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USING ONLINE AUCTIONS TO CHOOSE OPTIMAL PRODUCT CONFIGURATIONS

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Abstract

In the current environment, product design involves choosing from a vast array of components and subcomponents. By developing modular platforms and communicating with multiple suppliers, each product becomes a bundle of features. The multitude of potential product configurations poses a challenge in identifying optimal configurations to offer customers. For most companies, the greatest challenge is measuring consumers' marginal value for enhanced features. If this data were available, companies would offer those configurations with the highest margin. To date, consumers' value for product features was estimated using decision analysis techniques, surveys, or conjoint analysis. This research proposes a different methodology for measuring consumers' value. The emergence of active auction markets for a wide variety of products and services provides a venue for calibrating customer preferences. By offering different bundles of features, a company can measure the marginal increase in auction price obtained from enhanced features. Coupled with cost data, this information facilitates the evaluation of gross profit margin from offering different configurations. The methodology is assessed on used laptop computers sold via auction. Analyzing auction results indicates that consumers do value better features, and the incremental value of enhancements varies across features. Estimating cost differences from online posted prices in non-auction situations provide a foundation for estimating the efficient frontier of optimal bundles of features in a value-cost space. Data envelopment analysis is used in this context to define the efficient frontier. As online auction markets expand and evolve, this methodology could be implemented for many new products and services, which are offered as a bundle of features. Examples include many consumer electronics, travel packages, and communication services.

Keywords: Auctions, customer preferences, product configuration, pricing

Introduction

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 customers substantial leeway in customizing products, the vast majority of products are still preassembled and offered as a composite bundle. Optimal configuration of features and components into a finished product is a critical step in profit maximization. These problems are acute for consumer electronics manufacturers who often face a myriad of possible configurations combined with short product life cycles.

Companies often need assistance in setting profit maximizing prices; moreover, they may have no definitive guide to the optimal configuration of their products. Conceptually, the task of configuring different components and features into a single product is simple. With reliable estimates of consumers' willingness-to-pay for features and known component costs, a manufacturer would offer only those bundles of features that maximize gross margins. While conceptually simple, reliable data on consumer preferences for product features has been notoriously difficult to obtain. Cost plus percent markup is a very common method of pricing (Kahneman et al. 1986).

As online auction markets expand they offer an innovative opportunity to calibrate consumer preferences. Instead of relying on survey methods or simulated markets, companies can now elicit consumer preferences directly through online auction markets. The purpose and contribution of this study is to demonstrate the use of online auctions in identifying consumers' preferences in monetary terms for product features. With information about market value of product features, and cost data of different product bundles, a manufacturer can identify *efficient* product bundles. These products would incorporate the bundles of features that command the highest margin, enabling profit maximization.

Identifying customer preferences is a precursor to optimal feature configuration. Utility in recent years has been measured by decision analysis techniques such as Multi-Attribute Utility Theory (MAUT; Keeney and Raiffa 1976), conjoint analysis (Green and Srinivasan 1990; Howard and Sobol 2004), and experimental markets (Wertenbroch and Skiera 2002). These methods involve experimental survey studies, which utilize product evaluation from multiple subjects. It is possible that using associated data on sales prices for products offered at *auctions* can lead to an easier and more reliable method for specifying relative prices. Auction prices represent prices that people *actually* paid rather than what they *said* they would be willing to pay. Thus, knowledge of the demand curve for a particular product and, more importantly, products that are a combination of features derived from auction prices would more closely reflect consumer preferences. This enables profit maximization by offering the right configurations.

Historically, nonexperimental auctions have been infeasible for accurately measuring consumers' value over heterogeneous products. Physical auctions usually require assembly at a given site at a given time to present bids. Thus, because of the inconvenience, they do not reach large numbers of people and have not been employed to evaluate willingness-to-pay. Primarily, the in-person auction has been used to sell rare items that require examination such as antiques, jewelry, and fine art. The online auction, on the other hand, is readily employed for standardized products and attracts a wide number of viewers and bidders. This enables novel application for auctions. In this study we introduce a methodology for applying auctions in the product configuration domain. The auctions to which we refer are currently conducted online by such companies as eBay, Amazon.com, and Yahoo!

In the last few years sales of used desktop and laptop computers have been accomplished by listing prices on Internet sites. At the same time, sellers placed a fraction of their inventory of used laptop computers for sale in online auctions. 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. In a complex product, with sufficient data, the final selling prices at auctions are a good indicator of the demand for certain features, if one uses multivariate analysis to compare products' sale prices. Thus, online auctions can be used as a way to elicit consumer preferences and to infer optimal feature combinations offerings.

In this study we derive costs based on prices for used Dell laptop computers (offered on their Web site) and compare it with auction prices for similar configurations of Dell used laptop computers. These prices were observed in the same time period. Our aim is to develop an *efficient frontier* for optimal web site pricing. This methodology could also be used to choose optimal configurations for a wide variety of products. Thus, online auction prices could become a very important tool for corporate decision making with respect to the optimal configuration and pricing of a wide variety of products.

The remainder of this paper is organized as follows. The next section provides a review of the literature on product configuration and auctions. An overview of the methodology employed in this study is then provided. The data and analysis are described. The final section discusses the results and future possibilities for research.

Literature Review

Studies on Methods to Establish Pricing and Configuration

In recent years, a wide variety of articles have been presented in the marketing, decision science, and economics literature devoted to ideal product configuration and optimal pricing. Efforts to determine what a consumer is willing to pay for certain items or combinations of features in a particular product have been important marketing research concerns over the past decade. Willingness-to-pay has been tested from revealed preferences, from scanner data, and by simulation studies. When an experimental procedure is used, participants receive a participation fee that they can keep or spend on offered products. This provides them with needed liquidity. Usually, posted prices in real or simulated markets vary only within limited ranges. Thus, the transactions data reveals that the buyer's willingness-to-pay is higher or lower than the stated price, hence true willingness-to-pay remains unknown (Wertenbroch and Skiera 2002).

Another method for eliciting willingness-to-pay is conjoint analysis (Green and Srinivasan 1990; Howard and Sobol 2004). By allowing respondents to evaluate different alternatives, conjoint analysis can determine trade-offs among product attributes. Different methods of conjoint analysis can be used to evaluate preferences for attribute changes. There are numerous conjoint analysis studies on the value of product attributes in terms of respondents' utility. However, nowadays, prospective purchasers do not choose one attribute at a time; instead, they are confronted with choices that offer a "bundle" of attributes. For example, in a study of price premiums for hotel amenities (Goldberg et al. 1984), bundling considerations included such attributes as king-sized beds, built-in bar facilities, in-room movies, message services, and laundry services. Another study of pricing of product bundles by Kamel et al. (2003) show that regardless of whether products are durables or nondurables, conjoint analysis captures heterogeneity and predicts well. However, responses to this type of questioning may result in hypothetical answers, which lack external validity. Other methods of eliciting willingness-to-pay may be needed for cross-validation.

Another way of eliciting how much people will pay is the use of experimental auctions. This is a sealed bid or open auction where the highest bidder must buy the good in a real transaction. One common format is the Vickrey auction (Vickrey 1961), which is a second-price, sealed-bid auction. This format is desirable, because the bidders' dominant strategy is to bid according to his willingness-to-pay. Thus, the bidder is more likely to reveal his true preferences because if he underbids he is likely to lose the auction. Some critics have pointed out that in experimental Vickrey auctions, only a limited stock of goods is available, which may provide some incentive to bid more than the item is worth to assure "winning" the auction (Kagel 1995).

A more elaborate procedure was developed in 1964 by Becker, DeGroot and Marschak. It is applied by Wertenbroch and Skiera (2002) to measure consumers' willingness–to-pay at point of purchase. 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 they may and are obligated to buy the product. This should mitigate the overbidding found in Vickrey auctions (Kagel 1995) because it is more realistic. Nevertheless, this is still an experimental device and it may not predict purchases.

In conclusion, although there are many different experimental methods to determine willingness-to-pay, in some respect each of these methods is not completely realistic in determining *actual* preferences. One improvement is to study real auctions and see what people actually pay in a free and open market contest.

Online Auction Research

As online auctions gain popularity (Snir forthcoming) research on auction mechanisms and participants' behavior has grown. Research in this area shows that many theoretical predictions are reflected in market behavior, while a number of anomalies still exist. Research on online auctions for consumer electronics has found that auction prices are often lower than prices at online catalogs for identical items (Vakrat and Seidmann 1999). This is explained by the inconvenience of monitoring an auction until completion, risk aversion, and the delay in receiving the item.

When viewed as a marketplace for excess inventory, auctions differ somewhat from posted-price venues. There are a number of temporal effects that should be considered. First, consumers have a downward-sloping demand curve. Auction closing prices decrease, on average, with offered quantity, which varies daily. Second, computers exhibit obsolescence as new models and software are introduced, suggesting that prices decline over time (Pinker et al. 2000). Finally, there is empirical evidence that prices vary across days of the week, reflecting differences in the number of participants, and their impatience with waiting until the end of the auction (Lucking-Reiley et. al. 2000; Snir forthcoming), suggesting temporal controls.

Are studies employing online auction results suitable topics for publication in IS journals or at IS conferences? Benbasat and Zmud (2003) proposed five components of IT research that would qualify articles for publication in top IS journals. These were the IT artifact; IT managerial, methodological, and operational capabilities; IT managerial methodological and technological practices; IT usage and IT impact. Whinston and Geng (2004) suggest a policy of strategic ambiguity to deal with the gray areas that may not be the IT artifact. In this latter work, there is reference to an article on shill bidding which has become widespread in IT auctions because of anonymity on the Internet. Whinston and Geng point out that while this could be considered to be in the economics field of auction theory, the study raises problems of how shill bidding affects potential buyer participation and could be considered in terms of lack of trust in an online auction situation and how it affects potential buyer participation. Therefore, they consider it to be suitable for publication in IT journals and suggest that journals not considering gray areas "may unintentionally limit IS research" (p. 155).

In line with these views, we argue that the ability to use online auctions to set relative prices based on consumer preferences fits into Benbasat and Zmud's fifth category of economic impact of IT. Furthermore, using Whinston and Geng's principle of strategic ambiguity in determining suitable publications, it is acceptable, as is the article on the use of shills in auctions.

Methodology

As discussed earlier, the objective of this research is to provide a methodology for companies to identify efficient bundles of features to offer through a retail distribution channel. A bundle, in this context, is the set of features that are included in the product. With several features and several quality levels for each feature, the number of possible bundles is very large. The first step is to define the term *efficient* in this context. To do so, assume the company has information regarding customers' value for features and cost of providing these features. One possible definition for an efficient bundle is one where no other feasible bundle increases customer value at lower cost. We use a somewhat stronger definition. For a bundle to be efficient, no other feasible bundle, *or linear combination of bundles,* increases customer value at lower cost. Using this enhanced definition for some average cost target, a combination of bundles increases average customer value, relative to a single bundle. The *efficient frontier* is the set of all efficient bundles. Of the multitude of feasible bundles, only a small fraction are efficient. Two types of data are needed to develop the efficient frontier, a measure of consumer value and costs.

Auction Prices: Measuring Consumer Value

The crux of this research is distilling customers' willingness-to-pay based on an analysis of auction prices. Our objective here is to identify consumers' value for different bundles of products. We realize that the configurations offered in the auction market are a subset of the possible configuration choices facing the manufacturer. Hence, the goal is to identify consumers' marginal value for different features. For example, how much consumer value is generated by increasing laptop memory? To answer these types of questions, we make several assumptions regarding customer value.

A.1 Customers' values are independent, identical draws (IID) from a given distribution. This implies a "private-value" auction.

A.2 Customers have an additive utility function over product features.

Assumption A.1 suggests that we can interpret auction prices as reflections of willingness-to-pay. In this private-value auction, participants' bid strategically depending on exogenous factors. Online auctions of similar items should be viewed as a series of sequential auctions. 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. Weber's Theorem 3 (1983) shows that the expected prices in a sequential auction are identical (for a proof, see Snir forthcoming). Assume S items are offered in S sequential auctions to n risk-neutral bidders each of whom desires at most one item ($S < n$).[1] If bidders' private value of the items (denoted by X_i) is drawn IID from a continuous, non-negative, commonly known distribution, with c.d.f. of $F(X)$, the expected price at each auction equals the expected value of the $(S+1)^{st}$ highest order-statistic, out of n trials. Denote by R ($R = 1..S$) the sequential (rank) order of an auction within the S auctions, with price p_R. Then

$$\forall R=1..S \quad E[p_R] = E[X_{(S+1)}] = \frac{n!}{(n-S)!(S-1)!} \int [x \quad F(x)^{n-S} \quad [1-F(x)]^{S-1} \quad f(x)] \quad dx \tag{1}$$

This shows that expected auction prices vary with the supply (S) and bidder competition (n). It is assumed that these factors vary daily and across longer periods of time.

Assumption A.2 is used to determine the relationship between product attributes and value. It is restrictive in the sense that we do not allow interaction effects between product attributes. This assumption can be relaxed by incorporating interactions in the following regression analyses. However, since the data come from a natural experiment and not an experimental design, the available data do not permit a robust analysis of interaction effects. Future research should design product offers that enable analysis of interaction effects.

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[1]If there are more items than bidders equilibrium prices are all equal to zero and the seller could increase prices by offering fewer items.

Component Costs

Cost data is usually available to companies. Since the data for this study involves auction prices for used laptops, component cost cannot be readily determined. However, a surrogate measure for these costs is available. Identical laptops are offered for sale in a posted-price online catalog from the OEM. In deriving the efficient product bundles, we assume that prices for different feature bundles are proportionate to their respective cost.

Efficient Frontier

To determine which of these bundles are efficient we use a method adapted from data envelopment analysis (DEA), commonly called the VRS BCC model (variable returns to scale model, developed by Banker et al. 1984). DEA is an application of linear programming that has been used to measure the relative efficiencies of operating units with congruent goals and objectives (Anderson et al. 1994, p. 162). DEA can also be used to measure optimal product configurations. One such example is a study of desired features in a compact car (Staat et al. 2002). Another example is identifying "best buys" in the market of prepaid mobile telephony (Smirlis et al. 2004).

In this model, each of the feasible bundles is assessed against all other bundles to determine whether a *linear combination* of other bundles can generate more value at a similar weighted average cost.[2] A bundle's efficiency score measures how far it is from the efficient frontier. If no other combination of bundles generates more value at that cost, the efficiency score is equal to 1. The efficient frontier is the set of all bundles with an efficiency score of 1. Formally, the DEA model we utilize (analyzed separately for each bundle) is

$$\max_{u,v,v_f} \; y_0 v + v_f$$

$$\text{S.T.:} \quad yv - xu + v_f \leq 0$$
$$x_0 u = 1$$
$$u, v \geq 0$$
$$v_f \; \text{free}$$

Where

(x_0, y_0)	the cost and value of the bundle under consideration
x	a vector of costs of different bundles $x_i > 0$ ($i = 1,...,799$)
y	a vector of customer value of different bundles $y_i > 0$ ($i = 1,...,799$)
u	a scalar input weight appropriate to the bundle under consideration
v	a scalar output weight appropriate to the bundle under consideration
v_f	a bundle-specific scalar measuring its returns to scale

Profit Maximization

The DEA method described provides a tool for identifying efficient configurations. This is the set of possible configurations, not all of which should be offered by a manufacturer. To identify which configurations are profit-maximizing, a company is required to make additional assumptions about customers' utility function in their tradeoff of value and price. In addition, information is required about the magnitude of demand for different configurations. With this information, profit-maximizing prices and the set of viable configurations can be deduced. Since the required data is unavailable in our context, this analysis is beyond the scope of this paper.

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[2]If consumers' utility function is linear in value-cost space, with consumers varying in the linear parameter, then this methodology identifies consumers' preferred bundles.

Data and Analysis

We propose to use data from online auctions to estimate consumer value and preferences for different bundle configurations. As an example of online auctions' usefulness in measuring consumers' willingness-to-pay for different bundles, we use data from the market for used laptops.[3] There are a number of advantages to using this market. First, data is readily available, as many laptops 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 drop out of the bidding. This implies that participants' dominant strategy is to bid according to their private values, similar to Vickrey auctions.[4] Thus, we interpret auction closing prices as measures of willingness-to-pay, in accordance with equation (1).

eBay is one of the most successful online ventures, and the most vibrant online site. eBay boasts over 48 million active users and $12 billion in transactions facilitated in the year 2003, claiming to be the most popular online shopping site.[5] In the second quarter of 2004, $2.4 billion of computer merchandise was transacted via eBay. The large number of active members and the volume of transactions on eBay justify using online auctions for novel applications, which are not feasible in physical auctions.

Auction data for this study is based on online auctions on eBay from one reseller of off-lease laptops during January and February 2004. During this period, the reseller auctioned over 2,200 used computers, generating nearly $900,000 in revenue. Each auction was open for bidding for 3 days. To control for product heterogeneity, we limit the analysis to auctions of the most popular laptop offered, originally manufactured by Dell. This configuration is a refurbished, off-lease, Dell Latitude C600 with an Intel Pentium III processor. Other product features vary by machine. These features include CPU (700, 750, 850, and 1000 MHz), hard drive (6, 10, 12, 20, and 30 GB), memory (128, 192, 256, 320, and 512 MB), network card (modem, Ethernet card), DVD (CD-RW, DVD) and operating system (none, Windows 2000). This allows us to evaluate consumers' willingness-to-pay for varying bundles of features. Based on this auction data, we identify six product features incorporated into each bundle. Using combinatorial statistics, there are 800 different feasible bundles.

Data collection involved gathering data directly from the eBay Web site. Searching periodically for items offered by this reseller identified relevant computers, winning bids, and buyers' identities. Inspection of each auction revealed the number of bids and product features. In the two months of the study, 1,017 of these laptops were sold, generating almost $500,000 in revenue. Of these, 40 auctions concluded early because an item was purchased using the "Buy Now" service. This service allows a customer to buy the laptop at a predetermined (relatively high) price before the end of the auction. These observations are dropped from the dataset.[6] The remaining 977 auctions have a range of winning bids in these auctions from $376 to $781, with an average of almost $475, a standard deviation of $59.07, and a median price of $465.

Descriptive statistics are provided in Table 1. Price is a continuous variable with the other variables coded as indicator variables. Of the 977 auctions in the study, the most popular CPU is a 750 MHz processor. A total of 707 laptops had this processor. When looking at memory and hard drive, the most common levels are 256 MB (808 occurrences) and 20 GB (931 occurrences). Less than half the laptops have Ethernet cards (426) and DVD drivers are included in about a quarter of auctioned laptops (273). Slightly more than 10 percent of these laptops have an operating system (104). Of those including an operating system, the only one offered is Windows 2000.

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[3]It should be clear that this market is chosen because of data availability. It provides a useful example on how online auctions can be used to assess consumer preferences and the frontier of efficient product bundles. We do not suggest that the results of this be used directly for offering products. Product offerings in this market are determined by existing inventory and it is unreasonable to expect resellers to withhold products from the market or change product configuration because a specific configuration is inefficient.

[4]Assuming these are private value auctions. See Snir (forthcoming) for justification of this assumption.

[5]From http://pages.ebay.com/community/aboutebay/overview/index.html (visited March 1, 2004) based on Media Metrix data of total user minutes.

[6]Dropping these observations is important for understanding drivers of willingness-to-pay in online auctions. Having a "Buy-It-Now" option invariably increases seller revenue, by allowing impatient or risk-averse buyers an assurance of winning the auction by paying a premium.

Table 1. Descriptive Statistics for Auction Data

Variable	Notation	Mean Frequency	Standard Error
Price	P	\$474.53	\$59.07
Hard Drive – 10 GB	HD_{10}	0.033	0.1783
Hard Drive – 20 GB	HD_{20}	0.956	0.2055
Hard Drive – 30 GB	HD_{30}	0.011	0.1057
Memory – 128 MB	MEM_{128}	0.089	0.2854
Memory – 256 MB	MEM_{256}	0.829	0.3771
Memory – 320 MB	MEM_{320}	0.014	0.1191
Memory – 512 MB	MEM_{512}	0.068	0.2515
CPU – 700 MHz	CPU_{700}	0.011	0.1057
CPU – 750 MHz	CPU_{750}	0.726	0.4463
CPU – 850 MHz	CPU_{850}	0.258	0.4376
CPU – 1000 MHz	CPU_{1000}	0.005	0.0715
DVD	DVD	0.279	0.4489
NIC (Ethernet Card)	NIC	0.436	0.4962
Operating System – Windows 2000	OS_{2000}	0.107	0.3090

There are 974 observations in the auction dataset. Three observations are dropped because their features are insignificant in the following regressions.

We analyze auction data using a linear regression model with fixed-effects for the day the auction closes.[7] Controlling for daily factors is important in determining the marginal value of different features. Equation (1) shows that expected prices vary with exogenous factors (supply and bidding activity) that 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 of consumer electronics (Pinker et al. 2000) and differences in bidding activity (Lucking-Reiley et al. 2000). In one study, prices on weekends were lower than those on weekdays, which indicates lower opportunity costs on weekends, perhaps because weekend bidders are buying for personal use and midweek buyers are buying for business (Snir forthcoming).

Our statistical model for evaluating marginal value of laptop features is the price in auction i (P_i) as a function of product features, with fixed effects for auction-closing days (D_j):

$$P_i = \Sigma\alpha_j D_{j,i} + \Sigma\beta_j HD_{j,i} + \Sigma\beta_j MEM_{j,i} + \Sigma\beta_j CPU_{j,i} + \beta_9 DVD_i + \beta_{10}NIC_i + \beta_{11}OS_{2000,i} + \varepsilon_i \qquad (M1)$$

Results of this model are given in column (a) of Table 2. We include in this model only those features that have a statistically significant impact on price. Other available features (10 and 12 GB hard drives and 192 MB memory) are either too sparse in our data or consumers do not value them. Factors that do not have significant coefficients are not included in the analysis to assure that other coefficients are not confounded. The R^2 for this model is 67 percent justifying the use of auction data to measure customers' value for product features. Almost all remaining variables are significant at the .01 level, reflecting value of enhanced features. Laptops with 750 MHz processors and Ethernet cards are significant only at the .05 level.

Interpreting these results, our model estimates that for a popular configuration in our data, a laptop with 20 GB hard drive, 256 MB memory, 750 MHz processor, without a DVD, NIC, or operating system, would attain an average price of \$72.20 *higher than* the basic alternative of 6 GB hard drive, 128 MB of memory, 700 MHz processor, without a DVD, NIC, or operating system. When inspecting individual features, it appears that improvements in processor speeds command a higher premium than im-

[7]This is equivalent to including an Indicator variable for each day in the dataset.

Table 2. Statistical Analyses

Variable	Notation	Auction Analysis Model 1	Posted Price Analysis Model 2	Implied Cost Parameter
		(a)	(b)	(c)
Intercept		Fixed Effects – Auction Closing Day	519.25*** (8.314)	$259.62
Hard Drive – 6 GB	HD_6	*Base*	*Base*	$0.00
Hard Drive – 10 GB	HD_{10}	*Not Included*	19.43*** (7.902)	$9.72
Hard Drive – 12 GB	HD_{12}	*Not Included*	18.59* (10.848)	$9.29
Hard Drive – 20 GB	HD_{20}	28.70*** (6.140)	43.57*** (7.795)	$21.79
Hard Drive – 30 GB	HD_{30}	42.30*** (10.940)	76.54*** (9.462)	$38.27
Memory – 128 MB	MEM_{128}	*Base*	*Base*	$0.00
Memory – 192 MB	MEM_{192}	*Not Included*	22.19*** (9.645)	$11.10
Memory – 256 MB	MEM_{256}	24.34*** (4.292)	54.01*** (3.364)	$27.01
Memory – 320 MB	MEM_{320}	30.38*** (9.369)	69.98*** (4.907)	$34.99
Memory – 512 MB	MEM_{512}	62.58*** (5.777)	102.00*** (3.893)	$51.00
CPU – 700 MHz	CPU_{700}	*Base*	*Base*	$0.00
CPU – 750 MHz	CPU_{750}	19.16** (9.673)	13.85*** (4.648)	$6.92
CPU – 850 MHz	CPU_{850}	80.95*** (9.867)	108.48*** (4.635)	$54.24
CPU – 1000 MHz	CPU_{1000}	162.55*** (18.213)	247.55*** (5.557)	$123.77
DVD	*DVD*	33.24*** (5.819)	*Not Included*	$0
NIC (Ethernet Card)	*NIC*	8.88** (3.731)	25.27*** (3.181)	$12.63
Operating System – Windows 2000	OS_{2000}	34.62*** (3.886)	95.39*** (2.875)	$47.69
N		974	96	
R^2		0.67	0.99	

Standard Errors in parentheses
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

proving memory or hard drive. The difference between 700 and 1000 MHz is $162.55, on average, while the average premium for 30 GB hard drive over 6 GB is $42.30 and for 512 MB over 64 MB of memory is $62.58.[8]

In building the efficient frontier we use these results as measures of willingness-to-pay.[9]

Analysis of Component Costs

A second data source is used to distill costs of different components. During the same period, a subsidiary of Dell offered similar used laptops for sale using a posted-price online catalog. Data is available for 1,017 laptops of various configurations.[10] We use relative prices of these product offerings as a proxy for underlying component cost. In the posted-price market, similar laptops to those sold by auction are available for between $565 and $1,120, depending on configuration. The average price is $752.09, with a standard deviation of $124.85. The median price is $735. While the frequency of different configurations is unequal, laptops with similar configurations are offered at the same price. In order to reduce potential biases caused by unequal frequencies, we analyze only unique laptop configurations. A total of 96 different configurations of posted-price laptops are analyzed here. Using OLS regression of the 96 different configurations, we identify the marginal prices of different components. The model we use is

$$P_i = \alpha + \Sigma\beta_j HD_{j,i} + \Sigma\beta_j MEM_{j,i} + \Sigma\beta_j CPU_{j,i} + \beta_9 DVD_i + \beta_{10} NIC_i + \beta_{11} OS_{2000,i} + \varepsilon_i \qquad \text{(M2)}$$

Results of this model are given in column (b) of Table 2. This model is quite effective at identifying the marginal effects of different product attributes on offered price, with a R^2 of 99 percent. This also confirms that Dell uses an additive model of product attributes in pricing products, confirming model 2. Interaction effects do not need to be considered. In this regression analysis, all variables except DVD are significant at the .01 level.

Overall, it appears that Dell prices these laptops to generate more income from better features. Two notable exceptions can be seen in the data. First, 12 GB hard drives are priced *less* than 10 GB hard drives. Second, DVD drivers are not priced at a premium compared to CD-RW drivers. These anomalies may reflect price similarities in these components or that Dell does not believe customers would pay more for these features.

Inspection of prices of individual components shows that, similar to auction prices, differences in processor speed command the largest price differences. A 1000 MHz processor is priced $247.55 more than a 700 MHz, while the marginal difference in memory is $102 for 512 MB compared to 64 MB and for hard drives there is a $76.54 difference between 6 GB and 30 GB. When comparing prices in both venues, it is evident that Dell prices their laptops higher than auction prices and that the marginal price for features is higher in the posted-price venue than those attained in auctions. This is consistent with previous research on auctions (Vakrat and Seidmann 1999) and may reflect different customer segments utilizing these distribution channels. Customers would prefer to use the posted price channel if they are time constrained, preferring not to wait until the end of the auction, or risk averse, preferring the certainty of purchase over the uncertainty of the auction.

The coefficients in model 2 of Table 2 represent the marginal *prices* of changes in configurations, not the companies' *cost*. It is reasonable to assume that posted prices reflect a premium over costs. In calculating implied costs we assume that these prices

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[8]There may be some confounding between quality of features and other factors. In a controlled experimental design these problems could be addressed. First, some high quality features (e.g., 1000 MHz CPUs) are rarely offered, which may artificially inflate their price. The statistical analysis was also performed without low-frequency features and the marginal feature price remained almost unchanged for high-frequency features. Second, high quality features appear on laptops with shorter leases. Bidders may have bid more for these laptops because they had less usage than those with inferior features.

[9]The prices realized at the auction are not calibrated with expected prices in a retail market environment. First, from equation (1), expected prices vary with market size and supply. Both of these should be much larger in a retail market. Second, bidding behavior may cause auction prices to vary from the rational outcome. However, the relative differences in evaluation of different bundles is what is crucial here.

[10]This data is based on prices on February 24, 2004.

reflect a 100 percent markup over cost.[11] Column (c) of Table 2 indicates the implied cost parameter for each feature. These implied cost parameters are used in building the efficient frontier.

Efficient Frontier

There are a number of ways to combine cost and value to determine the efficient frontier. We choose to implement a version of data envelopment analysis (DEA) that inspects, for each bundle, whether there exists a combination of other bundles that improves on one dimension without lowering the other dimensions. If none exists, the focal bundle is deemed efficient.

In this paper, we are trying to identify which of the possible bundles of computer configurations are efficient in a cost–value space. Using auction prices, we measure consumer willingness-to-pay, a proxy for value. Posted prices in an alternate market provide us with the ability to infer cost. By identifying the efficient configurations in terms of consumer value and manufacturer cost, a retailer could choose which preconfigured products to offer in order to maximize profit. Using information on features and attributes, we can identify the universe of feasible bundles. For each feasible bundle (800 in this analysis), customer value (from model 1) and cost (from model 2) are assessed. Figure 1 graphs all 800 feasible bundles in a cost-value space.
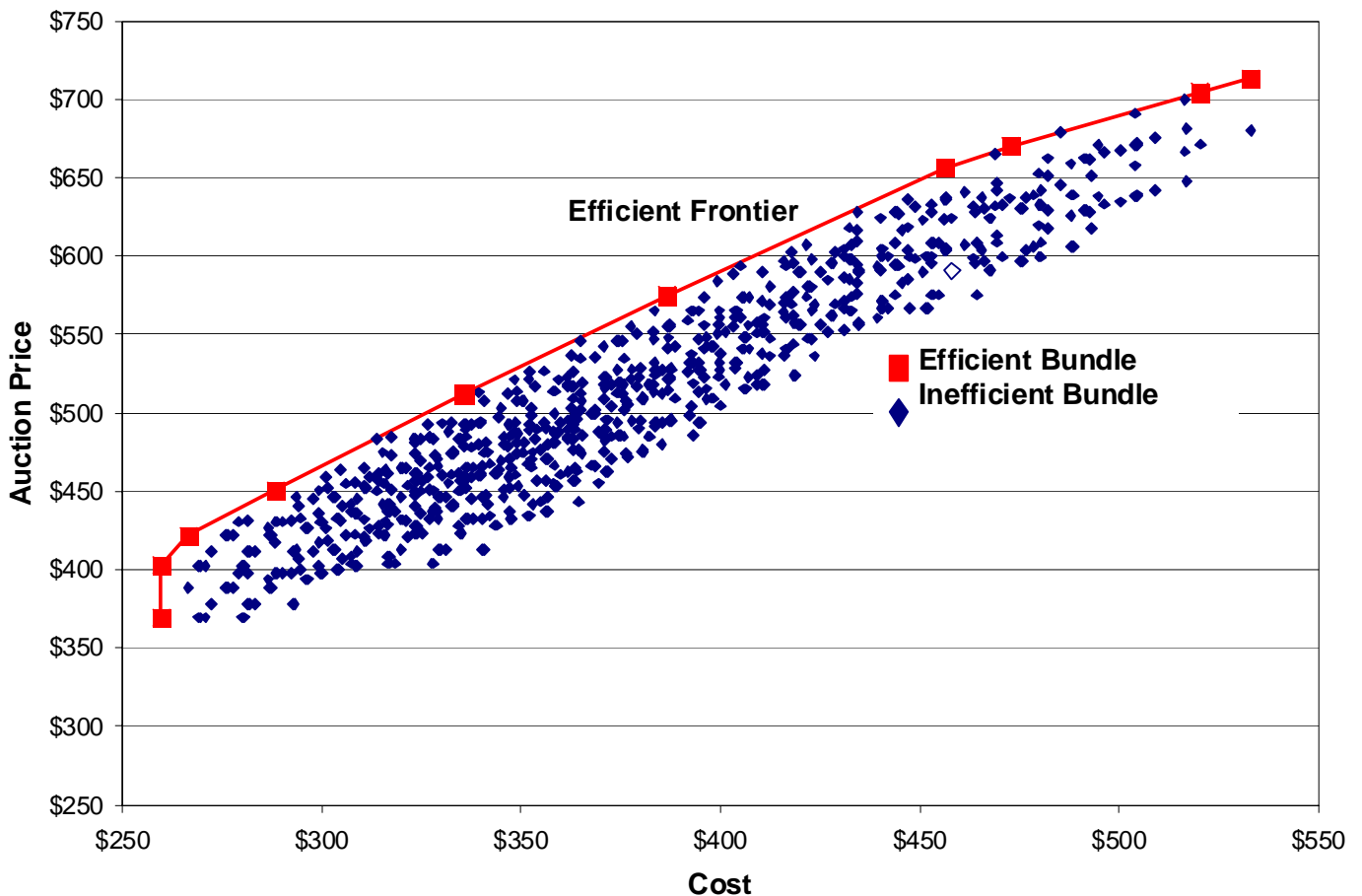
Figure 1. All Feasible Bundles and the Efficient Frontier (based on DEA)

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[11]This choice of markup percent (100%) is used to illustrate reasonable expectations, but it does not impact the identification of efficient bundles or the efficient frontier. Any other proportional relationship between price and cost would single out the same bundles as efficient.

Table 3. Efficient Bundles

Cost	Value	Value – Cost	CPU	Memory	HD	DVD	Network	OS
$259.62	$369.32	$109.70	700 MHz	128 MB	6 GB	CDRW	Modem	None
$259.62	$402.56	$142.94	700 MHz	128 MB	6 GB	DVD	Modem	None
$266.55	$421.72	$155.17	750 MHz	128 MB	6 GB	DVD	Modem	None
$288.33	$450.42	$162.09	750 MHz	128 MB	20 GB	DVD	Modem	None
$335.65	$512.21	$176.56	850 MHz	128 MB	20 GB	DVD	Modem	None
$386.65	$574.80	$188.15	850 MHz	512 MB	20 GB	DVD	Modem	None
$456.18	$656.40	$200.22	1000 MHz	512 MB	20 GB	DVD	Modem	None
$472.67	$670.00	$197.33	1000 MHz	512 MB	30 GB	DVD	Modem	None
$520.36	$704.61	$184.25	1000 MHz	512 MB	30 GB	DVD	Modem	W2K
$532.99	$713.50	$180.51	1000 MHz	512 MB	30 GB	DVD	Ethernet	W2K

Using the previous results, this is relatively straightforward, but one important factor needs to be identified. Since model 1 (based on auction data) is a fixed-effects model (controlling for the auction-closing day) the intercept for the regression model has to be specified. We use the weighted average for the fixed-effects (weighted by the number of auctions in each day) as the intercept. It is $369.32.

Discussion

The efficient frontier for the bundles analyzed here is depicted in Figure 1. Inspecting the graph, it is clear that numerous bundles are not efficient. In general, for many inferior bundles, a laptop manufacturer could offer a combination of product bundles at similar cost that had more value to customers (increasing profit) or he could offer a combination of bundles of equivalent value at lower cost, reducing cost without lowering price. The set of all efficient bundles includes those choices where increasing value requires higher cost. From the 800 feasible bundles, only 10 are efficient. Table 3 details these efficient bundles, which are on the efficient frontier line.

An example of an inefficient bundle is a laptop with 1000 MHz processor, 256 MB RAM, 6 GB hard drive, a CD-RW, with a modem, and Windows 2000 operating system. It costs $458.10 and has a customer value of $590.82 (denoted by a hollow diamond in Figure 1). The reseller can increase customer value at lower cost by offering a laptop with 1000 MHz processor, 512 MB RAM, 20 GB hard drive, DVD, with a modem, and without an operating system. This alternative would cost slightly less at $456.18 and generate higher value at $656.40. The cost differential is negligible, but the difference in customer value is $65.58.

Alternately, the reseller may want to maintain cost while charging a higher price (when offering a computer with greater customer value). To achieve this, he could offer a laptop with 1000 MHz processor, 512 MB RAM, 20 GB hard drive, DVD, with a modem, and without an operating system. The cost of this alternative is slightly higher at $456.18, while generating value of $656.40, $89.91 more than the current bundle

If companies have complete information about customers' tradeoffs across different product features, the task of identifying desired configurations would be relatively straightforward. Each feasible bundle's cost and customer value could be evaluated and those with the highest margin would be offered. One method of choosing desirable configurations is to offer only those which are on the efficient frontier in the value-cost space.

While value to the consumer is an important consideration in product configuration and pricing, it is notoriously difficult to elicit. In recent years, market analysts have relied on conjoint analysis and other methods. Conjoint analysis presents a "what if" type of structure rather than results of an actual purchase instance. This research develops and exemplifies a methodology for eliciting customer value based on multiple, sequential, online auction data. Using auction prices, when available, for similar purchase decisions offers greater external validity in identifying "what the market will bear." Thus, the seller can maximize profit based on transaction data.

Using data on laptop auctions on eBay, we identify a linear relationship using OLS between product features and auction price. All laptops analyzed in this research are Dell Latitude C600. These laptops vary along several dimensions: hard drive size, available memory, processor speed, DVD or CD-RW drive, network card, and operating system. The marginal increase in price of improving a feature is interpreted as the value of improving that feature. Consistent with expectations, better features attain higher prices in these auctions. Cost data is not readily available to us, but is estimated from online posted prices for similar laptops.

Once auction prices and costs are available, cost and value for all feasible bundles can be extrapolated. Data envelopment analysis is a useful technique to identify the efficient frontier in cost-value space. Optimal product configurations are those that define the efficient frontier. Moreover, these prices are available for products which have several attributes and are commonly sold in bundles.

A number of extensions are worthy of study in the context of this research. The data used to exemplify the efficient frontier methodology is based on auctions of used Dell laptops. Future studies should design the scope of offered products to facilitate better understanding of consumers' value for various components. A balanced design would assure that all attributes were offered sufficiently, so that scarcity would not be confounded with product features. In addition, when auctioning new products, age would not be confounded with feature quality.

Another extension of the method developed in the paper would be to identify trends in customer value by using online auctions. This could be applied in two ways for product configuration. In the product introduction phase, measuring trends in features' value would provide an estimate of obsolescence for each feature. Feature value should be discounted based on obsolescence. After product introduction, ongoing use of online auctions in parallel with retail sales could provide early indications regarding the velocity of obsolescence at both the feature level and the product level. In applying the DEA methodology an estimate is needed for customers' value in the retail environment. The relationship between auction results and retail value would depend on relative market sizes, which may vary by attribute. Profit maximization may also impact retail customer value. Firms' profit maximizing behavior would depend on market size, price elasticity, and cannibalization across products. This could reduce the scope of offered products to only a subset of the efficient bundles.

Identifying optimal bundles of attributes is a useful tool that could be used to maximize profits for many other items, not only computers, as studied in this analysis. Other products and services that are commonly offered as bundles include consumer electronics (e.g., televisions, digital cameras, camcorders), communications services (e.g., cable, Internet, wireless telephony), real-estate properties, hotel rooms (location, amenities), and cruise ship packages (room, flight, tours, ship type). As online auctions become more pervasive, there may be an opportunity for these markets to become sources of market research information.

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