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Music for a Song:
An Empirical Look at Uniform Song Pricing and its Alternatives

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Abstract

Economists have well-developed pricing theories that challenge the wisdom of the common practice of uniform song pricing. This paper explores the profit and welfare implications of various alternatives, including song-specific pricing, various forms of bundling, two-part tariffs, nonlinear pricing, and third-degree price discrimination, using survey-based data on nearly 500 students' valuations of 50 popular songs in early January, 2008. We find that various alternatives – including simple schemes such as pure bundling and two-part tariffs – can raise both producer and consumer surplus. Revenue could be raised by nearly 10 percent relative to profit-maximizing uniform pricing and by over a fifth relative to current $0.99 uniform pricing. Moreover, revenue could be increased by a tenth while maintaining consumer surplus at the high level accompanying current $0.99 uniform song pricing. While person-specific uniform pricing can raise revenue by three quarters, none of the non-discriminatory schemes raise revenue's share of surplus above 35 percent. Even with sophisticated pricing, much of the area under the demand curve for this product cannot be appropriated as revenue.

The prominence of the iTunes Music store, where essentially all songs sell for $0.99, has focused attention on uniform pricing. Economists have well-developed normative theories that raise questions, at least in theory, about the wisdom of uniform pricing. Alternatives to uniform pricing include song-specific pricing, various forms of bundling, two-part tariffs, and nonlinear pricing. Many of these approaches are well understood in theory.[1] But determining the amount of additional profit or consumer surplus available from using alternatives to uniform pricing is an empirical question.

Quantifying the surplus foregone by uniform pricing is a matter of current practical as well as academic interest. Apple has now sold over 4 billion songs at iTunes, 1.7 billion in 2007 alone (Christman, 2008). During the summer of 2007, some record labels declined to renew their contracts with Apple out of a desire for more flexibility in pricing.[2] In September 2007, Amazon launched a music downloading service featuring, among other things, song-specific, or "variable" pricing.[3]

In general, it is hard to know how much money uniform pricing leaves on the table because the sorts of data needed to evaluate this question – the full distribution of reservation across buyers and products – are hard to come by. Usually, researchers estimate some sort of demand system allowing inference about individuals' valuations of various quantities of various products.[4] If one could directly observe buyers' reservation prices for products, some sophisticated forms of pricing would be easily implementable.

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[1] See Stigler (1963), Adams and Yellen (1976), Schmalensee (1984), Armstrong (1999), Bakos and Brynjolfsson (1999) and others discussed below.
[2] David Carr, "Steve Jobs: iCame, iSaw, iCaved," *New York Times*, section C, page 1, September 10, 2007.
[3] Amazon's service also features music without digital rights management. See Ed Christman, "Amazon: Keeping it on the Down Low," Billboard, October 6, 2007.
[4] See, for example, Chu, Leslie, and Sorenson (2007) and other studies discussed below.

This paper pursues this goal using survey-based direct elicitation of students' valuations of the top 50 songs at iTunes as of early January, 2008.

The effect of sophisticated pricing on revenue has implications beyond pricing strategy. The welfare economics of imperfect competition depends crucially on the extent to which the social benefit of a product – the area under the demand curve – can be captured as revenue for the seller[5]. It's obvious that the producer surplus under single-price monopoly can fall short of fixed and variable costs even when the joint surplus would exceed costs. Hence, the market can fail to provide goods with benefit in excess of costs. Of course, whether sellers can capture surplus as revenue depends on the effectiveness of price discrimination. Perfect first degree price discrimination eliminates, or at least substantially mitigates, the underprovision problem.[6] But we do not know what share of surplus is appropriable as revenue. One of this paper's contributions is to show the share of revenue that is appropriable in one context.

The paper proceeds in five sections. First, we briefly discuss the pricing problem, along with the relevant theoretical and empirical literatures on various kinds of pricing. In section 2 we discuss our data. Section 3 presents our results on the size and distribution of surplus available under various pricing schemes, including current (uniform $0.99), revenue-maximizing uniform, song-specific pricing, two-part tariffs, nonlinear bundle-size pricing, pure bundling, (simple versions of) mixed bundling, and individual customer-specific pricing. Section 4 finds Pareto-improving pricing schemes that deliver the high level of consumer surplus that current pricing generates while allowing more producer surplus. Section 5 revisits the determination of profit-

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[5] See Spence (1976ab), Dixit and Stiglitz (1977), and Heal (1980) for elaboration of these arguments.
[6] See Edlin, Epelbaum, and Heller (1998) for a discussion of how price discrimination can bring about efficiency.

maximizing pricing schemes using a parametric approach (treating the distribution of valuations as multivariate normal). A brief conclusions follows.

We find that the current \$0.99 price is substantially below the uniform price that would maximize song revenue (between \$1.87 and \$1.99). Revenue-maximizing uniform pricing collects about 30 percent of surplus as revenue, while leaving about 40 percent of surplus as consumer surplus and the remaining 30 percent as deadweight loss. Current \$0.99 pricing, by contrast, collects nearly as much revenue but generates smaller deadweight losses (10-15 percent of surplus) and higher consumer surplus (55-60 percent of surplus).

Using the revenue-maximizing uniform price as the benchmark, we find that various alternative schemes such as pure bundling and two part tariffs could raise revenue by 5-10 percent while raising consumer surplus a quarter and reducing deadweight loss by half. Simple two-part schemes could provide at least the level of consumer surplus available with current (\$0.99) pricing while increasing revenue by over 10 percent. However, even the most effective schemes are able to appropriate only about a third of total surplus as revenue.

Fitting the valuation data to a multivariate normal distribution produces somewhat different results, which we attribute to the poor fit of the normal distribution to the observed valuations.

I. Theoretical Setup and Literature Review

1. Setup

Each consumer i has a reservation price for each song s (V_{is}). These reservation prices, in conjunction with the pricing schemes, determine whether the individual purchases 1 or 0 units of each song (and we assume resale impossible). Consumers evaluate bundles of songs by adding their valuations of each of the songs included in bundles.

The seller's problem is to choose a vector of prices P for the songs, or groups of songs, to maximize his profit. For example, if the seller is a uniform single-price monopolist selling 50 different products, then he chooses only one price, and the price of each bundle depends proportionally on the number of songs on the bundle. That is, if bundle k contains 5 songs, and p is the single price per product, then P_k=5p. With other pricing schemes, the P vector becomes more complicated. If the seller engages in component pricing, with a potentially different price for each song, then the bundle price is the sum of the prices of each of the elements of the bundle. If the seller employs a two part tariff, the first song has one price, while each additional song has another. If the seller engages in "bundle size pricing," then P_k simply depends – generally nonlinearly – on the number of elements in the bundle, so there are 50 separate prices to set. If the seller engages in mixed bundling, then each combination of products can potentially have its own price. With 50 products, the number of combinations is enormous. With 3 products, there are 7 possible bundles. Finally, with pure bundling, the seller sets a single price for the entire bundle of 50 songs.

Define V_{ik} as individual i's valuation of song bundle k. (The bundle could be an individual song, or any combination of the 50 songs available). Each consumer's problem is to maximize $V_{ik} - P_k$ by his choice of *k*, or which product (or bundle of songs) to consume.

Given a vector of prices along with the *V* vector for each individual, a computer can quickly determine how much revenue each scheme would collect. For some of these schemes – notably, nonlinear pricing and mixed bundling, the number of possible pricing schemes is large, so that even a fast computer can examine only a limited range of schemes (in particular for nonlinear pricing with more than about 5 separate prices, and for mixed bundling just a few products).

2. Related Literature

The textbook theory of single price monopoly (see, for example, Pindyck and Rubinfeld, 2006) provides a guide to profit-maximizing uniform pricing. The simplest alternative to uniform pricing (UP) is song-specific, or component pricing (CP). Analytically, it involves the same apparatus as UP, albeit with a single separate price per song. Song-specific pricing is currently employed by digital music sellers Amazon as well as Aimee Street.com, and many observers consider Apple's uniform prices a blunt instrument for revenue maximization.[7] Because UP is a constrained special case of CP – with equal prices for all songs – UP cannot produce more revenue than CP, and CP would in general be expected to produce more.

There is a substantial theoretical literature on sophisticated alternatives to uniform pricing. This body of work provides guidance about how pricing schemes other than uniform pricing can be expected to affect profits and other aspects of surplus. Stigler

[7] The puzzle of uniform prices arises in other product markets, for example in movie theater pricing. See Orbach and Einav (2007).

(1963) presented a two-product example showing that bundling could produce more revenue pricing the products separately when consumers' valuations of the products are negatively correlated. Adams and Yellen (1976) introduced mixed bundling (MB) with examples where mixed bundling produced more profit than either pure bundling (PB) or product-specific pricing. Schmalensee (1984) shows that PB can be more profitable than product-specific pricing even when the correlations of consumer valuations are positive. McAfee, McMillan and Whinston (1989) show that mixed bundling (MB) always beats pure bundling although – again – it results in complex pricing schemes.

A few recent papers outline the situations in which a firm can extract surplus by selling large multiproduct bundles. Bakos & Brynjolffson (1999) show that if the valuation of a large bundle is more predictable than the valuation of individual products, then as the number of products grows large, pure bundling extracts the entire surplus as revenue. Fang and Norman (2006) obtain related results with finite numbers of products. Armstrong (1999) also shows that when tastes are correlated across products – for example because of income differences across consumers – a menu of two-part tariffs is almost optimal.[8]

A few papers use characterizations of demand to create pricing schemes. Chu, Leslie, and Sorenson (2007) estimate demand for plays at a Palo Alto theater using data on purchases of individual play tickets as well as bundles. They use their estimated model to create profit-maximizing pricing schemes under uniform pricing, component pricing, pure bundling, bundle-size pricing, and mixed bundling. Relative to uniform pricing, component pricing raises revenue 1.4 percent, bundle size pricing raises revenue

[8] Sundararajan (2004) develops a model of optimal pricing for large bundles when there are costs of administration.

2.3 percent, and mixed bundling raises revenue 4 percent, but none of the alternatives to uniform pricing raises revenue by more than 5 percent.[9] McMillan (2007) estimates a model of demand for soft-drinks at a grocery store which he uses to calculate that uniform pricing would cost the store $60 in profit (on revenue of roughly $10,000).

Reiss and White (2005) estimate demand for electricity in the presence of a nonlinear price schedule and calculate counterfactual demand under alternative schedules. McManus (2007) estimates demand for nonlinearly-priced coffee – in various size cups – looking for evidence of quality shading. Crawford (2008) estimates a model of demand for cable television bundles which he uses to simulate effects of adding channels to available bundles. He estimates that bundling an average top-15 special interest cable network gives rise to a 4.7 percent increase in profit, a 4.0 percent decrease in consumer surplus, and a 2.0 percent increase in total surplus. [add KS reference]

II. Data

The basic data for this study are 465 individuals' valuations of the same 50 popular songs. Undergraduates – mostly freshmen – at Wharton were required to fill out an online survey which presented them with the top 50 songs at iTunes (as of January 11, 2008). Students were given instructions and paper worksheets in class on January 16 and 17. For each song, students were told to listen to a clip to remind themselves of the song, then to write down the maximum amount they would be willing to pay to get the song from the sole authorized source. Completion of the assignment was necessary for problem set credit to motivate students to participate carefully.

[9] They emphasize that bundle size pricing achieves 98 percent of the revenue of mixed bundling. It should be noted, however, that uniform pricing achieves 96 percent of mixed bundling's revenue. Said another way, bundle size pricing achieves 60 percent of mixed bundling's improvement over uniform pricing.

In particular, students were given the following instructions:

> Imagine that, unlike in current reality, there is only one authorized source for each song. Put aside what you know about prices at existing outlets because for this survey we're pretending that they don't exist.
>
> For each song listed in the survey, indicate the maximum amount you would be willing to pay to obtain it from the sole authorized source. **For this exercise, I'm asking you to report what it is worth to you, not what price you think would be fair or what price you are accustomed to paying. That is, I'm asking you to indicate the maximum amount you would be willing to pay to obtain it from the authorized source.**
>
> For example, if you already purchased it, then at the time you bought it, you were willing to pay at least the price you paid but you might have been willing to pay more. If you would prefer not to have it even if it were free, you would indicate 0.
>
> On the following pages, you will be presented with a list of songs and artists. In the space provided for each song, enter the maximum amount you are willing to pay for the song (for example 1.75, NOT $1.75). You must enter a dollar amount for each song.

The resulting dataset includes 23,250 observations on individual-song valuations for 465 people, as well as a small amount of information on the respondents: age (mostly 18-20), gender, race, self-reported level of interest in music (not interested, somewhat interested, very interested), and the size of their music library.

One concern with data collected in this way is that respondents would anchor on prices they know to be charged at actual websites. Most prominently, Apple charges $0.99 for all songs at iTunes. We are not interested in the students' beliefs about current pricing; we are interested in their maximum willingness to pay. Nearly all of the valuations are "reasonable": 98 percent of valuations fall on [0,10], and 86 percent fall on [0,2]. There is some clustering at the familiar price around $1 but not substantially more than the clustering on other multiples of $0.25. Of nearly 24,000 responses, there are 7257 zeroes. See Figure 1a, which shows the distribution of valuations between \$0 and \$2.[10]

The clustering of valuation responses at round and focal numbers (notably, zero, multiples of \$0.25, \$0.99, and \$1.99) gives rises to plateaus on the demand curve that create "sawtooth" spikes in the relationship between revenue and price. If we believe that the reported valuations are literally true, we can use the raw data to find optimal pricing schemes. But it's alternatively plausible to view reported valuations as truth plus some error. That is, perhaps people report valuation to the nearest multiple of \$0.25. Then the underlying distribution would be better approximated as a smoothed distribution resulting from reported valuations plus a zero-mean random error uniform between –\$0.125 and \$0.125. Given the clustering at (and near) zero, adding this error this produces some negative valuations, and we code negative smoothed valuations as zero. Figure 1b shows the distributions of valuations smoothed in this way. For the remainder of the paper, we perform all exercises on the smoothed data (we report many results on the raw data in the appendix for comparison). In section 5 below we fit the valuation data to multivariate normal distribution that also gives rise to a smooth function relating profits to prices.

A second concern is the more general question of whether surveys can elicit meaningful valuation information. It is well known that question wording affects responses. In earlier work on music valuation, questions asking for willingness to pay tend to elicit much lower valuations that questions asking for amounts required to give up music (Rob and Waldfogel, 2006). This is the familiar endowment effect (Knetsch and

[10] Another test of reasonableness, pursued below, is whether optimal prices charged to these valuations are close to actual prices. Of course, such a test involves the joint hypothesis of "reasonable" data and profit-maximizing pricing decisions.

Sinden, 1984). Sensitivity of results to question wording has led some researchers to be skeptical of survey responses (Diamond and Hausman, 1994). One response to this concern stems from the fact that the profit-maximizing prices implied by buy-based valuations in Rob and Waldfogel (2006) – similar to those used here – tend to be close to observed prices while those implied by sell-based valuations are far off. We find that below as well providing some assurance that the survey wording gets at the valuations relevant to the pricing decision. A second response is that here, people are valuing familiar items rather than, say, pristine Alaskan wilderness they have never seen.

Our survey approach to eliciting reservation valuations has antecedents in the marketing and operations literatures. Hanson and Martin (1990) employ direct elicitation of reservation values for an exercise reported in their study. Kalish and Nelson (1991) explore direct elicitation along with preference rating and ranking measures and find that reservation values do well in terms of fit while the other measures are superior in predicting choice on a holdout sample. Venkatesh and Mahajan (1993) survey respondents on their willingness to pay for performances of Indian music. The authors calculate revenue under component pricing, pure bundling, and mixed bundling. Jedidi, Jagpal, and Manchanda (2003) estimate an empirical model of survey respondents' reservation values of individual goods and bundles of two. While Jedidi, Jagpal, and Manchanda (2003) observe that self-stated reservation prices are subject to measurement error, especially for infrequently purchased products, the songs in our survey are familiar and commonly purchased.

Another check on whether the data are reasonable is whether the songs for which respondents frequently report high valuations are also the songs with higher sales. We cannot observe either respondent purchases or overall sales directly, but we can ask whether the songs our respondents claim a willingness to buy are also the songs selling more digital copies. The number of weeks a song has been on the "Billboard Hot Digital" chart, along with its peak single chart position, provide indirect measures of its cumulative sales.[11] A regression of the share of respondents reporting valuations of at least \$0.99 on these two sales proxies yields:

$$\underset{}{share(V > \$0.99)} = \underset{(0.052)}{0.352} + \underset{(0.0017)}{0.0033} * (chart\_weeks) - \underset{(0.0015)}{0.0044} * (chart\_peak), \text{ where}$$

chart_weeks indicates the number of weeks the song had been on the Billboard chart as of March 8, 2008; and *chart_peak* indicates the song's peak chart position. Standard errors are in parentheses, and the R-squared from this regression is 0.34. Results support the notion that the data are reasonable in some rudimentary sense: Songs on the chart longer have a higher simulated sales penetration in this sample, and songs with a lower chart peak (a higher peak rank) have higher penetration.

Table 1 reports the average valuations per song, as well as the median, 25th, and 75th percentile valuations. The most highly valued songs on the list have average valuations over \$2.00. They include "Stronger" by Kanye West, "Apologize" by Timbaland (feat. One Republic), and "The Way I Are" by Timbaland (feat. Keri Hilson & DOE). The lowest valued songs, with mean valuations below \$0.7, are those targeted at consumers younger than our college-student respondents. Examples include artists such as Alvin and the Chipmunks and Disney artists such as the Jonas Brothers and

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[11] The Billboard Chart, "Hot Digital Songs," is available at http://www.billboard.com/bbcom/charts, accessed March 14, 2008.

Miley Cyrus. The 25th percentile valuation for most songs is around $0.10, and the 75th percentile valuation is typically over $1.5.

Valuations vary substantially both within and across respondents. Figure 2 characterizes the distribution of cumulative valuations (e.g. how highly respondent values his top 10 songs, for example). This figure shows that the median valuation of (each individual's) top 10 songs among these 50 is about $20, while the 75th percentile valuation is about double that ($40), and the 25th percentile valuation is around $15. The flattening of each of these curves indicates substantial difference between the valuations of the most highly and least highly valued songs. Analyzed a different way, the valuation data indicate that the vast majority of the variation in the reported valuations arise across individuals, as opposed to songs. A regression of valuations on song fixed effects yields an R-squared of 4.4 percent. The R-squared from a regression on only individual effects is 39.5 percent, and the R-squared with both individual and song effects is 43.9 percent.

The correlations of song valuations across persons help to determine the extent to which non-uniform pricing schemes can capture additional revenue. For example, a common intuition from bundling theory is that bundling raises revenue more as products' valuations are less positively correlated. Song valuations are positively correlated. With 50 songs there are 1,225 pairwise song correlations. The mean correlation is 0.444, the median is 0.454, and the inter-quartile range runs from 0.347 to 0.546.[12] Figure 3 shows the whole distribution of pairwise correlations (using the smoothed data).

III. Results Using Different Pricing Schemes

[12] We revisit the pairwise correlations with bivariate tobits in Section V below.

This section implements various alternative pricing schemes using the empirical distribution of valuations directly. We adopt an alternative parametric approach in Section V below.

1. The Single-Price Monopoly Baseline

Figure 4 shows the empirical demand curve, treating all songs as a single good (music). The demand curve has a hyperbolic shape (although the curve based on raw data in the appendix Table 4a has noticeable "steps.") Given that marginal cost is zero, the surplus at stake in this pricing problem is the entire area under the demand curve, and it is $27,785 or about $60 per person.

We can calculate the profit-maximizing price – and breakdown of the available surplus – with a simple manipulation of the raw or smoothed data.[13] We order the valuation data from highest to lowest among the *n* (song x individual) valuations: $V_1, \ldots V_n$. Because *n* songs are sold when the price is V_n, we can calculate the revenue when we charge V_n per song as $n^* V_n$. Figure 5 shows the empirical revenue function relating $n^* V_n$ to *n* for smoothed data.

The revenue function has various local maxima, the highest of which occurs at a price of $1.87 – with 4351 songs sold – generating $8,158 in revenue (among the $27,785 available in total surplus with the smoothed valuations), or 29.4 percent of surplus. The associated consumer surplus is $11,607 (41.8 percent), and the deadweight loss is $8,020 (the remaining 28.9 percent). A $0.99 price, of interest both because it is the current

[13] Music selling has three parties: the artists, their labels, and the retailer. Currently, Apple pays a flat rate of $0.7 per song. Analysis of the retailer's pricing decision could then take the marginal cost to be $0.7. We will instead treat the problem as if the three parties acted collectively to maximize the pie that they split. To that end we treat the marginal costs as its technical value, zero.

price and because by inspection it is nearly profit-maximizing, produces somewhat less revenue ($7,364 versus $8,158) but sells substantially more songs (7,434) and generates substantially more consumer surplus ($16,317 versus $11,607) and much less deadweight loss ($4,105 versus $8,020). See Table 3.

Pricing at $0.99 rather than $1.87 sacrifices some profit (thinking narrowly of songs), but it adds a great deal more to consumer surplus than it takes away from profit. If we take our data literally, then we can say that the planner – Steve Jobs – values a $5000 increase in consumer surplus more than the loss in profit (roughly $800) effected by pricing at $0.99. Of course, this model describes the revenue from songs alone. Apple also sells a complementary good, the iPod. Lower song prices presumably raise consumers' willingness to pay for the iPod. Pricing songs at essentially $1 rather than nearly $2 generates more demand for the iPod. According to media accounts, iPod revenue was roughly four times iTunes revenue in 2007. We return to this at Section IV below when we examine Pareto-improving pricing schemes generating at least the consumer surplus achieved by current pricing.

Uniform pricing provides the pricing benchmark. There is $27,785 at stake here and in all that follows, we ask how various alternative pricing schemes divide the total possible surplus into revenue (PS), consumer surplus, and deadweight loss. Using the smoothed data, profit-maximizing uniform pricing delivers 29.4 percent of surplus as revenue, 41.8 as consumer surplus, and 28.9 as deadweight loss.[14]

[14] Optimal UP prices are reported without estimates of precision, but we can gain some insight into their precision by calculating optimal UP prices on bootstrap samples from our data. To this end, we draw 100 bootstrap samples (clustering on respondent) and recalculate calculate optimal prices. The resulting distribution of UP prices is quite tight: 90 percent of estimates are between $1.86 and $1.88.

2. Song-Specific "Component" Pricing

A conceptually simple alternative to uniform pricing across all songs is component pricing (uniform pricing within songs). It might be complicated in practice because it requires song-specific valuation information, but putting this practical complication aside, we can implement this with our data by simply calculating maximum revenue for each song as we calculated maximum revenue overall above. Table 3 reports the optimal song-specific prices based on both raw and smoothed data. With the smoothed data, the modal range is closer to $2 (see Figure 6). Songs range in price from $0.85 ("Crushcrushcrush" by Paramore) to $4.89 ("See You Again" by Miley Cyrus).

With smoothed data, song-specific pricing sells 5462 songs delivers 30.5 percent of surplus as revenue, 44.4 as consumer surplus, and 25.1 as deadweight loss. With 50 separate pricing instruments – one per song – we raise revenue by 3.8 percent relative to profit-maximizing uniform pricing. Consumer surplus goes up by 6.3 percent, and deadweight loss goes down by 13.0 percent.

2. Pure Bundling

Another simple alternative to uniform pricing is "pure bundling" (PB), in which the entire group of songs is offered, as a group, for a single price. Since Stigler (1963) and Adams and Yellen (1976), economists have understood the intuition that negative correlations in valuations allow a seller to capture more revenue by bundling products. As we have seen, sample song valuations tend to be positively correlated across individuals, although the typical correlation is around 0.5. Schmalensee (1984) shows that bundling can increase revenue even with positive correlations of valuations.[15] And as Bakos and Brynjolffson (1999) and Armstrong (1999) argue, as the number of products grows large, PB will approach perfect price discrimination as long as consumers' tastes aren't too highly correlated across products. How does pure bundling affect surpluses in our context? And how does this vary with the size of the bundles?

To calculate the optimal full (50-song) bundle price we sum the song valuations across songs within each individual to arrive at that individual's valuation of the entire bundle. We then calculate the revenue-maximizing bundle price, as we would under single price monopoly. The optimal 50-song bundle price is $36.08; and with it, 247 individuals buy the bundle, resulting in 12,350 songs sold. When we bundle all songs together, we are able to raise revenue by 9.2 percent relative to profit-maximizing uniform pricing (from 29.4 to 32.1 percent) relative to the benchmark. Consumer surplus increases by about a quarter, and deadweight loss declines over 40 percent. While pure bundling improves revenue, the resulting revenue falls far short of the perfect price discrimination revenue predicted by some theoretical models. The reason for this failure is that tastes are correlated across products, which arises, as Armstrong (1999) notes, "because of income or other systematic differences across consumers."[16]

We also explore how the effect of pure bundling on revenue varies with the size of the bundle, we calculate the maximal revenue for random song bundles, with 500 draws for each of the following bundle sizes: 2, 3, 4, 5, 10, and 25. See Table 4. Using the smoothed data, 2-song bundles *reduce* revenue by -0.1 percent on average relative to uniform pricing. Bundles of three raise revenue by 1.2 percent relative to uniform

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[15] Fang and Norman (2006) demonstrate similar results.

[16] With pure bundling we again bootstrap to determine the precision of our price estimate, and we find that 90 percent of 100 bootstrapped price estimates fall between $26.96 and $53.11.

pricing. At a bundle size of 5, pure bundling generates 3.3 percent more revenue than uniform pricing.

For larger bundles, pure bundling raises revenue more relative to uniform pricing: Ten-song bundles produce an average of 6.3 percent more revenue than bundle pricing. Twenty-five song bundles produce an average of 8.2 percent more revenue. The full 50-song bundle (there is only one such combination, so we do only one "draw") produces the 9.2 percent revenue improvement over uniform pricing that we found in Table 3. While larger bundles raise revenue, the rate of increase declines as bundle size increases. If the flattening continues, it appears that there would not be much more revenue benefit available to bundles larger than 50 (so that 50 is a "large" number, in the sense of the theory) and that much of the revenue benefit of large bundles is achieved with 10-song bundles.

3. Two-Part Tariffs

Another scheme we can explore is the two part tariff with a hookup fee (T) independent of the number of songs purchased and a per-song price (p). We have already explored two of its special cases: When p=0, this is pure bundling, and when T=0, this is uniform pricing. We explore this family of schemes as follows. Try a pair (T, p). Given the p, each individual would purchase some number of songs and would have some level of consumer surplus from the songs with valuations at or above p. If the individual's total consumer surplus exceeds T, he would pay the hookup fee, and then the revenue from that individual would equal p*(number of units purchased) + T. If T exceeds his consumer surplus, by contrast, then he would make no purchase.

Our goal is to find values of (T, p) that maximize revenue. If the revenue function were well-behaved, we could enlist hill-climbing algorithms to find the revenue-maximizing price pair. But we already have seen the suggestion – from the single-price monopoly revenue function – that the revenue surface on T and p will have many local maxima. As a result, we begin our maximization with a rather fine grid search over 41 values of $p \in \{0, 0.05, 0.1, \ldots, 2\}$ in conjunction with 801 values of $T \in \{0, 0.05, 0.1, \ldots, 40\}$. For this exercise we use only the smoothed data.

Figure 7a depicts the revenue surface from the grid search. By inspection it is not globally concave, and it is rather irregular, suggesting that search for revenue-maximizing prices might go awry.

Figure 8a shows the top 10 two part schemes for generating revenue identified by the grid search. The best combination identified by grid search is $T = 36.05$ with $p=0$. This produces slightly less revenue than the best pure bundling solution (a price of 36.08). The 10 highest-revenue two part tariffs identified by grid search are located in two regions of (T,p) space: around $T=35$ with $p<0.1$ and around $T=14$ with $p=0.9$. The top 1 percent of plans among the grid search – see Figure 8b – expand the set of bit, and the region containing top 10 percent of schemes look roughly like a fat line connecting $(T,p)=(35,0)$ with $(T,p)=(15,1)$.

Figure 7b illustrates the revenue surface in the neighborhood of most of the top values identified by grid search, and it shows the irregularity of the function being maximized. Given this irregularity, we use the top 10 grid search prices as starting values for searches using the Nelder-Meade simplex ("amoeba") algorithm. The best scheme thus identified is T=\$35.55, p=0.01. The top revenue available with a two part tariff on the smoothed data generates 9.5 percent more revenue than uniform pricing, and it generates nearly a quarter more consumer surplus. Interestingly, the best two-part tariff identified is very similar to the pure bundling scheme (*T*=\$36.08, *p*=0).

We explored the precision of the two-part tariff estimates by bootstrap sampling, clustered on participants, then recalculating the optimal tariff. Because each search is slow, we used a coarser grid for the resampling: $p \in \{0, 0.25, \ldots, 2\}$, $T \in \{0, 1, \ldots, 40\}$. The modal optimal tariff is *T*=36, *p*=0, which was best in 27 of 100 iterations. The median *T* and *p* are 30 and 0, respectively. Figure 7c represents the joint distribution of *T* and *p* from the re-sampling. Dot sizes are proportional to the frequency of the pair.

4. Nonlinear Bundle Pricing

Two part tariffs are a special case of more general nonlinear prices that vary with the number of units purchased, what Chu, Leslie, and Sorenson (2007) call, "bundle size pricing." As outlined in Wilson (1993), calculating a nonlinear tariff is straightforward in principle. Provided that the tariff crosses each individual's demand curve only one, from below, the nonlinear tariff can be calculated as a sequence of optimal prices, for the first, second, and n^{th} units, in this case for *n* up to 50. When we perform this exercise with our data, however, the resulting tariff has some problems. First, the optimal prices do not decline monotonically. Second, and more important, the number of buyers of successive numbers of units does not decline monotonically. Indeed, the number of persons buying, say, the 3^{rd} unit exceeds the numbers of buyers of the first unit. Single crossing does not hold, and as a result, the simple method cannot be employed for calculating the nonlinear tariff in this context.

Without a workable simple algorithm for determining the exact tariff, we are left with some other alternatives for computing an approximate nonlinear tariff, including a simple parameterization of the tariff and grid search. We deal with these in turn.

Prices must be non-increasing in the number of songs purchased, and prices must be positive. This suggests some restrictions. If t is an index for a song's position in the sequence, then a simple parameterization is $p(t) = \alpha * e^{\beta t}$, where $\alpha > 0$, $\beta < 0$. We perform a grid search over $\alpha \in \{0.25, 0.5, 0.75, \ldots, 100\}$, $\beta \in \{-2, -1.95, \ldots, 0\}$ to find the revenue-maximizing tariff in this family. The parameters that maximize revenue in this family are $\alpha = 40.25$, $\beta = -0.75$, and the associated tariff is illustrated in a budget constraint in Figure 9. The prices of the first ten songs are, in order: \$19.01, \$8.98, \$4.24, \$2.00, \$0.95, \$0.45, \$0.21, \$0.10, \$0.05, \$0.02. This tariff gives rise to \$8,919 in revenue, \$14,354 in consumer surplus, and \$4,511 in deadweight loss. That is, this approach does slightly better than pure bundling and not quite as well as the two part tariff.[17]

Our second approach is grid search. We have 50 different size bundles, each of which could in principle have its own price. If we started with a grid of 10 cent increments between 0 and \$10 per song, we would have 100^{50} combinations to check. Even with a fast computer this is impossible, but we can make grid search manageable with an admittedly arbitrary partition 50 songs into a nonlinear tariff with, say, 5 regions. We can employ a grid search over 5-dimensional price space.

The question is whether allowing more segments on the price schedule (beyond the two segments implicit in the two part tariff) give rise to substantial increases in revenue. From Figure 2 we have evidence that the individual indifference curves flatten

[17] It seems possible in principle to choose a high positive value of α and a large negative β to target any hookup fee for the first-unit price while approaching a zero unit price for all subsequent units.

quickly after the first few songs. So we begin with the following partition: a price p_1 for the first song, a second price p_2 for the songs 2 and 3, p_3 for songs 4 and 5, p_4 for songs 6-10, and p_5 for songs 11-40. We search $p_1 \in \{0,1,\ldots 40\}$, p_2 and $p_3 \in \{0,0.25,\ldots 5\}$, $p_4 \in \{0,0.25,\ldots,0.5\}$, and $p_5 \in \{0,0.25\}$. When we search among all possible combinations on the smoothed data, 118 pricing schemes are tied for the highest revenue ($8,892). These schemes include the scheme (36,0,0,0,0). In fact, all of the schemes share the two features. First, all have zero p_4 and p_5. Second, all share the feature that the purchase of all 50 songs costs $36. Because all schemes produce the same revenue, consumers all choose all 50 songs under each. Because the search is coarse, the best revenue identified falls short of the best revenue identified with finer searches among pure bundling and two part tariff schemes. Two things are interesting. First, a scheme that amounts to pure bundling, albeit among the coarse set of schemes in the grid, achieves the maximum revenue. In other words, it appears that simple one and two price schemes achieve the vast majority of what more complex 5-part schemes can achieve in this context. Second, a search among schemes unconstrained by the exponential parametric family produce results pretty similar to the two-parameter nonlinear schedule.

5. Comparing Mixed Bundling with Alternatives

One of the goals of this paper is to determine what share of the area under the demand curve can be appropriated as revenue with sophisticated pricing. Each of the schemes we have considered so far is a special case of mixed bundling (MB), which is known to produce the most revenue. To see how much revenue can be obtained, we need to explore mixed bundling. We do this in two parts. We first explore general mixed bundling (with 2^n-1 prices) for small bundles and using coarse grids for search. We then explore a practical specific form of mixed bundling: selling with a bundle price alongside a uniform à la carte price.

A Simple Implementation of General Mixed Bundling

Because of the large number of bundles, mixed bundling is difficult to implement with 50 products. The problem is made harder in our context by the irregularity of the revenue function, necessitating cumbersome grid search. For this reason, we examine the simpler problem of finding optimal mixed bundling pricing schemes for a much smaller set of products, 3. Even with 3 products, there are 7 bundle prices. To keep the problem manageable, we search over the following grids among prices between 0 and 3 in increments of 0.25 for one song bundles, between 0 and 6 for two song bundles, and between 0 and 9 for three song bundles. We use smoothed data to avoid the clustering at numbers like 0.99.

In the course of searching for the best mixed bundling schemes, we also find the best UP, CP, PB, 2-part, and BSP schemes on this coarse grid. This allows us to compare the performance of MB with all other schemes. Because each other scheme is special case of MB, we expect MB to provide the most revenue.

We want systematic insight into the relative performance of each of the pricing schemes, so we need to perform the 3-song analysis repeatedly, on different randomly selected groups of three songs. For example the first search included the songs "See You Again" by Miley Cyrus (song 1), "Don't Stop the Music" by Rihanna (2), and "Paralyzer" by Finger Eleven (3). The total surplus available with these songs is $1473.8. Table 5 reports results. The best uniform price is $1.00, and it delivers $395 as revenue, $848 as CS, and $231 as deadweight loss. Under component pricing, the best price for songs 1 and 3 is $1, and the best price for song 2 is $1.75. CP raises revenue 2 percent above its UP level. Pure bundling – at a PB price of $3.75 – delivers 3 percent more revenue than UP. A two-part tariff – with *T*=$1.25 and songs priced at $0.50 – delivers 6 percent more revenue than UP. BSP – at $2 for any one or two songs and $2.75 for any three – delivers 9 percent more revenue than UP. Finally, MB – with song 1 priced at $2, song 2 at $1.75, song 3 at $1.5, songs 1 and 2 at 2.75, songs 1 and 3 at 2, songs 2 and 3 at 2.25, and all three at 3 – generates 11 percent more revenue than UP.

These results may be specific to the three songs randomly chosen, so we repeat the analysis 10 times, and Table 6 reports average results. On average, MB beats UP by 8 percent. In order: BSP beats UP by 6 percent, 2-part and PB beat uniform pricing by 5 percent, and CP beats uniform pricing by 3 percent. BSP achieves roughly three quarters of the improvement that MB achieves over UP, and 2-part pricing and PB achieve nearly two thirds of the improvement of MB.

The glass is both half empty and half full. MB achieves more relative to UP than the next-best schemes, a third greater improvement than BSP and a 60 percent larger improvement than either PB or the two part tariff. But even with mixed bundling, revenue's share of surplus reaches an average of only 30.6 percent of surplus across the 10 song groups in Table 6 (compared with 28.4 percent for profit-maximizing uniform pricing).

Bundling alongside à la Carte Sales

We have analyzed pure bundling as though the à la carte option ceased to exist. It seems entirely possible that bundling, if pursued, would be added alongside existing à la carte sales. This possibility suggests a number of alternative pricing schemes to explore that constitute simple versions of mixed bundling. Consider a family of two parameter pricing schemes where p_A is the uniform à la carte price and p_B is the bundle price.

One question is, what unconstrained combination of $\{p_A, p_B\}$ maximizes revenue? A second question is, what p_B maximizes revenue, given that p_A is constrained to some value, such as its current value of $0.99.

The question of the best bundle price to complement an existing à la carte scheme is interesting in contrast to the question surrounding current policy debates concerning cable television.[18] Bundling is the default in that circumstance, and various constituencies are advocating à la carte pricing as a complement. Of course, the optimal values of p_A and p_B are related, so it may be difficult to change one without affecting the other.

As Table 7 indicates, when p_A and p_B are unconstrained, the revenue-maximizing combination is a bundle price of $36.05 with a single song price of $20. Bundle sales are the same as under pure bundling, and only a single song is sold à la carte. Revenue is almost identical to the pure bundling without à la carte sales case. The differences arise, first, because the unconstrained problem was solved with a 5-cent-increment search and, second, because in the unconstrained case, one person purchases a single song rather than the bundle while 247 people buy the bundle, same as with pure bundling. The $20 à la carte price arises because we top-coded valuations at $20. Given the prices are chosen to

[18] See, for example, Crawford and Cullen (2007).

maximize revenue, the introduction of an à la carte option does not bring about a low à la carte price.

Our second exercise is the determination of an optimal bundle price when the à la carte price is constrained to its current level of \$0.99. Given this constraint, the best bundle price is \$34.11, and 104 people buy the bundle, while 4114 songs are sold à la carte. Selling only à la carte at \$0.99 generates \$7364 in revenue, while unconstrained pricing (in the $\{p_A, p_B\}$ family) produces \$8924 in revenue. Maintaining the à la carte price at \$0.99 significantly handicaps the ability for bundling to raise revenue.

6. Third Degree Price Discrimination

One class of pricing schemes we have not yet explored is schemes that treat people differently according to exogenous characteristics (as opposed to endogenous behavior of how many songs to buy, given the schedule). Examples of these could, in principle, include price discrimination by race, gender, geography, or income. It should be noted that many such forms of price discrimination are both illegal and, at times, morally questionable. Our exploration of this class of pricing schemes is merely aimed at determining what classes of pricing schemes could, in principle, fulfill non-uniform pricing's promise of making surplus appropriable.

Before proceeding further it makes sense to note that the vast majority of the variation in valuations occurs between individuals as opposed to between products (within individuals). This suggests that schemes that can divide consumers according to their valuations will be able to extract more of their valuations as producer surplus.

A conceptually simple scheme is person-specific pricing. Third-degree pricing schemes – price discriminating by type of person – are special cases, so this will give an upper bound on the effect of such schemes on the distribution of surplus. To calculate the person-specific profit-maximizing price, we create person-specific demand curves, ordering their valuations from highest to lowest. We then find the maximum revenue. The valuation associated with maximal revenue for each person is the person-specific revenue-maximizing price.

The profit-maximizing person-specific prices on smoothed has a median of $1.30. See Figure 10. Revenue with person-specific pricing is $14,532 or 52 percent of total surplus (see Table 8). This is substantially more than the revenue with the other pricing schemes. Consumer surplus is substantially lower with this scheme (less than a quarter of surplus, compared with about half under the other schemes), and deadweight loss declines a tenth. The maximally discriminatory scheme has a large positive effect on producer surplus and negative effects on consumer surplus. Because the benefit to sellers exceeds the harm to buyers, deadweight loss declines.

Person-specific pricing may be difficult to implement if it's hard to know each individual's demand curve *a priori*. This raises the question of what revenue improvement third degree price discrimination schemes based on observable characteristics can achieve. To this end we explore schemes based on the scant observables in our data: gender, ethnicity, whether a respondent is a resident alien, and age (whether under 20). See Table 8. Using smoothed data, the increases are 3.9 percent and 0, respectively. Despite the large revenue enhancing effects of individually customized uniform prices, forms of third degree price discrimination that might more feasibly be implement produce only negligible revenue improvements.

IV. Pareto Improving Pricing Schemes

Within each family of prices (e.g. single price uniform pricing or two part tariffs), each particular scheme gives rise to particular values of consumer and producer surplus. For example, when p=0 under uniform pricing, then the entire surplus is distributed to consumers. By contrast, as p rises, producer surplus rises (to a point) and consumer surplus falls. Figure 11 depicts, in PS-CS space, the surpluses resulting from the entire family of uniform prices from the grid: {0, 0.01, …, 4.99}. The figure includes vertical lines at the consumer surplus associated with current pricing schemes. It's clear in this picture that song pricing at $0.99 forgoes some profit.

It's clear that various different schemes can produce more revenue than current uniform pricing. But the decision to price uniformly at $0.99 may reflect a conscious strategy to deliver high consumer surplus from music, for example in order to maintain demand for complementary hardware. By some estimates Apple's iPod revenue in fiscal 2006 was $8.2 billion, over four times its iTunes revenue.[19] That one can get more revenue from alternative song pricing schemes does not demonstrate a superior alternative to uniform pricing at $0.99. Superiority requires accomplishing the objective achieved by the uniform $0.99 pricing, then delivering additional benefit.

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[19] See Dan Frommer, "Apple's iPod Growth Curve: More, Cheaper iPods." Silicon Valley Insider, February 22, 2008, at http://www.alleyinsider.com/2008/2/apples_ipod_growth_curve_more_cheaper_ipods, accessed March 14, 2008.

One approach to this question is to examine all pricing schemes that deliver at least the level of consumer surplus delivered by current uniform pricing. For this exploration, we examine the two part tariffs. Specifically, we examine the (*T, p*) combinations delivering *at least* the level of consumer surplus delivered by uniform pricing at $0.99 ($16,317 using the smoothed data). Among these schemes, do any deliver more revenue than uniform $0.99 pricing? Figures 12a and 12b provide some insight into this using the smoothed data. There are numerous Pareto-improving (*T, p*) combinations, delivering more of both consumer *and producer* surplus than current pricing allows. Figure 12a shows schemes that deliver over $8,500 in revenue (compared with the $7,364 produced by uniform $0.99 pricing) while delivering more consumer surplus than the $16,317 produced with uniform $0.99 pricing. Figure 12b depicts the Pareto-improving plans in (*T,p*) space, and they lie roughly on a line between *T*=$25 when *p*=$0 and *T*=$0 when *p*=$0.95. Using the smoothed data, there are two-part schemes delivering over 10 percent more than the revenue under current pricing while also delivering as much consumer surplus as current pricing allows. These results suggest that alternative pricing schemes could raise revenue while delivering current levels of consumer surplus.

V. Parametric Demand

In order to implement pricing schemes we need a characterization of the distribution of reservation prices across persons and products. Given the nature of our data – based on direct elicitation of each person's valuation of each product – one approach is obvious: use the observed valuation responses directly (perhaps with some smoothing to deal with the bunching of observations at multiples of $0.25). The major shortcoming of this approach is the irregularity of the resulting revenue functions and surfaces, which make it hard to efficiently identify revenue-maximizing solutions.

An alternative that allows for smoother revenue functions is to fit the valuation data to a parametric family, such as the multivariate normal. This is likely to give rise to revenue functions that smoother in their prices and which, as a result, should be easier to efficiently search to revenue-maximizing solutions.

To this end we fit our data to a 50-variate normal distribution, via the following steps. First, we estimate the mean and standard deviation of each song's valuation distribution using 50 separate univariate tobit models (because so many of the observations are clustered at zero). We also require an estimate of the 1225 correlations across songs (50*49/2=1225). We obtain each of these correlations from 1225 bivariate tobits, using two songs at a time.

We then have a full characterization of the joint distribution of valuations, which we simulate for 2000 hypothetical individuals (and their valuations of each of the 50 songs). We recode negative valuations as zero; because individuals can freely dispose of any songs, additional songs do not reduce the value of a bundle.

Given the simulated valuations we can readily calculate profit-maximizing prices as well as the distribution of surplus among consumers, producers, and deadweight loss, for various schemes. Table 9 reports results.

The optimal UP price is $2.14, about 15 percent above its value in Table 3 (based on smoothed data). This price delivers 41.7 percent of surplus as revenue (compared with 29.4 percent in Table 3). Song-specific (CP) pricing raises revenue by 6.9 percent relative to UP, almost double its benefit (3.8 percent) above. Pure bundling maximizes revenue with a bundle price of \$66.35, over twice its value from the nonparametric approach on smooth data. Pure bundling raises revenue by 3.9 percent above UP revenue (compared with its 9.2 percent improvement above).

Even with parametric demand, the revenue surface is not sufficiently well-behaved to be maximized reliably by direct application of amoeba. Instead, we begin with a coarse grid: $T \in \{0,1,\ldots,80\}$, $p \in \{0,0.25,\ldots,3\}$. The best scheme identified in the grid search is *T*=\$21, *p*=\$1.25, which produces a 14.1 percent revenue improvement relative to UP. Using the top 10 grid search solutions as starting values for ameoba, we can do slightly better: *T*=\$18.36, *p*=\$1.43, which raises revenue by 15.0 percent relative to UP.

The differences between the optimal prices identified using the parametric and nonparametric approaches are substantial, and these differences raises a question of which approach is more reliable. The benefits of the parametric approach are smoothness and parsimony. But these benefits come at a cost that is larger as the data's fit with the normality assumption is poorer. Figure 13 compares the underlying distribution of (smoothed) valuations with a normal distribution fit to these data. The data appear not to be normal, which explains why the optimal prices for the parametric and nonparametric approaches differ.

Conclusion

Using survey data on individuals' valuations of 50 popular songs, we are able to directly calculate the revenue – and overall division of surplus – from various pricing schemes. We have two major results, one positive and one negative.

First, various alternative schemes – including simple schemes such as pure bundling and two-part tariffs – can raise both producer and consumer surplus. Revenue could be raised by nearly ten percent relative to profit-maximizing uniform pricing and by over a fifth relative to current $0.99 uniform pricing. Moreover, revenue could be increased by a tenth while maintaining consumer surplus at the high level accompanying $0.99 uniform song pricing.

Uniform pricing delivers about 30 percent of surplus as revenue, and while various alternative pricing schemes can raise revenue substantially, none of the self-selecting schemes raise revenue's share of surplus above 35 percent. And while individual specific pricing – an extreme form of third degree price discrimination – raises revenue by about 75 percent, third degree price discrimination based on available observable criteria raises revenue only a few percent. Hence, results based on these data indicate that even with sophisticated pricing, much of the area under the demand curve is beyond the reach of appropriation by sellers. For products with substantial fixed costs, this leaves open the possibility of inefficient under-provision.

We are aware that this analysis covers a particular product and a small and potentially unrepresentative sample of consumers. Further study with other samples and other products can help clarify our understanding of both pricing strategy and surplus appropriation in product markets.

Table 1: Survey Songs and their Valuations

Song name	mean	25th pctile	median	75th pctile
Apologize (feat. OneRepublic) - Timbaland	$2.37	$0.59	$1.39	$2.67
Big Girls Don't Cry (Personal) - Fergie	$1.16	$0.08	$0.53	$1.22
Bubbly - Colbie Caillat	$1.47	$0.08	$0.68	$1.73
Clumsy - Fergie	$0.78	$0.04	$0.29	$1.01
Crank That (Soulja Boy) - Soulja Boy Tell 'Em	$2.00	$0.28	$1.01	$2.10
Crushcrushcrush - Paramore	$0.58	$0.01	$0.13	$0.71
Cyclone (feat. T-Pain) - Baby Bash	$1.29	$0.08	$0.56	$1.45
Don't Stop the Music - Rihanna	$1.40	$0.11	$0.63	$1.44
Feedback - Janet	$0.63	$0.01	$0.11	$0.57
Hate That I Love You (feat. Ne-Yo) - Rihanna	$1.30	$0.10	$0.55	$1.47
Hero/Heroine (Tom Lord-Alge Mix) - Boys Like Girls	$0.77	$0.02	$0.26	$1.00
Hey There Delilah - Plain White T's	$2.02	$0.15	$0.94	$2.02
How Far We've Come - Matchbox Twenty	$1.41	$0.10	$0.69	$1.47
Hypnotized (feat. Akon) - Plies	$1.15	$0.06	$0.48	$1.12
I Don't Wanna Be In Love (Dance Floor Anthem) - Good Charlotte	$1.06	$0.06	$0.47	$1.20
Into the Night (feat. Chad Kroeger) - Santana	$1.49	$0.09	$0.71	$1.53
Kiss Kiss (feat. T-Pain) - Chris Brown	$1.45	$0.12	$0.85	$1.70
Love Like This - Natasha Bedingfield	$1.04	$0.06	$0.43	$1.06
Love Song - Sara Bareilles	$1.02	$0.05	$0.37	$1.07
Low (feat. T-Pain) - Flo Rida	$1.60	$0.11	$0.88	$1.93
Misery Business - Paramore	$0.69	$0.01	$0.17	$0.90
No One - Alicia Keys	$1.59	$0.13	$0.83	$1.86
Our Song - Taylor Swift	$0.81	$0.01	$0.12	$0.80
Over You - Daughtry	$1.22	$0.05	$0.47	$1.12
Paralyzer - Finger Eleven	$1.11	$0.03	$0.34	$1.17
Piece of Me - Britney Spears	$0.77	$0.01	$0.11	$0.85
Ready, Set, Don't Go - Billy Ray Cyrus feat. Miley Cyrus	$0.59	$0.00	$0.09	$0.58
Rockstar - Nickelback	$1.39	$0.06	$0.50	$1.47
S.O.S. - Jonas Brothers	$0.68	$0.01	$0.15	$0.76
See You Again - Miley Cyrus	$0.68	$0.00	$0.09	$0.59
Sensual Seduction (Edited) - Snoop Dogg	$1.18	$0.04	$0.29	$1.07
Shadow of the Day - Linkin Park	$1.24	$0.07	$0.52	$1.23
Sorry - Buckcherry	$0.64	$0.00	$0.13	$0.76
Start All Over - Miley Cyrus	$0.47	$0.00	$0.08	$0.32
Stay - Sugarland	$0.64	$0.00	$0.10	$0.59
Stop and Stare - OneRepublic	$1.05	$0.07	$0.44	$1.10
Stronger - Kanye West	$2.79	$0.87	$1.74	$3.04
Sweetest Girl (Dollar Bill) [feat. Akon, Lil Wayne & Niia] - Wyclef Jean	$1.79	$0.14	$0.88	$1.98
Take You There - Sean Kingston	$1.37	$0.13	$0.78	$1.58
Tattoo - Jordin Sparks	$0.94	$0.04	$0.39	$1.00
Teardrops On My Guitar - Taylor Swift	$0.92	$0.01	$0.17	$0.93
The Great Escape - Boys Like Girls	$1.11	$0.05	$0.44	$1.25
The Way I Am - Ingrid Michaelson	$0.91	$0.02	$0.26	$0.97
The Way I Are (feat. Keri Hilson & D.O.E.) - Timbaland	$2.24	$0.42	$1.13	$2.61
Through the Fire and Flames - Dragonforce	$0.73	$0.00	$0.11	$0.90
Wake Up Call - Maroon 5	$1.55	$0.17	$0.87	$1.92
When You Were Young - The Killers	$1.61	$0.17	$0.90	$1.98

Witch Doctor - Alvin and the Chipmunks	$0.69	$0.00	$0.08	$0.43
With You - Chris Brown	$1.34	$0.08	$0.49	$1.14
Won't Go Home Without You - Maroon 5	$1.43	$0.17	$0.86	$1.57

Notes: The list is the top 50 songs on iTunes January 11, 2008. Respondents indicated their maximum willingness to pay for each song from its hypothetical sole authorized source. These data are smoothed. An error, uniform on [-.125,.125] is added to each reported valuation. Resulting valuations below zero are re-coded as 0. Finally, valuations are top-coded at $20.

Table 2: Song-Specific Revenue Maximizing Prices

song	*Price (smoothed Data)*	*Price (raw data)*
Apologize (feat. OneRepublic) - Timbaland	$1.88	$1.98
Big Girls Don't Cry (Personal) - Fergie	$1.84	$0.99
Bubbly - Colbie Caillat	$1.72	$1.50
Clumsy - Fergie	$0.90	$0.99
Crank That (Soulja Boy) - Soulja Boy Tell 'Em	$1.88	$1.99
Crushcrushcrush - Paramore	$0.85	$0.99
Cyclone (feat. T-Pain) - Baby Bash	$1.93	$0.99
Don't Stop the Music - Rihanna	$2.88	$0.99
Feedback - Janet	$1.90	$1.99
Hate That I Love You (feat. Ne-Yo) - Rihanna	$1.82	$2.00
Hero/Heroine (Tom Lord-Alge Mix) - Boys Like Girls	$0.93	$0.99
Hey There Delilah - Plain White T's	$4.88	$5.00
How Far We've Come - Matchbox Twenty	$0.88	$1.00
Hypnotized (feat. Akon) - Plies	$0.88	$0.99
I Don't Wanna Be In Love (Dance Floor Anthem) - Good Charlotte	$0.87	$0.99
Into the Night (feat. Chad Kroeger) - Santana	$2.86	$0.99
Kiss Kiss (feat. T-Pain) - Chris Brown	$1.83	$0.99
Love Like This - Natasha Bedingfield	$1.88	$1.99
Love Song - Sara Bareilles	$0.88	$0.99
Low (feat. T-Pain) - Flo Rida	$1.86	$2.00
Misery Business - Paramore	$0.86	$0.99
No One - Alicia Keys	$1.86	$2.00
Our Song - Taylor Swift	$1.94	$1.99
Over You - Daughtry	$2.83	$0.99
Paralyzer - Finger Eleven	$0.96	$0.99
Piece of Me - Britney Spears	$1.85	$0.99
Ready, Set, Don't Go - Billy Ray Cyrus feat. Miley Cyrus	$0.78	$0.99
Rockstar - Nickelback	$1.92	$1.99
S.O.S. - Jonas Brothers	$0.89	$0.99
See You Again - Miley Cyrus	$4.89	$0.98
Sensual Seduction (Edited) - Snoop Dogg	$1.84	$2.00
Shadow of the Day - Linkin Park	$0.83	$0.99
Sorry - Buckcherry	$0.90	$1.00
Start All Over - Miley Cyrus	$0.88	$0.99
Stay - Sugarland	$0.93	$0.99
Stop and Stare - OneRepublic	$0.88	$0.99
Stronger - Kanye West	$1.88	$2.00
Sweetest Girl (Dollar Bill) [feat. Akon, Lil Wayne & Niia] - Wyclef Jean	$1.87	$1.99
Take You There - Sean Kingston	$1.88	$0.99
Tattoo - Jordin Sparks	$1.88	$0.99
Teardrops On My Guitar - Taylor Swift	$1.93	$0.99
The Great Escape - Boys Like Girls	$1.88	$2.00
The Way I Am - Ingrid Michaelson	$1.90	$2.00
The Way I Are (feat. Keri Hilson & D.O.E.) - Timbaland	$1.86	$1.99
Through the Fire and Flames - Dragonforce	$2.90	$0.99
Wake Up Call - Maroon 5	$1.87	$1.99

When You Were Young - The Killers	$1.88	$1.99
Witch Doctor - Alvin and the Chipmunks	$2.93	$3.00
With You - Chris Brown	$1.74	$0.99
Won't Go Home Without You - Maroon 5	$1.87	$0.99

Table 3: Division of the Surplus under Various Revenue Maximizing Pricing Schemes (Smoothed Data)

	Dollars			*Shares of Total Surplus*			*Relative to Uniform Monopoly*		
	PS	CS	DWL	PS	CS	DWL	PS	CS	DWL
Single Price Monopoly, p=$1.87	8158	11607	8020	29.4%	41.8%	28.9%	0.0%	0.0%	0.0%
Single Price Monopoly, p=$0.99	7364	16317	4105	26.5%	58.7%	14.8%	-9.7%	40.6%	-48.8%
Song-Specific Monopoly	8471	12336	6978	30.5%	44.4%	25.1%	3.8%	6.3%	-13.0%
Pure Bundling [20]	8911	14343	4532	32.1%	51.6%	16.3%	9.2%	23.6%	-43.5%
Two Part Tariff [21]	8931	14358	4497	32.2%	51.7%	16.2%	9.5%	23.7%	-43.9%
Nonlinear exponential[22]	8919	14354	4511	32.1%	51.7%	16.2%	9.3%	23.7%	-43.8%

Valuation data smoothed by adding uniform $\varepsilon \in [-0.125, 0.125]$.

[20] Bundle price = $36.08.
[21] Hookup fee = $35.55, per-unit price = 0.01.
[22] Price of the t^{th} song is governed by the two-parameter exponential function $p(t)=\alpha e^{\beta t}$.

Table 4: Pure Bundling Relative to Uniform Pricing as Bundle Size Increases

	Uniform Pricing			*Pure Bundling*			
# Products in Bundle	Revenue	Quantity of songs	Price per song	Revenue	Revenue relative to UP	Quantity of songs	Average Price per song
2	327.3	223.3	1.58	326.8	-0.1%	7285	1.19
3	493.3	321.4	1.63	499.2	1.2%	8400	1.03
4	641.3	409.5	1.66	657.6	2.6%	8995	0.94
5	796.3	492.4	1.70	822.8	3.3%	9505	0.89
10	1632.9	941.0	1.79	1733.7	6.2%	10905	0.81
25	4073.8	2174.7	1.87	4408.1	8.2%	11765	0.76
50	8158.5	4351.0	1.88	8911.3	9.2%	12350	0.72

Notes: each revenue, quantity, price triple results from 500 randomly selected bundles of the number of products listed in the first column, for the pricing approach listed in the first row (except for last row, which is based on the single possible bundle of 50 songs). Calculations based on the smoothed data. Comparisons to UP refer to profit-maximizing UP, not $0.99 UP.

Table 5: Selling Three Songs by Various Schemes

	PS		CS		DWL	
Type	Actual	Rel to UP	Actual	Rel to UP	Actual	Rel to UP
Uniform pricing	395.0	1.00	848.3	1.00	230.5	1.00
Component Pricing	403.8	1.02	758.5	0.89	311.6	1.35
Pure Bundling	408.8	1.03	604.8	0.71	460.3	2.00
Two Part	420.3	1.06	782.2	0.92	271.3	1.18
Bundle Size Pricing	429.3	1.09	800.8	0.94	243.8	1.06
Mixed Bundling	437.3	1.11	768.4	0.91	268.1	1.16

Note: Maximal revenue for each pricing scheme from coarse grid search: among prices between 0 and 3 in increments of 0.25 for one-song bundles, between 0 and 6 for two song bundles, and between 0 and 9 for three song bundles. The three songs are: See You Again by Miley Cyrus, Don't Stop the Music by Rihanna, and Paralyzer by Finger Eleven.

Table 6: Average Performance of Various Pricing Schemes

	PS		*CS*		*DWL*		
Type	Actual	Standardized	Actual	Standardized	Actual	Standardized	q
Uniform pricing	538.0	1.00	914.3	1.00	439.9	1.00	349.8
Component Pricing	552.8	1.03	924.1	1.01	415.4	0.94	380.8
Pure Bundling	562.3	1.05	940.9	1.03	389.1	0.88	537.0
Two Part	567.1	1.05	973.5	1.06	351.6	0.80	481.0
Bundle Size Pricing	571.3	1.06	982.6	1.07	338.3	0.77	544.8
Mixed Bundling	579.7	1.08	966.3	1.06	346.3	0.79	499.5

Note: averages from 10 separate groups of three songs.

Table 7: Bundling with and without à la Carte Sales

	à la carte		bundle				
	price	quantity	price	quantity	PS	CS	DWL
p_A=0.99, no bundle	$0.99	7438	NA	NA	7364	16317	4105
Bundle only	NA	NA	$36.08	247	8911	14343	4532
p_A=0.99, bundle	$0.99	4114	$34.11	104	7620	16966	3199
Unconstrained	$20	1	$36.05	247	8924	14349	4512

Table 8: Third Degree Price Discrimination

Smooth Data[23]	Dollars			Relative to Uniform Monopoly		
	PS	CS	DWL	PS	CS	DWL
gender	8159	11621	8005	0.01%	0.12%	-0.19%
ethnicity	8474	12852	6459	3.87%	10.73%	-19.46%
resident alien	8162	11611	8013	0.05%	0.03%	-0.09%
age	8160	11610	8016	0.02%	0.03%	-0.05%
person-specific	14532	6150	7104	78.13%	-47.01%	-11.42%

[23] PS-maximizing prices with smoothed data: (male, female)=(1.87, 1.88); (American Indian/Alaskan,Black Non-Hispanic,White Non-Hispanic,Other,Asian,Hispanic)=(2.89,4.88,0.87,0.59,1.88,1.85); (alien, non-alien)=(1.88,1.87); (under 20, 20 and up)=(1.87,1.88).

Table 9: Pricing Results based on Multivariate Normal Distribution of Reservation Prices

	unit price	Hookup fee	*Share of Surplus* PS	CS	DWL	*Relative to Uniform Pricing* PS	CS	DWL
Uniform Pricing	$2.14	Na	41.7%	35.8%	22.5%	0.0%	0.0%	0.0%
UP (99)	$0.99	Na	21.7%	72.5%	5.8%	-53.8%	80.0%	-77.0%
CP	$2.22	Na	44.6%	31.8%	23.6%	6.9%	-11.2%	5.1%
PB	Na	$66.35	43.3%	34.0%	22.6%	3.9%	-5.0%	0.8%
Two Part Tariff								
grid	$1.25	$21.00	47.8%	34.7%	17.5%	14.6%	-3.2%	-22.0%
amoeba	$1.43	$18.36	48.0%	32.7%	19.3%	15.0%	-8.7%	-13.9%

Notes: Respondent valuation data are fitted to a 50-variate normal, which is then simulated (for 2000 observations on 50 songs). We calculate revenue-maximizing prices for the simulated data. We calculate exact values for UP, CP, and PB. Two-part tariffs are explored using a grid search described in the text. We then search from the 10 best grid search solutions using amoeba.

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Figure 1a: Distribution of Raw Valuations on [0,2]

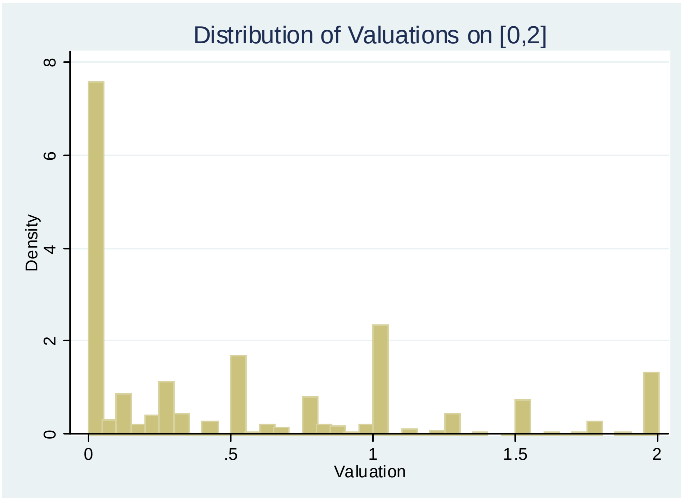


Figure 1b: Distribution of Smoothed Valuations on [0,2]

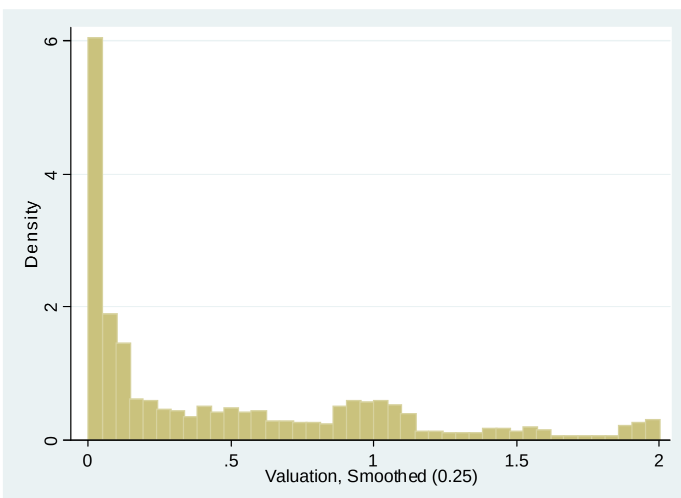


Figure 2: Valuations across Individuals and Quantities of Music

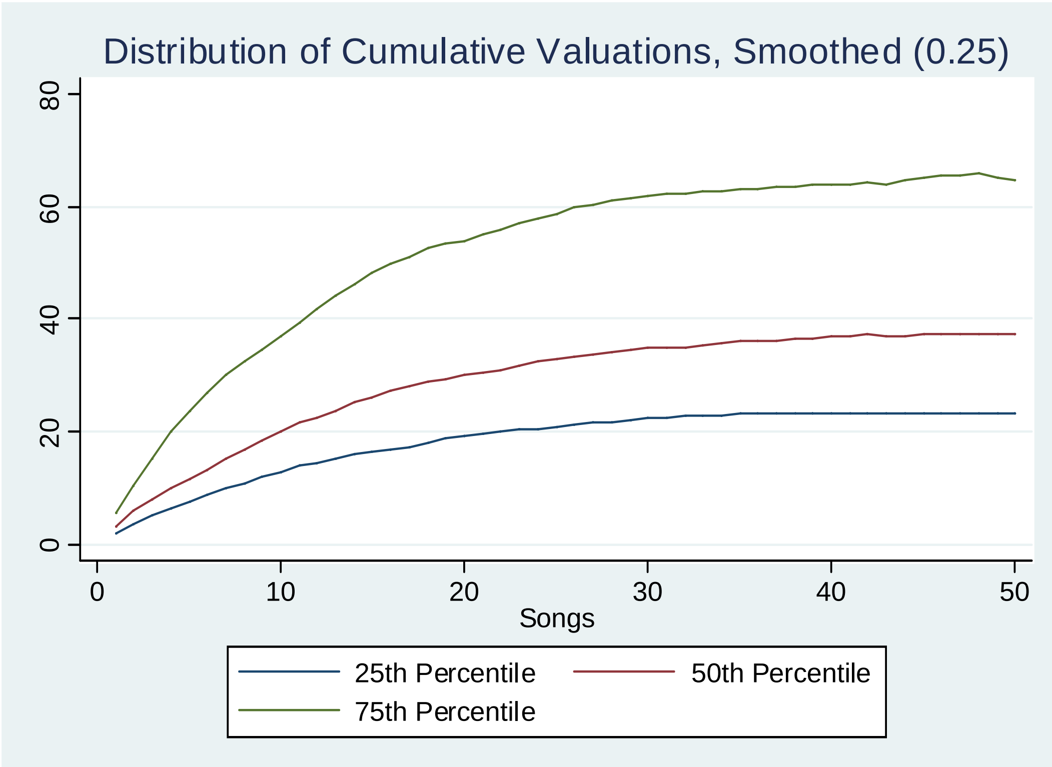


Figure 3: Pairwise Correlations of Song Valuations

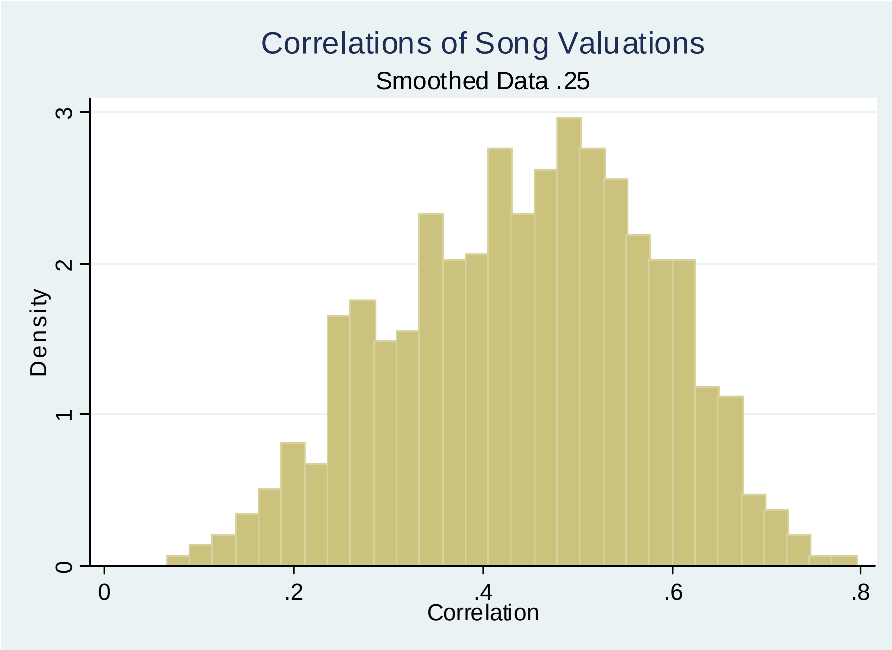


Figure 4: Overall Demand Curve, Smoothed Data

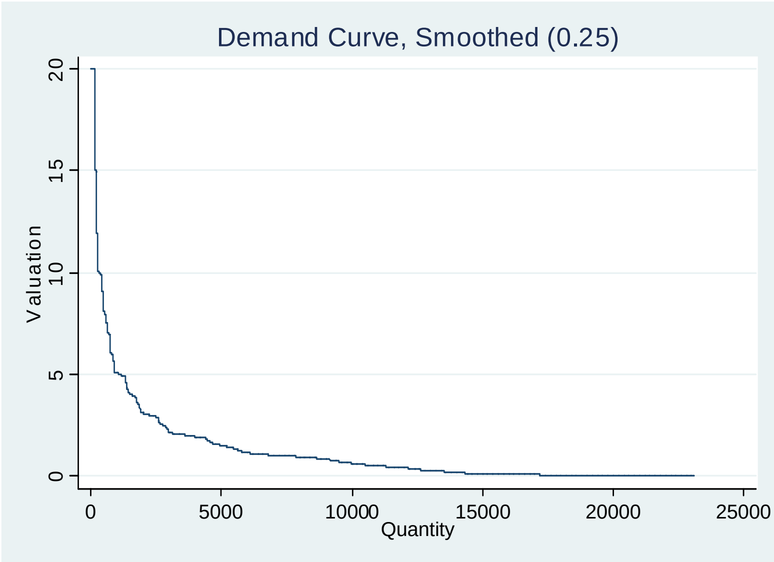


Figure 5: Single Price Revenue Function on Smoothed Data

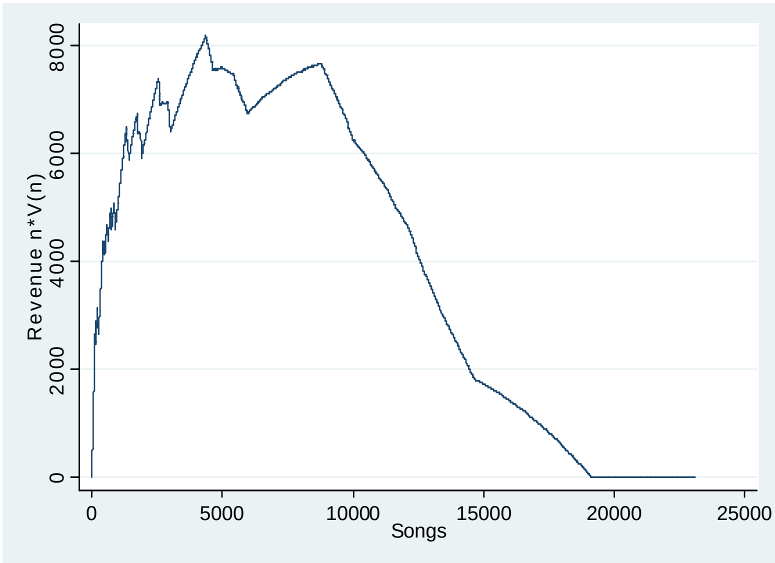


Figure 6: Distribution of Song-Specific Revenue Maximizing Prices, Smooth Data

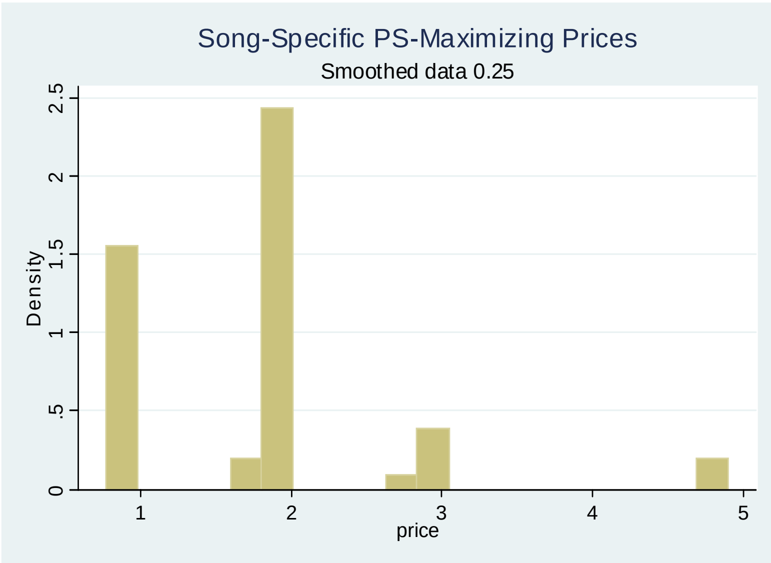


Figure 7a: Grid-Search Revenue Surface for Two-Part Tariff

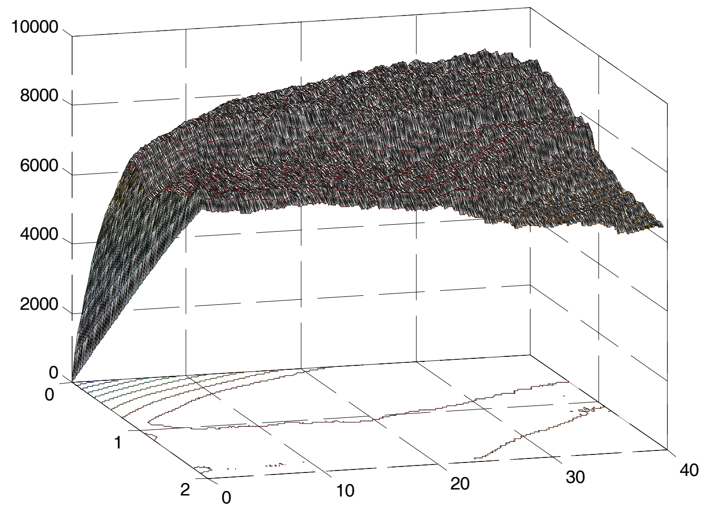


Figure 7b: Two Part Tariff Revenue Surface in Neighborhood of Best Grid Search Values

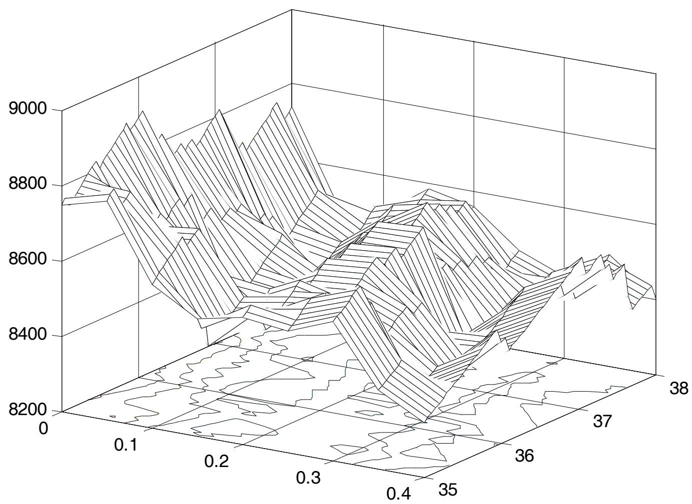
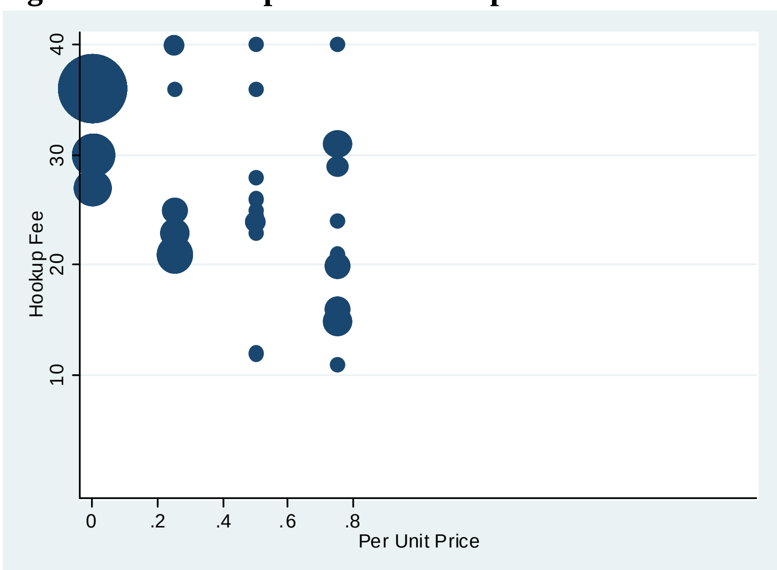


Figure 7c: Bootstrap Estimates of Optimal Two Part Tariffs



Note: 100 replications of sample, clustered on participant. For each iteration we search over $p \in \{0, 0.25, \ldots, 2\}$ and $T \in \{0, 1, \ldots 40\}$. Dot size is proportional to frequency: $(T,p)=(36,0)$ is the modal result.

Figure 8a: Best Two Part Tariffs (Smoothed Data)

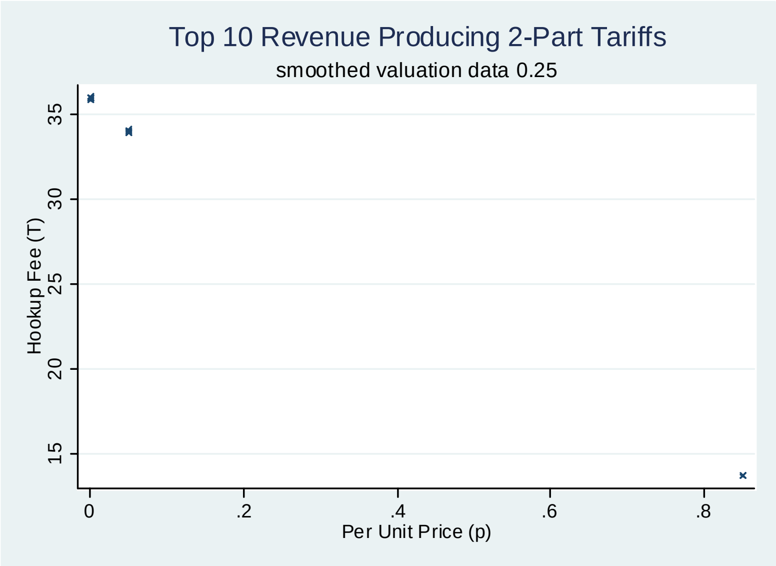


Figure 8b: Top Ten Percent of Two Part Tariffs (Smoothed Data)

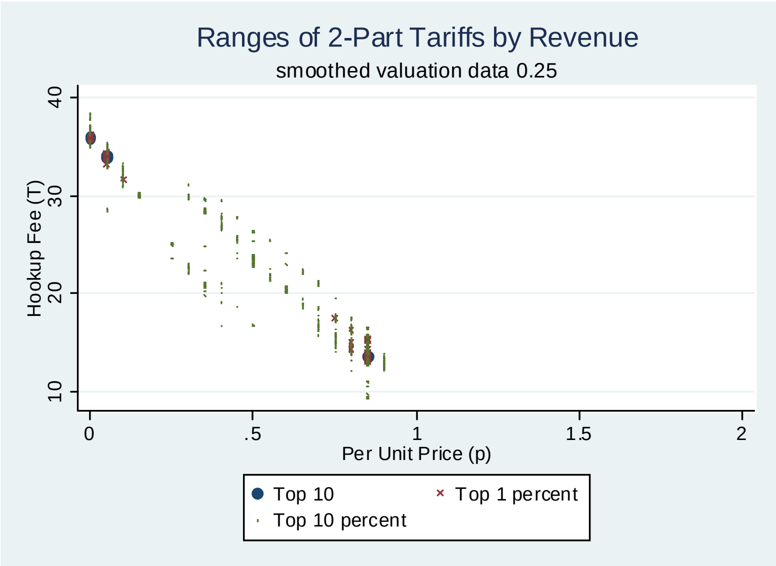


Figure 9: Nonlinear Tariff in Exponential Family

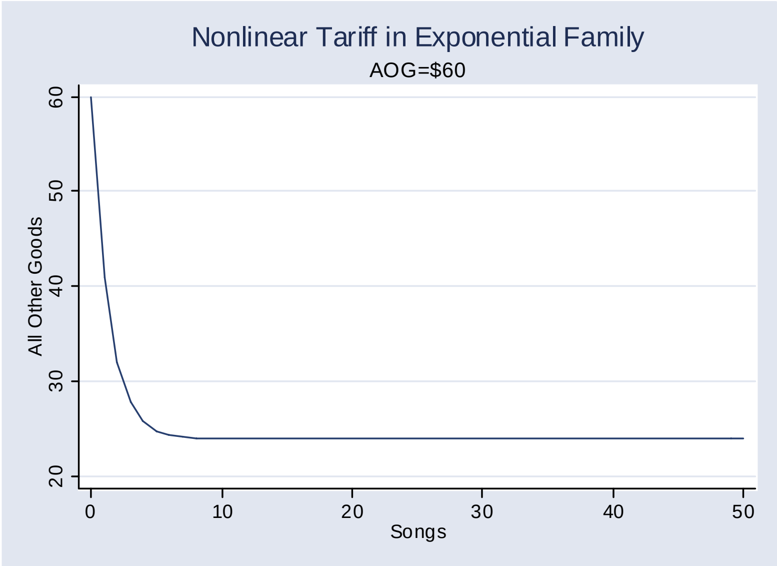


Figure 10: Distribution of Revenue Maximizing Person-Specific Prices (smooth data)

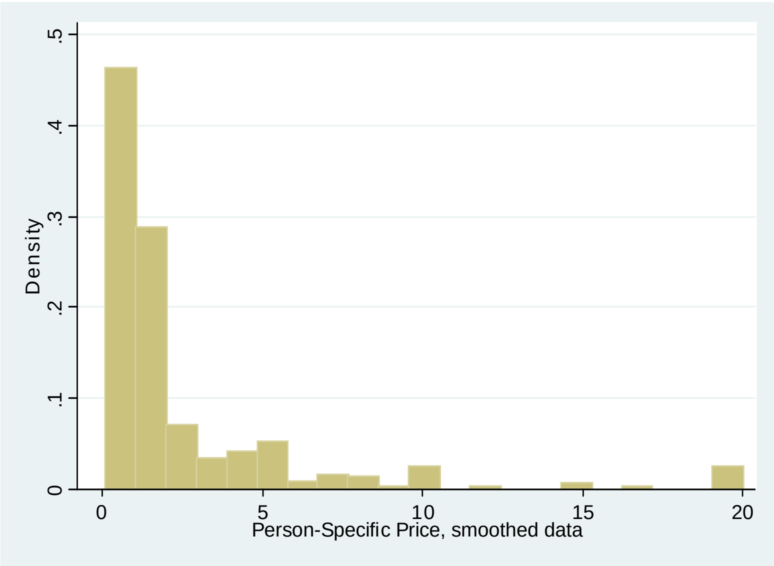


Figure 11: Welfare Tradeoff under Uniform Pricing, Smooth Data

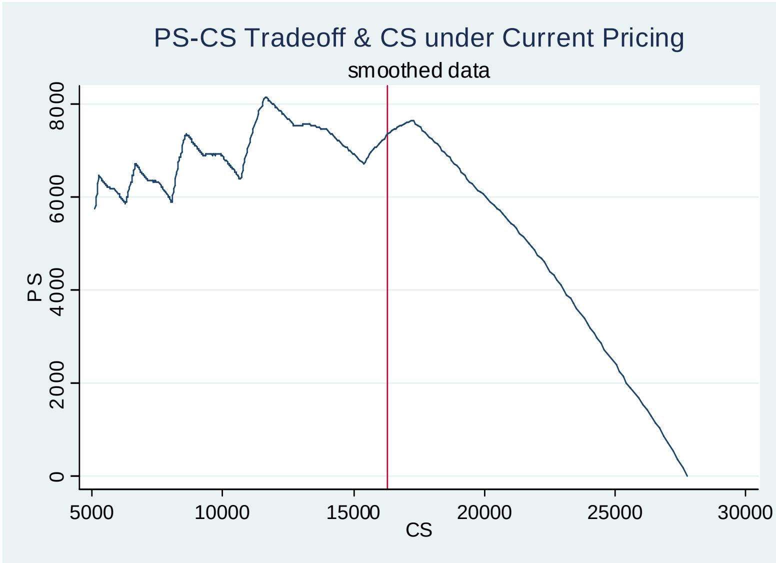
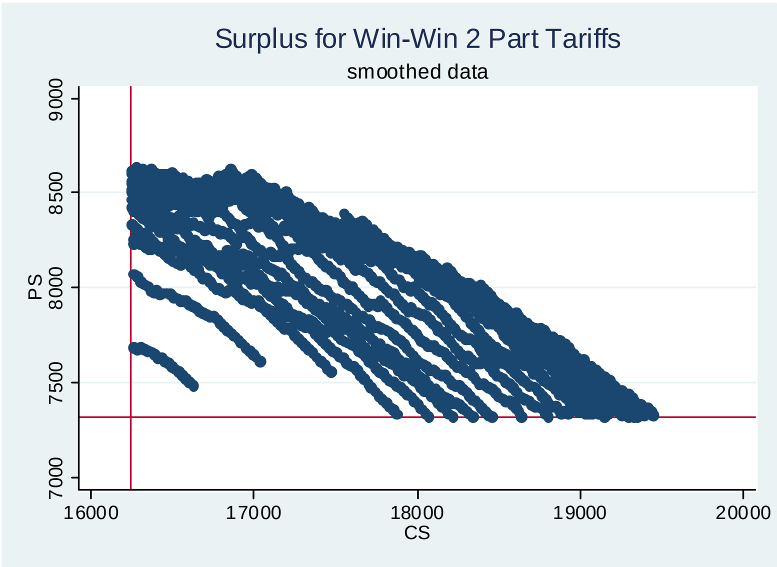


Figure 12a: Revenue and CS with Pareto-Improving Two Part Tariffs



Note: Figure compares CS and PS available with two-part tariffs with the surplus available with current uniform p=$0.99 pricing.

Figure 12b: Pareto-Improving Two Part Tariffs

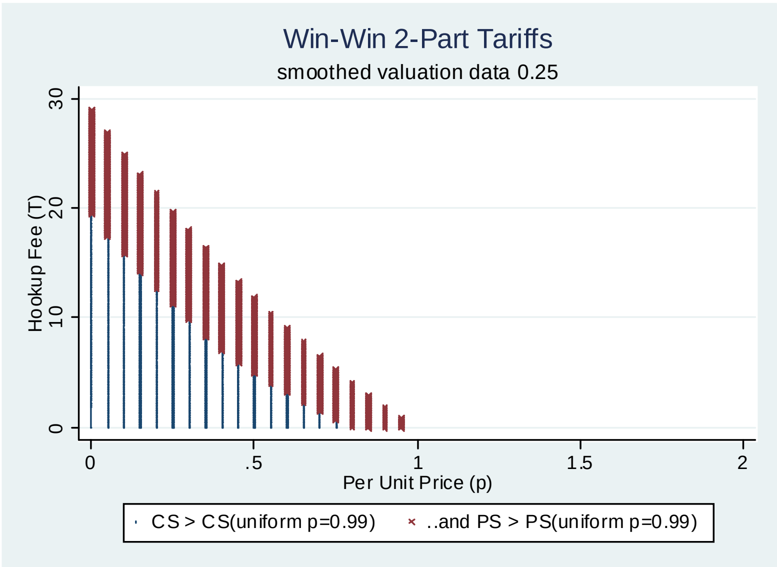
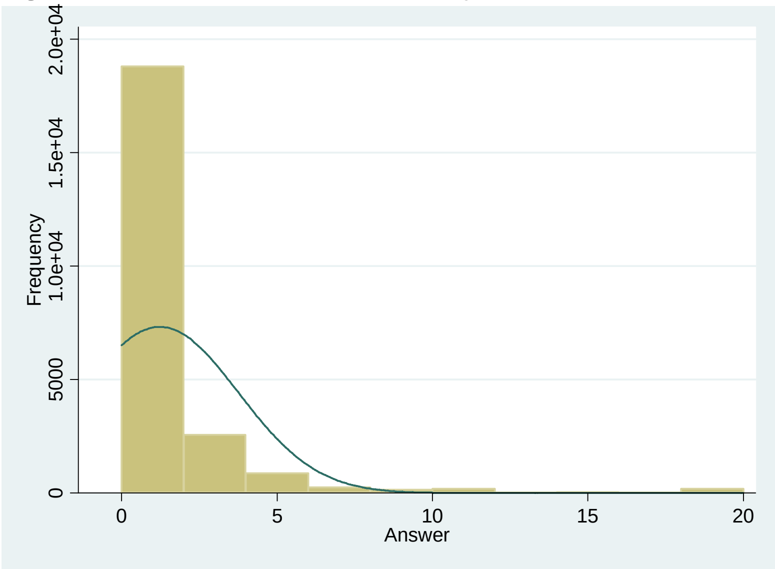


Figure 13: The Data and Normality



Appendix: Results based on Raw Data

Table 3a: Division of the Surplus under Various Revenue Maximizing Pricing Schemes (Raw Data)

	Dollars			*Shares of Total Surplus*			*Relative to Uniform Monopoly*		
	PS	CS	DWL	PS	CS	DWL	PS	CS	DWL
Single Price Monopoly, p=$1.99	8603	11070	7828	31.3%	40.3%	28.5%	0.0%	0.0%	0.0%
Single Price Monopoly, p=$0.99	8497	16207	2796	30.9%	58.9%	10.2%	-1.2%	46.4%	-64.3%
Song-Specific Monopoly	9012	13364	5125	32.8%	48.6%	18.6%	4.8%	20.7%	-34.5%
Pure Bundling	8710	14305	4485	31.7%	52.0%	16.3%	1.2%	29.2%	-42.7%
Two Part Tariff	9075	14092	4334	33.0%	51.2%	15.8%	5.5%	27.3%	-44.6%

Table 8a: Third Degree Price Discrimination with Raw Data

Raw Data[24]	*Dollars*			*Relative to Uniform Monopoly*		
	PS	CS	DWL	PS	CS	DWL
gender	8677	12100	6723	0.86%	9.30%	-14.12%
ethnicity	9042	12100	6358	5.10%	9.30%	-18.78%
resident alien	8788	15029	3683	2.15%	35.76%	-52.95%
age	8608	11057	7835	0.06%	-0.12%	0.09%
person-specific	14973	5910	6617	74.04%	-46.61%	-15.47%

[24] PS-maximizing prices with raw data: (male, female)=(0.99, 1.99); (American Indian/Alaskan,Black Non-Hispanic,White Non-Hispanic,Other,Asian,Hispanic)=(3,4.99,0.99,0.75,1.99,2); (alien, non-alien)=(2,0.99); (under 20, 20 and up)=(1.99,2).

Figure 4a: Overall Demand Curve, Raw Data

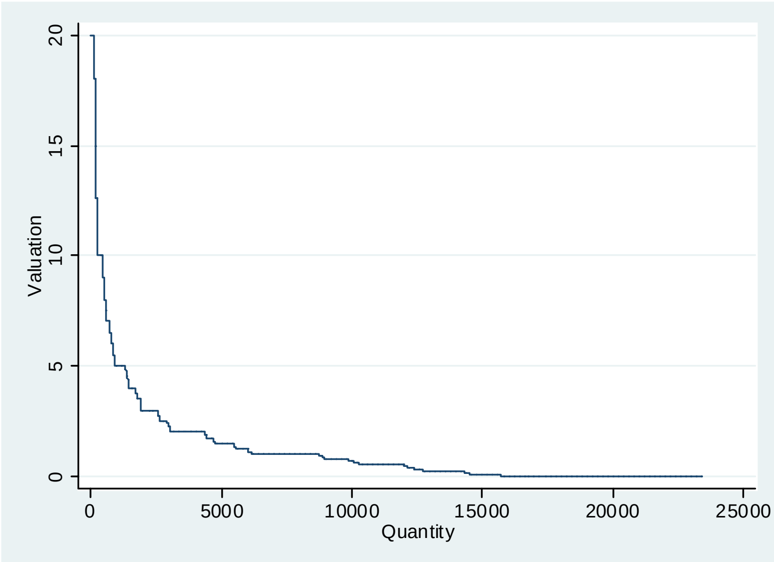


Figure 5a: Single Price Revenue Function on Raw Data

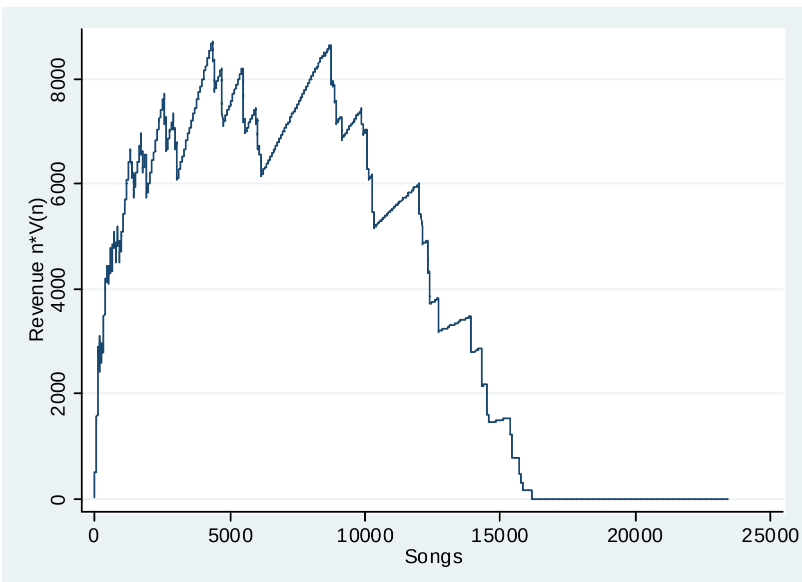


Figure 6a: Distribution of Song-Specific Revenue Maximizing Prices, Raw Data

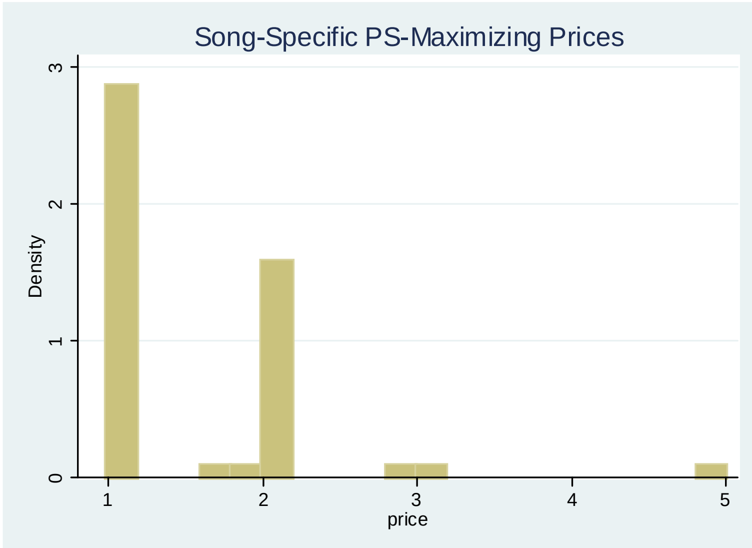


Figure 10a: Distribution of Revenue Maximizing Person-Specific Prices (raw data)