Leveraging Online Auctions: Capturing Willingness to Pay and Optimizing Product Assortment

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Abstract

Designing optimal product configurations and assortments is a complex task and is likely to continue to be quite challenging as firms seek to provide consumers with more and more options. On the one hand, modularization and outsourcing enable companies to choose from a plethora of potential bundles of attributes. On the other hand, shorter product life cycles increase the opportunity cost of rolling out unsuccessful product configurations and assortments. Thus, it is reasonable to expect that new tools may be required to effectively introduce product configurations and assortments that can realize higher margins. Our aim in this paper is to develop and illustrate a comprehensive framework for identifying efficient product configurations and product assortments. Specifically, we show both theoretically and empirically that it is possible to leverage online auctions, such as those conducted by eBay, Amazon.com and Yahoo! for the purpose of capturing reliable estimates of a consumers’ willingness-to-pay, which can be then used to identify optimal product configurations, product assortments and in setting profit maximizing prices. To illustrate the proposed methodology we use data from a series of eBay auctions for digital cameras conducted in 2007.
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Introduction

Price setting and determining optimal product assortment are still two of most daunting challenges facing marketing managers. Conceptually, the task of configuring different components and attributes into a single product is simple. With reliable estimates of consumers’ willingness-to-pay (WTP) and known component costs, a firm could offer only those bundles of features that maximize profit. While conceptually simple, this approach depends on reliable data on consumer preferences, which has been notoriously difficult to obtain. Consequently, cost plus percent markup continues to be the most common method of price setting (Noble and Gruca 1999).

Attempts at getting reliable estimates of WTP have generally focused on preferences and consumer utility. And there is a rich history of methods, ranging in analytical sophistication, for making inferences about consumer preferences and deriving empirical demand functions; for example, Multi-Attribute Utility Theory, MAUT, (Keeney and Raiffa 1976), the Analytic Hierarchy Process (Saaty 1980), conjoint analysis (Green and Srinivasan 1990) and choice modeling (Louviere, Hensher and Swait 2000) have all been used to estimate consumer preferences and utility. All of these methods, however, capture stated preferences as opposed to revealed preferences. As we discuss shortly, it is well known that stated preferences may not be incentive-compatible, which means that they lack incentive structures that are aligned with actual purchase behaviors. In such cases, the preference structures uncovered by these methods may not predict actual purchase behaviors very well and, obviously, can lead to less than optimal price setting decisions.

Recently, several researchers have argued for measuring consumers’ WTP at the point of purchase, or if not possible, at least designing studies, which capture stated preferences, to be incentive-aligned (Wertenbroch and Skiera 2002; Ding, Grewal and Liechty 2005). However, designing incentive-aligned studies that are consistent with
actual purchase behaviors is not easy since it requires that any incentive provided to the respondent be directly linked to decisions that are made in response to the experimental manipulations. It is for this reason that most of the work demonstrating the benefits of designing incentive-aligned conjoint or incentive-aligned contingent valuation studies have considered inexpensive product categories, usually less than $20, e.g., carbonated soft drinks, snacks, and Chinese dinners (Green and Srinivasan, 1990). For a whole range of product categories the design of an incentive-aligned conjoint or contingent valuation study does not appear to be practical, given the non-trivial purchase price that respondents would have to pay. However, it is for these very product categories that price setting and determining the optimal configuration of features is profoundly important. Take, for example, technology, or more specifically consumer electronics. In these product categories the practice has generally been to indiscriminately add features without understanding WTP or feature value.\footnote{Recently, Thompson, Hamilton and Rust (2005) have provided an interesting discussion of what they refer to as feature fatigue.} In addition, as modern manufacturing techniques rely more on modularity and component interchangeability in assembling products, manufacturers must choose the optimal bundle of features to incorporate in offered products. While some manufacturers allow consumers substantial leeway in customizing products, and though we are beginning to learn more about the benefits of mass customization (Dellaert and Stremersch 2005), the vast majority of products are still pre-assembled and offered as a composite bundle; consequently, optimal configuration of features and components into a finished product continues to be critical. Another, and perhaps even larger, challenge is developing optimal assortments of products within a product line that varies in terms of quality offered. These sorts of problems are particularly acute in the case of technology products for these manufacturers face shorter and shorter product life cycles and a myriad of possible configurations (Fisher, 1997).
Contribution

So what can manufacturers of higher-end products and services do to better optimize product-line assortments through understanding WTP? In this study we argue for, and demonstrate a method of, leveraging online auctions, such as those conducted by eBay, Amazon.com and Yahoo!, for the purpose of determining consumers’ WTP and optimizing product assortments and price setting decisions. Our position is that as online auction markets expand, they offer an innovative opportunity to measure consumer preferences. Instead of relying on survey methods or simulated markets, firms can now elicit consumer preferences directly, unobtrusively, and in an inherently incentive-aligned manner.

Specifically, we show that it is possible to use data on selling prices for products offered at auctions for the purpose of capturing reliable estimates of WTP and deriving empirical demand functions for higher-priced products, in our case digital cameras. Auction prices represent prices that people actually paid rather than what they said they would be willing to pay. Consequently, with information about market value of product features, and cost data of different product configurations, a manufacturer can identify efficient product configurations – bundles of features and product assortments that enable profit maximization.

To illustrate the proposed methodology we use data from a series of eBay auctions conducted in May through December 2007. One active and robust segment in the online marketplace is the trade of digital cameras. Several companies offer digital cameras via auction, and realize active bidding on these offers. Online auctions allow potential buyers to bid for these items. Generally, a minimum price is specified and a set time is allowed for the bidding. We show that the final selling prices at auctions can be used to estimate demand for certain attributes and features, provided that one uses appropriate techniques. Our aim is to develop an “efficient frontier” for optimal assortment pricing and to show that online auctions can be used as a way to elicit consumer preferences. As such, we believe that online auction prices can become a very important tool for corporate decision making with respect to determining optimal
product configurations, selecting a product line assortment, and in price setting decisions.

It is important to note that the contribution of this work is not limited to the problem setting used to illustrate the proposed methodology. For example, as we mentioned, consumer electronics (e.g., televisions, computers, camcorders) represent a broad category of products that can benefit greatly from our approach since product configuration and assortment decisions have to be finalized well before national rollout, and consequently any early information on consumer preferences, as can be gleaned from online auctions, would be extremely valuable; in addition, the proposed approach can be deployed on an ongoing basis in order to continuously modify product assortments and pricing by identifying trends in consumer value through the repeated monitoring of online auctions. For example, in the product introduction phase, measuring trends in feature value would provide an estimate of obsolescence for each attribute. Feature value could then be discounted based on obsolescence. After product introduction, ongoing use of online auctions in parallel with retail sales could provide early indications regarding the speed of obsolescence at both the feature level and the product level. Finally, product bundling is yet another pervasive problem setting that can benefit from using an approach that can provide reliable indications of a consumers’ WTP– for example, cruise-line travel packages are frequently offered as a bundle of room type, flight, tours and ship type, and in communication services, firms are increasingly offering tiered configuration of land-line, wireless telephony, and Internet service to their customers.

The remainder of this paper is organized as follows: In the next section we discuss the benefits of experimental and online auctions. Next, we lay out the theory on which our methodology for measuring consumer value and determining profit-maximizing prices is based. We follow this discussion with a detail description of the proposed estimation approach. Then we describe the data and present results. Finally, we conclude with a discussion of a framework for applying the proposed method to the
case where a firm must assemble new products from existing modules or bundling products and services from multiple providers.

Auctions

The reason competitive markets work is because, over time, we have stumbled on processes which force people to reveal what they really want and how much they want it. (John Kay, Financial Times, March 17, 1999).

Experimental Auctions

Experimental auctions have been of interest to game theorists and behavioral economists for some time. The attractiveness of experimental auctions is directly tied to the notion of incentive compatibility. An auction is said to be incentive compatible if participants are rationally motivated to reveal the truth about their valuations. In his seminal paper, Vickrey (1961) argued for the importance of incentive compatibility. Vickrey auctions, as they are called, are often conducted as a sealed or open bid auction where the highest bidder must buy the good in a real transaction; specifically, a Vickrey auction is a second-price, sealed-bid auction. In a sealed-bid auction, the purchase price is determined solely by the other participants’ bids. When one item is auctioned, it is awarded to the individual with the highest bid, at the price of the second-highest bid. In a multi-unit auction when \( n \) units are offered, the \( n \) highest bidders are awarded units at the price of the \((n + 1)\)th-highest bid. This format is desirable in that a bidder’s dominant strategy is to bid according to his/her WTP, revealing underlying preferences, because underbidding will likely lead to losing the auction. Some critics have pointed out that in experimental Vickrey auctions only a limited stock of goods is available while in real-life situations supply is, for all intent and purposes, unrestricted. Therefore, there maybe some incentive for a person to bid more than the item is worth to ensure that they “win” the auction (Kagel 1995). A more elaborate procedure was developed in 1964 by Becker, DeGroot and Marschak (BDM). Under the BDM protocol
purchasers are encouraged to offer a price for a product which should be the highest price $s$ they are willing to pay for the product. Then a price $p$ is randomly determined. Only when $p$ is less than $s$ are they obligated to buy the product. This format has been found to mitigate the overbidding found in Vickrey auctions (Kagel, 1995). Behavioral economists have widely used BDM-type random preference elicitation procedures to estimate WTP for a variety of consumer goods (see e.g., Kagel, Harstad and Levin 1987; Kahneman, Knetsch, and Thaler 1990; Wertenbroch 1998).

Despite the benefits of incentive compatibility, experimental auctions are not free from limitations. In the context of this study, three limitations warrant attention. First, experimental auctions have been restricted to inexpensive consumer goods, such as carbonated soft drinks, snacks, meals, etc., usually costing less than $20$. The use of these protocols when more expensive products and services are involved faces, what appears to be, serious practical challenges both in terms of participation rates (i.e., selection bias) and the use of incentives (the larger the incentive the greater the likelihood that participants’ WTP is distorted by the windfall character of the extra compensation). Second, in BDM-type studies participants consideration sets are usually limited to a narrow set of alternatives, when compared to actual purchase options; for example, in the BDM study reported by Wertenbroch and Skiera (2002), which attempted to estimate consumers’ WTP at point of purchase, participants were not presented with any substitute products – WTP was captured in the context of a single product offering. Third, experimental auctions are subject to demand artifacts and to hypothetical bias as is any study conducted in a lab – being scrutinized and knowing that one’s behavior is being monitored can lead people to act differently than when in a market setting.

**Online Auctions**

Estimates of online consumer auction sales by some accounts will reach $65$ billion by $2010$ (Forrester Research 2006). It is reasonable to expect that the number of auction sites will increase in concert. With the rapid increase in the number and volume of
online auctions, these will continue to grow in importance as a platform for investigating exchange mechanisms. Research into online auctions has focused on such issues as auction format (Lucking-Reily 1999), winner’s curse (Bajari and Hortaçsu 2003), consumer rationality (Park and Bradlow 2005; Spann and Tellis 2006) and last minute bidding phenomenon (Roth and Ockenfels 2002). Though the success of this research stream has led to the use of auction theory in developing and enhancing a vast array of auctions in diverse areas such as treasury debt sales, timber logging rights, spectrum use rights, and even Initial Public Offerings (Klemperer, 2000), little research has focused on how to leverage online auctions for optimal price setting and determining optimal product assortments.

As we discuss below, online auctions represent a fertile platform for estimating WTP and feature value, and when combined with supply side feature cost, can provide a framework for determining the profit maximizing product assortment combinations. Online auctions hold great promise since they are conducted in market settings, outside of the lab and consequently are, for the most part, free of the limitations associated with experimental auctions. In particular, i) online auctions are, by definition, always incentive compatible, ii) products offered at auction have varied prices and specifically high-priced products are frequently auctioned, iii) no incentives are needed, iv) the range of products offered is consistent with what the seller, not the researcher, chooses to sell, and finally, v) the “experiment” occurs in the field – outside the lab.

We propose to use auctions as a platform for measuring consumer value by interpreting auction prices as reflections of a consumers’ WTP. This is permissible since we assume that consumers’ value can be treated as independent, identical draws, which implies a “private-value” auction. In private-value auctions, participants’ bid strategically, depending on exogenous factors. Specifically, a series of online auctions of similar items can be viewed as a series of sequential auctions. Thus, in a series of sequential auctions, a rational bidder’s strategy incorporates both the number of subsequent auctions in a short time period, and the number of other bidders competing against him; consequently, expected prices in sequential auctions are identical (Weber
1983; Snir 2006), and expected auction prices vary with the supply and bidder competition, which establishes the conditions necessary for viewing auction prices as reflections of a consumers’ WTP.

**Theoretical Development**

The objective of this research is to demonstrate how online auctions can be used to identify “efficient” configurations of attribute and features to offer. A configuration, in this context, is the set of attributes and features that are included in the product. We assume the standard setting in which the number of attributes and features result in a very large number of potential configurations to consider. We assume an additive linear value function where the value of product configuration $j$ is given by

$$v_j = \sum_{m=1}^{M} a_{jm} w_m,$$

where $a_{jm}$ denotes the feature $m$, $m = 1, \ldots, M$, in product $j$, and $w_m$ is the value of feature $m$.\(^2\) We also assume that consumers have preference for value, based on a taste parameter which is denoted by $\theta$. The cost of each product configuration is denoted by $c_j$. To define “efficient” assume the firm has information regarding a consumers’ value for a feature and cost of providing the feature. For a configuration to be efficient no other feasible configuration, or linear combination of configurations, increases consumer value at lower cost. The “efficient frontier” is the set of all efficient configurations.

[Place Figure 1a here]

**Consumer Value and Efficient Configurations**

Figure 1a can be used to illustrate the concept of efficiency. In the figure there are 6 product configurations (including the Null product configuration) in the cost-value

\(^2\) Assuming an additive utility function is restrictive in the sense that we do not allow interaction effects between product attributes and features. However, i) additive utility functions have been shown to provide good approximations (cf. Einhorn 1970; Green and Devita 1979) and ii) this assumption can be relaxed by incorporating interactions.
space (with cost along the horizontal axis). In this example only product configurations Null, B, and E are efficient. For each of the other product configurations there exists a linear combination of the efficient configurations that offers similar value at lower cost. For example, a linear combination of product configurations B and E would dominate product configuration C. Similarly, product configuration D is dominated by product configuration E. Note that efficient product configurations are only to the left of product configuration E, which offers the highest value. Product configurations to the right of product E have higher cost and lower value, and are dominated by product configuration E. As can be seen in Figure 1a, not all product configurations are efficient. In fact, if consumers have an additive value function over product features, and if consumers differ in their preference for value, there is only a small subset of product configurations that are efficient.

Consumers can differ with respect to their preferences for product value. Define a consumer by his/her preferred configuration. A consumer with taste preference $\theta_{j}$ is assumed to have a multiplicative utility function: $U(\theta, u_{k}) = \theta_{j}u_{k}$. We describe the preferred configuration for consumer with taste preference $\theta_{j}$ as having value, $v_{j}$, at price $p_{j}$. When deciding on a price to bid, we assume consumers maximize their expected surplus or utility net of price: $U(\theta_{j}, v_{j}) = \theta_{j}v_{j} - p_{j}$. If we assume that consumers compare each product configuration against all other potential product configurations, surplus maximization by the consumers means that consumer preference type $\theta_{j}$ generates more utility from purchasing designated configuration with value $v_{j}$ than any other configuration, given the prices. Formally:

$$\theta_{j}v_{j} - p_{j} = \max_{k \in J} (\theta_{j}v_{k} - p_{k}),$$

where the maximization is over $J$, the set of product configurations. If we compare two configurations that have positive market share with $p_{j} > p_{k}$, sold to consumers with taste $\theta_{j}$,

\[3\] In a strict sense this also assumes a linear multiplicative utility function in value and taste.
preference $\theta_j$ and $\theta_k$, respectively, it must be that $(v_j - p_j) > (v_k - p_k)$ and $\theta_j > \theta_k$, and therefore we see that the assumption of surplus maximization generates incentive compatibility constraints.

The challenges in using a consumers’ utility function to identify efficient product configurations are that the value of each configuration, $v_j$, must be determined so that i) configurations are ordered in increasing price and value, ii) configuration $j$ sold at price $p_j$ corresponds to consumer type $\theta_j$, and iii) consumer types are monotonically increasing in realized prices.

Traditionally, a seller offering products in an online auction has information regarding the configurations that are purchased and realized priced. Information regarding both taste parameters ($\theta_j$) and corresponding value ($v_j$) is unavailable. In order to identify a utility level for each configuration we make an assumption regarding the relationship between taste and realized price for a configuration, i.e. $\theta_j=f(p_j)$. The following specifies a method for determining values, $v_j$, which adheres to the incentive compatibility constraints, assuming known values for $\theta_j$.

Determining $v_j$:

1. Define a null configuration with
   \[ v_0 = p_0 = \theta_0 = 0. \]

2. Set
   \[ v_j = v_{j-1} + \frac{p_j - p_{j-1}}{\theta_j} \]  
   \[ (1) \]

Thus, to assign a utility level a given product configuration, consumer type, and prices, utility is set so that consumer type $\theta_j$ is indifferent between product configurations $j$ and $j-1$. (Equation (1) can be alternately specified as $\theta_j v_j - p_j = \theta_j v_{j-1} - p_{j-1}$. ) This assures that the utility for consumer type $\theta_j$ is maximized, when presented with product configuration $j$. 
Social Surplus

The socially optimal set of product configurations maximizes the difference between consumer utility and firm cost, ignoring the transfer price paid to the firm. For consumer type $\theta_j$, product configuration $j$ generates utility $\theta_j v_j$ at cost $c_j$ to the manufacturer. The social surplus from this configuration is $\theta_j v_j - c_j$. Previously we discussed the “efficient frontier” of configurations, independent of consumer utility, as depicted in Figure 1a. It can be shown that this set is also the set that maximizes social surplus. This is used as the optimal product assortment.

As shown in Figure 1b, we can identify the socially efficient configuration assigned to each consumer type. For a consumer type with a low value of $\theta$ say $\theta_1$, the slope in cost-value space is very steep, and the Null product configuration is efficient since a low value of $\theta$ corresponds to placing little weight on product value and therefore abstaining from purchasing, at the extreme. The slope of cost-value efficient frontier line is $\frac{1}{\theta_1}$. For each consumer type there is also a corresponding angle with the y-axis. The angle that $\theta_1$ makes with the value axis is small. As a consumer’s preference for value increases (higher values of $\theta$, say $\theta_2$) product configuration B offers more social welfare than the Null product. Finally, at high values of $\theta$, say $\theta_3$, product value is heavily weighed, and product configuration E maximizes social welfare. The critical values for $\theta$ which lead to switching between product configurations depend on the slopes of the lines connecting the configurations in cost-value space – we discuss this point further in the next section.

[Place Figure 1b here]

Profit Maximization

In developing the profit maximizing behavior of the firm we assume that the firm has some monopoly power, selling multiple products in the posted-price market. Similar results can be
attained under different competitive assumptions.\(^4\) To identify profit-maximizing prices, the primary consideration is to target a product configuration \(j\) to consumer type \(\theta\). We consider only those configurations that lie on the efficient frontier, denoted by a superscript \(e\). The incentive compatibility constraints for each preference type require that

\[
\theta_j v^e_j - p^e_j \geq \max_{k \in J^e} (\theta_j v^e_k - p^e_k),
\]

where the maximization is over all efficient product configurations, \(J^e\).

Define \(\theta^e_j\) as the least quality sensitive consumer type that purchases configuration \((c^j, v^j)\). Hence, consumers of types \(\theta^e_j \leq \theta \leq \theta^e_{j+1}\) purchase configuration \((c^j, v^j)\), and demand for this configuration is \([G(\theta^e_{j+1}) - G(\theta^e_j)]\), where \(G(\theta)\) denotes the cdf of consumers’ taste distribution. The firm’s objective is to maximize profit, which is the sum of demand for each configuration multiplied by the product configuration margin. In maximizing profit, the firm simultaneously sets prices \((p^e_j)\) and market share \((\theta^e_j)\) for each configuration. The market is segmented by consumers that buy a specific configuration, including those that choose not to purchase. Similarly, a price is set for each product configuration. From the incentive compatibility constraints, an optimal strategy from the firm’s perspective, if market segments (i.e., consumer types) are known, is to take the price of the null configuration as \(p^e_0 = 0\), and for each sequential segment set the price such that the least value-sensitive consumer, \(\theta^e_j\), is indifferent between this designated product configuration and its immediate predecessor. Thus, the firm’s problem is to segment the market, by choosing threshold values for each configuration \(\theta^e_j\). Stated formally the firm’s problem is:

\(^4\) For example, if the posted-price market is competitive, prices will equal marginal cost. It can be shown that setting prices equal to marginal cost is consistent with incentive compatibility (Wolfstetter 1999).
\[
\begin{align*}
\max_{\{p'_j, \theta'_j\}} \pi &= \sum_{j=0}^{J'} \left[ G(\theta'_{j+1}) - G(\theta'_j) \right] \left( p'_j - c'_j \right),
\end{align*}
\]
where the maximization is over prices and indifferent types: \((p'_j, \theta'_j)\) subject to incentive compatibility:

\[
(\theta v'_j - p'_j) \geq \max_{k'=0,...,J'} \left( \theta v'_{k} - p'_k \right) \quad \forall \left[ \theta'_j, \theta'_{j+1} \right], \quad j=0',...,J'.
\]

Profit maximizing prices for a monopolist offering efficient configurations \((c'_j, v'_j)\) can be set as follows (with optimal values denoted by \(*\)).

Setting Profit Maximizing Prices:

1. Identify the cutoff types for each configuration as:

\[
\begin{align*}
\theta'_j &= \text{Solve} \left[ \theta = \gamma(\theta) + \frac{c'_j - c'_{j-1}}{v'_j - v'_{j-1}} \right] \quad (2)
\end{align*}
\]

where \(\gamma(\theta)\) is the inverse hazard rate, which is assumed monotonically non-increasing:

\[
\gamma(\theta) = \frac{1 - G(\theta)}{g(\theta)}.
\]

2. Set \(p'_0 = 0\) for the null configuration \((c'_0, v'_0) = (0, 0)\).

3. Set

\[
\begin{align*}
p'_j &= \theta'_j \left( v'_j - v'_{j-1} \right) + p'_{j-1} \quad (3)
\end{align*}
\]

Estimation Approach

In this section we develop a method of estimation which is consistent with the theoretical development presented in the preceding section.

*Estimating feature value:* To determine consumer value for a product configuration requires determination of the value that a consumer places on each

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\(^5\) This method results from Bhargava and Choudhery (2001) and Snir and Sobol (2004).
constituent feature. From the online auction we can determine closing bid prices and the features corresponding to auctioned product. Taking the closing bid price as the consumers’ WTP we regress bid price on the set of features to determine feature value controlling for a number of factors that can potentially influence bidding behavior:

\[ p_j = \sum_{m=1}^{M} \hat{w}_m a_{jm} + \hat{b}A_j + \epsilon_j \]  

(4)

where \( \hat{w}_m \) is the estimated value of feature \( a_{jm} \). The term \( \hat{b}A_j \) captures the influence on bid price of potential moderator factors, such as the day the auction closed, the number of bids and opening bid – we discuss these factors in more detail in the next section.

To accommodate heterogeneity in taste distributions we take a discrete support point approach and estimate a semi-parametric random coefficients regression model. Heterogeneity is introduced by allowing feature values and covariate parameters to vary over (a few support points). Letting \( w'_m \) denote the feature value associated with support point \( s \) we can write equation (4) as

\[ p_j = \sum_{m=1}^{M} \hat{w}^s_m a_{jm} + \hat{b}'A_j + \epsilon_j \]  

(5)

As we discuss below, we can accommodate heterogeneity in tastes in one of two ways. If consumer types (i.e., segments) can be identified and reached then we can use the feature values \( \hat{w}^s_m \) directly to determine optimal product configurations, product assortments and pricing for each consumer segment separately; in other words, we segment the market according to consumer segments and target a specific product assortment to each segment. This may require correlating purchasing behavior with individual factors, to identify precursors to participation in a segment. In cases where consumer segments cannot be easily identified or reached, because of a lack of individual level information on the bidders, or for other reasons, we can determine the optimal “mass market” product configurations, product assortment and pricing, accommodating heterogeneity in tastes, by taking a weighted average of feature values
where the weights reflect the relative size of each consumer segment (denoting the size of segment $s$ by $\omega_s$): $\hat{v}_j = \sum_{s=1}^{S} \omega_s \hat{v}^s_j$.

Determining feature cost: To determine the set of efficient configurations requires knowledge of the cost of providing feature $a_{jm}$. Component costs could conceivably be provided by the firm on the basis of internal cost accounting systems. Alternatively, we can attempt to derive the marginal cost of each component feature. In the next section we describe an approach that uses manufacturer suggested retail price (MSRP) as a proxy for the underlying component cost – first, we use MSRP to determine the marginal price of a feature and then assume a markup over cost percentage to back in marginal cost.

Identifying efficient configurations: To determine which product configurations are efficient we use a variable returns to scale model adapted from Data Envelopment Analysis (DEA). This method, commonly called the VRS BCC model, was developed by Banker, Charnes, and Cooper (1984). We modify the conventional VRS BCC model by including the null configuration, which reflects the no purchase option. DEA is essentially an application of linear programming that has been used to measure the relative efficiencies of operating units with congruent goals and objectives.\(^6\)

In this model each feasible product configuration is assessed against all other configurations to determine whether a linear combination of other configurations can achieve similar value at lower weighted average cost. A product configuration’s efficiency score, denoted by $\delta$, measures how far it is from the efficient frontier – i.e., the fraction of cost needed relative to the configurations under consideration. When $\delta=1$, a more efficient opportunity does not exist, and a configuration is deemed efficient. More formally, the model is:

$$\begin{align*}
\min_{\lambda} \quad & \delta \\
\text{subject to} \quad & \end{align*}$$

\(^{6}\) There is a rather extensive literature on DEA. Interested readers can consult Cooper, Seiford and Tone (2000) for a review of models, applications and extant literature.
\[ \sum_{k=1}^{j} \lambda_k v_k - v_j \geq 0 \]  
\[ \sum_{k=1}^{j} \lambda_k c_k - \delta c_j \leq 0 \]  
\[ \sum_{k=1}^{j} \lambda_k = 1, \lambda_k \geq 0 \forall k, \]  
where the minimization is over the envelopment weights \( \lambda \).

The intuition underlying this approach is that each configuration is evaluated in terms of whether a weighted average of other configurations can achieve the same value at lower cost. The first constraint (7) requires that the weighted average value be at least as high as that of the configuration under consideration. The second constraint (8) measures the possibility of realizing lower cost using the same weights. The third constraint (9) assures that only feasible configurations are compared.

This approach is also consistent with maximizing social welfare, as previously discussed. The following Proposition formalizes this (see the Appendix for the proof):

Proposition: If consumers' value is additive over product attributes and utility is linear in value, the set of socially optimal configurations is the set of efficient configurations calculated by the VRS BCC DEA model.

The intuition for this result is that the VRS BCC model described by equations (6)-(9) generates a subset of the convex hull of potential configurations, in the cost-value space (see, for example, Figure 1b). For a specific type, parameterized by \( \theta \), social welfare is linearly related to cost and value \((c_j, v_j)\). For any type, identifying socially efficient configurations involves a linear objective function. The slope of the linear objective function is \( \frac{1}{\theta} \), in cost-value space, over the set of possible configurations. Note that the axes in this analysis, as shown in Figure 1B, have value along the y-axis. In other words, critical values for consumer types are defined by the term \( \frac{1}{\theta} \). It is known, from linear
programming, that if an optimal solution exists, it is at an extreme point. The VRS BCC model identifies these extreme points. Since consumers differ in their taste parameter, $\theta$, different extreme points are optimal for different consumers.

**Setting optimal prices:** Setting optimal prices requires knowledge of the consumer threshold values, $\theta^*$, associated with the set of efficient product configuration. With knowledge of $(c^*_j, v^*_j)$ we use equation (2) to solve for $\theta^*$. Once cutoff values for $\theta^*$ are determined the market share of each product configuration can also be computed from taking $[G(\theta^*_{j+1}) - G(\theta^*_j)]$. Prices are then determined sequentially, starting from the null configuration and increasing to the next efficient product configuration. The price for the null configuration is set at zero, corresponding to the segment of unserved consumers in the market. Each other product configuration is priced to maximize profits, based on $\theta^*_j$, the threshold type for that configuration along with $(c^*_j, v^*_j)$ and $(c^*_{j-1}, v^*_{j-1})$.

**Estimation Steps:** To summarize, the estimation approach discussed above can be described in terms of five distinct steps:

- Step 1: Estimate the value that consumers place on each feature.
- Step 2: Estimate the component cost of each feature.
- Step 3a: Compute the imputed cost and prices for all possible configurations.
- Step 3b: Convert the imputed price of a configuration to a measure of value.
- Step 4: Identify efficient product configurations, using DEA.
- Step 5: Set optimal prices for each efficient product configuration.

**Data and Analysis**

**Data Description**

We use data from auctions of Canon digital cameras to estimate WTP and consumer value for different attributes and features. Specifically, auction data for this study are based on online auctions on eBay from one seller of Canon digital cameras for
the May-December 2007 time period. Each auction was open for bidding for less than a week. There are a number of advantages to using this market. First, data is readily available, as many digital cameras are sold daily via online auctions such as those conducted by eBay. Second, these purchases of durable products are moderately expensive. Consumers expend some effort in identifying available alternatives and choosing among them. Decisions regarding whether to bid, on which auction to bid, and how much to bid, reflect deliberation. Hence, it can be expected that auction prices are calibrated with preferences. Finally, eBay auctions are conducted as Oral English auctions, where the winning bid rises until all but one bidder drops out of the bidding. This implies that participants’ dominant strategy is to bid according to their private values, similar to Vickrey auctions, and thus we feel confident in interpreting auction closing prices as a bidders’ WTP.

To control for product heterogeneity, we limit the analysis to auctions of one brand of cameras – new point and shoot cameras manufactured by Canon. Product attributes that vary in the data are, the sensor resolution measured in mega-pixels (MP), the optical zoom of the lens, whether the camera has a small or large form, and whether it includes Image Stabilization technology. This allows us to evaluate a consumers’ WTP for varying configurations. Configuration can be described in terms of four component product attributes which are described in Table 1.

[Place Table 1 here]

Data collection involved gathering data directly from the eBay website. Searching periodically for items offered by this seller identified relevant cameras, winning bids and buyers’ identities. Inspection of each auction revealed the number of bids and product configurations purchased. In the seven months of the study, 2,099 of these cameras were sold, generating over $500,000 in revenue. Of these, 427 auctions concluded early because an item was purchased using the “Buy It Now” service. This service allows a consumer to buy the camera at a predetermined (relatively high) price before the end of the auction. We keep these auctions in the analysis and include an
indicator variable for the type of auction. The range of winning bids is $20 to $441, with an average above $250 and a standard deviation of $72.59. Table 2 provides descriptive statistics of the realized auction price and the frequency of each feature across the 2,099 auctions analyzed.

[Place Table 2 here]

As mentioned earlier, it is also important to control for other factors that might influence bidding behaviors. In particular, controlling for daily factors is important in determining the marginal value of different attributes. We expect that prices would vary with two exogenous factors, supply and bidding activity, which likely change daily. Previous research in the area of online auctions suggests that there may be substantial differences in auction prices across days because of obsolescence (Pinker, Seidmann and Vakrat 2000) and differences in bidding activity on weekdays and weekends (Snir 2006), as well as on the basis of the supply of products available over the course of the bidding cycle. Even over short periods of time as seven months there is some obsolescence in selling cameras due to natural causes (i.e., product feature enhancement occurs continuously) or because of market saturation, which reflects the fact that the pace of selling cameras on eBay is faster than the pace of new buyers joining the market. As some buyers exit the market, because they have filled their need, the competition among buyers decreases and auction closing prices go down. Thus, we define a covariate to represent end-day-counter, which identifies the day the auction closed, starting from January 1, 2004. Three additional covariates used to control for differences across auctions are whether the auction format was “Buy It Now” or a traditional auction, the number of Bids received in the auction, and the Opening bid set by the seller.

Figure 2 shows the pattern of mean prices paid by the day the auction ended (Panel A) and with the supply of products available (Panel B). From Figure 2, Panel B the relationship between average realized auction prices and end-day has a slight downward slope. Panel C shows that average bidding prices are also negatively
correlated with supply—in general as supply of auctions decreases average bidding prices increase. These effects justify the use of fixed-effects for end-day.

[Place Figure 2 here]

Analysis

*Step 1: Estimate the value that consumers place on each feature.* As discussed previously, to derive the utility of a product configuration we take the closing bid price as the consumers’ WTP and regress prices paid on the feature that together define the product that was auctioned, controlling for four covariates previously introduced: end-day, buy-it-now, opening bid and number of bids.

Table 4 presents parameter estimates for the model. The first two rows of this table report the relative size of each consumer segment and the explained variance ($R^2$'s). From the homogenous taste model, we see that parameter estimates for the buy-it-now covariate is slight and not significant, suggesting that auction format does not impact auction price. This justifies including these auctions in the analysis. The number of bids has a significant impact on auction price, with an additional value of over $0.50 for each additional bid. The opening bid does impact the realized price in an auction significantly.

[Place Table 4 here]

Turning to the feature parameter estimates, we note the following: First, all of the feature value coefficients are statistically significant. Furthermore the value placed by consumers on better features is increasing. Notable from the results is that the small camera form is valued by consumers by over $100 and the value of Image Stabilization is more than $50.

---

8 In reporting results, we express prices and costs in dollars; value is expressed in units.
Step 2: Estimate the component cost of each feature. In this problem setting, manufacturer marginal cost information was not available. Instead, we derive component cost by utilizing an independent data source; specifically, MSRP for new cameras specified by the manufacturer. Twenty-three (23) different camera configurations are analyzed. The first step in computing marginal costs of an attribute levels is to model MSRP as a function of product features: \( PP_i = f(F_{i,j}) \).

Table 5 provides summary results. The fit of this model is relatively good, \( R^2 = .88 \), which suggests that an additive model of features in pricing products is a reasonable approximation. Not all marginal feature effects are statistically significant at the .05 level. While the results of this analysis do raise some concerns, we use the imputed marginal prices. In practice a manufacturer would have detailed data on component cost to build the assortment and pricing model. Inspection of costs of individual components shows that, similar to auction prices, differences in resolution command the largest price differentials. A 10 MP camera is priced $137 more than a 3 MP camera. It is important to note that Image Stabilization has almost no impact on MSRP, while customers do place substantial value on this feature.

[Place Table 5 here]

The marginal feature coefficients provided in Table 5 represent the marginal prices of changes in a feature, not marginal component cost. To convert marginal prices to implied marginal cost requires knowledge of general or specific component markups. In computing implied marginal component costs we assume that the estimated marginal prices reflect a 100% markup (over cost).\(^9\)

Step 3a: Compute the imputed cost and prices for all possible configurations. There are in total 96 potential configurations which could be offered. For each feasible configuration cost is computed by summing up the component marginal cost of each

---

\(^9\) The percent markup assumed does not impact the identification of efficient configurations or the efficient frontier—that is, any other proportional relationship between price and cost would single out the same configurations as efficient.
feature offered. Component marginal costs for each feature appear in the last column of Table 5. Computing prices is slightly more complicated. Since the heterogenous model is a fixed-effects model (i.e., we control for auction-closing day behaviors) the model intercept needs to be imputed from the parameter estimates shown in Table 4. Here we use the weighted average for the fixed-effects (weighted by the number of auctions in each day) as the intercept for each auction that each consumer segment participated in. Weighted intercepts are also provided in Table 4.

**Step 3b: Convert the imputed prices of a configuration to a measure of value.** There are several ways to convert prices to value. Since we have accounted for differences in tastes, we use the relationship of the imputed price for each configuration to the average price for a consumer segment to first arrive at a measure of a consumer types’ taste preference for a given product configuration: viz:

$$\theta_j = \frac{\hat{p}_j}{\bar{p}}.$$

Next, we determine the value of each product configuration by using equation (1) by setting $u_0 = p_0 = \theta_0 = 0$, for the null configuration and iteratively calculating the value of all other product configurations.

**Step 4: Identify efficient product configurations.** Figure 3, depict the efficient frontiers for the 96 feasible configurations for heterogenous mass market model produced from the BCC VRS model. A description of each efficient product configuration is provided in Table 6. In addition to specifying each configuration it includes for each the cost, value, optimal cutofft taste parameter, market share, optimal price, and computed auction price. Two points should be mentioned: First, as discussed earlier, it is clear that the vast amount of product configurations are not efficient which suggests that for many of the product configurations located in the inferior of the efficient frontier, a camera manufacturer could offer a combination of product configurations at similar cost that have more value to customers (increasing profit) or that a combination of
configurations of equivalent value at lower cost could be offered, without lowering value.

[Place Figure 3 and Table 6 here]

**Step 5: Set optimal prices for each efficient product configuration.** To set optimal, profit maximizing prices requires that the distribution of each $\theta$ be known. In this analysis we take $\theta \sim N(\mu(\theta), \sigma(\theta)^2)$. At this step we can also compute the market share associated with each efficient product configuration in each consumer segment market according to $G(\theta_{j+1}^{*s}) - G(\theta_j^{*s})$. Table 6 provides costs, value, $\theta_j^{*s}$, market shares and optimal prices for all efficient product configurations.

**Discussion**

As demonstrated by the application described above online auctions can be leveraged to provide information valuable in determining optimal product configurations, product assortments and prices. From a product configuration perspective, the modeling approach identified which features are most valued, accounting for heterogenous tastes. If consumer segments can be identified then different product configurations can be targeted to specific consumer segments, either through messaging or channel selection. If consumer segments cannot be identified and targeted directly, then this approach can benefit the firm by bringing to market a product configuration assortment that reflect different tastes as well. In terms of product assortments, this approach can help the firm in determining the complexion of products it should offer as well as the breadth of its product offering by swapping inefficient product configurations and assortments for assortments that can increase consumer surplus and/or allow the firm to maximize profits by setting optimal prices.

Assume, for example, that the firm is taking a mass-marketing approach to its' product assortment decisions–i.e., specific consumer segments cannot be explicitly

---

10 Given the definition of $\theta$, we get $\mu(\theta) = 1$ and $\sigma$ as the standard deviation of values for segment $s$. 
targeted. Under a mass-marketing scenario a camera with Resolution 10 MP, 4x Optical Zoom, large camera form, including Image Stabilization should not be part of the firm’s product assortment offering. This camera costs $237 and generates customer value of 647.39 (denoted by a hollow diamond in Panel A, Figure 3). This level of customer value can be maintained at lower cost by offering Optimal Configuration #7 with Resolution 5 MP, 6x Optical Zoom, small camera form, including Image Stabilization (see Table 6). This alternative efficient product configuration would cost substantially less at $171.26, while generating slightly higher value at 651.54. Customers are nearly indifferent between either configuration, while the cost savings is $65.74. Alternately, the manufacturer can maintain cost while providing more value and increasing price; specifically, Optimal Configuration #8 with Resolution 8 MP, 6x Optical Zoom, small camera form, including Image Stabilization should be offered instead. This alternative would be slightly less expensive at $236.18, while generating substantially higher value at 716.54, 69.15 more than this inefficient product configuration.

Concluding Remarks

The ultimate usefulness of the proposed methodology rests on the firm’s ability to transfer the estimation protocol described above to other channels, such as posted-price catalogs and/or brick and mortar retailers or their websites. A fertile application area is in the optimal design of new product assortments. Frequently manufacturers and intermediaries have the ability to change product assortment. To do so may require assembling new products from existing modules or bundling products and services from multiple providers. As these opportunities arise the methodology developed here can be applied effectively to identifying the optimal product assortment, including prices for the different configurations offered within the assortment. To apply this methodology using online auctions the following procedures (or variants) should be followed:

1. Identification of key features. These may be based on physical modules that have to be assembled together (e.g., camera component), products from different
vendors that are bundled (e.g., flight and hotel room), or electronic configuration of digital products (the size of available online storage). The set of feasible configurations should be determined from all possible combinations of features.

2. **Cost identification.** As part of the process of identifying features that may be valued by consumers, it is important to identify feature cost, as well as the relationships among features. It may be that costs are additive, sub-additive, or super-additive when combined in different configurations.

3. **Experimental design.** Similar to discrete choice analysis, experimental designs can be used to determine which sets of product configurations to auction. Fractional designs and fractional factorials can be used to increase the precision of parameter estimates by ensuring that the sets of product configurations auctioned have appropriate statistical properties relating to the number of times specific features are offered and the relationship among features.

4. **Online auction.** Offering the chosen set of configurations using an online website is an effective and inexpensive method for identifying consumers’ WTP. The time required for setting up and running most types of auctions is fairly short, with only minor auction-related costs. The overall financial impact of the experiment may be positive, because auction winners pay for their items. The cost of producing the items sold is usually covered by the auction revenue. When conducting the online auction it is helpful to use a second-price, sealed-bid (Vickrey) auction mechanism (as on eBay). These types of auctions induce participants to bid their true WTP for items. The data gleaned from these auctions provides a direct measure of consumer preferences.

5. **Estimating feature value.** The results of the online auctions should be analyzed to determine consumers’ value for each feature. It is important that the analysis of auction results should correspond to assumptions regarding how consumer preferences are generated. Some factors to take into consideration include heterogeneity of different groups of consumers participating in the auction, the relationship between auction participants and consumers who will purchase the
product in the posted-price market, distribution of consumer types, and linear additivity of value.

6. *DEA Analysis.* Based on the statistical analysis of feature value and marginal component cost, the cost and value of each potential configuration can be calculated. DEA analysis is then applied to the set of potential configurations to identify those that are efficient. Offering these configurations maximize profit and determines the optimal product assortment. Only these products are offered in the posted-price market.

7. *Setting prices.* The price and market share for each efficient configuration is then determined.

Designing optimal product configurations and assortments is a complex task and is likely to continue to be quite challenging as firms seek to provide consumers with more and more options. On the one hand, modularization and outsourcing enable companies to choose from a plethora of potential bundles of attributes. On the other hand, shorter product life cycles increase the opportunity cost of rolling out unsuccessful product configurations and assortments. Thus, it is reasonable to expect that new tools may be required to effectively introduce product configurations and assortments that can realize higher margins. Our aim in this paper is to develop and illustrate an approach for identifying efficient frontiers for assortment and to show that online auctions can be used as a way to elicit consumer preferences, so that sellers can improve pricing strategy, optimally configure products, and optimize product assortments. As online auctions continue to grow in popularity we expect that increasing attention will be directed at leveraging their unique features to provide a platform for better marketing decision making.
References


Table 1
DIGITAL CAMERA ATTRIBUTE AND FEATURE DESCRIPTIONS

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image Resolution</td>
<td>4, 5, 6, 7.1, 8, 10 MP</td>
</tr>
<tr>
<td>Optical Zoom</td>
<td>3x, 4x, 6x, 12x</td>
</tr>
<tr>
<td>Camera Size</td>
<td>Large, Small</td>
</tr>
<tr>
<td>Image Stabilization</td>
<td>None, Included</td>
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</tbody>
</table>
## Table 2
DESCRIPTIVE STATISTICS

<table>
<thead>
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<th>Attribute</th>
<th>Feature</th>
<th>Mean/Frequency</th>
<th>Standard Error</th>
</tr>
</thead>
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<td>$72.59</td>
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<td>Image Resolution</td>
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<td>0.2385</td>
</tr>
<tr>
<td>Image Resolution</td>
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<td>0.052</td>
<td>0.2229</td>
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<tr>
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<td>0.206</td>
<td>0.4047</td>
</tr>
<tr>
<td>Image Resolution</td>
<td>7.1 MP</td>
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<td>0.4836</td>
</tr>
<tr>
<td>Image Resolution</td>
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<td>0.033</td>
<td>0.1783</td>
</tr>
<tr>
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<td>10 MP</td>
<td>0.020</td>
<td>0.1417</td>
</tr>
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<td>0.4966</td>
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<td>0.4845</td>
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<td>0.4996</td>
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<tr>
<td>Image Stabilization</td>
<td>Included</td>
<td>0.232</td>
<td>0.4222</td>
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Table 4
SUMMARY OF PARAMETER ESTIMATES

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<th>Covariate</th>
<th>Parameter Estimates</th>
<th>Homogeneous</th>
</tr>
</thead>
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<tr>
<td>Size (%)</td>
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<td>100</td>
</tr>
<tr>
<td>( R^2 )</td>
<td></td>
<td>.934</td>
</tr>
<tr>
<td>\textit{Buy It Now}</td>
<td></td>
<td>1.13</td>
</tr>
<tr>
<td>\textit{Bids}</td>
<td></td>
<td>0.54\textsuperscript{a}</td>
</tr>
<tr>
<td>\textit{Opening}</td>
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<td>0.15\textsuperscript{a}</td>
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<td>Resolution 5 MP</td>
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<td>9.69\textsuperscript{a}</td>
</tr>
<tr>
<td>Resolution 6 MP</td>
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<td>48.95\textsuperscript{a}</td>
</tr>
<tr>
<td>Resolution 7.1 MP</td>
<td></td>
<td>53.28\textsuperscript{a}</td>
</tr>
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<td>Resolution 8 MP</td>
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<td>93.86\textsuperscript{a}</td>
</tr>
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<td>Resolution 10 MP</td>
<td></td>
<td>155.05\textsuperscript{a}</td>
</tr>
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<td>28.20\textsuperscript{a}</td>
</tr>
<tr>
<td>Optical Zoom 6x</td>
<td></td>
<td>73.28\textsuperscript{a}</td>
</tr>
<tr>
<td>Optical Zoom 12x</td>
<td></td>
<td>128.78\textsuperscript{a}</td>
</tr>
<tr>
<td>Small Form</td>
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<td>105.02\textsuperscript{a}</td>
</tr>
<tr>
<td>Image Stabilization</td>
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<td>52.39\textsuperscript{a}</td>
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<tr>
<td>Intercept**</td>
<td></td>
<td>106.35</td>
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\textsuperscript{a} t-statistic: \( p < 0.01 \)
\textsuperscript{b} t-statistic: \( p < 0.05 \)
** Weighted Intercept
<table>
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<th>Component Price</th>
<th>Implied Cost</th>
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<td>$67.50</td>
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<td>$5.00</td>
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<td>Resolution 6 MP</td>
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<td>$41.67</td>
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<td>$87.85</td>
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<td>$69.93</td>
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<td>$136.99</td>
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<td>$45.00</td>
<td>$22.50</td>
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<td>Optical Zoom 12x</td>
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<td>Image Stabilization</td>
<td>&lt;em&gt;n.s.&lt;/em&gt;</td>
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<sup>a</sup> t-statistic: \( p < 0.01 \)

<sup>b</sup> t-statistic: \( p < 0.05 \)
Table 6
SUMMARY OF EFFICIENT CONFIGURATIONS

Homogenous Sample ($\bar{x} = 1; s = 0.3065$)

<table>
<thead>
<tr>
<th></th>
<th>Cost Value</th>
<th>$\theta_j$</th>
<th>Share</th>
<th>Optimal Price ($p_j^*$)</th>
<th>Auction Price</th>
<th>Optical Zoom</th>
<th>Resolution</th>
<th>Small Form</th>
<th>Image Stabilized</th>
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<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
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<tr>
<td>2</td>
<td>67.50</td>
<td>418.15</td>
<td>0.820</td>
<td>0.323</td>
<td>$158.74$</td>
<td>3 x</td>
<td>4 MP</td>
<td>No</td>
<td>No</td>
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<tr>
<td>3</td>
<td>72.50</td>
<td>435.66</td>
<td>0.8605</td>
<td>0.0011</td>
<td>$173.80$</td>
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<td>5 MP</td>
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<td>No</td>
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<td>4</td>
<td>111.02</td>
<td>569.42</td>
<td>0.8614</td>
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<td>$289.03$</td>
<td>3 x</td>
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<td>5</td>
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<td>5 MP</td>
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<tr>
<td>6</td>
<td>138.52</td>
<td>609.69</td>
<td>1.079</td>
<td>0.015</td>
<td>$330.86$</td>
<td>4 x</td>
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<td>7</td>
<td>171.26</td>
<td>651.54</td>
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<td>0.157</td>
<td>$376.49$</td>
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<td>236.18</td>
<td>716.54</td>
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<td>9</td>
<td>295.15</td>
<td>752.13</td>
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<td>10</td>
<td>362.21</td>
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<td>$589.20$</td>
<td>12 x</td>
<td>10 MP</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>
Figure 1

ILLUSTRATION OF EFFICIENCY SCORES

Panel A

Panel B

$\theta_1 < \theta_2 < \theta_3$
Figure 2

GRAPHS

Panel A – Price as a function of Quantity Offered
Panel B – Obsolescence: Average Daily Price and Daily Supply
Figure 3

EFFICIENT FRONTIERS

Panel A – Homogeneous Sample
Proof of Proposition: The socially optimal set of products maximizes the difference between consumer utility and the firm’s cost, ignoring the transfer price paid to the vendor. For consumer of type $\theta$ configuration $j$ generates utility $\theta v_j$, at cost $c_j$. The social surplus from this configuration is $\theta v_j - c_j$. Denote the set of feasible configurations as $D = \{ c_j, v_j \}_{j=0}^J$. Maximizing social surplus involves maximizing a linear objective function over the finite set $D$. The slope of the objective function is $\frac{1}{\theta}$, in cost-value space. From the Fundamental Theorem of Linear Programming there exists an optimal solution at a vertex of the convex hull of set $D$ (for a proof see, e.g., Dahl, 2001). Hence for any given value of $\theta$ (for a specific type) the optimal solution is at a vertex of the convex hull. When $\theta$ is restricted to being non-negative, only a subset of vertices is optimal. This subset includes those vertices where $v_j \leq \max\{ v_k \}$. The DEA model identifies these vertices. Since consumers differ in type, $\theta$, different customer types maximize social welfare at different vertices. Q.E.D.