Optimal Pricing for a Menu of Service Plans – An Application to the Digital Music Industry

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Abstract

Services vary widely in whether they offer their customers only subscription-based plans, *à* la carte plans or a mix of both. A priori, it is not obvious which type of plans a retailer should offer and what their optimal prices would be. What makes this analysis complex is that such decisions have to incorporate consumers' expectation of usage, which may itself be influenced by the offered pricing schemes. To determine optimal prices for a menu of plans then, it is necessary to accommodate the two way dependence between the offered pricing schemes and consumers' expected usage.

This paper addresses such issues for optimal pricing for a menu of plans. We propose an economics-based utility model and analyze how consumers choose among subscription-based and *à* la carte plans. The model is applied in the context of the digital music industry and is estimated using data from a choice-based conjoint experiment. We find that consumers' utility from the service is lower if they are charged under a subscription-based pricing scheme than under an *à* la carte plan. Our model also allows us to infer consumers' underlying expected usage from their choices of service plans. We use the inferred demand to identify the type of plans a retailer should offer and their optimal prices. An additional benefit of the model is to determine the optimal price that record labels ("manufacturers") should charge retailers. Our results show that record labels may be overcharging the music retailers to the detriment of overall channel profits.

Keywords: optimal menu; conjoint analysis; service plans.

1 Introduction

Services have long recognized the need to offer several types of pricing plans to attract customers with differing willingness-to-pay. The variety of plans include, but are not limited to, a two-part tariff where consumers pay a monthly fee for access to a service along with a per use price, a pay-per-use plan where users pay only for what they consume, and complex multi-part tariffs under which users are charged at differing per-unit rates based on whether their consumption is below or above a threshold (see, e.g., Lambrecht and Skiera 2006; Lambrecht, Seim and Skiera 2007; Narayanan, Chintagunta and Miravete 2007; Reiss and White 2005). More generally, these pricing schemes can be categorized as either subscription-based or *à* la carte and services vary widely in whether they offer their customers only one type of pricing scheme or a mix of both.

A typical subscription-based pricing plan is the two-part tariff. Much past research has explored the optimality of two-part tariffs and its effect on customer retention and usage (Danaher 2002; Oi 1971; Schmalensee 1981). Increasingly, however, many services are adopting a subscription-based pricing structure that has a monthly fee but imposes a maximum consumption on consumers. These pricing plans, termed as quota pricing or bucket pricing, are popular for such entertainment products as digital music, DVD rentals and others where there may be capacity constraints (Sun, Sun and Li 2006). For instance, eMusic, a digital music retailer, offers three BP subscription plans - $11.99 per-month for 24 downloads, $15.89 per-month for 35 downloads and $20.79 per-month for 50 downloads. Similarly, Netflix and Blockbuster offers plans where there is a limit to the number of DVDs that a customer may keep at a time. From customers' perspective, a choice among such plans involves a careful consideration of both the imposed upper limit on usage and how much they expect to use the service as there is no possibility of over-consumption. From a retailer's viewpoint, once a customer chooses a bucket pricing plan, the revenue from the customer is the monthly fee.[1]

[1]Bucket pricing plans are distinct from two-part tariffs as, unlike the latter, there is an upper limit on consumption. In addition, in a two-part tariff, the overall revenue from a customer depends

A common *à* la carte pricing scheme is the pay-per-use plan, where customers are charged on a per-unit basis and there is no monthly fee or an upper limit on consumption. For instance, iTunes offers songs on a per-song basis. Recently, Tata Docomo, a wireless service company in India, began charging its customers on a pay-per-second basis. Some health clubs also charge customers on a per-visit basis (Della Vigna and Malmendier 2006). With such type of pricing, customers may choose based on the applicable per-unit rate and how much they expect to use the service (Lemon, White and Winer 2002; Nunes 2000). From a retailer's perspective, it is important to understand customers' expectations of usage as they directly impact its revenue. An additional issue is that consumers' usage is most likely influenced by the imposed per-unit price (Iyengar, Ansari and Gupta 2007). Thus, the per-unit rate of a service affects both whether a consumer will use the service and how much.

As these examples indicate, services differ in the types of plans they offer. A priori, it is not obvious which type of plans (just subscription, only *à* la carte or a mix of both) a retailer should offer and what their optimal prices would be. Such decisions have to incorporate how consumers choose among the different types of plans. What makes this analysis complex is that underlying these consumer decisions are their usage expectations, which are influenced by the offered pricing schemes. Put differently, consumers' usage expectations influence what plan they choose and the pricing schemes of offered plans, in turn, affects their expected usage. Thus, for determining optimal prices for a menu of plans, it is necessary to accommodate this two way dependence between the offered pricing schemes and consumers' expected usage.

This paper addresses such issues for optimal pricing for a menu of plans. We investigate how consumers choose among multiple plans, which are either subscription-based or have an *à* la carte pricing scheme. We then study which mix of plans is optimal for a retailer to offer and what their prices should be. To achieve these objectives, we propose an economics-based utility model and apply it in the context

on the access fee, the usage rate and how much the consumer uses the service.

of the digital music industry. With the rapid decline in its overall revenues, the music industry provides an interesting setting to understand the interplay between consumers' demand and pricing decisions of retailers. Given their popularity for entertainment products, and in particular for our application to digital music, we use a bucket pricing scheme and a pay-per-song plan as representative of a subscription-based and *à* la carte pricing, respectively. Our model is estimated using choice-based conjoint data. We infer consumers' underlying consumption rate from their choices of service plans and then use the inferred demand curve to identify optimal prices for a menu of plans. An additional benefit of the model is that it allows us to estimate the optimal price that record labels ("manufacturers") should charge the retailers.

Past research using conjoint analysis has developed a variety of pricing models. Mahajan, Green and Goldberg (1982) described a method for estimating own- and cross-elasticities. Kohli and Mahajan (1991) introduced an approach for optimal pricing. Jedidi, Jagpal and Manchanda (2003) described a method for estimating consumer reservation prices for product bundles. One assumption common across these studies is that consumer usage rates do not depend on price. This assumption is approximately, if not perfectly, satisfied for some products, for example such durable goods as washing machines and refrigerators. However, for earlier described services, how much consumers use the service is likely to vary with its per-unit rate. Thus, pricing models developed in past research cannot be directly applied. Other research has used either secondary data or natural experiments to capture how consumers choose among pricing plans (Lambrecht et. al 2007; Narayanan et. al 2007). While such data are more realistic, they suffer from limited variability in prices, which makes it difficult to determine optimal prices. Such a limitation can be addressed by using field experiments in which prices are systematically changed. However, these are hard to carry out and are rare (for an exception see Danaher 2002). Our work is closest to that of Iyengar, Jedidi and Kohli (2008), who show how multi-part prices, typically used by wireless services, can be included within a conjoint setting. Our modeling framework differs from theirs in two important ways. First, substantively, they only consider a situation in which customers are choosing among all subscription-based plans. Our key interest is how consumers choose among subscription-based and à la carte pricing and its effect on a retailer's menu of offered plans. This difference in the focus of research affects our data collection, the model specification and the managerial implications that emerge from its application. Second, methodologically, in contrast to their quadratic utility specification, we use a more parsimonious logarithmic utility function to capture diminishing returns from the service. The latter type of utility function is more consistent with our application and we show that our model performs better.

Our results show that consumers' utility from the service is lower if they are charged under a bucket pricing scheme vis à vis a pay-per-song scheme. This finding has implications for what plans a service provider should offer. Assuming that a retailer faces a linear per-song cost, we show that if it offers a single plan, it should be a pay-per-song scheme. With an offering of multiple (two) plans, we find that both the type of offered plans and their prices depend on a retailer's cost structure. Interestingly, when a retailer faces a low per-song cost, it is optimal for it to offer two bucket pricing plans. Intuitively, this is similar to a strategy that many other services such as restaurants adopt to attract customers when, due to a low per-unit cost, they offer buffet ("all-you-can-eat") pricing. With an increase in per-song cost, it becomes optimal for the retailer to offer a menu of both types of plans, i.e., a combination of a bucket pricing plan and a pay-per-song plan. Finally, we estimate the optimal price that record labels should charge retailers and find that they currently may be overcharging.

The remainder of the paper is organized as follows. Section 2 describes the proposed model. Section 3 reports the application of the model to the digital music industry and we compare our proposed model against an alternative economics-based utility model. Section 4 examines the implications of our model for the optimal menu of service plans. In Section 5, we consider the optimal pricing from the viewpoint of record label companies. Section 6 concludes the paper.

2 Model

We propose a model in which a consumer is considering a service provider that offers a menu of service plans - some of these plans have a bucket pricing (BP) scheme while others have a pay-per-use (PPU) scheme. For ease of exposition, we use the context of the digital music industry to illustrate various facets of the model.

Let $\mathcal{P} = \{\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, \ldots, \mathcal{P}_J\}$ denote a set of J service plans. Let $\boldsymbol{x}_j = (x_{j1}, \ldots, x_{jm})'$ denote a vector of m *non-price* attributes (e.g., service features) associated with service plan $\mathcal{P}_j \in \mathcal{P}$. For music plans, these attributes may be the audio quality of the offered music (e.g., CD quality) or the genre of offered music (e.g., Popular Top 40 music). Let

$$R_{ij} = \gamma_{ij0} + \sum_{k=1}^{m} \gamma_{ik} x_{jk}, \tag{1}$$

denote the attribute-based utility consumer i associates with service plan $\mathcal{P}_j$, $1 \leq i \leq I,\ 1 \leq j \leq J$. Note that equation (1) does not include any price related attribute - we will specify such attributes later using economic budget constraints. The γ_{ij0} term is a constant specific to service plan $\mathcal{P}_j$. It represents the value of a service plan that is not explained by the vector x_j of features. The γ_{ik} are regression (part-worth) coefficients that capture the effect of the non-price attributes on utility.

We use an indicator variable to denote whether a plan has a BP or a PPU scheme: d_j is 1 if $\mathcal{P}_j$ has a BP scheme, else d_j is 0. For example, suppose a music retailer offers two plans – Plan 1 with \$10 access fee and an allowable monthly number of 20 downloads and Plan 2, which charges consumers on \$0.95 on a per-song basis. In this case, for Plan 1, the indicator variable takes a value of 1 while for Plan 2, the indicator variable is 0. If plan $\mathcal{P}_j$ has a bucket pricing scheme then, let f_j denote the monthly fee and A_j be the upper limit on consumption. If, however, $\mathcal{P}_j$ is a PPU plan then, we use p_j to represent the per unit rate.

Let $\mathcal{P}_0^i$ denote an individual-specific composite (outside) good with unit price p_i^w. Suppose consumer i has a budget w_i. A consumer can either spend the entire budget on the composite good alone, or spend some of it on the composite good and the rest to buy a service plan.

Suppose consumer i cannot choose more than one service plan. Let $n_{ij}(\geq 0)$ denote the units of service that consumer i will use if she selects plan $\mathcal{P}_j$. In the context of a digital music, n_{ij} represents the number of songs that consumer i downloads while using music plan j. Let z_{ij} denote the number of units of the composite good and $u_i(n_{ij}, z_{ij})$ denote the utility the consumer obtains from consuming the service units and the composite good. We assume that consumer i maximizes her utility function subject to the budget constraint

$$p_i^w z_{ij} + (d_j f_j + (1 - d_j)\ p_j n_{ij}) \leq w_i. \tag{2}$$

Note that when plan $\mathcal{P}_j$ has a bucket pricing scheme (i.e., d_j=1), the relevant price-related attribute in the budget constraint is the access fee (f_j). And, when plan $\mathcal{P}_j$ has a PPU scheme (d_j=0), the relevant price attribute is the per-unit rate of service (p_j).

A utility maximizing consumer will exhaust the budget. Without loss of generality, we normalize the unit price of the composite good to $p_i^w = 1$. Then the utility for consumer i who selects plan $\mathcal{P}_j$, consumes n_{ij} units of the service and $z_{ij} = w_i - (d_j f_j + (1 - d_j)p_j n_{ij})$ units of the composite good can be written as

$$u_i(n_{ij}, w_i - (d_j f_j + (1 - d_j)p_j n_{ij})). \tag{3}$$

Setting $n_{ij} = 0$ and $f_j = 0$ in equation (3) gives the utility $u_i(0, w_i)$, for a consumer who does not adopt any of the J plans.

We assume the following form of utility function:

$$\begin{aligned} u_i\Big(n_{ij}, w_i - (d_j f_j + (1 - d_j)p_j n_{ij})\Big) = \qquad & R_{ij} + \beta_{i1}\log(n_{ij} + 1) + \\ & \beta_{i2}\Big(w_i - (d_j f_j + (1 - d_j)p_j n_{ij})\Big). \end{aligned} \tag{4}$$

Our proposed utility has good properties. It increases monotonically with the attribute-based utility R_{ij} of plan $\mathcal{P}_j$ and the logarithmic specification for n_{ij}, the number of units of the service, parsimoniously captures the diminishing marginal returns from consumption of the service. We require $\beta_{i1} > 0$ and $\beta_{i2} > 0$ to represent such preferences of consumers.[2] The utility function reduces to $u_i(0, w_i) = \beta_{i2} w_i$ when the consumer makes no choice from $\mathcal{P}$. Later, we compare our model with an alternative quadratic utility model that also allows for satiation (Lambrecht et. al 2007, Iyengar et. al 2008).

Note that the utility for a consumer from the service is dependent on how much she consumes the service (see Equation (4)). As the consumers are assumed to be utility maximizers, they will consume a quantity that maximizes their utility. Thus, the consumer- and plan-specific optimal consumption, n^*_{ij}, is obtained by maximizing the utility of using the service subject to the budget constraint. Specifically,

$$n^*_{ij} = \begin{cases} A_j & \text{if } \; d_j = 1, \\ \frac{\beta_{i1}}{\beta_{i2} p_j} - 1 & \text{if } \; d_j = 0. \end{cases} \tag{5}$$

Note that when a plan has a BP scheme then, the optimal consumption for a consumer is the maximum allowed consumption under the plan, A_j. However, when the plan has PPU scheme, the optimal consumption is determined by considering the marginal utility from an additional unit of service together with the marginal price.

Substituting the optimal consumption n^*_{ij} from equation (5) for n_{ij} in equation (4) completes the specification of the utility function. In a discrete choice model, consumer i will choose service plan $\mathcal{P}_j \in \mathcal{P}$ if and only if she obtains greater utility from having the service plan than from not having it, and if that plan has the maximum utility in the choice set $\mathcal{P}$.

A key benefit of the proposed model is its ability to infer consumption quantities at different prices from choice data for a PPU plan. This is vital for optimal pricing. For determining revenues from a service plan, we need to ascertain two quantities of interest: (1) the probability that a consumer will opt into the plan and (2) the consumption under the plan. In our model, for a plan with bucket pricing scheme, the optimal consumption under the plan is the maximum allowed consumption (which

[2]These restrictions arise from Slutsky negativity constraints, which ensure quasiconcavity of the utility function (Hurwicz and Ozawa 1971).

is observed). For a PPU plan, however, consumption is latent and the per-unit price influences this consumption. Thus, it is necessary to incorporate the link between price and consumption. Self-stated consumption data from consumers can be used in this regard. This method, however, treats consumption as independent of prices and, as past research has shown, can lead to meaningless results (Iyengar et. al 2008).[3]

2.1 Model estimation

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 or observation. If consumer i contributes T_i such observations, then the total number of observations in the data is given by $T = \sum_{i=1}^{I} T_i$. Let $y_{ijt} = 1$ if the choice of plan $\mathcal{P}_j$ is recorded for observation 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. Let n^*_{ijt} denote the optimal consumption (see equation (5)) for service plan $\mathcal{P}_j$ in observation t. Then the random utility of plan $\mathcal{P}_j$ on the t^{th} choice occasion is given by:

$$U_{it}(n^*_{ijt}, z_{ijt}) = u_{it}(n^*_{ijt}, z_{ijt}) \; + \; \epsilon_{ijt}, \tag{6}$$

where $u_{it}(n^*_{ijt}, z_{ijt})$ is the systematic utility component of service plan $\mathcal{P}_j$ as specified by equations (4) and (5). The utility of no-choice alternative is $U_{it}(0, w_i) = u_{it}(0, w_i) + \epsilon_{i0t}$. Across the J+1 alternatives, we assume that $\boldsymbol{\epsilon}_{it} = (\epsilon_{0it}, \epsilon_{1it}, \ldots, \epsilon_{Jit})'$ is normally distributed with null mean vector and covariance matrix $\boldsymbol{\Sigma}$.

Following the random utility framework, consumer i will choose service plan $\mathcal{P}_j$ if and only if she obtains greater utility from having the service plan than from not having it, and if that plan has the maximum utility across the J plans. Let $\boldsymbol{\beta}_i = (\gamma_{i10}, \; \ldots, \gamma_{iJ0}, \gamma_{i1}, \ldots, \gamma_{im}, \; \beta_{i1}, \beta_{i2})'$ be the vector of consumer i's utility parameters. To capture consumer heterogeneity, we assume that the individual-level parameters $\boldsymbol{\beta}_i$ are distributed bivariate normal with mean vector $\bar{\boldsymbol{\beta}}$ and covariance

[3] This result is similar to that noted by Jedidi and Zhang (2002) who find low correlations (0.28-0.43) between consumers' self stated willingness-to-pay at different price levels and the model inferred willingness-to-pay.

matrix $\mathbf{\Lambda}$.

We adopt a Bayesian framework for inference about the parameters. Our model estimation approach follows the standard Bayesian estimation of the multinomial probit model except for two differences. First, as optimal consumption n^*_{ijt} is latent for the PPU plan, we have to calculate its value using equation (5) in every iteration of the MCMC sampler and include it in the systematic component of the utility function. Second, to ensure the quasi-concavity of the utility function, we have to enforce the two Slutsky restrictions on the individual-level parameters: $\beta_{i1} > 0$ and $\beta_{i2} > 0$. We enforce these restrictions by reparametrizing $\beta_{i1} = \exp(\tau_{i1})$ and $\beta_{i2} = \exp(\tau_{i2})$ where τ_{i1} and τ_{i2} are unconstrained individual-level parameters. With these two restrictions, the normality assumption holds for parameters τ_{i1} and τ_{i2} but no longer holds for β_{i1} and β_{i2}. 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). We use proper but noninformative priors. Finally, we assume that the utilities of the plans are independent given $\boldsymbol{\beta}_i$ i.e., $\mathbf{\Sigma}$ is a block diagonal matrix. The details of the Bayesian estimation procedure are available from the authors upon request.

3 Application to digital music industry

The music industry provides an interesting setting to understand the interplay between consumers' demand and pricing decisions of both retailers and record labels. The industry is witnessing an upheaval with a decline in overall revenues. In 2006, the overall revenue from music sales (including the sales of compact discs (CD) and digital music) was \$ 11.75 Billion. In 2007, the revenues decreased to \$10.37 Billion and by 2008, they were even lower at \$8.48 Billion (RIAA 2009). An important reason for this decrease in revenues is that the sales of CDs have declined and consumers are flocking to online digital retailers to satisfy their need for music.[4] Given

[4] The revenues from CD sales declined from \$7.5 Billion in 2007 to \$5.5 Billion in 2008. At the same time, the revenue from the digital channel has increased from \$0.8 Billion in 2007 to around \$1.02 Billion in 2008 (RIAA 2009).

the increasing importance of digital music, both music retailers and record labels such as Universal Music Group and Sony BMG have to determine how their pricing decisions affect consumers' demand.

We illustrate our proposed model using data from a conjoint study of digital music plans that we collected in collaboration with a music service provider. As noted earlier, our use of conjoint data is motivated by the limited price variability in field data, which makes it difficult to characterize consumers' price sensitivity. The conjoint survey was sent to some of the customers of the service provider and other consumers who had professed interest in its service. All together, we have over 600 respondents. We use a random sample of 300 respondents and their data from this study to estimate our proposed model.

To design our conjoint experiment, we conducted a pilot study using another random sample of over 350 consumers, each of whom was a subscriber to a digital music plan. We determined the attributes to include in our conjoint design by asking these respondents to state the three most important attributes when choosing a digital music service. Access fee, the maximum allowable number of monthly downloads, per-song price and features such as audio quality and type of available music were the most frequently mentioned attributes. The brand of the retailer (with the exception of iTunes) was not among the frequently mentioned attribute of the service provider. This is consistent with the finding that, apart from iTunes, retailers are not differentiated from each other (NPD Group 2007). As our primary research interest is to understand how consumers respond to different pricing structures, we do not include the brand of the digital music retailer in the conjoint design.[5] To

[5]Past work in choice-based conjoint has included brand name as an attribute to capture differences across brands in the choice of the overall profile. Such inclusion helps to address the issue of competition. For instance, Iyengar et. al (2008) included the brand name of wireless service provider in their conjoint design. Using data collected from a choice-based conjoint, they estimated the single profit maximizing plan that one of the service providers should introduce given the plans offered by the competitors. In the current context, however, merely an inclusion of brand name will not suffice. This is because it is likely that consumers may wish to satisfy their music consumption by choosing a bundle of retailers that offer different types of music. For instance, a consumer may have a monthly membership with eMusic to access music from independent bands and, at the same time, may purchase popular songs from iTunes. This is clearly an interesting area of future research, which merges past work on consumers' choice of assortments (Bradlow and Rao 2000, Hoch, Bradlow and Wansink 1999) together with past work on pricing of service plans. We discuss

establish an empirically viable range for the pricing components of a digital music service, we asked each participant to state the maximum access fee (per-song price) that she would be willing to pay for a music service which had a BP (PPU) plan. From the results, we identified \$5 to \$25 as a feasible range for the monthly access fee and \$0.20 to \$1.30 as a feasible range for per-song rate. The market rates at the time of the study fell within these ranges (eMarketer 2007).

3.1 Study design

Following the results of the above pilot study, we selected five attributes for creating the conjoint profiles: (1) access fee, (2) number of maximum available song downloads, (3) per-song rate, (4) audio quality and (5) type of music available.

For a BP plan, access fee is the monthly charge to a customer for using the music service and the number of available song downloads refers to the maximum consumption limit on the units of service. For a PPU plan, per-song rate is the price that the consumer pays for downloading a song. We divided the ranges of the access fee variable into three parts - \$0 ("low"), \$5 to \$15 ("medium"), and \$15 to \$25 (high). The per-song rate is divided into three parts as well - \$0.20 to \$0.55 (low), \$0.55 to \$0.90 (medium), and \$0.90 to \$1.30 (high). For a BP plan, the number of available plan downloads is not independent of the access fee as plans with high access fee tend to have more available downloads. We describe shortly how we reflect this in our design. For the audio quality, we use three levels - CD quality, MP3 256 kbps high fidelity compressed audio and MP3 128 kbps low fidelity compressed audio. Finally, for the type of music, we use three levels as well - Very popular Top 40, Somewhat popular and diverse and Obscure / Deep Catalog. The respondents were given several examples of what type of artists are present in each category.[6] Figure 1 shows an example of the one of the choice sets of the conjoint

this in the conclusions.

[6]After several conversations with the music service provider, we gave the following examples of artists/genre to convey the type of music available in the three categories. In the Very popular Top 40 category, the artists are Fergie, Beyonce, Gwen Stefani, Jay-Z and Foo Fighters; somewhat popular and diverse artists/genre are Bjork, George Harrison, Norah Jones, Jazz and Blues; Obscure/ Deep Catalog artists/genre are World music, Twisted Sister, Charlie Daniels, Electronic Experimental and Youssou N'Dour.

survey.

Include Figure 1 here

Each choice set evaluated by participants featured three plans. To ensure that no choice set had a dominating alternative, we first generated three orthogonal plans with 27 profiles each from the full factorial design (Addelman 1962). Next, we ordered the twenty seven profiles from each orthogonal plan from least to most preferred using the average attribute importance weights from the pilot survey. Then the three alternatives with equal ranks were used to form the choice set.

Recall that each alternative has a "low", "medium" or "high" level of access fee. If an alternative has a "low" level of access fee (i.e., access fee = $0), then it is a PPU plan. For this alternative, we randomly select a value from the appropriate range for per-song level attribute to obtain the price per song. If, however, an alternative has either a "medium" or "high" level of access fee, we first randomly select a value for the access fee from the appropriate range. Next, we select a value from the appropriate range for per-song level attribute. Then, we divide the randomly generated access fee value of the plan by its generated cost per song to obtain the maximum available downloads. This way we ensure that the maximum available number of songs is related to the access fee of the plan, and the actual prices vary continuously across choice sets and respondents. Note that our situation is different from that in previous research (e.g., Bradlow, Hu and Ho 2004) where some levels of an attribute are missing and consumers have to impute such missing levels. In the present context, some attributes are simply *not defined* for one or the one type of plans (e.g., monthly allowable downloads are not defined for a PPU plan).

Each participant in our study evaluated twenty seven choice sets, each of which had three digital music plans. Their task was to either reject all plans in a choice set, or to select one plan among the alternatives. We controlled for the order and position effects by randomizing the order of profiles across participants.

3.2 Model specification

We use the above data to estimate the proposed model. Let $CDQual_j$, $MP3\_256_j$, $PopTop_j$, $SwhatPop_j$, and d_j denote dummy (0/1) variables representing the respective presence or absence of CD audio quality, MP3 256 kbps audio quality, the availability of Very Popular Top 40 songs, Somewhat popular songs and bucket pricing scheme in plan $\mathcal{P}_j$. We select MP3 128 kbps and Obscure / Deep Catalog as the base levels for the audio quality and type of music availability, respectively. We then specify the following utility function for the proposed model where for simplicity we omit the subscript t denoting choice occasion:

$$\begin{aligned} U_{ij} = \beta_{i0} + \beta_{i1} \log\,(n^*_{ij}+1) + \beta_{i2} z_{ij} + \beta_{i3}\ CDQual_j + \beta_{i4}\ MP3\_256_j\ + \\ \beta_{i5}\ PopTop_j + \beta_{i6}\ SwhatPop_j + \beta_{i7}\ d_j + \epsilon_{ij}, \quad (j = 1,\ 2,\ 3). \end{aligned} \tag{7}$$

Each of the parameters in the above equation is specified at the individual-level[7]; n^*_{ij} is the expected consumption (i.e., number of monthly songs) as defined in equation (5); and

$$z_{ij} = \begin{cases} -f_j & \text{if } d_j = 1, \\ -p_j(n^*_{ij}) & \text{if } d_j = 0. \end{cases} \tag{8}$$

Note that the term w_i does not appear in the empirical budget constraints in equation (8) unlike the budget constraints shown in equation (2). This is because in a choice model setting, the term $\beta_{i2} w_i$ enters the utility of each alternative and hence cancels out.

3.3 Alternative Model

Past research (Iyengar et. al 2008, Jensen 2006, Lambrecht et. al 2007) has also used a quadratic utility function to capture diminishing marginal returns. We specify

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

such a model in our context.

$$U_{ij} = \alpha_{i0} + \alpha_{i1}\ (q^*_{ij}) - (q^*_{ij})^2 + \alpha_{i2} z_{ij} + \alpha_{i3}\ CDQual_j + \alpha_{i4}\ MP3\_256_j +$$
$$\alpha_{i5}\ PopTop_j + \alpha_{i6}\ SwhatPop_j + \alpha_{i7}\ d_j + e_{ij}, \quad (j = 1,\ 2,\ 3). \tag{9}$$

Here, (similar to our model) the optimal consumption, q^*_{ij}, depends on the pricing scheme of the plan. For model identification, the coefficient of the squared term is set to -1.

For a plan with bucket pricing,

$$q^*_{ij} = \begin{cases} \frac{\alpha_{i1}}{2} & \text{if } 0 \leq\ q^*_{ij} \leq\ A_j, \\ A_j & \text{if } q^*_{ij} >\ A_j. \end{cases} \tag{10}$$

If a plan has PPU scheme, the expected consumption is $q^*_{ij} = \frac{\alpha_{i1} - p_j \alpha_{i2}}{2}$. The term z_{ij} is similar to Equation (8).

Note that, similar to our model, the consumption under a PPU plan is a function of the pay-per-use price. In contrast to our model, the optimal consumption may be lower than the maximum allowable consumption under a plan with a bucket pricing scheme.

We assume that the person-specific vector $\boldsymbol{\alpha}_i = (\alpha_{i0}, \ldots, \alpha_{i7})'$ of coefficients follows a multivariate normal distribution with mean vector $\bar{\boldsymbol{\alpha}}$ and covariance matrix $\boldsymbol{\Lambda}_\alpha$; and we assume that $\boldsymbol{e}_i = (e_{i0}, e_{i1},\ e_{i2},\ e_{i3})'$ is a vector of error terms, normally distributed with zero mean and covariance matrix $\boldsymbol{\Psi}$. Note that both models have an equal number of parameters.

3.4 Results

We used Markov Chain Monte Carlo (MCMC) methods for estimating the above two 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 results based on 100,000 draws retained after discarding the initial 50,000 draws as burn-in iterations.

We use 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 simply the ratio of the observed marginal densities of the quadratic utility model and our model. We use the MCMC draws to obtain an estimate of the log-marginal likelihood for each of the two models. The log-marginal likelihood of our model is -3880.67 and that of the quadratic utility model is -3890.04, resulting in a log BF of 9.37. This provides strong evidence of the empirical superiority of our proposed model (see Kass and Raftery 1995, p. 777).[8]

We also compare the predictive validity of the two models. For each respondent, we randomly select 22 of the 27 choice sets for model estimation and use the remaining 5 for out-of-sample prediction. The mean hit rate across respondents and holdout choice sets is 72.0% for our model and 68.4% for the quadratic utility model. Our proposed model shows higher predictive validity than a quadratic utility model.

We now discuss the parameter estimates from our model. Those from the alternative model are available from the authors upon request. 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 1 reports the results.

Insert Table 1 here

We find that parameter associated with the presence of a bucket pricing scheme is negative and significant. This suggests that consumers' utility from the service is lower if they are charged under a bucket pricing scheme vis *à* vis a pay-per-song scheme.[9] Thus, the type of pricing scheme offered can impact how much utility a consumer derives from the service. Other results show that the presence of CD quality or MP3 256 kbps audio as compared to MP3 128 kbps adds significantly to

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

[9]This result is consistent with the finding that revenues from subscriptions within a digital channel have fallen from $0.2 Billion in 2007 to $0.18 Billion in 2008 (RIAA 2008). Some anecdotal evidence also suggests that it is generally hard to initiate subscriptions with consumers (New York Times 2009a).

the utility of a service. In addition, as compared to Deep Catalog artists, the availability of Very popular Top 40 (Somewhat Popular) artists decreases (increases) the utility of the service. That Very popular Top 40 artists are less preferred than Deep Catalog artists is likely be due to the fact that the service provider we collaborated with does not have songs from any popular Top 40 artists. Thus, the respondents of our survey, who are either customers of this music service provider or professed interest in the service, may not be favorably inclined towards popular artists. Finally, both of the constrained parameters ($\hat{\beta}_1$ and $\hat{\beta}_2$) are significant and the constraints are binding.

4 Optimal retailer pricing

In this section, we use simulations to illustrate how our model can specify the optimal pricing for service plans. Before discussing the results, we briefly describe a few assumptions for the simulations.

Recall that, given the lack of differentiation among retailers, we did not incorporate brand name of the retailer in the conjoint design. Thus, in the following simulations, we assume that there is a single representative retailer which is profit maximizing. Additionally, we assume that record labels charge online digital music companies on a per-song basis. While there are many types of contractual agreements between record labels and retailers (Krasilovsky, Shemel, Gross and Einstein 2007, Kusek and Leonard 2008), an often used contract is linear per-song pricing. The per-song cost for a retailer, however, can vary based on the contract it negotiates with record labels. For instance, the music provider we collaborated with noted that a "Popular Top 40" song may have a cost of as high as \$0.60 per song while a "Somewhat Popular" song will have a cost of around \$0.30 per song. Hence, we identify optimal plans for a retailer at differing per-song cost it may face ranging from \$0.10-\$0.60 per-song. Finally, to isolate the effect of plan type and the associated prices on the various quantities of interest, we fix the level of the other two plan features to their preferred levels - audio quality is set to "CD quality" and type of music availability is set to "Somewhat Popular".

First, we describe the optimal pricing of a single plan that a profit maximizing retailer may offer. Next, we extend the analysis to the pricing of a menu of plans.

4.1 Single plan

Suppose a retailer is considering offering a single plan. What plan should it offer, i.e., a bucket pricing plan or a pay-per-song plan? And, how should it price the plan? On the one hand, our model indicates that merely the presence of a bucket pricing plan will result in consumers being less likely to opt into the service. However, a bucket pricing plan has two plan features, the access fee and the associated monthly downloads, that a retailer can manipulate. With a PPU plan, in contrast, consumers, will be more likely to opt into the service. However, the retailer has less flexibility in that the pay-per-song price determines both the probability of a consumer to opt into the service and how much she will consume in a month. We examine these questions on the effect of pricing scheme on various quantities of interest such as the penetration rate of the service, expected monthly consumption and profits.

For a BP plan, there are two design factors - the access fee and monthly number of downloads. To identify the optimal BP plan, we perform the following grid search. We vary the access fee in increments of \$1 from \$5 - \$40 per month and the monthly number of downloads in increments of 4 songs from 5 - 80 songs per month. Thus, there are $36 \times 20 = 720$ grid points and each combination of the two design factors defines a BP plan.

For a given value of per-song cost (e.g., \$0.20 per-song) to the service provider, we calculate its contribution margin from each offered BP plan as follows. For every customer, we use their customer-specific parameters from an MCMC draw to compute the probability whether a consumer will choose the single offered plan (i.e., subscribe to the service) and, if so, their usage. We combine the probability of choice of service with the revenue (based on the plan's access fee) and the per-song cost to calculate the expected contribution for a plan. We then average the expected contribution across all MCMC draws and customers to obtain our simulation outcomes. In summary, we calculate the contribution margin for each plan and then identify the plan with the highest margin. We repeat this calculation for differing values of per-song cost ($0.10-$0.60 per-song) to the service provider.

Table 2 describes the BP plan with the highest expected contribution per-consumer at differing values of per-song cost.

Insert Table 2 here

We do a similar grid search to find the optimal PPU plan. Here, we vary the single design factor, per-song rate, in increments of $0.01 from $0.05 -$1.30. As before, we identify the plan with highest total expected contribution. Table 3 describes the service plan with the highest expected contribution for the service provider.

Insert Table 3 here

The results provide an indication of per-song markup that a profit maximizing retailer will impose. For instance, when the cost is $0.20 per-song, a retailer will charge consumers around $0.50 per-song, which is a markup of $0.30 per-song. Also, note that when the cost is between $0.50-$0.60 per-song, the model-predicted optimal price for a song is between $0.93-$1.10. Interestingly, some reports (AudioMicro 2008, CNN 2008, Reuters 2007) suggest that iTunes faces a cost of around $0.65 per-song and, in turn, charges consumers $0.99 for a song.[10] This price is similar to the model-predicted optimal value.

Several points are worth noting when comparing the characteristics of the optimal plans in Table 2 and Table 3. We make these comparisons at the same cost level. First, as expected and providing face validity to our results, the per-song rate for the optimal bucket pricing plan (= Access Fee / Number of Monthly Downloads) is lower than the per-song price for a PPU plan. For example, at a variable cost of $0.30 per-song, the optimal bucket pricing plan has a monthly access fee of $27 and includes 53 songs per month. This translates to a price per song of around 52 cents. At the same per-song cost, the PPU plan has a $0.65 per-song rate. Second, the

[10]On April 7, 2009, iTunes adopted a variable pricing scheme with a tiered structure.

penetration rate of an optimal PPU plan is higher than the corresponding BP plan. For instance, at the cost of $0.30 per-song, the penetration rate of the BP (PPU) plan is 25% (54%). One of the sources for this difference in the penetration rate is our earlier finding that consumers' utility from the service is significantly lower if they are charged under a bucket pricing scheme vis $\grave{a}$ vis a pay-per-song scheme. Third, and managerially most relevant, when the retailer offers only a single plan the expected profit from a PPU plan is always higher than that from a BP plan. This is true for any level of cost. For instance, at a cost of $0.30 per-song, the expected monthly profit for the BP (PPU) plan is around $2.80 ($4.50) per-customer. This indicates that if a service provider introduces a single plan, it should be a PPU plan.

4.2 Menu of plans

We extend our earlier analysis to a menu of two plans. As for the case of a single plan, we use our model to answer questions about the type of offered plans and their optimal prices.

If a retailer offers two bucket pricing plans then, to maximize profits, the optimal levels of the access fee and number of available downloads for each plan have to determined. To do so, we perform the following grid search. For each of the two offered plans, we vary the access fee in increments of $2.50 from $5.0 - $40.0 and the number of monthly downloads in increments of 5 songs from 5-80 songs per months. Thus, there are $15 \times 15 \times 15 \times 15 = 50625$ grid points. Each grid point is a combination of two BP plans. For each combination of two offered plans and for a given level of per-song cost that a retailer faces, we compute its total expected contribution margin as follows. We calculate the probability of choice of each plan and combine it with the revenue (based on the plan's access fee) and the per-song cost to calculate the expected contribution for that plan. We then add the expected contribution from each plan to form the total expected contribution from an offering. We perform such a calculation for each combination of two BP plans and identify the one that provides the highest margin. As before, we identify the optimal set of plans that a retail should offer at differing values of per-song cost.

Table 4 describes the service plans with the highest combined expected contribution for the service provider.

Insert Table 4 here

A comparison of the results in Table 4 and those in Table 2 (the single optimal bucket pricing plan) shows that (a) offering two plans slightly increases the penetration rate of the service provider as it now appeals to more customers and (b) the overall profit from offering two plans is higher than that from a single plan.[11]

If a retailer offers a menu of both types of plans then, to maximize profits, the optimal level of access and number of downloads for the BP plan and the per-song rate for the PPU plan have to be determined. We identify the optimal combination for a menu of both types of plans by performing the following grid search. For the BP plan, we vary the access fee in increments of \$2.50 from \$5.0 - \$40.0 and the number of monthly downloads in increments of 5 songs from 5-80 songs per month. For the PPU plan, we vary the per-song rate in increments of \$0.025 from \$0.05 -\$1.30. Thus, we have a total of $15 \times 15 \times 50 = 11250$ grid points. Table 5 describes the service plans with the highest combined expected contribution for the service provider based on various levels of cost per-song that it may face.

Insert Table 5 here

A comparison of the results in Table 4 and Table 5 indicates that a retailer's per-song cost plays an important role in determining both the optimal set of plans that it should offer and their prices. Additional analysis shows that for low variable cost ($<$ \$0.15 per song), the optimal combination of two bucket pricing plans leads to *higher* monthly expected profits per-customer as compared to the optimal menu of both types of plans. With high variable cost ($>$ \$0.20 per song), we find a reversal - the optimal menu of both types of plans leads to higher monthly expected profits

[11] We ignore the retailer's cost of increasing the number of plans as it is likely to be extremely small, in contrast to traditional product line expansions (Iyer and Seetharaman 2003).

per-customer.[12]

Why is this happening? At a low per-song cost, a retailer can offer a high number of monthly downloads to entice consumers to select a BP plan. Intuitively, this is similar to a strategy that many other services (e.g., restaurants) adopt to attract customers when, due to a low per-unit cost, they offer a buffet ("all-you-can-eat") pricing scheme (Nahata, Ostaszewki and Sahoo 1999). In the present context, coupled with a high number of offered monthly downloads, the retailer charges a high access fee as well. This increases the overall expected revenue. With an increase in per-song cost, however, it is optimal for the retailer to constrain the maximum number of songs that consumers can download. This is coupled with a decrease in the monthly access fee. Both factors decrease the probability that a customer will opt into the service as well as the revenue conditional on choice of the service. As a result, the total expected revenue (and profit) from the two BP plans becomes lower than that from the menu of both types of plans.

Thus far, we showed how our model can help in determining the optimal set of plans and its prices. An additional benefit of the model is that it allows us to estimate the optimal price that record labels ("manufacturers") should charge the retailers. Next, we describe such an analysis.

5 Optimal record label pricing

There is some controversy in the music industry about the price per-song that record labels should charge the digital music retailers. Anecdotal evidence suggests that record companies charge as high as $0.60 per song (BillboardBiz 2005, Reuters 2007, AudioMicro 2008). Is this price per-song optimal or are the record labels overcharging the digital music retailers? Our demand estimates provide some guidance on this issue.

For the following set of results, we assume that there is a single representative record label and retailer and both are profit maximizing. We first describe the

[12] We find that the monthly expected profits from the two types of plan menus is the same when the variable cost is 18 cents per-song.

optimal price that a record label should charge a retailer assuming that the latter offers a single plan. Next, we extend it to a scenario when a retailer offers a menu.

5.1 Retailer with single plan

Tables 2 and 3 show that when a profit maximizing retailer offers a single plan, it will offer a PPU plan. Thus, for the single plan scenario, we only need to investigate channel profits under the PPU plan. As the cost per-song to the record labels (the "wholesale" cost) is unknown, we consider several values – \$0.00, \$0.05, \$0.10, and \$0.15– and show how the cost affects the pricing decisions of the channel members. Table 6 shows the results.

Insert Table 6 here

The results show that, even at zero cost per-song, a record label should charge about \$0.23 per-song to a retailer, which in turn will chard around \$0.54 per-song to a consumer. This is a classic case of double marginalization (Tirole 1993). In the music industry, there is no evidence of vertical integration or franchisee agreement to alleviate this problem. Thus, we only consider a scenario in which the channel members are not integrated. At this price, the expected monthly profit for a record label (retailer) is about \$4.17 (\$5.58) per-consumer.

How do these profit levels compare with those in a scenario when the record label charges \$0.60 per song (as suggested by anecdotal evidence)? Given the record label price of \$0.60 per-song, a profit maximizing retailer will charge \$1.07 per-song to the consumers (See Table 3). At this per-song rate, the retailer will make an expected monthly profit of \$2.11 per-consumer, which is around \$3.50 (= \$5.58-\$2.11) lower than their optimal profits. The record label will make an expected monthly profit of about \$2.69 per consumer, which is around \$1.50 (=\$4.17 -\$2.69) lower than its corresponding optimal profit. Thus, overall expected monthly channel profits are lowered by around \$5.00 per-consumer, which is about 50% lower than the optimal channel profits.

Note that even at a cost of \$0.15 per-song, a record label should charge a retailer about \$0.40 per-song. In fact, our analysis shows that for it to be optimal for a record label to charge \$0.60 per-song, its cost should be as high as \$0.35 per-song, which seems unlikely. This suggests that record labels may be overcharging the retailers to the detriment of both their profits.

5.2 Retailer with a menu of plans

Our earlier results (see Tables 4 and 5) show that a retailer's per-song cost can influence both the type of plans that it offers (either two BP plans or a menu involving a BP and a PPU plan) and their prices. Here, we consider the profit implications when the retailer has a menu with both types of plans.[13] Table 7 shows the results.

Insert Table 7 here

The results show that even at zero cost, the record label should charge about \$0.20 per-song. At this price, the expected monthly profit for the record label (retailer) is around \$5.10 (\$7.13).

We compare the optimal profits with those under a scenario when a record label charges \$0.60 per-song. A profit maximizing retailer will choose a bucket pricing plan with an access fee of \$25 with 25 included songs and a pay-per-song plan with a per-song rate of \$1.12 (see Table 5). With such a plan menu, the retailer will make an expected monthly profit of just under \$2.50 per-customer. This is around \$4.60 (\$7.13 - \$2.50) less than the optimal monthly profits per-customer. The record label, in turn, will make an expected monthly contribution of \$3.00 per-customer. This is around \$2.10 (=\$5.10-\$3.00) less than its corresponding optimal profits. Thus, the expected monthly profits for the channel are lowered by \$6.70 per-customer as compared to the optimal profits, which is a reduction by around 54%.

Finally, the results show that even at a high cost per-song of \$0.15, record labels should charge retailers around \$0.33 per song. This corroborates our earlier finding that the record labels may be overcharging the retailers.

[13] As noted in Table 7, even with zero cost, a record label should charge a retailer about \$0.20 per-song. At this cost level, a profit maximizing retailer will choose a menu of both types of plans over offering two bucket pricing plans (see Table 5).

6 Conclusions

Services widely vary in whether they offer their customers only subscription-based plans, *à* la carte plans or a mix of both. Such decisions have to incorporate consumers' expectation of usage, which may itself be influenced by the offered pricing schemes. To determine optimal prices for a menu of plans then, it is necessary to accommodate the two way dependence between the offered pricing schemes and consumers' expected usage.

In this paper, we propose an economics-based utility model to address optimal pricing for a menu of plans. We analyze the effect of the two types of pricing schemes (subscription-based and *à* la carte) on consumers' choices and estimate our model using choice-based conjoint data. The model is applied to the digital music industry. From consumers' choices of service plans, we infer their demand for digital music and then use the estimated demand curve to determine optimal prices for a menu of plans. An additional benefit of the model is that it allows us to estimate the optimal price that record labels should charge the retailers. We do so and find that record labels may currently be overcharging the retailers to the detriment of overall channel profits.

While we study the digital music industry, the broad issues of manufacturer-retailer interactions, its effect on a retailer's menu, and how consumers respond to the offered plans are applicable to many other services. For instance, DVD rental services such as Netflix and Blockbuster offer various bucket pricing plans, which limit either the number of DVDs that may be rented in a month or the number that can be with a customer at a given time. These companies have to decide the number and type of plans to offer based on how customers' usage rate affects their revenues and any contractual agreement they may have with studios. As another example, in the car share industry, a company such as ZipCar offers a two-part tariff plan with a monthly fee and a per-mile rate as well as a pay-per-mile plan with no monthly fee. ZipCar's profits are clearly linked to how much its customers expect to use the service and how that affects their choice among the two types of offered plans. Our model, with suitable modifications, can address such issues within these other service contexts.

Our research can be extended in several directions. We collected our data using a choice-based conjoint experiment. Future research may consider collecting data using field experiments in which prices are systematically changed. A related area is the use of CRM databases or natural experiments. Although such data are more realistic, they suffer from limited variability in prices over time as compared to data from a field experiment. Our model can also be extended further. One area of future research is to consider the effect of competitive actions and reactions on the plan menus, extending the line of work described by Choi, DeSarbo and Harker (1990). Such an extension should consider that consumers, in order to satisfy their consumption, may purchase plans from various retailers. For instance, a consumer may have a monthly membership with eMusic to access music from independent bands and, at the same time, may purchase popular songs from iTunes. This is an interesting area of future research, which merges past work on consumers' choice of assortments (Bradlow and Rao 2000; Hoch, Bradlow and Wansink 1999) together with research on pricing of services. Another interesting model extension would be to incorporate how the availability of various plan features may also affect consumers' usage rate and thereby their willingness-to-pay for such features.

References

Addelman, Sidney (1962), "Orthogonal main-effect plans for asymmetrical factorial experiments," *Technometrics,* 4, 21–58.

Albert, James and Siddhartha Chib (1993), "Bayesian Analysis of binary and polychotmous response data," *Journal of the American Statistical Association*, 88, 669–679.

AudioMicro (2008), "Royalty Rates for Various Types of Music Licensing, " December 10, Available at -
http://www.audiomicro.com/royalty-free-music-blog/royalty-free-music/royalty-rates-for-various-types-of-music-licensing/, last accessed, July 19, 2009.

BillboardBiz (2005), "New York AG Investigates Download Pricing, " December 27, Available at -
http://www.allbusiness.com/retail-trade/miscellaneous-retail-retail-stores-not/4382963-1.html, last accessed, July 19, 2009.

Bradlow, Eric T. and Vithala R. Rao (2000), "A Hierarchical Bayesian Model for Assortment Choice," *Journal of Marketing Research,*37, 2, 259–268.

Bradlow, Eric T., Ye Hu and Teck H. Ho (2004), "A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles," *Journal of Marketing Research,* 41, 4, 369–381.

Chib, Siddhartha and Edward Greenberg (1995), "Understanding the Metropolis-Hastings Algorithm," *American Statistician,* 49, 327–335.

Choi, Chan S., Wayne S. DeSarbo and Patrick T. Harker (1990), "Product Positioning under Price Competition," *Management Science,* 36, 175–199.

CNN (2008), "Apple's Digital Music Showdown," September 30, Available at -
http://money.cnn.com/2008/09/30/technology/itunesthreat.fortune/index.htm, last accessed July 15, 2009.

Danaher, Peter (2002), "Optimal Pricing of Subscription Services: Analysis of a Market Experiment,"*Marketing Science,* 21, 2, 119–138.

Della Vigna, Stefano and Ulrike Malmendier (2006), "Paying Not to Go to the Gym," *American Economic Review,* 96, 694–719.

eMarketer (2007), “Digital Falls Short,” November, 1-16.

Geman, Stuart and Donald Geman (1984), “Stochastic Relaxation, Gibbs distributions and the Bayesian restoration of images,” *IEEE Transactions of Pattern Analysis and Machine Intelligence,* 6, 721–741.

Haaijer, Marinus E., Wagner A. Kamakura and Michel Wedel (2000),“The No-Choice Alternative in Conjoint Choice Experiments,” *International Journal of Marketing Research,* 43, 1, 93–106.

Hoch, Stephen J., Eric T. Bradlow and Brian Wansink (1999), “The Variety of an Assortment,” *Marketing Science,*18, 4, 527–546.

Hurwicz, Leonid and Hirofumi Ozawa (1971), “On The Integrability of Demand Functions,” in *Preferences, Utility and Demand: A Minnesota Symposium*, New York: Harcourt Brace Jovanovich, Inc.

Iyengar, Raghuram, Kamel Jedidi and Rajeev Kohli (2008), “A Conjoint Approach to Multipart Pricing,” *Journal of Marketing Research,*, 45, 195–210.

Iyengar, Raghuram, Asim Ansari and Sunil Gupta (2007), “A Model of Consumer Learning For Service Quality and Usage,” *Journal of Marketing Research,* 44, 529–544.

Iyer, Ganesh and P.B. Seetharaman (2003), “To Price Discriminate or Not: The Choice of Station Type in Retail Gasoline Markets,” *Quantitative Marketing and Economics,* 1, 155–178.

Jedidi, Kamel, Sharan Jagpal and Puneet Manchanda (2003), “Measuring Heterogenous Reservation Prices for Product Bundles,” *Marketing Science,* 22, 107–130.

Jedidi, Kamel and John Z. Zhang (2002), “Augmenting Conjoint Analysis to Estimate Consumer Reservation Price,” *Management Science,* 48, 1350–1368.

Jensen, Sissel (2006), “Implementation of Competitive Nonlinear Pricing: Tariffs with Inclusive Consumption,” *Review of Economic Design,* 10 (1), 929.

Kass, Robert E. and Adrian Raftery (1995), “Bayes Factors,” *Journal of the American Statistical Association*, 90, 773–795.

Kohli, Rajeev and Vijay Mahajan (1991), “A Reservation Price Model for Optimal Pricing of Multiattribute Products in Conjoint Analysis,” *Journal of Marketing*

Research, 28, 347–354.

Krasilovsky, William M., Sidney Shemel, John M. Gross and Jonathan Feinstein (2007), "This Business of Music," 10'th Edition, Watson-Guptill Publications, New York, NY.

Kusek, David and Gerd Leonhard (2008), "The Future of Music: Manifesto for the Digital Music Revolution," Berklee Press, Boston, MA.

Lambrecht, Anja and Bernd Skiera (2006), "Paying Too Much and Being Happy About It: Existence, Causes and Consequences of Tariff-Choice Biases," *Journal of Marketing Research,* 43 (May), 212-23.

Lambrecht, Anja, Katja Seim and Bernd Skiera (2007), "Does Uncertainty Matter? Consumer Behavior Under Three-Part Tariffs," *Marketing Science,* 26, 5, 698–710.

Lemon, Katherine N., Tiffany B. White and Russell S. Winer (2002), " Dynamic Customer Relationship Management: Incorporating Future Considerations into the Service Retention Decision," *Journal of Marketing,* 66, 1–14.

Mahajan, Vijay, Paul E. Green and Stephen M. Goldberg (1982), "A Conjoint Model for Measuring Self- and Cross-Price/Demand Relationships," *Journal of Marketing Research,* 19, 334–342.

Narayanan, Sridhar, Pradeep K. Chintagunta and Eugenio J. Miravete (2007), "The Role of Self-Selection, Usage Uncertainty and Learning in the Demand for Local Telephone Service," *Quantitative Marketing and Economics,* 5, 1-34.

NPG Group (2007), "The NPD Group: Legal Music Downloads Were Fastest Growing Digital Music Category in 2006," March 14, Available at -
http://www.npd.com/press/releases/press_0703141.html, last accessed, October 15, 2009.

Nahata, Babu, Krzysztof Ostaszewski and Prasanna Sahoo (1999), "Buffet Pricing," *Journal of Business,* 72, 2, 215–228.

Nunes Joseph C. (2000), "A Cognitive Model of People's Usage Estimations," *Journal of Marketing Research,* 37, 397–409.

New York Times (2009a), "Looking at Life as One Big Subscription," Saturday, October 10, Available at -

http://www.nytimes.com/2009/10/11/business/11every.html?_r=2, last accessed, October 15, 2009.

Oi, Walter Y. (1971), "A Disneyland Dilemma: Two-part Tariffs For A Mickey Mouse Monopoly," *Quarterly Journal of Economics,* 85, 1, 77–96.

Recording Industry Association of America (2009) - Key Statistics,
http://www.riaa.com/keystatistics.php, last accessed October 15, 2009.

Reiss, Peter C. and Matthew W. White (2005), "Household Electricity Demand, Revisited," *Review of Economic Studies,* 72, 3, 853-883.

Reuters (2007), "Indie labels plan to pull out of digital service," May 4, Available at - http://www.reuters.com/article/entertainmentNews/idUSN0448718620070505, last accessed, October 15, 2009.

Schmalensee, Richard (1981), "Monopolistic Two-Part Pricing Arrangements," *Bell Journal of Economics,* 12, 2, 445–466.

Sun, Baohong, Yacheng Sun and Shibo Li (2006), "When Advance Purchase need to be Made for Future Consumption An Empirical Investigation of Consumer Choice under Bucket Pricing," Working Paper, Carnegie Mellon University.

Tirole, Jean (1993), "The Theory of Industrial Organization," Cambridge, Massachusetts: MIT Press.

Plan1		Plan2		Plan3	
Monthly Fee	$0	Monthly Fee	$13.99	Monthly Fee	$16.99
Price Per Song	$0.85	Number of Songs	40	Number of Songs	25
Audio Quality	MP3 128 kbps	Audio Quality	CD Quality	Audio Quality	MP3 256 kbps
Available Music	Somewhat popular / Diverse	Available Music	Obscure / Deep Catalog	Available Music	Popular Top 40

I choose Plan 1 ___ Plan 2 ___ Plan 3 ___None ___

Figure 1: An Example of Choice Set of Three Digital Music Plans

Table 1
Parameter Estimates for the Proposed Model

Variable	Variable Label	Parameter Label	Posterior Mean
Consumption	$\log(n^*_{ij}+1)$	β_1	**1.31**
			(1.21, 1.43)
Income Effect	z_{ij}	β_2	**0.09**
			(0.08, 0.10)
CD Quality	$CDQual$	β_3	**0.79**
			(0.62, 0.95)
MP3 256 kbps	$MP3\_256$	β_4	**0.82**
			(0.69, 0.96)
MP3 128 kbps	$MP3\_128$		0
Popular Top 40	$PopTop$	β_5	**-0.92**
			(-1.08, -0.76)
Somewhat Popular	$SwhatPop$	β_6	**0.17**
			(0.09, 0.17)
Obscure	$Obscure$		0
Bucket-pricing plan	δ	β_7	**-1.10**
			(-1.31, -0.90)
Intercept		β_0	**-4.15**
			(-4.57, -3.71)

We fix the variance of the utility of the no-choice alternative to 1.0.

The utility variances of the three profiles in the choice set are estimated to be 0.78, 0.73 and 0.85.

Table 2
Optimal Single Bucket Pricing Plan

Retailer Cost per-song ($)	Access Fee ($)	Number of Downloads	Penetration Rate	Expected Monthly Demand*	Expected Monthly Profit* ($)
0.10	25	80	0.47	37	7.97
0.20	30	80	0.34	27	4.71
0.30	27	52	0.25	13	2.81
0.40	26	41	0.19	8	1.83
0.50	25	33	0.15	5	1.27
0.60	23	25	0.11	3	0.92

Expected Monthly Demand and Profit are per-customer.

Table 3
Optimal Single Pay-per-use Plan

Retailer Cost per-song ($)	Price per-song ($/song)	Penetration Rate	Expected Monthly Demand*	Expected Monthly Profit* ($)
0.10	0.34	0.81	37	8.96
0.20	0.50	0.66	21	6.16
0.30	0.65	0.54	13	4.50
0.40	0.77	0.46	9	3.41
0.50	0.93	0.38	6	2.65
0.60	1.07	0.32	5	2.11

Expected Monthly Demand and Profit are per-customer.

Table 4

Optimal Plan Menu with Bucket Pricing Plans

	Plan 1		Plan 2		Total Menu		
Retailer Cost per-song ($)	Access Fee ($)	Number of Downloads	Access Fee ($)	Number of Downloads	Penetration Rate*	Expected Monthly Demand*	Expected Monthly Profit* ($)
0.10	27.50	80	25.00	75	0.53	40	10.30
0.20	32.50	80	30.00	75	0.43	33	6.68
0.30	30.00	55	27.50	50	0.32	17	4.16
0.40	27.50	40	25.00	35	0.25	9	2.83
0.50	27.50	35	25.00	30	0.20	7	2.00
0.60	27.50	33	22.50	25	0.17	5	1.31

Penetration rate, Monthly demand and Monthly Profit are the sum across the two plans. The latter two are calculated per-customer.

Table 5

Optimal Plan Menu with Both Types of Plans

	Plan 1		Plan 2	Total Menu		
Retailer Cost per-song ($)	Access Fee ($)	Number of Downloads	Price per-song ($)	Penetration Rate*	Expected Monthly Demand*	Expected Monthly Profit* ($)
0.10	25.00	80	0.43	0.76	35	10.03
0.20	30.00	80	0.56	0.66	26	7.64
0.30	27.50	55	0.68	0.56	16	5.06
0.40	27.50	40	0.89	0.44	9	3.90
0.50	25.00	30	0.99	0.39	7	3.06
0.60	25.00	25	1.12	0.34	5	2.48

Penetration rate, Monthly demand and Monthly Profit are the sum across the two plans. The latter two are calculated on a per-customer level.

Table 6

Optimal Record Label Pricing with Retailer Per-song rate Plan

Record label Cost per-song ($)	Optimal Record label Price per-song ($/song)	Optimal Retailer Price per-song	Record label Monthly Expected Profit* ($)	Retailer Monthly Expected Profit* ($)
0.00	0.23	0.54	4.17	5.58
0.05	0.27	0.60	3.28	4.92
0.10	0.35	0.70	2.80	3.91
0.15	0.40	0.77	2.30	3.41

Expected Monthly Profits are calculated on a per-customer level.

Table 7

Optimal Record Label Pricing with Retailer Menu of Plans

Record label Cost per-song ($)	Optimal Record label Price per-song ($/song)	Optimal Retailer Pricing			Record label Monthly Expected Profit* ($)	Retailer Monthly Expected Profit* ($)
		Plan 1		Plan 2		
		Access Fee ($)	Downloads	Price per-song ($)		
0.00	0.20	30.00	80	0.56	5.11	7.13
0.05	0.30	27.50	55	0.68	4.05	5.19
0.10	0.30	27.50	55	0.68	3.24	5.19
0.15	0.33	28.57	50	0.74	2.45	4.75

Expected Monthly Profits are calculated on a per-customer level.