B2B Data-driven and Value-based Pricing Strategies, Price Setting, and Price Execution

Web Appendices

Web Appendix A

Estimating WTP using CVM

Estimating WTP using CVM is straightforward using a binary choice model such as a logistic regression or a Probit model (Cameron and James 1987). In such a choice model, the decision of whether to buy or not is modeled through a latent utility function that depends on product characteristics and consumer background variables. Let p_i be the price of the new product given to consumer i. Let I_i be a variable that indicates whether consumer i decided to buy $(I_i = 1)$ or $(I_i = 0)$. Let:

$$U_i = x_i * \hat{\beta} + \epsilon_i \qquad \text{(WA.1)}$$

be the latent utility of the product concept, where x_i is a vector of explanatory variables that includes product characteristics (excluding price) and individual-specific consumer background variables, $\hat{\beta}$ is a vector of associated parameters, and ϵ_i is an error term. Then the corresponding binary choice model is given by:

$$I_i = \begin{cases} 1, & U_i - p_i > 0 \\ 0, & otherwise \end{cases} \qquad \text{(WA.2)}$$

Since the price coefficient is set to -1, $U_i - p_i$ measures consumer surplus and U_i is therefore a direct measure of WTP. Therefore, in the model above, the $\hat{\beta}$ parameters capture the marginal WTP for each of the explanatory variables included in the model. This can be overcome by using the "sequential bids" CVM discussed above. However, as stated previously, "sequential bidding" CVM experiments are subject to "starting point" bias.

Web Appendix B

Estimating WTP Using Conjoint Analysis

Consider, for example, a heavy-engineering goods manufacturer wanting to quantify its customers' average incremental WTP for faster delivery of its products. Let's assume that the firm is considering rolling out an expedited 10-day delivery option in concert with its status-quo 30-day delivery option, which is currently priced at $150. Similar expedited delivery services run somewhere between $200-$300. The firm elects to explore two possible price options, namely $150 and $250 for the two delivery duration options. This yields two-delivery time options (10 days vs. 30 days) and two price levels ($150 vs. $250). Hence, each respondent in the conjoint will be confronted with four possible ratings/ranking/choice tasks with/without the no-choice option.

One can then pool the observations across all respondents to assess how the firm's customers, on average, trade off price and delivery times. The underlying primitives that govern the data-generating process can be recovered using either ordinary least squares (OLS) for a ratings-based conjoint, an ordered-regression for rankings-based conjoint, or via a maximum-likelihood estimator in the case of choice-based conjoint (CBC). Without any loss of generality, let's assume these repeated tasks were presented in a ratings-based conjoint experiment and the resulting regression coefficients are as reported in Table WB.1 below.

Table WB.1: Conjoint Analysis Experiment Results

Variable	Coefficient	Std. Err	t-stat
Intercept	2.7	1.0	2.7
30 days vs. 10 days	9.6	0.9	10.9
$250 vs. $150	40.6	0.9	46.1

Source: Adapted from Hauser (2018)

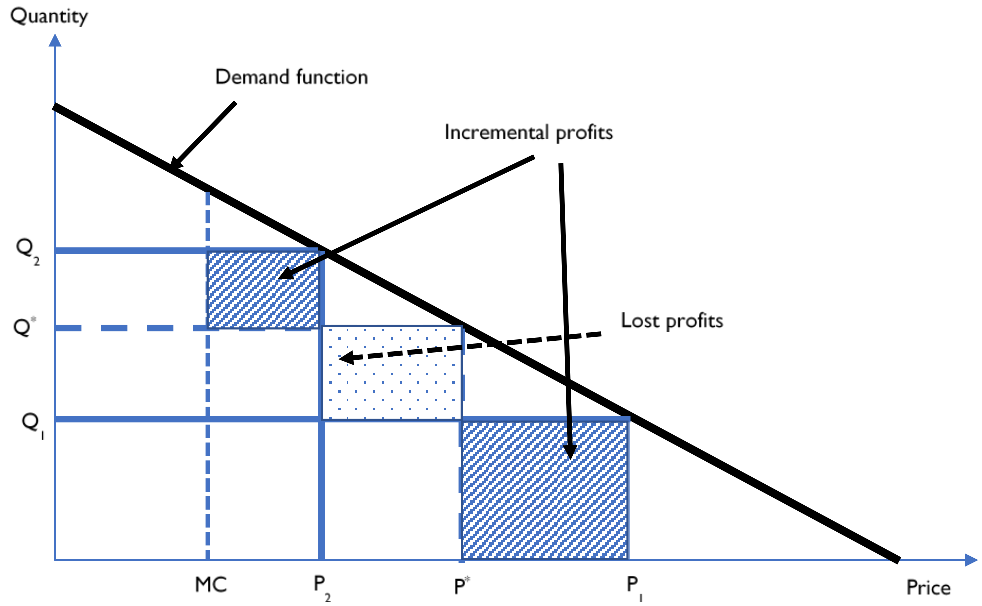
Regression coefficients above are referred to as part-worths and denote the incremental utility (or disutility) that respondents perceive going from the base level of an attribute ($250 and 30 days in this setting) to another level of the same attribute ($150 and 10 days, in this example). For example, 9.6 above implies that, on average, our respondents would get 9.6 utils if the delivery times were expedited from 30 days to 10 days. Similarly, the regression coefficients for price, imply that respondents, on average, get 40.6 utils when the price drops from $250 to $150. To compute the average WTP, we need to convert these incremental utils to monetary units. Since going from $250 to $150, a difference of $100, yields our respondents 40.6 utils, the value of each util is $(250 - 150)/40.6 = \$2.46/util$. To calculate our respondents' average WTP for 10-day expedited shipping over status-quo 30-day shipping, we simply covert their incremental 9.6 utils into dollar equivalents. This is obtained by $(\$2.46) * 9.6 = \$23.65$. Given the ease with which one can undertake WTP using conjoint analysis, not surprisingly, it has been much leveraged by firms spanning both B2B and B2C settings.

Web Appendix C

Nonlinear Pricing Example

Consider a commodity sold by a monopoly supplier at a uniform unit price. The demand for the commodity is characterized by a simple downward-sloping demand function. Such a demand function does not distinguish between multi-unit purchases by a single customer or single-unit purchases by many customers. The monopolist needs to trade off increased profits from selling additional units by lowering the price against the lost profits from existing sales at higher prices. Consequently, the monopoly supplier will set a price p^* above marginal cost, which is suboptimal from a social welfare perspective (since it excludes some customers who are willing to pay more than the product costs). If, on the other hand, the monopolist was able to segment her customers and charge two prices for the *same* product as illustrated in Figure WC.1 below, some customers will be charged price $p_1 > p^*$, while other customers will be charged $p_2 < p^*$ (thereby increasing social welfare, as more customers are being served now). Such a form of price discrimination is prudent if $Q^* \, (p^* - MC) < Q_2 (p_2 - MC) \; + Q_1 \, (p_1 - MC)$. Hence, such a form of price discrimination is a win-win proposition for both customers and the firm.

Figure WC.1: Illustration of Price Discrimination



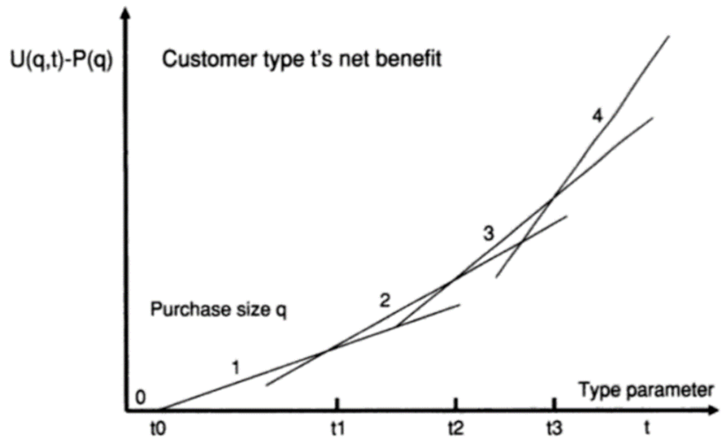
However, such a form of price discrimination is harder to undertake in B2B settings. One, B2B firms, unlike their B2C peers, are not as equipped with pricing analytics competencies to estimate/qualify a customer's WTP. Since a customer's WTP is critical to undertaking the aforementioned form of market segmentation, price discrimination of this form is not going to be feasible for many B2B firms. Two, such segmentation would require differentiation of the product or service so that the buyer perceives different values for the different prices. Three, to sustain such a form or price discrimination, the seller must possess some degree of market power to be able to limit the resale market, either through direct control or due to high transaction costs.

Instead of segmenting based on customers' WTP, in most B2B settings, nonlinear pricing is facilitated via quantity discounting, a form of second-degree discrimination. Herein, prices are based on some observable characteristic(s) of the purchase (e.g., volume), which is correlated with the customer's preferences.[1] Central to the analysis of nonlinear pricing is the objects demand profile denoted by $N(p, q)$, which describes the distribution of purchase sizes in response to each uniform price p. That is, if p is fixed and q is increased, then the graph of $N(p, q)$ depicts the declining number of customers purchasing each successive q-th unit. This is the same as the number of customers purchasing at least q units, so that for each fixed price p, the demand profile $N(p, q)$ is the right-cumulative distribution function of the customers' purchase sizes. In summary, for each price p the demand profile $N(p, q)$ specifies the number or fraction of customers purchasing at least q units. Because this number is usually directly observable in the data, the demand profile can be measured using observational data. This requires, of course, that information about customers' purchase sizes is accumulated and recorded. It is in this sense that demand profile is a disaggregated version of the demand function: *the demand data is disaggregated according to the size of the purchase.*

Figure WC.2 below shows how the distribution of purchases is predicted from ordinary models of customers' benefits in which each customer is described by a parameter t indicating her type. Assuming a particular benefit function $U(q, t)$ and tariff $P(q)$, the diagram plots a customer's net benefit from each purchase size $q = 0, \dots 4$ as a function of the type parameter t. For simplicity, this function is assumed to be linear and to increase as the type parameter increases. As q increases, a customer's gross benefit increases. But for each fix type t, there comes a point where the next increment in the gross benefit is less than the increment in the tariff, namely the marginal price for the next unit, whereupon she ceases to purchase additional increments.

[1] See Wilson (1993) for a more detailed discussion of the microeconomic foundations of nonlinear pricing.

Figure WC.2: Distribution of Purchases by Customer Type t



Source: Wilson (1993)

Figure WC.2 shows for each type t the net benefit corresponding to the optimal purchase size, which is the largest quantity for which the marginal benefit of the last unit purchase exceeds the marginal price charged. Such a model predicts that customers purchasing exactly q units adjust with the type parameters between t_{Q-1} and t_Q , as shown in Figure WC.2. Those purchasing the q-th increment are all those purchasing at least q units, namely those described by the Type parameters exceeding t_{Q-1}. Conversely, the firm can use the observed distribution of purchase sizes to estimate the distribution of types in the population: again, the number actually purchasing at least q units in the estimated number with type parameters exceeding t_{Q-1}.

The second interpretation of the demand profile $N(p,q)$ is that it describes the distribution of customers' willingness to pay. If we fix q an increased marginal price p, then the demand profile measures the declining number of customers willing to pay this price for the q-th increment. Thus, the demand profile specifies for each q-th unit the number or fraction $N(p,q)$ of customers willing to pay price p for that unit. This interpretation is useful in applications based on parameterized models of customer behavior. For instance, suppose volume bands are indicated by parameter t. The benefit cost analysis indicates that type t obtains the dollar benefit $U(q,,t)$ from purchasing q units, and therefore the marginal benefit $v(Q,T) \equiv \frac{\partial u(q,t)}{\partial(q)}$ from the q-th unit.

Estimation of the Demand Profile

The demand profile is comparatively easy to estimate when the firm has ample demand data realized at a variety of prices. When there is no historical price variation, estimation of the demand profile or its price elasticity is usually based on a parameterized model of customers' benefits.

Suppose the firm has used several uniform prices in the past. Furthermore, the firm has also recorded for each price the distribution of customer purchase sizes. The process of estimating the demand profile begins by representing historical prices (or price levels) that have been charged as an increasing sequence of p_j, where j is an index that distinguishes the different prices. Similarly, q_k represents the possible purchase sizes by increasing sequence k, where k is an index that distinguishes several volume bands. Correspondingly, for each price p_j, the data provide a measure n_{jk} of the number or fraction of potential customers whose purchase size was in volume band k when the price was p_j. The direct estimate of the demand profile is then:

$$N(p_j, q_k) = \sum_{l \geq k} n_{jl} \qquad \text{(WC.E1)}$$

at these prices and quantities. That is, if the data in the array n_{jk} are represented as a spreadsheet with rows indexed by prices and columns indexed by volume bands, then the demand profile is a new array obtained by replacing each element by the sum of elements further along in the same row.

Usually this estimate is insufficient because it does not cover all possible prices and quantities that might be relevant for the rate design. A variety of methods are available to obtain smooth estimates of the demand profile. For example, Press et al. (1986) fits spline-curves to obtain direct empirical estimates of the demand profile using regression analysis. In a regression model, for each price p_j, an estimate is made of the demand profile $N(p_j, q)$, which is construed as a function of the purchase size q.

For analytical convenience, we assume that the price function or price tariff $p(q)$ is continuous and show how it can be determined given the disaggregated demand profile $N(p_j, q\ )$. We also assume that for any quantity Q, $N(p_j, q\ )$ is declining in p (fewer customers will buy the q-th unit as a unit price increases), that is, $\frac{\partial N(p,q\ )}{\partial(p)} < 0$. For any price level p, the number of customers who will buy the q-th unit declines with q that is $\frac{\partial N(p,q\ )}{\partial(q)} < 0$, and the rate of decline decreases with p. The last condition is a common technical assumption often referred to as a single crossing property, which guarantees that the demand function for the different units q will not intersect each other.

Let us now consider the problem of a monopolist who wants to determine a unit price function $p(q)$ that will maximize its profit function, assuming that each unit costs the same to produce. For simplicity let's assume that q can only take on integer values. The profit for the monopolist is given by:

$$\pi = \sum_{q=1}^{Q} N(p(q), q\ ) * (p(q) - c) \qquad \text{(WC.E2)}$$

Hence this profit function is separable with respect to q, so in order to maximize this function with respect to $p(q)$, we need to maximize each of the terms within the profit function. Thus, the necessary conditions for maximum profit are:

$$\pi = \frac{\partial}{\partial(p(q))}\{N(p(q), q\ ) * (p(q) - c)\} = 0\ \forall q = 1,2,3,4,5 \qquad \text{(WC.E3)}$$

This gives the optimality condition:

$$[p(q) - c] * \frac{\partial N(p(q), q\ )}{\partial(p(q))} + N(p(q), q\ ) = 0 \qquad \text{(WC.E4)}$$

If the elasticity of demand for the q-th unit is:

$$\eta(q) = -\frac{\frac{\partial N(p(q),q\,)}{\partial(p(q))}}{\frac{N(p(q),q\,)}{p(q)}} = -\frac{\frac{\partial N(p(q),q\,)}{N(p(q),q\,)}}{\frac{\partial(p(q))}{p(q)}} \qquad \text{(WC.E5)}$$

then our optimality condition becomes:

$$\frac{[p(q)-c]}{p(q)} = \frac{1}{\eta(q)} \qquad \text{(WC.E6)}$$

This result is often called the *inverse elasticity* rule. Our optimality condition implies that the optimal "percentage markup" for each incremental unit should be inversely proportional to the demand elasticity for that unit. The intuitive justification for this rule is that high demand elasticity entails stronger response to the same percentage change in price. Thus, a monopolist who faces a tradeoff between reduced sales (in units) versus increased profit per sale, in choosing the optimal markup will opt for a lower percentage markup when demand elasticity is more elastic.

Next, we illustrate how best to use observable demand profiles to design an optimal nonlinear price tariff. We assume here that the available data provide estimates of demand for each of the several prices denoted by p and several purchase sizes denoted by q. These estimates can be represented as a tabular array in which rows correspond to different prices, and the columns correspond to different purchase sizes, and an entry in the table indicates the number of fraction $n(p(q), q\,)$ of customers who at price p will purchase q units. This is the form in which demand data is ordinarily accumulated if appropriate care is taken to record customers' purchases for each price p that has been offered by the firm; and at each price p the firm observes the distribution of purchase sizes amongst its customers. Furthermore, the key idea in the analysis that follows recognizes that the tariff can be interpreted as imposing a different charge for each successive increment in the purchase size. Does a tariff represented as a schedule in which capital $P(q)$ is the total amount charged for a purchase size q can also be represented as a schedule in which a price $p(q)$ per unit is charged for the q-th increment in the purchase size. For example, if the possible purchase sizes are integral amounts $q = 0,1,2, \ldots$

then $p(q) = P(Q) - P(Q-1)$ is the price charged for the q-th unit. This idea also recognizes that a customer buying the q-th item must also buy all lesser increments. This is the same as saying that the demand for the q-th increment is the demand for all purchases is at least as large as q.

Using the tabular array $n(p, q)$, the demand for the q-th increment at price p is therefore the number of customers purchasing q or more. That is,

$$N(p, q) = \sum_{x \geq q} n(p, x) \qquad \text{(WC.E7)}$$

Suppose for a B2B producer, the Table WC.1 below tabulates the observed demand profile.

Table WC.1: Observed Demand Profile

p	q:	$N(p,q)$ 1	2	3	4	5 units		$\overline{D}(p)$
\$2/unit		90	75	55	30	5		255
\$3		80	65	45	20	0		210
\$4		65	50	30	5	0		150
\$5		45	30	10	0	0		85
$p(q)$:		\$4	\$4	\$3	\$3	\$2/unit		\$4
$P(q)$:		\$4	\$8	\$11	\$14	\$16		
$R(p(q), q)$:		\$195	\$150	\$90	\$40	\$5		
Total Profit :							\$480	\$450
'CS'(q) :		\$45	\$30	\$40	\$5	\$0	\$120	\$85
'TS'(q) :							\$600	\$535

Each column in Table WC.1 corresponds to a market segment for purchase sizes/volume bands $q = 1,2, \ldots 5$ units, respectively. The entry in the first column and the first row, for instance, shows that at least one unit is purchased by 90 customers if the price is \$2 per unit. The number of customers who purchased exactly one unit is 15 since 75 customers purchased at least two units. It's worth highlighting that the demand profile is non-increasing along each row and down each column.

Assuming the marginal cost to supply each unit is c=\$1.00, the optimal price is \$4 for the first unit. This can be assessed by computing the profits for each cell within column $N(p, q) = 1$ at the corresponding row value price level $p = \$2, \$3, \$4, \$5$. The profit contribution from a price of \$2.00, for instance, is the demand of 90 units at this price times the profit margin at this price, which is equal to ($2 – $1) = $1.00/unit yielding a total contribution of $90, which is less than the contribution of 65* ($4 - $1) = $195 which is obtained from the optimal price of $4 per unit.

Similarly, the profit contribution from the third increment, i.e., $q = 3$, is $55, $90, $90, or $40 from the four possible prices, and the maximum of these is $90, obtained when either the price is $3 or the next higher price is $4, although we have indicated that the lower price is chosen. The entries in the table that correspond to optimal choices of prices are italicized. The optimal prices shown in the table imply a tariff $P(q)$ that charges $4, $8, $11, $14 and $16 for purchase sizes 1, 2, 3, 4 and 5 respectively. The price of $2.00, for instance, is the demand of 90 units at this price times the profit margin at this price, which is equal to ($2 – $1) = $1.00/unit yielding a total contribution of $90, which is less than the contribution of 65* ($4 - $1) = $195, which is obtained from the optimal price of $4 per unit. While not employed in this example, in addition to the observed realization in the data, one can also employ regression to estimate the corresponding demand profiles at prices not observed in the current data, but within the range of the observed prices taken to market.

Also shown in the table Table WC.1 is $\overline{D}(p)$, the aggregate demand function. $\overline{D}(p)$ indicates a total demand if the firm charges a uniform price p for all units. Note that $\overline{D}(p) = \sum_{q=1\ldots5} N(p,q)$. The optimal uniform price is the one that maximizes the aggregate profit contribution $\overline{D}(p) * (p - c)$. For example, as shown in the table above, the optimal uniform price is $4, which delivers a profit contribution of $450 from the sales of 150 units. In contrast, the optimal tariff above yields a higher profit contribution of $480 from the sales of 185 units, corresponding to an average price of $3.60 per unit.[2] Also shown in the table Table WC.1 are the minimum estimates of consumers and total

[2] In some industries, such as commodity markets, the objective of price discrimination is to promote conservation. In such settings. Unlike quantity discounting, the marginal price function increases with quantity. Such price tariffs are referred to as *increasing block tariffs*.

surplus denoted by capital CS and capital PS based on the demand profiles indicating the numbers of customers willing to pay higher prices and those charged. For example, 45 customers are willing to pay $1 more than the $4 charged for the first unit.

As you can see above, this simple illustration highlights the advantage of nonlinear pricing. Offering price breaks for large purchase sizes stimulates demand that would otherwise not have been realized at a higher uniform price. This structure has a further advantage in that it increases the firm's profit without disadvantaging any customer, since the optimal price schedule charges no more for each unit than does the optimal uniform price. The gains from nonlinear pricing evident in this example stemmed from heterogeneity amongst customers. Segmenting the market into volume bands enables the seller to offer low prices for the larger purchase sizes selected by some customers. These discounts are equally available to all customers, but only those customers demanding higher purchases are likely to take advantage of this opportunity. This illustrative example shows demand profiles that summarize heterogeneity amongst customers afford designing and the analysis of nonlinear tariffs.

An important caveat to note is that the previous discussion assume that benefits and demand behaviors are exogenous. That is, these behaviors are unaffected by the introduction of nonlinear pricing. However, it is quite plausible that the price tariff impacts quantity choice. This is particularly true in settings when the timing of product purchase may be temporally separated from the time of consumption (Nunes 2000; Lambrecht and Skiera 2006; Lambrecht, et al. 2007).

For example, in B2C settings, a mobile phone customer may commit to a specific nonlinear price schedule offered by a service provider anticipating a certain level of consumption of cellphone minutes post purchase (Miravete 2002, 2007; Danaher 2002; Narayanan, et al. 2007; Iyengar, et al. 2007). However, post purchase, the actual cellphone consumption of these customers may be very different than what they had anticipated at the time of purchase. Such behavioral biases have also been shown in other B2C settings including utility consumption (Hewitt and Hanemann 1995; Reiss and White 2005).

We believe such biases are very likely to also be present in B2B settings like healthcare services, manufacturing, and staffing services, where demand is highly stochastic. Yet to the best of our knowledge, we are unaware of any scholarly research in marketing showcasing these biases, or lack thereof, in B2B markets.

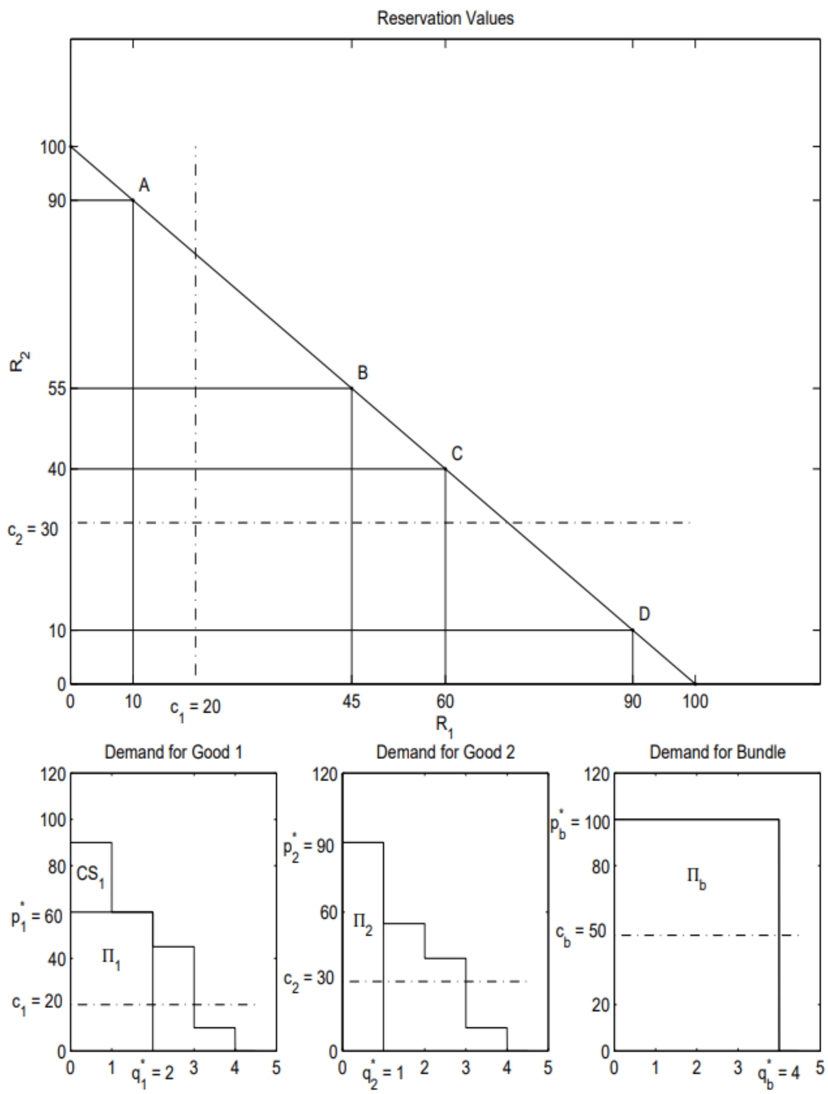
Various methods have been proposed to address this simultaneity between price tariff and post-purchase consumption. The most noteworthy of these solutions was proposed by Burtless and Hausman (1978). Specifically, the method infers the optimal expected consumption pattern given a customer's chosen price tariff. The post-purchase consumption is separately modeled as a deviation from the optimal expected consumption as a result of the nonlinear price schedule.

Web Appendix D

Background Literature on Product Bundling

The literature on bundling has a long history beginning with Stigler (1963). Seminal work by Stigler (1963), Adams and Yellen (1976), McAfee et al. (1989), Bakos and Brynjolfsson (1999), and Armstrong (1999) highlight that bundling can be a very effective strategy for a monopolist to sort customers in a manner similar to 2^{nd}-degree price discrimination. This is because bundling reduces heterogeneity in consumer valuations, which allows a monopolist to better price discriminate (Schmalensee 1984, Salinger 1995). While firms clearly benefit, consumer welfare generally falls, particularly when bundling requires consumers to purchase products in which they have little interest. These price discrimination incentives are best illustrated in Figure WD.1 in the example from Adams and Yellen (1976) below.

Figure WD.1: An Example of the Discriminatory Incentives to Bundle



Source: Adams and Yellen (1976)

Suppose there are two goods $(1,2)$ and four consumers $(A - D)$ whose willingness-to-pay (WTP) for each good is represented by a point in the top panel of Figure WD.1. The bottom three panels show the demand for each good (if offered separately) and demand for the bundle of both goods implied by these reservation values. Marginal costs are $c_1 = 20$ for good 1 and $c_2 = 30$ for good 2.

Unbundled sales imply optimal prices of $p_1^* = 60$ and $p_2^* = 90$, yielding consumer surplus of $\$30$ and (combined) profits of $\$140$. Consumer surplus and profits in each market (if any) are labelled by CS and Π in the figure. Under bundling, however, the negative correlation in tastes for each component imply that all consumers have a WTP of $\$100$, which yields bundled profits of $\$200$. Hence, bundling permits this monopolist to extract all available consumers surplus.

The reduction in preference heterogeneity in this illustrative example (and associated surplus extraction) generalizes and is the primary benefit of bundling. However, in a more general setting, whether bundled sales are preferred to component sales depends on three critical features of preferences and costs. First, what is the extent of heterogeneity reduction possible from bundling? This increases with the negative correlation in preferences for bundle components, a point made clear in this illustrative example. Second, what are the marginal costs for components? Since bundling requires that consumers purchase all goods included in the bundle, some below-cost sales of components can result (e.g., consumers A and D in the example), reducing the gains from bundling. Third is that bundling requires firms to charge a single price. When consumer tastes for components differ considerably (e.g. multiply WTP for one of the example goods by a positive scalar), bundling is less attractive than component sales, since highly divergent product valuations temper product bundling's ability to capture consumers' surplus.

Subsequent research investigating when it is optimal to bundle has either relaxed the negative correlation assumption of Adams and Yellen (1976) and/or allowed substitutes and complements. For example, Lewbel (1985) accommodates substitutability and complementarity, and identifies conditions when the monopolist may choose a pure bundling strategy or pursue a pure components strategy. Venkatesh and Kamakura (2003) relax the additivity assumption of Adams and Yellen (1976) and show that these 2^{nd}-degree price discrimination benefits accrued to the firm from bundling applies to settings in which goods are both complements or substitutes. However, the monopolist's gains from bundling depends on the marginal costs of producing the products (bundles) and the degree of substitutability and complementarity. Kopalle et al. (1999) propose a market-growth model and find that as the scope for market expansion decreases, it may be more prudent to shift from a mixed bundling to a pure components strategy.

Extant research has extended the bundling literature to consider multiple goods as well as multiple consumer types. Spence (1980) generalized the principles of the single-product pricing problem to the case of several products using a nonlinear programming formulation and showed some cases in which the problem can be solved in closed form. Armstrong (1996) found that it is usually optimal to leave some consumers unserved in order to extract more revenue from the other, higher-value consumers. Rochet and Chone (1998) found that it is sometimes optimal to induce a degree of "bunching," so that consumers with different tastes are forced to choose the same bundle of products. Bakos and Brynjolfsson (1999) show that pure bundling can often be optimal when marginal costs are sufficiently low. However, they show that pure bundling is not optimal when consumers are budget constrained or when consumers do not value all goods, or when marginal costs are significant.

Beyond investigating when it is optimal to bundle, some scholars have investigated questions pertaining to how best to price a bundle and/or what products/services to bundle. For example, Hanson and Martin (1990) use mixed integer programming to determine optimal prices as well as the composition of product bundles targeted to different market segments. In contrast, instead of asking consumers for their reservation prices, as is the case with Hanson and Martin (1990), Chung and Rao (2003) use consumers' stated choice data and a product attribute model of consumer utility in a pure bundling setting to find market segments and optimal bundle pricing of products spanning multiple categories.[3] The Chung and Rao (2003) attribute-based modeling framework accommodates complementarity in the attributes of the products (components). Jedidi et al. (2003) propose a modeling framework to capture consumers' joint distribution of reservation prices for products and

[3] Gabor and Granger (1965) point out that self-stated reservation prices can lead to significant measurement error, especially for infrequently purchased products.

bundles when products are either complements or substitutes. Unlike the Chung and Rao (2003) framework, which is limited to a pure bundling strategy, Jedidi et al. (2003) use their calibrated model to choose the optimal product-line pricing strategy – pure components, pure bundling, or mixed bundling. While Jedidi et al. (2003) find mixed bundling to be optimal in most scenarios, they also find that a uniformly high-price policy is likely to be optimal when the reservation prices for the individual products and the bundle are very heterogeneous. However, when the demand for a product or the bundle is relatively homogeneous, this policy is likely to be suboptimal. In such cases, it may be necessary to charge lower prices for some products or bundles in order to capture consumer surplus.

Follow-up studies focus on what products to bundle. These studies introduce the idea that allowing customers to self-select the goods in the bundle (rather than having the goods predesignated) can often improve outcomes while maintaining simplicity in the pricing mechanism (Chen 1998, Chuang and Sirbu 1999, MacKie-Mason, Riveros, and Gazzale 2000). Bakos and Brynjolfsson (1999) show that when the marginal cost of each good is low and valuation is determined by a common distribution function across goods, offering all goods for a fixed price ("pure bundling") is optimal. This greatly simplifies the bundling and pricing problem.

Hitt and Chen (2005), investigate a similar question as Bakos and Brynjolfsson (1999), however, in situations when goods have a small but non-negligible marginal cost and when consumers value only a subset of all available goods. While not the focus of the Hitt and Chen (2005) study, such nonnegligible marginal cost situations arise in many B2B settings in which firms incur nonnegligible costs, including distribution costs, monitoring costs, enforcement costs, etc. These costs can be significant, even for goods with low or zero marginal production costs, such as software titles (Hitt and Chen 2005).

Hitt and Chen (2005) introduce the concept of *customized bundling*, a pricing strategy that gives consumers the right to choose up to a quantity M of goods drawn from a larger pool of N different goods for a fixed price. In a full bundling setting for N goods, firms could offer up to 2^{N-1} possible bundles, each at a (possibly) different price. However, this bundle composition problem is known to be computationally intractable and difficult to solve in closed form except for small numbers of goods (Hanson and Martin 1990). Furthermore, such an exhaustive bundling strategy potentially imposes significant burdens on customers to evaluate a large menu of bundles and requires that firms have exact reservation prices for all possible bundles and all consumers. Consequently, offering an exhaustive set of bundle compositions is rarely implemented in practice. In contrast, the *customized bundling* strategy greatly simplifies the complexity of the problem, especially for large numbers of goods, and enables known results on nonlinear pricing to be applied to otherwise intractable bundling problems.

Web Appendix References

Adams, William J. and Janet L. Yellen (1976), "Commodity bundling and the burden of monopoly," *The Quarterly Journal of Economics*, 475-498.

Armstrong, Mark (1996), "Multiproduct nonlinear pricing," *Econometrica: Journal of the Econometric Society*, 51-75.

Armstrong, Mark (1999), "Price discrimination by a many-product firm," *The Review of Economic Studies*, 66 (1), 151-168.

Bakos, Yannis and Erik Brynjolfsson (1999), "Bundling information goods: Pricing, profits, and efficiency," *Management Science*, 45 (12), 1613-1630.

Burtless, Gary and Jerry A. Hausman (1978), "The effect of taxation on labor supply: Evaluating the Gary negative income tax experiment," *Journal of Political Economy*, 86 (6), 1103-1130.

Cameron, Trudy A. and Michelle D. James (1987), "Estimating willingness to pay from survey data: An alternative to pre-test-market evaluation procedure," *Journal of Marketing Research,* 26 (November), 389-95.

Chen, Fanfruo (1998), "Echelon reorder points, installation reorder points, and the value of centralized demand information," *Management Science*, 44 (12-part-2), S221-S234.

Chuang, John Chung-I and Marvin A. Sirbu (1999), "Optimal bundling strategy for digital information goods: Network delivery of articles and subscriptions," *Information Economics and Policy*, 11 (2), 147-176.

Chung, Jaihak and Vithala R. Rao (2003), "A general choice model for bundles with multiple-category products: Application to market segmentation and optimal pricing for bundles," *Journal of Marketing Research*, 40 (2), 115-130.

Danaher, Peter J. (2002), "Optimal pricing of new subscription services: Analysis of a market experiment," *Marketing Science*, 21 (2), 119-138.

Hanson, Ward and R. Kipp Martin (1990), "Optimal bundle pricing," *Management Science*, 36 (2), 155-174.

Hauser, John R. (2008), "Note on conjoint analysis," MIT Sloan Courseware.

Hewitt, Julie A. and W. Michael Hanemann (1995), "A discrete/continuous choice approach to residential water demand under block rate pricing," *Land Economics*, 173-192.

Hitt, Lorin M. and Pei-yu Chen (2005), "Bundling with customer self-selection: A simple approach to bundling low-marginal-cost goods," *Management Science*, 51 (10), 1481-1493.

Iyengar, Raghuram, Asim Ansari, and Sunil Gupta (2007), "A model of consumer learning for service quality and usage," *Journal of Marketing Research*, 44 (4), 529-544.

Jedidi, Kamel, Sharan Jagpal, and Puneet Manchanda (2003), "Measuring heterogeneous reservation prices for product bundles," *Marketing Science*, 22 (1), 107-130.

Kopalle, Praveen K., Aradhna Krishna, and João L. Assunção (1999), "The role of market expansion on equilibrium bundling strategies," *Managerial and Decision Economics*, 20 (7), 365-377.

Lambrecht, Anya, Katja Seim, and Bernd Skiera (2007), "Does uncertainty matter? Consumer behavior under three-part tariffs," *Marketing Science*, 26 (5), 698-710.

Lambrecht, Anya 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 (2), 212-223.

Lewbel, Arthur (1985), "Bundling of substitutes or complements," *International Journal of Industrial Organization*, 3 (1), 101-107.

MacKie-Mason, Jeffrey K., Juan F. Riveros, and Robert S. Gazzale (2000), "Pricing and Bundling Electronic Information Goods: Evidence from the Field," MIT Press: Cambridge, MA.

McAfee, R. Preston, John McMillan, and Michael D. Whinston (1989), "Multiproduct monopoly, commodity bundling, and correlation of values," *The Quarterly Journal of Economics*, 104 (2), 371-383.

Miravete, Eugenio J. (2002), "Estimating demand for local telephone service with asymmetric information and optional calling plans," *The Review of Economic Studies*, 69 (4), 943-971.

Miravete, Eugenio J. (2007), "The limited gains from complex tariffs," CEPR Discussion Papers.

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), 1-34.

Nunes, Joseph C. (2000), "A cognitive model of people's usage estimations," *Journal of Marketing Research*, 37 (4), 397-409.

Press, William H., Brian P. Flannery, Saul A. Teukolsky, William T. Vetterling (1986), "Numerical recipes: The art of scientific," Cambridge University Press.

Reiss, Peter C. and Matthew W. White (2005), "Household electricity demand, revisited," *The Review of Economic Studies*, 72 (3), 853-883.

Rochet, Jean-Charles and Phillipe Choné (1998), "Ironing, sweeping, and multidimensional screening," *Econometrica*, 66 (4), 783-826.

Salinger, Michael A. (1995), "A graphical analysis of bundling," *Journal of Business*, 85-98.

Schmalensee, Richard (1984), "Gaussian demand and commodity bundling," *Journal of Business*, S211-S230.

Spence, A. Michael (1980), "Multi-product quantity-dependent prices and profitability constraints," *The Review of Economic Studies*, 47 (5), 821-841.

Stigler, George J. (1963), "United States vs. Loew's Inc.: A note on block bundling," *The Supreme Court Review, ed. PB Kurland*, 153-57.

Venkatesh, R. and Wagner Kamakura (2003), "Optimal bundling and pricing under a monopoly: Contrasting complements and substitutes from independently valued products," *The Journal of Business*, 76 (2), 211-231.