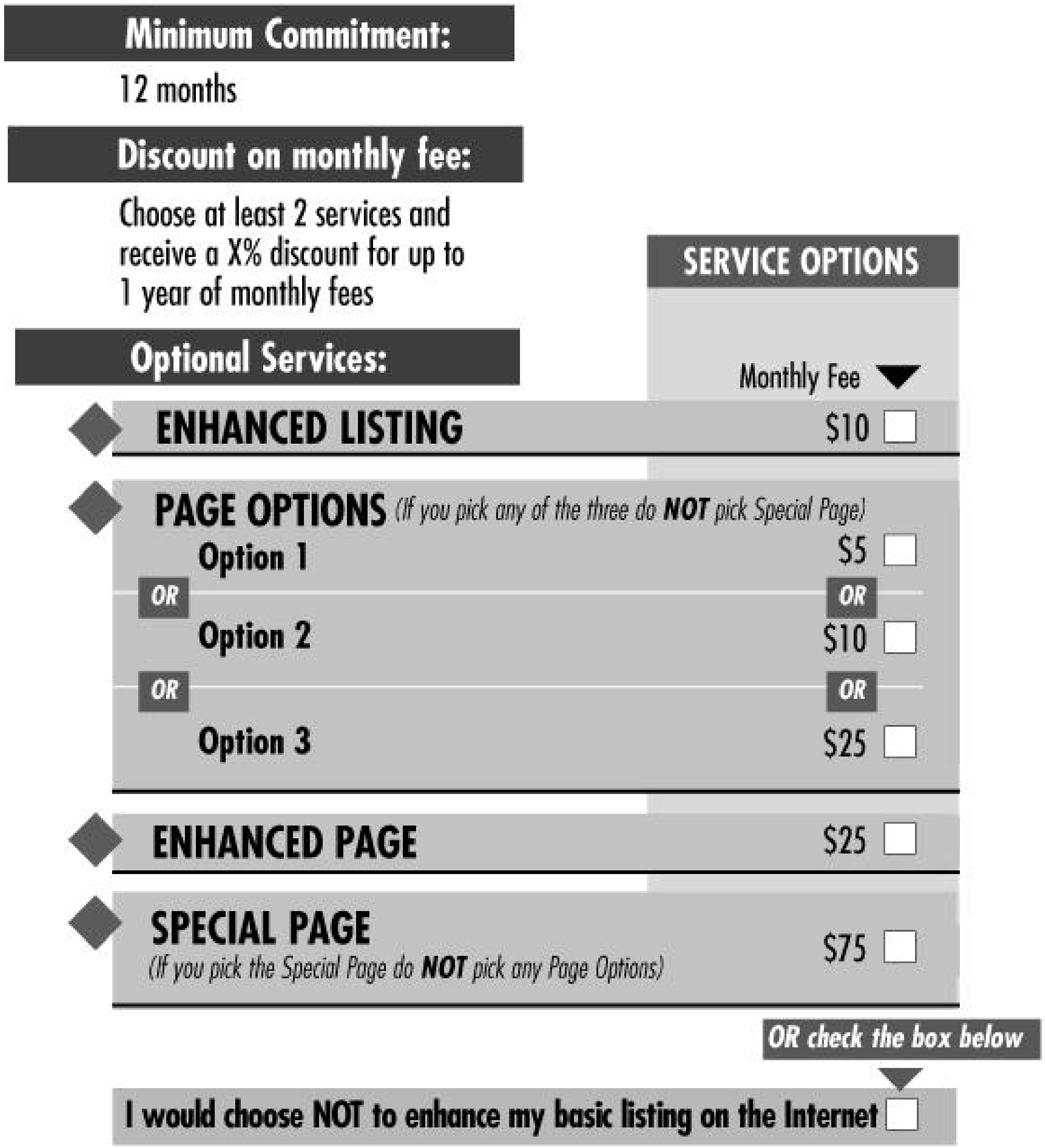
**Expected Revenues for Different Menu Scenarios (12 month commitment)**

| *Scenario* | *Price Levels* | | | | | | *Discount Structure* | *Total Revenue*[a] | |
|---|---|---|---|---|---|---|---|---|---|
| | *EL* | *P1* | *P2* | *P3* | *EP* | *SP* | | *Restricted Likelihood* | *Unrestricted Likelihood* |
| *1* | *10* | *50* | *70* | *90* | *50* | *300* | *X%* | \$84.72 (3.05) | \$105.45 (3.64) |
| *2* | *10* | *50* | *70* | *90* | *50* | *300* | *2X%* | \$99.32 (6.62) | \$112.84 (7.85) |
| *3* | *10* | *75* | *95* | *125* | *75* | *200* | *X%* | \$94.09 (2.36) | \$120.56 (4.41) |
| *4* | *10* | *75* | *95* | *125* | *75* | *200* | *2X%* | \$101.21 (2.71) | \$120.35 (4.96) |
| *5* | *40* | *25* | *45* | *55* | *75* | *100* | *X%* | \$69.46 (1.71) | \$83.47 (2.65) |
| *6* | *40* | *50* | *45* | *55* | *75* | *100* | *2X%* | \$76.79 (1.54) | \$86.41 (2.41) |
| *7* | *40* | *50* | *70* | *90* | *75* | *300* | *X%* | \$101.58 (3.44) | \$126.64 (4.37) |
| *8* | *40* | *50* | *70* | *90* | *75* | *300* | *2X%* | \$121.88 (3.82) | \$140.32 (4.75) |
| *9* | *40* | *75* | *95* | *125* | *75* | *300* | *None* | \$128.63 (2.88) | \$174.08 (6.87) |
| *10* | *40* | *75* | *95* | *125* | *75* | *300* | *2X%* | \$141.31 (2.96) | \$177.38 (6.42) |

[a] Standard deviations in parentheses.

**Figure 1**

**A (Disguised) Menu of Customized Service Options**


Minimum Commitment:
12 months
Discount on monthly fee:
Choose at least 2 services and receive a X% discount for up to 1 year of monthly fees
Optional Services:
SERVICE OPTIONS
Monthly Fee
ENHANCED LISTING $10
PAGE OPTIONS *(If you pick any of the three do **NOT** pick Special Page)*
Option 1 $5
OR
Option 2 $10
OR
Option 3 $25
ENHANCED PAGE $25
SPECIAL PAGE $75
*(If you pick the Special Page do **NOT** pick any Page Options)*
OR check the box below
I would choose NOT to enhance my basic listing on the Internet

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