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Multipart pricing is commonly used by service providers such as car rentals, prescription drug plans, health maintenance organizations, and wireless telephony. The general structure of these pricing schemes is a fixed access fee, which sometimes entitles users to a certain level of product use; a variable fee for additional use; and still another fee for add-on features that are priced individually and/or as bundles. The authors propose a method using conjoint analysis for multipart pricing. The method reflects the two-way dependence between prices and consumption and incorporates consumers' uncertainty about their use of a service. The proposed method estimates both choice probabilities and usage levels for each consumer as functions of the product features and the different price components. The authors then use these estimates to evaluate the expected revenues and profits of alternative plans and pricing schemes. They illustrate this method using data from a conjoint study of cell phone services. They compare the results with those obtained from using several competing models. Finally, they use the proposed procedure to identify the optimal set of features in a base plan and the pricing of optional features for a provider of cell phone services.

Keywords: conjoint analysis, multipart pricing, optimal product design

A Conjoint Approach to Multipart Pricing

The use of conjoint analysis to study the effect of price changes on market demand dates back at least to the 1970s (Johnson 1972; Jones 1975). Since then, marketing researchers have developed a variety of pricing models using conjoint analysis. Mahajan, Green, and Goldberg (1982) describe a method for estimating self- and cross-elasticities using conjoint analysis. Kohli and Mahajan (1991) introduce an approach for optimal pricing using conjoint data. Jedidi and Zhang (2002) further develop this method to allow for the effect of new product introduction on category-level demand. Jedidi, Jagpal, and Manchanda (2003) describe a method for estimating consumer reservation prices for product bundles.

Each of these methods assumes that a product is sold at a single price and that a consumer cannot upgrade or add features to a product by paying an additional fee. Another assumption common to these methods is that consumer usage rates do not depend on price. These assumptions are approximately, if not perfectly, satisfied for some products—for example, durable goods such as washing machines and refrigerators. However, there are also categories of products and services in which one or more of these assumptions are not appropriate. For example, some services charge not one price but two prices and charge additional fees for add-on features. Examples are car rentals; some health maintenance organization (HMO) plans; prescription drug plans; photocopying services; memberships to health clubs, museums, and zoos; and telephone services (Danaher 2002; Narayanan, Chintagunta, and Miravete 2007). Some of these services charge an additional variable fee. For example, institutional users pay a per-page charge for copies on a photocopy machine, and members of an HMO pay a deductible for each visit to a doctor or each purchase of a prescription drug. Other services, such as car rentals, cell phone services, and museum and health club memberships, charge a fixed fee and allow "free" use up to a certain level, beyond which consumers must pay a usage-based unit rate. This induces a two-way dependence of price and consumption; the price a provider charges influences consumption, and the price a consumer pays depends on his or her usage level. Some services allow customers to purchase optional features, such as rollover minutes for cell phone services and extra life insurance for car rentals and air travel. Other services, such as HMO and prescription drug plans, do not allow service enhancements but offer alternative plans with bundles of add-on features. Still other services, such as cable television, allow unlim-

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ited use for a monthly fee but allow consumers additional subscriptions to options, such as digital channels, high-definition broadcasts, pay-per-view programming, broadband Internet access, and Internet protocol telephony.

The purpose of this article is to describe a conjoint model for the multipart pricing of products and services. Our demand analysis approach has its roots in labor economics (Burtless and Hausman 1978; Hall 1973; Hausman 1985; Moffitt 1990). Labor economists are concerned with the prediction of changes in the labor supply when a new, typically multipart tax structure is imposed on people. The two-way dependence between prices and consumption in the current context parallels the simultaneity between tax rate and hours of work. We represent the mutual dependence of prices and consumption in our proposed conjoint model using an approach that Burtless and Hausman (1978) and Hausman (1985) developed. We extend this approach in three ways. First, we incorporate the effect of consumption on consumer choice. Second, we allow for the possibility that consumers are unsure about how much of a service they will use, an important aspect in models of multipart pricing (Lambrecht, Seim, and Skiera 2007; Lambrecht and Skiera 2006; Lemon, White, and Winer 2002; Narayanan, Chintagunta, and Miravete 2007; Nunes 2000). Third, we estimate both choice and usage from choice-set experiments. Consumers are presented a series of choice sets and are asked to choose, at most, one multiattribute alternative from each set. As is common in conjoint analysis, we do not require consumers to estimate their consumption of a chosen alternative. Instead, we infer the latter within the model, using information on the choices that consumers make and do not make. To the best of our knowledge, this article is the first to suggest how the simultaneity of prices and consumption, as well as consumers' uncertainty about their usage levels, can be incorporated in conjoint analysis, in choice simulations, and in the product-design decisions for which conjoint analysis is often used.

In its most general form, the proposed model permits (1) a fixed fee that is charged by a firm for a duration of time (e.g., a daily rate for car rental, a monthly charge for cell phone or cable television use, an annual HMO membership fee), (2) a base level of use to which a person paying the fixed fee is entitled, (3) a variable fee for use beyond the base level, and (4) an option for consumers to add service features at an additional price. How much of the service a consumer uses depends on the utility obtained from additional use. We allow the usage rate to differ from one person to another. An important feature of the proposed model is that it does not require users to consume all the "free" units to which they are entitled upon paying a fixed charge. This is consistent with empirical evidence. For example, there are no usage limits to cable service, but most people do not use it all the time. Similarly, many cell phone users do not exhaust all their free minutes (Iyengar, Ansari, and Gupta 2007). We accommodate this kind of behavior by assuming a quadratic utility function. The parameter values of the linear and quadratic terms determine whether a consumer has constant or diminishing marginal utility and whether there is an unobserved level of use beyond which the utility decreases for a consumer.

In our model, a consumer's usage rate depends on both the number of free units available upon payment of the fixed fee and the per-unit price for use of the service beyond the free units. We allow for individual differences in usage rates and in consumers' preferences for alternative services. We model consumer choice among alternative services and the level at which a consumer uses a service in a probabilistic framework. We aggregate across consumers (1) to obtain estimates of the market penetration and usage of a service, (2) to identify an optimal plan that maximizes profit for a service provider, and (3) to find the optimal prices for service options, such as Internet access and rollover minutes, that are offered by providers of cell phone services. We compare the proposed method with six other competing models.

We organize the rest of the article as follows: We begin by describing the proposed model. Next, we report an application of the model to the pricing of cell phone services and compare the results with those obtained using other null models. Then, we examine the implications of our model for the design of optimal service plans and the pricing of service features. We report the results of a small Monte Carlo simulation that assesses the performance of our estimation procedure. We conclude with our contributions and key results.

MODEL

Model Development

We consider a three-part pricing scheme that comprises a base (access) fee, a free usage allowance, and a per-unit (variable) charge for the use of a service in excess of the allowance. For example, the Basic Plus cell phone plan from T-Mobile charges a monthly access fee of \$29.99, offers 300 monthly free minutes, and charges \$.40 per minute for any excess usage. A two-part tariff plan is a special case when there is no usage allowance. A plan with zero variable fee but unlimited usage allowance is called a "flat-fee plan," and a plan with zero access fee and zero usage allowance is called a "pay-per-use plan."

Consider a choice set with J service plans.[1] Let $x_j = (x_{j1}, \ldots, x_{jm})'$ denote a vector of m nonprice attributes (e.g., service features, service providers) associated with service plan j. Let I denote the number of consumers and v_{ij} denote the attribute-based utility consumer i associates with service j. We assume the following functional form for v_{ij}:

$$(1) \quad v_{ij} = \gamma_{ij0} + \sum_{k=1}^{m} \gamma_{ik} x_{jk}, \text{ for all } i = 1, \ldots, I, j = 1, \ldots, J.$$

We emphasize that v_{ij} does not depend on the price of service plan j. The γ_{ij0} term is a constant specific to service plan j. It represents the value of a service plan that is not explained by the vector x_j of features. The γ_{ik} are regression (partworth) coefficients that capture the effect of the nonprice attributes on utility.

We assume that consumer i cannot choose more than one service plan. Let f_j denote the base fee (fixed cost). We assume that there is an individual-specific composite (outside) good with unit price p_i^w. We also assume that consumer i has a budget of w_i. The budget does not need to be observable, but its existence must be postulated to develop

[1]In practice, multipart tariff pricing mechanisms are used for pricing both products and services. For simplicity, we use service or service plan to indicate products as well.

an economic model. A consumer can spend the entire budget on the composite good or can spend some of it on the composite good and the rest to buy one of the J service plans.

Let A_j denote the number of free units that are offered with plan j, let p_j denote the per-unit price for the consumption of each unit of the service exceeding the quantity A_j, let z_{ij} denote the number of units of the composite good, and let n_{ij} denote the number of units of the service consumer i expects to use if he or she selects plan j. Consistent with the literature on multipart pricing (Lambrecht, Seim, and Skiera 2007; Lambrecht and Skiera 2006; Narayanan, Chintagunta, and Miravete 2007; Nunes 2000), we assume that the consumer is uncertain about the value of n_{ij}. Subsequently, we describe a model for this uncertainty.

Let $u_i(n_{ij}, z_{ij})$ represent the utility consumer i obtains from consuming n_{ij} units of service j and z_{ij} units of the composite good. We assume that the consumer maximizes his or her utility, subject to a budget constraint. This constraint takes one of the following forms, depending on whether the quantity consumed is above or below the free units:

$$\text{(2)} \quad \text{Constraint I: } p_i^w z_{ij} + f_j \leq w_i \quad \text{if } 0 \leq n_{ij} \leq A_j.$$

$$\text{(3)} \quad \text{Constraint II: } p_i^w z_{ij} + f_j + p_j(n_{ij} - A_j) \leq w_i \quad \text{if } n_{ij} > A_j.$$

Note that, on the one hand, the marginal cost of using an extra unit of the service depends on the level of consumption; it is p_j if consumption exceeds A_j and zero if otherwise. On the other hand, the consumption itself depends on the pricing scheme. It is this simultaneity between price and consumption that we want to capture in our model.[2]

A utility-maximizing consumer will exhaust the budget. That is, Equations 2 and 3 will be satisfied as equalities. Without loss of generality, we normalize the unit price of the composite good to $p_i^w = 1$. We assume that the utility function for consumer i has the following form:

$$\text{(4)} \quad u_i(n_{ij}, z_{ij}) = v_{ij} + \beta_{i1}n_{ij} + \beta_{i2}n_{ij}^2 + \beta_{i3}z_{ij},$$

where

$$\text{(5)} \quad z_{ij} = \begin{cases} w_i - f_j & \text{if } 0 \leq n_{ij} \leq A_j \\ w_i - f_j - p_j(n_{ij} - A_j) & \text{if } n_{ij} > A_j \end{cases}.$$

Observe that the utility function reduces to $u_i(0, w_i) = \beta_{i3}w_i$ when the consumer chooses no alternative from a choice set.

The quadratic utility specification of Equation 4 is often used in both the marketing and the economics literature streams (see, e.g., Erdem and Keane 1996; Jensen 2006; Miravete and Röller 2004).[3] We require $\beta_{i2} < 0$ to represent the preferences of consumers who have diminishing marginal utility in the consumption of the service, and we require $\beta_{i3} > 0$ to denote a positive income effect.[4] If β_{i2} is sufficiently small, the utility increases up to a level of consumption, beyond which it decreases. This is useful for representing the preferences of consumers for whom consumption beyond a particular level (e.g., cell phone use, television viewership) is a nuisance.

We now consider the uncertainty in n_{ij}, or the number of units of the service consumer i expects to use if he or she selects plan j. We assume that n_{ij} is a random variable with mean n_{ij}^*, or the quantity that maximizes the consumer utility for plan j (Equation 4) subject to the budget constraint (Equation 5). That is,

$$\text{(6)} \quad n_{ij} = n_{ij}^* + \delta_{ij},$$

where δ_{ij} is an error term. We assume that δ_{ij} has a normal distribution with zero mean and a consumer-specific variance θ_i^2. This approach to modeling usage has the benefit of allowing both the mean consumption and the usage uncertainty to affect plan choice.[5]

We obtain the value of n_{ij}^* using the method that Hausman (1985) describes. Let n_{ij}^{*a} denote the value of n_{ij}^* when $n_{ij} \leq A_j$, and let n_{ij}^{*b} denote its value when $n_{ij} > A_j$. At most, one of these two candidate optima will be feasible (i.e., will lie in the proper consumption interval). The values of n_{ij}^{*a} and n_{ij}^{*b} are obtained from the first-order conditions with respect to n_{ij} that maximize Equation 4 subject to Equation 5:

$$\text{(7)} \quad n_{ij}^{*a} = \frac{-\beta_{i1}}{2\beta_{i2}},$$

$$\text{(8)} \quad n_{ij}^{*b} = \frac{-\beta_{i1} + p_j\beta_{i3}}{2\beta_{i2}}.$$

The term n_{ij}^{*a} can take any real value, but it is a feasible solution to the consumer's decision problem only if it lies between 0 and A_j. Similarly, n_{ij}^{*b} can take any real value, but it is feasible only if it is greater than A_j. If $n_{ij}^{*a} > A_j$ and $n_{ij}^{*b} < A_j$, there is no interior solution, and the consumer will choose A_j. It follows that the optimal quantity for consumer i under plan j is given by

$$\text{(9)} \quad n_{ij}^* = \begin{cases} n_{ij}^{*a} & \text{if } 0 \leq n_{ij}^{*a} \leq A_j \\ n_{ij}^{*b} & \text{if } n_{ij}^{*b} > A_j \\ A_j & \text{if otherwise} \end{cases}.$$

This solution is unique because the budget set is convex and the utility function is quasi concave (see Hausman 1985, p. 1257).

Both n_{ij} and z_{ij} are random variables, the latter because its value depends on n_{ij}. The uncertainty in consumption implies that Equation 4 is a stochastic utility function. In such a situation, consumers use expected utility, which incorporates their usage beliefs, for making a choice decision. The expected utility of plan j for consumer i is given by

[2]Our model can be generalized to situations in which the pricing scheme has a multipart (more than two), increasing-block structure—that is, a pricing scheme in which the per-unit price increases with increasing consumption (see Reiss and White 2005).

[3]The individual-specific term $\beta_{i3}w_i$, which captures the effect of income on utility, cancels out in a choice model. This is because only differences in utilities are relevant.

[4]These restrictions imply risk aversion and arise from the Slutsky negativity constraints, which ensure quasi concavity of the utility function (Hurwicz and Ozawa 1971).

[5]We thank an anonymous reviewer for suggesting the inclusion of usage uncertainty in our model.

$$E[u_i(n_{ij}, z_{ij})] = v_{ij} + \beta_{i1}E[n_{ij}] + \beta_{i2}E[n_{ij}^2] + \beta_{i3}E[z_{ij}]. \tag{10}$$

A discrete choice model predicts that the consumer will choose a service plan if and only if he or she obtains greater expected utility from having the service plan than from not having it and if that plan has the maximum expected utility in the choice set. This choice depends on both the features of a plan and a consumer's expected consumption. Nunes (2000, p. 398) provides empirical evidence in support of such a simultaneous choice process. For example, cell phone plans advertise the number of free minutes presumably because consumers take expected consumption into account when choosing plans. Note that a consumer's choice provides information on expected consumption. As Wilson (1993) suggests, heavy users tend to prefer service plans with high access fees and low per-unit prices, whereas light users tend to prefer plans with low access fees and higher per-unit prices.

A notable benefit of the proposed model is its ability to infer consumption at different prices from choice data. This is important in situations in which the objective of the firm is either profit or share maximization. If the objective is the latter, it is important that different consumers be weighed differentially on the basis of their expected consumption when inferring aggregate market shares. Self-stated consumption data from consumers can be used in this regard. However, this method treats consumption as independent of prices and can lead to meaningless results, as we show in the empirical section. Another benefit from the model is quantifying the amount of usage uncertainty and its impact on choice. A final benefit is the proper characterization of the impact of changes in the prices and free units. Equations 4 and 5 imply that the per-unit price (p_j) and the free units (A_j) have an impact on utility only if $n_{ij} > A_j$. Thus, our model predicts that if all consumers use no more than A_j units, an increase in the per-unit rate will have no effect on the choice probability of a service plan. This contrasts with the predictions of choice models that do not capture these nonlinear effects in the budget constraint.

Model Estimation

We estimate the proposed conjoint model using a hierarchical Bayesian, multinomial probit approach. Consider a sample of I consumers, each choosing, at most, one plan from a set of J service plans. Let t indicate a choice occasion. If consumer i contributes T_i such observations, the total number of observations in the data is given by $T = \Sigma_{i=1}^{I} T_i$. Let $y_{ijt} = 1$ if the choice of plan j is recorded for choice occasion t; otherwise, $y_{ijt} = 0$. Let j = 0 denote the index for the no-choice alternative. Thus, $y_{i0t} = 1$ if the consumer chooses none of the service plans. The random utility of plan j on the tth choice occasion is given by

$$U_{it}(n_{ijt}, z_{ijt}) = u_{it}(n_{ijt}, z_{ijt}) + \varepsilon_{ijt}, \tag{11}$$

where $u_{it}(n_{ijt}, z_{ijt})$ is specified by Equation 4 and ε_{ijt} is a random error term. The utility of the no-choice option is given by $U_{it}(0, w_i) = u_{it}(0, w_i) + \varepsilon_{i0t}$. We assume that $\varepsilon_{it} = (\varepsilon_{0it}, \varepsilon_{1it}, \ldots, \varepsilon_{Jit})$ is normally distributed with null mean vector and covariance matrix Σ. Note that there are two error components in Equation 11. The first component is the consumer-level uncertainty in usage (Equation 6) and is embedded in $u_{it}(n_{ijt}, z_{ijt})$. The second component is the choice error, ε_{ijt}, which is known to the consumer but unknown to the researcher. This interpretation of the error structure is consistent with the structural modeling tradition (see Erdem and Keane 1996, p. 6).

The choice of a service plan depends on its overall expected utility, which, in the presence of choice error, is given by

$$\tilde{U}_{ijt} = E[U_{it}(n_{ijt}, z_{ijt})] = E[u_{it}(n_{ijt}, z_{ijt})] + \varepsilon_{ijt}, \tag{12}$$

where $E[u_{it}(n_{ijt}, z_{ijt})]$ is given by Equation 10. Note that ε_{ijt} appears in the overall expected utility because it is unobservable to the researcher. Because $u_{it}(0, w_i)$ does not depend on consumption, the overall expected utility of the no-choice alternative is $\tilde{U}_{i0t} = U_{it}(0, w_i)$.

In line with the random utility framework, consumer i chooses service plan j if and only if he or she obtains (1) greater expected utility from having the service plan than from not having it and (2) the highest expected utility from plan j across the J available plans. Equivalently, consumer i chooses service plan j if

$$\tilde{U}_{ijt} = \max_{1 \le l \le J} \tilde{U}_{ilt} \ge \tilde{U}_{i0t} \tag{13}$$

and does not choose any plan if

$$\tilde{U}_{ijt} < \tilde{U}_{i0t}, \quad j = 1, \ldots, J. \tag{14}$$

Let $\beta_i = (\gamma_{i10}, \ldots, \gamma_{iJ0}, \gamma_{i1}, \ldots, \gamma_{im}, \beta_{i1}, \beta_{i1}, \beta_{i3})$ denote the vector of regression parameters, and let θ_i denote the parameter for the uncertainty in the quantity used by consumer i. Let P_{ijt} be the probability that consumer i chooses service plan j on choice occasion t, given β_i, θ_i, and Σ, and let P_{i0t} be the no-choice probability (for the derivation of these probabilities when there is no uncertainty, see Jedidi, Jagpal, and Manchanda 2003). Then, the conditional likelihood, $L_i|(\beta_i, \theta_i, \Sigma)$, of observing the choices consumer i makes across the T_i choice occasions is given by

$$L_i|(\beta_i, \theta_i, \Sigma) = \prod_{t=1}^{T_i}\prod_{j=0}^{J} P_{ijt}^{y_{ijt}}. \tag{15}$$

To capture consumer heterogeneity, we assume that the individual-level regression parameters, β_i, are distributed multivariate normal with mean vector $\overline{\beta}$ and covariance matrix Ω. We further assume that $\log(\theta_i)$ is normally distributed with mean μ_θ and variance τ_θ^2. The unconditional likelihood, L, for a random sample of I consumers is then given by

$$L = \prod_{i=1}^{I}\int L_i|(\beta_i, \theta_i, \Sigma) f(\beta_i|\overline{\beta}, \Omega)\, g[\log(\theta_i)|\mu_\theta, \tau_\theta^2] d\beta\, d\theta, \tag{16}$$

where $f(\beta_i|\overline{\beta}, \Omega)$ is the multivariate normal $N(\overline{\beta}, \Omega)$ density function and $g[\log(\theta_i)|\mu_\theta, \tau_\theta^2]$ is the univariate normal $N(\mu_\theta, \tau_\theta^2)$ density function.

The likelihood function in Equation 16 is complicated because it involves multidimensional integrals, which makes classical inference using maximum likelihood methods difficult. We circumvent this complexity by using Markov chain Monte Carlo (MCMC) methods, which avoid the need for numerical integration. We adopt a Bayesian framework for inference about the parameters. The MCMC methods yield random draws from the joint posterior distribution, and inference is based on the distribution of the drawn samples. We use a combination of data augmentation (Albert and Chib 1993), the Gibbs sampler (Geman and Geman 1984), and the Metropolis–Hastings algorithm (Chib and Greenberg 1995). Finally, we use proper but noninformative priors.

Our model estimation approach follows the standard Bayesian estimation of the multinomial probit model except for three differences. First, because consumption is not observed, we calculate its value using the draws of β_i and θ_i from the MCMC sampler. We use the value of β_i to calculate optimal consumption n^*_{ijt} using Equation 9. We use the value of θ_i to generate the quantity uncertainty, δ_{ij}. We input these two quantities to compute the consumption value n_{ij} using Equation 6. Second, because the choice decision is based on expected utility, we generate a large sample of n_{ij} (as described previously). For each sample value of n_{ij}, we calculate the utility using Equations 4 and 5. The average of these utilities produces an estimate of the expected utility. Third, to ensure the quasi concavity of the utility function, we enforce the two Slutsky restrictions on the individual-level parameters: $\beta_{i2} < 0$, and $\beta_{i3} > 0$. We enforce these restrictions by reparametrizing $\beta_{i2} = -\exp(b_{i2})$ and $\beta_{i3} = \exp(b_{i3})$, where b_{i2} and b_{i3} are unconstrained individual-level parameters. With these two restrictions, the normality assumption holds for parameters b_{i2} and b_{i3} but no longer holds for β_{i2} and β_{i3}.

For the Bayesian estimation, we use the following set of noninformative priors for all the population-level parameters: Suppose that $\bar{\beta}$ is a $p \times 1$ vector and that Ω^{-1} is a $p \times p$ matrix. Then, the prior for $\bar{\beta}$ is a multivariate normal with mean $\eta_\beta = 0$ and covariance $C_\beta = \text{diag}(100)$. The prior for Ω^{-1} is a Wishart distribution, $W[(\rho R)^{-1}, \rho]$, where $\rho = p + 1$ and R is a $p \times p$ identity matrix. For μ_θ, we set a univariate normal prior with mean $\eta_\theta = 0$ and variance $C_\theta = 100$. The prior for τ^2_θ is an inverse gamma IG(a, b) with a = 3.0 and b = 2.0. Finally, we assume that the utilities of the plans are independent given β_i and θ_i; that is, Σ is a block diagonal matrix. Let σ^2_j be the variance of choice error ε_{ijt} (see Equation 12). We set an inverse gamma prior IG(3.0, 2.0) on this variance.[6]

Subsequently, we report the results of a small simulation that assesses the robustness of our MCMC estimation procedure. The results indicate that our MCMC algorithm does well in recovering the true parameters.

AN APPLICATION

We illustrate the proposed model using data from a conjoint study of cell phone plan choices. The participants in the study were 72 undergraduate marketing students at two large northeastern universities.[7] We use the data from this study to estimate the proposed model and compare its results with those obtained using six null models. Some of these null models use information about the current plans the participants used, the attributes of these plans, and self-reported usage (in minutes) of participants' respective plans. On average, the participants reported using 540 minutes of cell phone services per month. This is close to the national average of 600 minutes per month in 2005 (Cellular Telecommunications and Internet Association 2006).

To design our conjoint experiment, we conducted a pilot study using a convenience sample of 33 undergraduate students, each of whom was a subscriber to a cell phone service plan. We determined the attributes to include in our conjoint design by asking these participants to state the three most important attributes when choosing among service plans. We also asked them to indicate the three most popular service providers in this category. Access fee, per-minute rate, monthly free minutes, the service provider's name, rollover, and Internet access were the most frequently mentioned attributes, and Verizon, Cingular, AT&T, and T-Mobile were the most popular service providers. To establish an empirically viable range for the pricing components of a cell phone service, we asked each participant to state the maximum access fee and per-minute rate that he or she would be willing to pay for a cell phone service. From the results, we identified \$15–\$90 as a feasible range for access fee and \$.15–\$.60 as a feasible range for per-minute rate. The market rates at the time of the study fell within these ranges.

Study Design

Following the results of the pilot study, we selected six attributes for creating the conjoint profiles: (1) access fee, (2) per-minute rate, (3) plan minutes, (4) service provider, (5) Internet access, and (6) rollover of unused minutes. After defining these six attributes in the questionnaire, we presented each participant with a sequence of 18 individualized choice sets in show-card format. Each choice set had three wireless plans, which are described using the six attributes.[8] The participants' task was to choose an alternative (i.e., no choice is permitted) from each choice set. We controlled for the order and position effects by counterbalancing the position of the service providers and randomizing the order of profiles across participants. Figure 1 presents an example of a choice set used in the study.

To ensure that no choice set had a dominating alternative, we used a utility-balance-type approach for designing the choice sets (see Huber and Zwerina 1996). We first generated three orthogonal plans with 18 profiles, each from the full factorial design (Addelman 1962). We ordered the 18

Figure 1

AN EXAMPLE OF A CHOICE SET OF THREE WIRELESS PLANS

Plan Features	*Plan 1*	*Plan 2*	*Plan 3*
Service provider	Verizon	Cingular	T-Mobile
Access fee	\$31.99	\$30.99	\$49.99
Plan minutes	230 min	430 min	360 min
Per-minutes rate	\$.38/min	\$.47/min	\$.40/min
Internet access	No	No	Yes
Rollover	No	No	No
I choose: None ___	Plan 1 ___	Plan 2 ___	Plan 3 ___

[6]The details of the Bayesian estimation procedure are available on request.

[7]The use of students as participants limits the generalization of our results to other populations.

[8]The participants were told that all the three plans offer free nights and weekend minutes. For all other plan features that they may be thinking of (e.g., free in-network calls, assortment of handsets), the respondents were told to assume that all the plans were equivalent.

profiles from each orthogonal plan from least to most preferred using the average attribute importance weights from the pilot survey. We then selected the three alternatives with equal ranks to form a choice set.

We retained Verizon, Cingular, and T-Mobile as service providers but dropped AT&T because it had already merged with Cingular at the time of the study. We included Internet access and rollover as additional binary (yes/no) features. Access fee refers to the monthly charge to a customer for using the wireless service. Per-minute rate is the marginal cost to the consumer for each minute of use in excess of the free minutes. We divided the ranges of each variable into "low," "medium," and "high" categories for both the access fee ($15–$40, $40–$65, and $65–$90) and the per-minute rate ($.15–$.30, $.30–$.45, and $.45–$.60). Service plans with higher access fee typically have more free minutes (plan minutes). To reflect this reality in the design of our stimuli, we computed the cost of a free minute (i.e., the ratio of the access fee to the number of free minutes) for a large number of plans that were available on the market at the time of the study. The empirical range of this cost varies from $.04 to $.15; the corresponding number of free minutes per month varies between 100 minutes and 2000 minutes. We created three levels for this cost range: "low" ($.04–$.06), "medium" ($.06–$.09), and "high" ($.09–$.15). We randomly selected a value from the appropriate range for each attribute level appearing in a hypothetical service plan. To determine the monthly free minutes, we divided the randomly generated access fee value of the plan by its generated cost per free minute. Thus, the actual prices and the number of free minutes vary continuously across choice sets and respondents. Note that we do not present the pricing and free-minute attributes using their low, medium, and high levels but rather using their exact values, which we draw randomly from their respective intervals in the conjoint design.

Model Specifications

We use the data to estimate the proposed model and six null models.[9] We selected the latter to examine whether the proposed method provides any improvements in predictions and/or offers new insights.

Let f_j denote the monthly access fee, let p_j denote the per-minute rate for usage beyond the free minutes, and let A_j denote the number of free minutes per month (in hundreds of minutes) for plan j. Let $CING_j$, $TMOB_j$, VER_j, $ROLL_j$, and INT_j denote 0/1 dummy variables representing the absence or presence of Cingular, T-Mobile, Verizon, rollover, and Internet access, respectively, in plan j. We selected Verizon as the base level for brand name.

We specify the following utility function for the proposed model (for simplicity, we omit the subscript t denoting choice occasion):

$$u_{ij} = \beta_{i0} + \beta_{i1}n_{ij} + \beta_{i2}n_{ij}^2 + \beta_{i3}z_{ij} + \beta_{i4}CING_j + \beta_{i5}TMOB_j + \beta_{i6}ROLL_j + \beta_{i7}INT_j, \quad j = 1, 2, 3. \tag{17}$$

[9]We thank the review team for suggesting several of these null models.

Each of the parameters in Equation 17 is specified at the individual level,[10] and n_{ij} is the quantity as defined in Equation 6. Furthermore,

$$z_{ij} = \begin{cases} -f_j & \text{if } 0 \leq n_{ij} \leq A_j \\ -f_j - p_j(n_{ij} - A_j) & \text{if } n_{ij} > A_j \end{cases}. \tag{18}$$

Note that in contrast to the budget constraint (Equation 5), the empirical budget constraint (Equation 18) does not contain a w_i term. This is because in a choice model setting, the $\beta_{i3}w_i$ term enters the utility of each alternative and thus cancels out.

We estimate two special cases of our proposed model. First, to assess the impact of uncertainty, we estimate a model in which we assume that consumers have no consumption uncertainty, or equivalently, $n_{ij} = n_{ij}^*$. We call this model the "proposed model–no uncertainty." Second, as empirical evidence (e.g., Lambrecht, Seim, and Skiera 2007) suggests, our model allows for the possibility that consumers do not use all their free minutes (underage). As a benchmark, we estimate the special case of our model that requires consumers to exhaust all free minutes (i.e., no underage, but overage is possible). We call this model the "proposed model–no underage."

We also compare our model with three alternative choice-based conjoint specifications. The first model is the following standard, main-effects conjoint model:

$$U_{ij} = \alpha_{i0} + \alpha_{i1}f_j + \alpha_{i2}p_j + \alpha_{i3}A_j + \alpha_{i4}CING_j + \alpha_{i5}TMOB_j + \alpha_{i6}ROLL_j + \alpha_{i7}INT_j + e_{ij}, \quad j = 1, 2, 3. \tag{19}$$

We assume that the person-specific vector $\alpha_i = (\alpha_{i0}, \ldots, \alpha_{i7})'$ of parameter estimates in this conjoint model follows a multivariate normal distribution with mean vector $\bar{\alpha}$ and covariance matrix Ω_α, and we assume that $e_i = (e_{i0}, e_{i1}, e_{i2}, e_{i3})'$ is a vector of error terms, normally distributed with zero mean and covariance matrix Ψ. We call this model the "standard conjoint model."

The next two benchmark models extend this main-effects conjoint model in different ways. One of these, the "interaction-effects model," also includes interaction effects between pairs of the access-fee, per-minute-rate, and free-minutes attributes. The other, the "nonlinear-effects model," reflects nonlinear price effects in a manner analogous to Goett, Hudson, and Train's (2000, p. 9) model. This model adds to the conjoint model in Equation 19 logarithmic terms in the access fee, per-minute rate, and free minutes.[11]

Finally, we test a "monthly cost model," in which the utility is a function of the monthly cost of the plan and its

[10]The intercept β_{i0} is estimable because the data collection allows for a no-choice option (Haaijer, Kamakura, and Wedel 2000). With this specification, the utility of the no-choice option is set to zero.

[11]We also estimated a nonlinear model with a quadratic specification. However, because of multicollinearity, we encountered convergence problems in estimation. Another approach to capture nonlinearity is to treat the attributes as discrete variables with three levels each, as in traditional conjoint. Although this is feasible, it is difficult to implement in the context of our study. First, the usage allowance A_j is not independent of access fee and per-minute rate. Second, our model requires continuous attributes. Therefore, by using continuous attributes for some models and discrete ones for others, the comparison of results across models becomes muddied because of the loss of information.

features ($CING_j$, $TMOB_j$, VER_j, $ROLL_j$, and INT_j). To calculate the cost of a plan, we use the self-stated consumption for each consumer along with the plan's free minutes, access fee, and per-minute rate.

Model Performance Results

We used MCMC methods for estimating the models. For each model, we ran sampling chains for 150,000 iterations. In each case, convergence was assessed by monitoring the time series of the draws. We report the results based on 100,000 draws retained after discarding the initial 50,000 draws as burn-in iterations.

Goodness of fit. We used Bayes factor (BF) to compare the models. This measure accounts for model fit and automatically penalizes model complexity (Kass and Raftery 1995). In our context, BF is the ratio of the observed marginal densities of a particular null model to our model. We used the MCMC draws to obtain an estimate of the log-marginal likelihood (LML) for each of the models. Table 1 reports the LMLs for all the models and log-BF relative to our proposed model. The results provide evidence of the empirical superiority of our proposed models with and without uncertainty (see Kass and Raftery 1995, p. 777).[12]

The standard conjoint and the monthly cost models perform poorly. The former fails to capture important nonlinear and interaction effects, and the latter does not correct for the effect of prices on consumption (which is fixed at the self-stated monthly usage for each consumer). The interaction- and the nonlinear-effects models perform better than these two models. However, although both models have a larger number of parameters, they have poorer fits than that of the proposed models, with or without uncertainty. A comparison of the log-BF for the proposed model with uncertainty with models without uncertainty or underage suggests that it is more important to capture satiation effects than to model the uncertainty in consumption.

Predictive validity. For each participant, we randomly select 16 of the 18 choice sets for model estimation and use the remaining 2 for out-of-sample prediction. The last column of Table 1 reports the mean hit rate across participants and holdout choice sets for each model. All models have hit rates that are significantly higher than the 25% chance criterion. Consistent with the previous LML results, the standard conjoint and the monthly cost models have relatively poor predictive validity. All other models (except the no-underage model) have holdout hit rates that are statistically indistinguishable.

[12]Kass and Raftery (1995) suggest that a value of log BF greater than 5.0 provides strong evidence for the superiority of the proposed model.

Table 1
MODEL PERFORMANCE COMPARISON

Model	*LML*	*Log-BF*	*Hit Rate*
Proposed model–uncertainty	932.65	—	68.2
Proposed model–no uncertainty	944.71	12.06	69.4
Proposed model–no underge	977.79	45.14	65.9
Standard conjoint	1186.19	253.54	58.3
Interaction effects	977.82	45.17	67.3
Nonlinear effects	952.03	19.38	68.9
Monthly cost	1280.1	347.45	52.1

The results in Table 1 collectively suggest that it is important to reflect the effect of plan characteristics and various aspects of consumption, such as usage quantity, uncertainty, and satiation, in a choice model. Although satisfactory in terms of holdout hit rates, the nonlinear- and interaction-effects models are ad hoc in their specification. Subsequently, we discuss the implications of this on demand estimation and optimal pricing recommendation.

Reliability of estimates. As we noted previously, an important benefit of our model is its ability to infer expected consumption for each consumer. We assess the reliability of these estimates by correlating consumers' self-stated, monthly consumptions (minutes of cell phone use) with our model estimates. We compute the latter given each participant's self-stated per-minute rate p_j and free minutes A_j for his or her current wireless service plan. For our sample, this correlation is .70, which provides good evidence for the reliability of our consumption estimates.

As a further check for the reliability of our consumption estimates, we perform a regression that relates the self-stated monthly consumption to the model predicted consumption ($\hat{n}_{ij}$). We obtain the following regression equation (standard error in parentheses):

$$\text{Self-stated consumption} = \underset{(94.89)}{35.80} + \underset{(.20)}{1.14} \times \hat{n}_{ij}.$$

The results suggest that respondents slightly overstate their monthly consumption. However, we fail to reject a test of a null intercept and a slope of 1.0.

Estimation Results

We now discuss the parameter estimation results from our proposed models. As is common in Bayesian analysis, we summarize the posterior distributions of the parameters by reporting their posterior means and 95% posterior confidence intervals. Table 2 reports the results.

In all three models, most of the unconstrained parameter estimates have the expected sign and are "significant." The main effect of quantity ($\hat{\beta}_1$) is positive, and its significance validates the importance of accounting for consumption in a choice model. For the brand effects, in general, consumers are indifferent between Verizon and T-Mobile, which they marginally prefer to Cingular. This weak brand effect is consistent with a Harris Interactive (2004) study, which reports a yearly 14% switching rate among service providers and a 32% customer satisfaction rate. The presence of rollover and Internet access adds significantly to the utility of a wireless service. Both the constrained parameters ($\hat{\beta}_2$ and $\hat{\beta}_3$) are significant, and the constraints are binding. Thus, there is a significant, diminishing utility from consuming additional minutes and a positive income effect.

A comparison of the models with and without uncertainty in usage quantities suggests that a failure to account for uncertainty is likely to result in an underestimation of the magnitude of quantity effects. This result is consistent with the findings in the psychometric literature that ignoring measurement error can lead to biased regression parameter estimates (Jedidi, Jagpal, and DeSarbo 1997). Similarly, the comparison between the no-uncertainty model and the no-underage model suggests that not allowing consumers to leave free minutes on the table produces a

Table 2
PARAMETER ESTIMATES FOR PROPOSED MODELS: POSTERIOR MEANS AND 95% CONFIDENCE INTERVALS

Variable	*Variable Label*	*Parameter Label*	*Uncertainty Model*	*No-Uncertainty Model*	*No-Underage Model*
Quantity	n_{ij}	β_1	**2.59** (2.44, 2.73)	**1.73** (1.60, 1.84)	**.87** (.71, 1.04)
Quantity^2	n^2_{ij}	β_2	**–.29** (–.32, –.25)	**–.12** (–.13, –.10)	**–.03** (–.05, –.02)
Income effect	z_{ij}	β_3	**.07** (.05, .08)	**.07** (.05, .08)	**.06** (.05, .08)
Cingular	CING	β_4	**–.19** (–.30, –.06)	**–.29** (–.47, –.14)	**–.28** (–.50, –.11)
T-Mobile	TMOB	β_5	**–.12** (–.21, –.02)	–.15 (–.33, .02)	–.13 (–.30, .01)
Verizon	VER		0	0	0
Rollover	ROLL	β_6	**.38** (.26, .49)	**.37** (.20, .55)	**.30** (.16, .44)
Internet	INT	β_7	**.27** (.09, .46)	**.23** (.02, .44)	**.21** (.04, .38)
Intercept		β_0	**–.78** (–1.16, –.39)	**–1.38** (–1.96, –.82)	–.27 (–.25, .86)
Uncertainty	θ	μ_θ	.06 (–.07, .19)	—	—

Notes: Parameters in boldface are significant at the 95% level.

downward bias in the magnitude of the quantity effects. This happens because the latter model forces consumers to exhaust all their free minutes, thus artificially increasing consumption (n_{ij}).

Recall that the parameter θ_i^2 captures consumption uncertainty. We assumed that $\log(\theta_i)$ is distributed across consumers according to a normal distribution with a mean μ_θ and a variance τ_θ^2. We obtain the following estimates for these parameters (monthly consumption is measured in hundreds of minutes): $\hat{\mu}_\theta = .06$, and $\hat{\tau}_\theta^2 = .22$. Using the MCMC draws for log (θ_i), we calculate the individual-specific estimates of θ_i^2 Across consumers, we find a mean monthly uncertainty of $\overline{\theta}^2 = 167$ minutes and a standard deviation of $\text{std}(\theta^2) = 133$ minutes. Using market-level data for a wireless service company, Iyengar, Ansari, and Gupta (2007, p. 25) find an average monthly uncertainty of 181 minutes, which is close to our estimate. The results for heterogeneity (which we do not report here because of space constraints but are available on request) suggest that consumers in this sample appear to be more heterogeneous in the squared quantity and income effects than in the effects of quantity, wireless service provider, and service features.

Table 3 reports the estimation results from the conjoint null models.[13] For the standard conjoint model, all the parameter estimates have the expected sign. Access fee and free minutes are significant at the $p < .05$ level; per-minute rate is significant only at the $p < .10$ level. The lack of significance in the latter case may be due to the ad hoc way the per-minute price enters the utility function. Recall that for our proposed model, the per-minute price has no effect (negative effect) on utility if consumption is lower (higher) than the plan's free minutes. In contrast, for the standard conjoint model, because the per-minute rate is specified as a covariate and always affects the utility function regardless of consumption, there is an aggregation of effects over these two consumption regions, and this may have led to the nonsignificance. Preference for wireless services is greater for plans with more free minutes and lower access fees and per-minute rates. The results also suggest that consumers are indifferent between the brands and that rollover adds significantly to the utility of a wireless service. However, Internet access has a nonsignificant effect. The results from the standard conjoint model do not provide information about consumers' expected consumption of services.

Within the interaction-effects model, only the interaction between access fee and free minutes is significant. The inclusion of this interaction term renders the main effect of access fee nonsignificant and increases the impact of the main effect of free minutes almost sixfold. Usage allowance in this model is still the most important driver of choice, but its importance diminishes with higher access fees. The results of the nonlinear-effects model show that consumer responses to changes in access fees and free minutes are nonlinear. However, at the population level, the nonlinearity in response to changes in per-minute rate is not significant.

Demand Estimation

We compare the predictions of the models for the demand of a wireless plan offered by T-Mobile with the attribute levels for Verizon and Cingular set at the values associated with their most popular wireless plans. At the time of the study, the most popular plan that Cingular offered provided 400 free minutes, charged a $40 access fee and $.40 per minute for excess calling time, and allowed for rollover. Verizon's most popular plan offered identical attribute levels as that of Cingular but did not permit rollover. T-Mobile offered a plan similar to that of Verizon but with 500 free minutes per month. We examine how the demand for T-Mobile is affected by variations, one factor at a time, in the access fee, the per-minute rate, and the num-

[13]We do not report the results for the monthly cost model because of its poor model fit and holdout prediction. The details are available on request.

Table 3

PARAMETER ESTIMATES FOR CONJOINT NULL MODELS: POSTERIOR MEANS AND 95% CONFIDENCE INTERVALS

Variable	*Variable Label*	*Standard Conjoint*	*Interaction Model*	*Nonlinear Model*
Access fee	f_j	**–6.40**	–.40	**–15.50**
		(–7.90, –5.10)	(–2.80, 1.70)	(–19.90, –11.80)
Per-minute rate	p_j	–.59	–1.12	.01
		(–1.24, .09)	(–3.23, .62)	(–.03, .04)
Free minutes	A_j	**16.90**	**92.90**	**8.54**
		(12.90, 21.90)	(72.80, 117.01)	(6.81, 11.11)
Cingular	CING	–.08	**–.34**	**–.33**
		(–.32, .14)	(–.59, –.10)	(–.60, –.09)
T-Mobile	TMOB	.09	–.21	–.14
		(–.13, .35)	(–.46, .03)	(–.38, .09)
Verizon	VER	0	0	0
Rollover	ROLL	**.30**	**.42**	**.42**
		(.11, .49)	(.20, .66)	(.19, .67)
Internet	INT	.16	.24	.27
		(–.06, .38)	(–.03, .52)	(–.01, .57)
Intercept		**2.18**	.77	**–7.55**
		(1.65, 2.72)	(–.43, 1.80)	(–8.51, –6.66)
Access × minutes	$f_j \times A_j$	—	**–135.02**	—
			(–170.01, –109.50)	
Access × rate	$f_j \times p_j$	—	–.50	—
			(–5.40, 3.90)	
Rate × minutes	$p_j \times A_j$	—	15.10	—
			(–6.21, 41.10)	
Log access	$\ln(f_j)$	—	—	**2.90**
				(1.73, 4.27)
Log minute rate	$\ln(p_j)$	—	—	–.40
				(–1.68, .94)
Log free minutes	$\ln(A_j)$	—	—	**–3.67**
				(–4.99, –2.75)

Notes: Parameters in boldface are significant at the 95% level.

ber of free minutes offered to consumers. For example, holding the access fee at \$40 and the per-minute rate at \$.40, we attempt to predict how variations in the number of free minutes affect consumer choice and the sales revenues of T-Mobile. Consumer choice is simply the mean predicted choice probability for a given T-Mobile wireless plan. Similarly, expected sales revenue is the dollar amount that a consumer is expected to pay given his or her consumption level, the access fee, and the per-minute rate of the T-Mobile wireless plan times the choice probability of the plan.

Impact on choice probability. Figure 2 shows how the mean choice probability of a T-Mobile wireless plan varies as a function of per-minute rate, free minutes, and access fee for the proposed model and each of the conjoint null models. For all models, this choice probability decreases with an increasing per-minute rate and access fee. Except for the nonlinear-effects model, this probability increases with increasing free plan minutes.

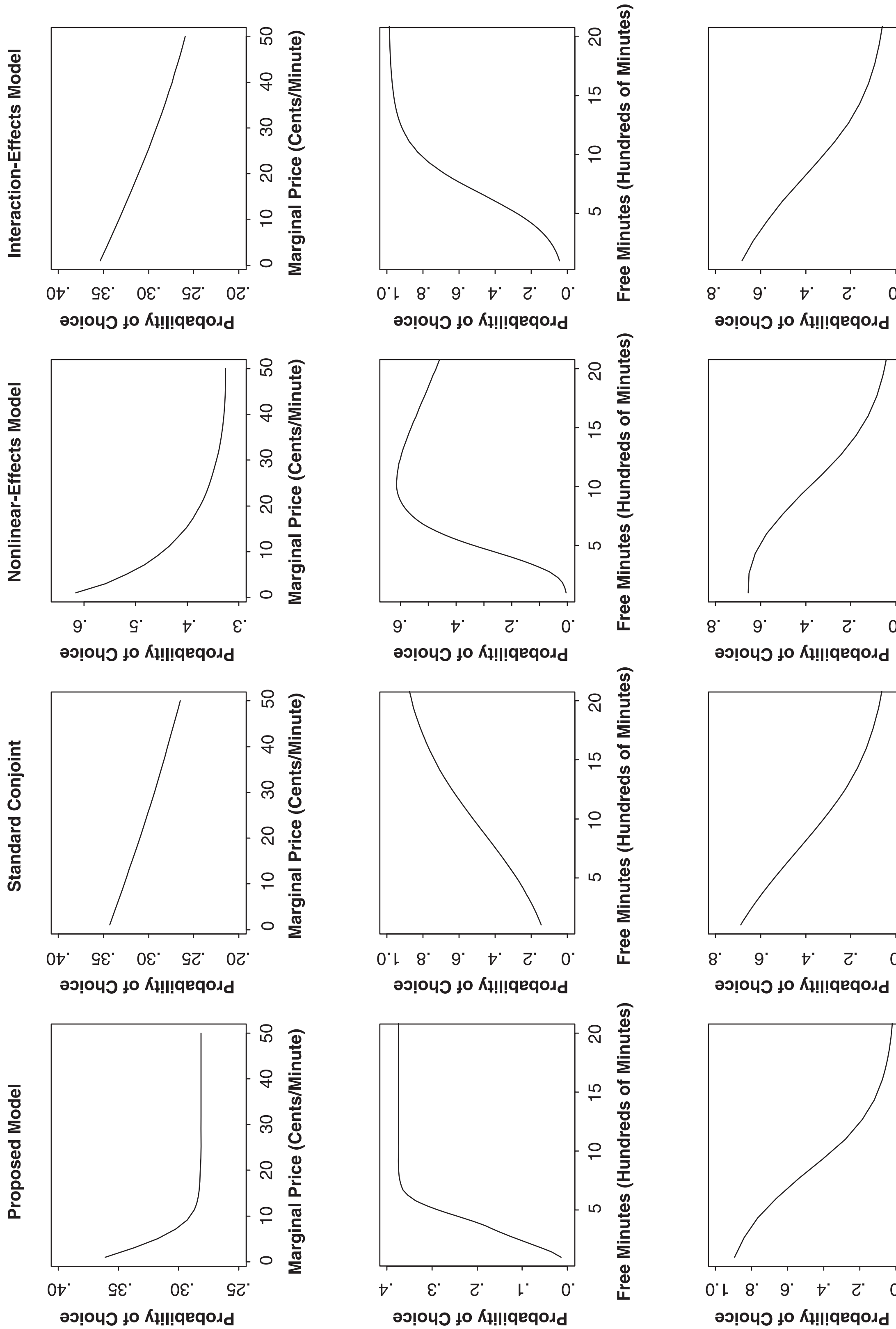
There are differences in the shapes and the magnitudes of the response curves. We first examine the impact of a change in the per-minute rate (marginal price). The proposed model and the nonlinear-effects model suggest a nonlinearity in consumers' responses to changes in the per-minute rate. The other two null models indicate a perfectly decreasing linear trend. In contrast to these latter models, changes in marginal price do not have any effect beyond the \$.25 (\$.30) per minute for the proposed (nonlinear-effects) model. Why is this happening? The answer lies in how each model specifies the effect of per-minute prices.

Recall that the proposed model accounts for the effect of per-minute price through the budget constraints that are used to find consumption. Thus, depending on where consumption lies on the budget set, two possible outcomes can result from a marginal price change. It is possible that consumption for a consumer lies beyond the allowable free minutes (i.e., $n_{ij} > A_j$), in which case a reduced per-minute price would lead to an increase in consumption and utility and, thus, increased choice probability. It is also possible that consumption lies on the flat part of the budget constraint (i.e., $n_{ij} < A_j$), in which case a change in per-minute price could leave the consumption and choice probability of a consumer unaffected. We examined the occurrence of such a scenario in this simulation and found that expected consumption is always less than A_j for all consumers when the per-minute rate exceeds \$.25. The nonlinear-effects model appears to capture some of these aspects, but the interaction-effects model fails to do so. In contrast, situations of this kind do not arise under the standard conjoint model, as the per-minute price enters linearly in the utility function (i.e., as a covariate), and therefore increases in per-minute price always result in decreased choice probability.

Next, we examine the impact of a change in the number of free minutes. Except for the standard conjoint model, all models suggest a nonlinearity in consumers' responses to changes in a plan's free minutes. The proposed (interaction-effects) model shows an S-shaped response curve in which increases in free minutes have no impact if A_j exceeds 900 (1300) minutes per month. Surprisingly, the nonlinear-effects model suggests an ideal-point-type utility function

Figure 2

COMPARISON OF FOUR MODELS ON PREDICTED CHOICE PROBABILITY AS A FUNCTION OF MARGINAL PRICE, FREE MINUTES, AND ACCESS FEE



in which the choice probability increases up to approximately 1000 minutes and then decreases afterward.

These results stem from the different ways the models account for free minutes. They are part of the budget constraint in the proposed model, but they appear only as covariates in the other models. In our model, an increase in the number of free minutes has no effect on the level of consumption and utility for consumers for whom $n_j \leq A_j$. For the other consumers, this change increases the utility, and thus the choice probability, for a plan. However, it is important to note that as A_j increases, the proportion of unaffected consumers gets larger, possibly reaching 100% after a certain threshold (900 minutes in our case). Increasing the number of free minutes beyond this level makes little difference on either the consumption or the choice probabilities of consumers. Here, unlike the results for the effect of marginal price, the interaction-effects model appears to capture some of these aspects, whereas the nonlinear-effects model fails to do so. As we expected, the standard conjoint model does not capture these nonlinear effects as the free minutes enter linearly in the utility function.

Finally, the models also differ in the magnitude of the predicted choice probability (at 1500 monthly free minutes, the predicted choice probabilities are 37%, 56%, 96%, and 74% for the proposed, nonlinear-effects, interaction-effects, and standard conjoint models, respectively). Changes in access fee result in response functions that are (reverse) S shaped for all the models. This similarity in shape is not surprising, because in all models, access fee affects consumer utility, regardless of the level of consumption.[14]

Impact on expected revenues. We obtain the dollar revenue from a particular plan with an accounting formula that adds the access fee of the plan to the revenues from consumption in excess of the free minutes, if applicable. For the proposed model (null models), this excess is the difference between the expected (self-stated) consumption and the plan's allowable free minutes. To obtain the expected revenue, we simply multiply the dollar revenue by the expected choice probability of the plan. Figure 3 shows how the mean expected revenue varies as we vary the per-minute price, the number of free minutes, and the access fee. For the proposed model, there is always a revenue-maximizing value for these variables (while keeping two fixed)—approximately $.06 for the per-minute price, 900 minutes for the free plan minutes, and $30 for the monthly access fee.

The results from the null models are peculiar. They are mainly because intended (self-stated) consumption is treated as exogenous and is not adversely affected by increases in the per-minute rate or by decreases in free minutes. First, expected revenues are always increasing with an increasing per-minute price. For the null models, an increasing per-minute rate has two effects: (1) It reduces the choice probability (see Figure 2), and in contrast to the proposed model, (2) it always increases the dollar revenues from a chosen plan if consumption exceeds the free minutes. The net effect of these two forces resulted in an upward-sloping revenue curve for the null models. Second, in the standard conjoint (nonlinear-effects) model, the impact of free minutes on expected revenues is U shaped (inverted U shaped).

Finally, expected revenues decline with an increasing access fee. This result is due to the trade-off between probability of choice, which decreases with an increasing access fee, and revenue, which increases with an increasing access fee. The net result of this trade-off appears to be a decrease in expected revenue.

Summary. The empirical analysis highlights two important benefits of the proposed model. First, it parsimoniously captures the nonlinear effects of the various components of a multipart pricing scheme in a theoretically meaningful way. Although the nonlinear-effects model captures the nonlinearity in the effect of marginal price and the interaction-effects model captures the nonlinearity in free minutes, neither model captures both effects simultaneously. Second, our model infers consumer expected consumption while allowing for usage uncertainty. None of the null models are capable of such inference. Most important, these benefits are achieved with no loss in model fit and predictive validity.[15]

Optimal Service Plan

For the purpose of illustration, suppose that T-Mobile were a new entrant in a market in which Cingular and Verizon already offered cell phone services. What plan should T-Mobile offer its customers, and how should it price the plan? Should it include Internet access and/or rollover minutes as part of its basic plan? If it offers these services as add-ons, what prices should it charge for each? To examine these questions, we consider the data from our respondents who did not have T-Mobile as their current service. This subset of consumers constitutes 89% of our sample. We set T-Mobile's monthly variable cost for offering services to its customers at $30 (T-Mobile USA 2005). We then perform a grid search to identify the optimal service plan for T-Mobile.

We evaluate all possible combinations of the design factors at discrete points: (1) access fee in increments of $3, ranging from $25 to $90 per month; (2) per-minute rate in increments of $.02, ranging from $.01 to $.50 per minute; (3) free minutes in increments of 85 minutes, ranging from 100 to 2250 minutes; (4) Internet access (present or absent); and (5) rollover minutes (present or absent). Thus, there are $20 \times 20 \times 25 \times 2 \times 2 = 40,000$ grid points. We then identify the plan with the highest total expected contribution margin for T-Mobile. We do so by using each person's current service plan as his or her status quo option. For the proposed model, we use the estimated utility functions to compute the choice probabilities and usage quantity for each person and target plan. Similarly, for the conjoint null models, we use each person's respective estimated utility function to infer the choice probability for T-Mobile versus the status quo and then use the self-stated usage rates to compute the expected margin for each consumer. We average the

[14]Note that respondents exhibit a greater degree of price (access fee and per-minute rate) sensitivity in hypothetical conjoints tasks than they do in real life (Verlegh, Schifferstein, and Wittink 2002).

[15]The figures for the expected quantity for the four models are available on request.

Figure 3
COMPARISON OF FOUR MODELS ON EXPECTED REVENUE AS A FUNCTION OF MARGINAL PRICE, FREE MINUTES, AND ACCESS FEE

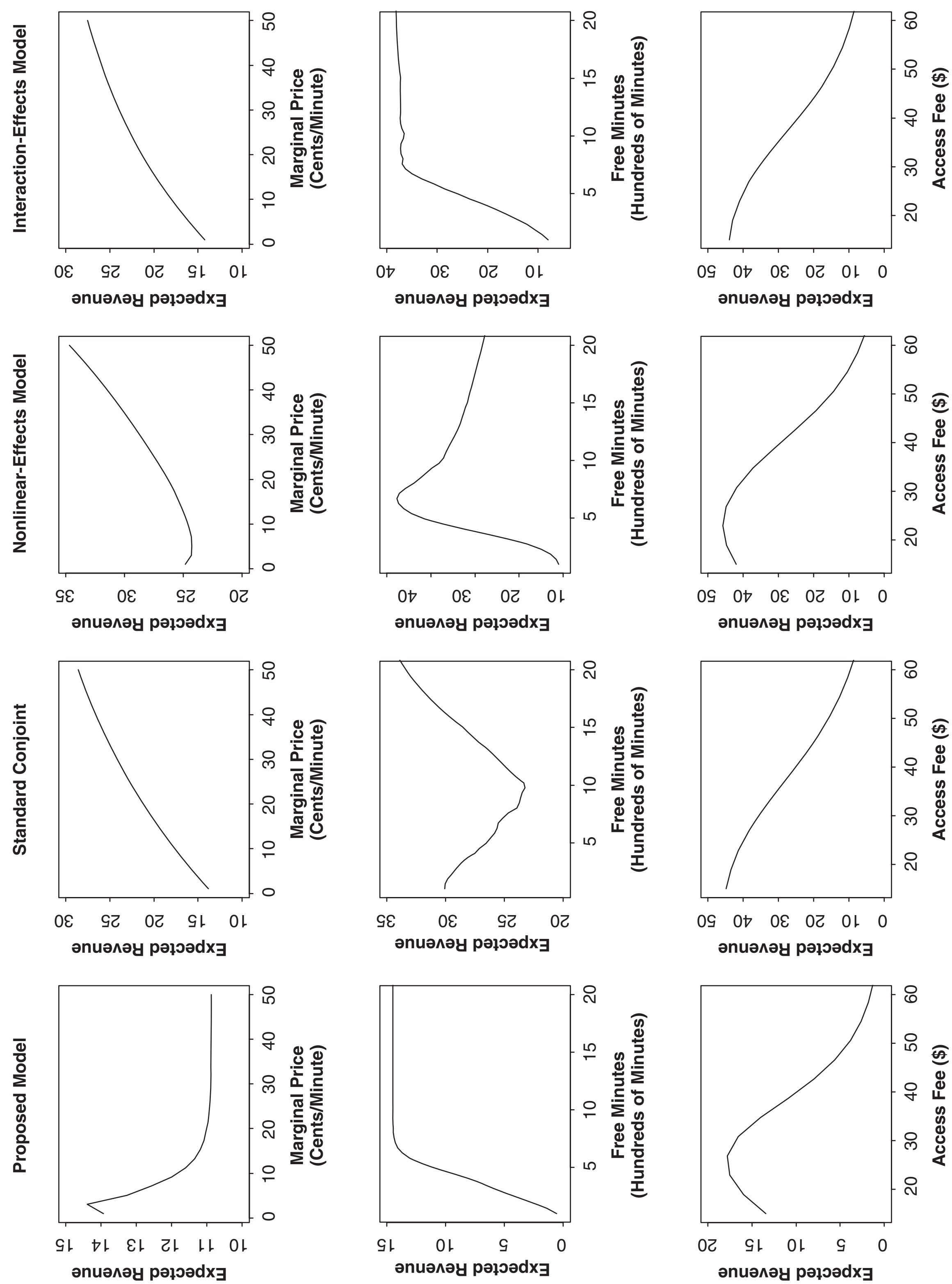


Table 4

OPTIMAL T-MOBILE PLANS OBTAINED USING THE PROPOSED MODEL AND THE CONJOINT NULL MODELS

	Proposed Model	*Standard Conjoint*	*Interaction Effects*	*Nonlinear Effects*
Access fee	$59	$25	$90	$25
Per-minute rate	$.04	$.50	$.50	$.50
Free minutes	369	100	100	369
Rollover	Yes	Yes	Yes	Yes
Internet	Yes	Yes	Yes	Yes
Choice probability	.38	.62	.17	.65
Expected profit per customer	$13.40	$128	$48	$57

expected profit across consumers. Table 4 describes the service plans with the highest expected contribution for T-Mobile, one obtained using the proposed method and the others obtained using the conjoint null models.

All plans identify Internet access and rollover minutes as features of an optimal plan. However, they differ substantially on the other three features—access fee, per-minute rate, and free minutes.

In 2005, T-Mobile reported an average profit of $27 per customer per month (T-Mobile USA 2005). This is closer to the $13.40 expected profit per customer per month for the optimal plan obtained using the proposed method than it is to the $128, $48, and $57 per customer per month obtained using the standard conjoint, interaction-effects, and nonlinear-effects models, respectively. These latter numbers appear to be relatively high because they ignore the effect of the per-minute rate and the free minutes on the usage rate. Therefore, the latter models select a substantially higher per-minute rate. If we use the proposed model to assess the profitability of the optimal plans identified by the conjoint null models, we find that it should make an expected profit of –$.58, $.55, and –$3.12 per customer per month for the standard conjoint, interaction-effects, and nonlinear-effects models, respectively. We also find that the latter null models, respectively, project a profit of $8.81, $6.71, and $7.38 per customer per month for the optimal plan identified by the proposed model. This suggests that the optimal plans identified by the null models will fare poorly if we include the effect of per-minute rate on consumption and choice.

Next, we examine the sensitivity of the optimal solution identified by the proposed method to changes in the price per minute. The reason for doing this is that the $.04 per-minute rate identified by the optimal solution appears far from the $.40 per minute that is typical in the cell phone industry. A possible reason for this deviation is that the profit function might be flat over a range of the per-minute rate charged to consumers. To examine this issue, we vary the per-minute rate in $.10 increments, from $.10 per minute to $.50 per minute. We also perform an analysis using a $.01 per-minute rate. We then use the grid search described previously to identify the profit-maximizing plan, given a fixed, per-minute rate.

The results suggest that the average profit per customer is relatively flat over the range of the variable rate. When the per-minute rate is $.01 ($.50) per minute, we obtain an expected profit per customer per month of $13.25 ($13.00). In addition, at a rate of $.40 per minute, this expected profit is less than the optimal value of $13.40 by only $.40. The effect on profits of this per-minute-rate increase is compensated by the offer of 806 (= 1175 – 369) extra free minutes. The corresponding optimal T-Mobile plan has its highest profit when the access fee is $66, which is $7 higher than the fixed fee for the proposed optimal plan in Table 4. A comparison of the optimal plans obtained using the proposed model and the conjoint null models, with the per-minute rate constrained to $.40 per minute, appears in Table 5. These plans, similar to those shown in Table 4, are quite different.

Feature Pricing

A common practice in the cell phone industry is to unbundle features and offer one or more of these as add-on features to a base plan. In the current example, a single plan featuring both Internet access and rollover minutes allows customers no choice of add-on features. It might sometimes be beneficial for customers, and possibly the firm, to have a base plan that excludes one or both of these features and offers them—separately, together, or both—as add-ons for additional fees. The optimization problem for T-Mobile in

Table 5

OPTIMAL T-MOBILE PLANS OBTAINED USING THE PROPOSED MODEL AND THE CONJOINT NULL MODELS WHEN THE PER-MINUTE RATE IS $.40

	Proposed Model	*Standard Conjoint*	*Interaction Effects*	*Nonlinear Effects*
Access fee	$66	$25	$90	$25
Free minutes	1175	100	100	369
Rollover	Yes	Yes	Yes	Yes
Internet	Yes	Yes	Yes	Yes
Choice probability	.36	.61	.18	.65
Expected profit per customer	$13.00	$104	$44	$46

this example requires the consideration of mixed bundling and the additional pricing of optional features for users who can buy those features they find most useful. Next, we describe the method for determining the base plan and the prices of Internet access and rollover minutes as optional features.

For each consumer in our sample, we introduce four T-Mobile plans in his or her consideration set. Each consumer then has five plans in his or her choice set—a status quo option and the four T-Mobile plans. In the following discussion, we refer to a plan with no rollover and no Internet connection as a "basic" plan. The other three plans include the rollover feature, the Internet, or both. We constrain the free minutes to be the same for all the four T-Mobile plans and set the per-minute rate at \$.40 per minute. We calculate the access fees for the four plans and their common free minutes to maximize the sum of the expected profits across the four T-Mobile plans. Table 6 describes these plans.

These results suggest that T-Mobile should include Internet access in its base plan. It should charge a monthly fee of just over \$62 and give 1250 free minutes. It should offer rollover minutes as an optional feature and price it at \$66.79 – \$62.14 = \$4.65. The results in Table 6 show that the probability of choice for T-Mobile across the four plans is .41 (= .01 + .03 + .14 + .23), and the overall expected profits per customer is just over \$14.37 per month (= \$.31 + \$.90 + \$4.54 + \$8.62). Both values are higher than the corresponding values from a single optimal plan with a \$.40 per-minute rate (see Table 6). For example, the expected profit of \$14.37 is \$1.37 higher than the \$13.00 expected profit per customer from the single plan.

Simulated Testing

We performed a small-scale simulation experiment to assess how well the estimation procedure recovers the true simulated parameters. For generating choice data, we used the same conjoint design as we used in our empirical application. For simplicity, however, we ignored brand name, Internet access, and rollover and kept only access fee, free minutes, and marginal price as plan features. We set $\beta = (\overline{\beta}_1, \overline{\beta}_2, \overline{\beta}_3)' = (2.5, -2.5, 1.5)'$, $\Omega = \text{diag}(.2, .2, .2)$, $\mu_\theta = 0$, $\tau^2_\theta = .2$, and $\Sigma = \text{diag}(1.0, .5, .5, .5)$ to generate the choice data. Note that the variance of the utility of the no-choice option is fixed to 1.0.

We used the same priors that we presented in the "Model Estimation" subsection. We used 20 Monte Carlo replications to study the variations of parameter estimates across the generated samples. For each of the 20 data sets, we estimated the model parameters on the basis of 100,000 draws retained after discarding 50,000 draws as burn-in iterations. We checked convergence by visual inspection of the trace plots of the various parameters. For each of the 20 replications, convergence was achieved before the burn-in period.

Table 7 reports the true parameters and their respective average estimates across the 20 Monte Carlo samples. The table also includes 95% coverage for each parameter. This coverage is the proportion of the Monte Carlo samples in which the 95% posterior interval spanning the 2.5th to the 97.5th percentile of the MCMC draws covers the true parameter. Table 7 shows an excellent recovery of the true population-level parameters. The average mean square error is .01, which is low. In addition, the coverage properties are excellent. On average, 98% of the posterior intervals contain the true parameter. Finally, the recovery of the individual-level parameters (not reported in Table 7) is excellent. (The average mean square error is .02.) In summary, the results of this simulation suggest that our estimation procedure performs well in recovering the true parameters.

Table 6

FEATURE PRICING FOR THE PROPOSED PLANS

Plans	*Access Fee*	*Probability of Choice*	*Mean Expected Profit*
Basic	\$62.14	.01	\$ .31
Basic + Internet	\$62.14	.03	\$ .95
Basic + rollover	\$66.79	.14	\$4.54
Basic + rollover + Internet	\$66.79	.23	\$8.62

Notes: Per-minute rate is set at \$.40 per minute. Optimal free minutes are 1250 minutes.

Table 7

PARAMETER RECOVERY FOR SIMULATED DATA USING THE PROPOSED MODEL

Variable	*Parameter Label*	*True Value*	*Average Estimate*	*95% Coverage*
Quantity	β_1	2.50	2.59	.95
Quantity^2	β_2	–2.50	–2.49	1.00
Income effect	β_3	1.50	1.35	.95
Heterogeneity (quantity)	ω_{11}	.20	.15	.95
Heterogeneity (quantity^2)	ω_{22}	.20	.19	1.00
Heterogeneity (income)	ω_{33}	.20	.18	1.00
Utility variance	σ_{11}	.50	.56	.95
Utility variance	σ_{22}	.50	.58	1.00
Utility variance	σ_{33}	.50	.56	1.00
Uncertainty (mean)	μ_θ	.00	.03	1.00
Uncertainty (variance)	$\tau^2{}_\theta$	.20	.23	1.00

CONCLUSIONS

Multipart pricing is used by providers of services such as wireless telephony, xerography, car rentals, HMO plans, and prescription drug plans. These pricing schemes require consumers to pay a per-unit fee for usage beyond some "free" (possibly zero) number of units. We propose a method that uses conjoint analysis to assess the impact of such pricing schemes on consumer choice and usage. An important aspect of our model is that it accounts for the two-way dependence between consumption and price. That is, it accounts for the notion that the price charged by the provider influences consumption, while the price a consumer pays depends on his or her usage level. We incorporate this simultaneity by proposing a model in which consumers allocate budgets while accounting for the structure of nonlinear pricing schemes. The model allows for inference of consumption and usage uncertainty. It is estimated using choice data.

We describe an application that compares the proposed model and two of its special cases with four null models. We find that the proposed model has a better fit and predictive validity and that it produces reliable, individual-level consumption estimates. A standard conjoint model that uses service attributes to predict choices does especially poorly, indicating that it might not be appropriate for modeling nonlinear pricing schemes. Extensions of the standard conjoint model that include nonlinear and interactions effects improve model fit and predictive validity. However, these models are not parsimonious, and they do not permit estimation of usage quantity. In addition, they do not fully capture the nonlinear effects induced by multipart pricing schemes.

A comparison of the two special cases of our model suggests that consumption satiation is more important than consumption uncertainty when modeling nonlinear pricing effects. Ignoring consumption uncertainty results in an underestimate of the quantity a consumer uses.

We use the proposed and conjoint null models to assess the impact of plan features on demand for a wireless service provider. In contrast to the null models, the demand curves produced by the proposed model properly capture the impact of changes in per-minute rate, free minutes, and access fee and always identify finite values for which these features maximize revenue. We use the parameter estimates to characterize an optimal wireless plan that maximizes profit for a service provider. The optimal plan obtained using the proposed model is more consistent with industry practice than the optimal plans identified using the null models. We illustrate how the proposed model can be used to price optional features such as rollover and Internet access.

A useful area for further research would be to examine computationally efficient methods for optimal selection of product features and prices. The current approach of explicit enumeration is reasonable if there are a small number of attributes, as in our application. For larger problems, more efficient procedures are necessary. A related area of research is the development of methods for optimal design of product lines and feature bundles. Models that consider the effect of competitive actions and reactions (e.g., Choi and DeSarbo 1994; Choi, DeSarbo, and Harker 1990) on multipart pricing would also be useful to examine.

Finally, a potential area of related research is the use of preference functions other than those used herein. There has been substantial recent interest in the mathematical representation of noncompensatory preference models and choice processes (e.g., Kohli and Jedidi 2007; Yee et al. 2007). It is likely that consumers use some form of noncompensatory processes for screening and evaluating service plans, especially those that have many features and part prices.

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