International Journal of Management Science
Vol 11, No 3, Special Issue, December 2005

An Exploratory Study on the New Product Demand Curve Estimation Using Online Auction Data

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(Received May 2005 ; Revised Nov. 2005 ; Accepted Nov. 2005)

ABSTRACT

As the importance of time-based competition is increasing, information systems for supporting the immediate decision making is strongly required. Especially high-tech product firms are under extreme pressure of rapid response to the demand side due to relatively short life cycle of the product. Therefore, the objective of our research is proposing a framework of estimating demand curve based on e-auction data, which is extremely easy to access and well reflect the limited demand curve in that channel. Firstly, we identify the advantages of using e-auction data for full demand curve estimation and then verify it using Agent-Based-Modeling and Tobin's censored regression model.

Keywords: Online Auction, Demand Estimation, Yield Management, Multi Channel Management, Consumer Channel Choice

1. INTRODUCTION

One of the essential requirements of a firm for taking a competitive advantage and gaining the special business value is analyzing its target customers' demand accurately at the right time. When a firm tries to launch its new product, if it would miss a good opportunity for product launching due to a heavy cost and lengthy lead time of demand analysis, the firm can easily lose the customer base to its competitors in spite of more sophisticated demand analysis. Especially, in

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case of a firm dealing with high-tech product, the time-based competition is extremely important for the successful marketing, because of the short product-life-cycle of high tech product [4, 8]. High-tech products change rapidly with the technological innovation and R&D progresses, thus they reach the maturity stage earlier than other kinds of goods and have a relatively short life-cycle. In order to fit in with this timely demand analysis, various Decision Supporitng Systems (DSSs) intended to meet the business intelligence of product marketing process have been proposed. One of the most fundamental obstacles making managers reluctant to invest these DSSs was the high costs and the suspicious results of the investment. For this reason, the purpose of this paper is proposing a strategic demand estimation model for practical DSSs based on e-auction data.

The ultimate purpose of estimating demand curve is to support a firm's decision making of optimal production and pricing level. In many other areas including marketing, some complex pricing strategies based on diffusion model are proposed [2, 5, 6]. They commonly suggest continuous analyzing and updating of product price according to the diffusion pattern and it requires the high accessibility of customer data. In this reason, this paper suggests an approach using the e-auction data which helps estimating customers' demand curve in a time and cost effective way.

This method could reduce traditional barriers such as the cost for collecting market information and the time taken to process these huge volumes of information. We can gain customers' partial demand curve in e-auction because the last bidding data of every participant reflects their price limit in that channel, which gives great insight to our research for demand estimation. The important fact that we should pay great attention is that different channels attract different segment of customers. Most customers visit not only electronic channels (e.g. e-auction, and e-posted-price shop, reverse auction) but also offline channels. Since each channel may bear different transaction costs to its patrons, the realized demand curves may be specific to given choice of channel. For example, e-auction may take longer time to execute a purchase and riskier than other channels, but customers can gain items in relatively low prices there. In this reason, it is imperative to estimate the full demand curve from one partially revealed by e-auction channel. Therefore, in this paper, we

(1) identify the advantages of using e-auction data to estimate the demand curve, which have not been studied yet, to the best of our knowledge.
(2) propose the framework of estimating the full demand curve from the partial one obtained from e-auction data. Through this, we identify what kind of in-

formation should be maintained by a firm to utilize this approach.
(3) verify our approach using Agent-Based-Modeling (ABM) so that we demonstrate how e-auction data can be very valuable assets to firms, which have been discarded so far.

2. LITERATURE REVIEW AND MOTIVATION

Our focal interest in this paper is reducing the latency in introducing new product and speeding the launching process for high-technological products which are extremely demanding time-based competition. More important point we should consider is that the objective of time-based competition is changing from speeding up the manufacturing to the strategy acceleration - speeding up decision making, using technology to accelerate feedback, using alliances for agility [7]. Time-based strategy requires speeding up the flow of information, which can be realized through the cutting-edge systems analyzing amount of information rapidly to support manager's timely decision making process. Our DSS model for new product introduction basically requires 2 main processes. First one is capturing partial demand curve for new item in the e-auction channel and estimating full demand curve from partial one. Second one is utilizing the estimated demand data in decision making process and our research is more focusing on the first step by providing a specific methodology for demand-curve finding.

Studies of the demand estimation model have been conducted in various ways but to our best knowledge, there are little approaches similar to ours. Brokhoff and Rao [3] proposed a conjoint analysis model for technologically new product demand estimation and calibrated the potential data sources for his model considering the difference of multi-channel members but his model mainly analyzed the different demand of channel members when the firm took a pre-announcement strategy. Weiner [9] also suggested conjoint analysis model based on the data from 1-to-1 interview with offline shopping mall customers. He developed a full-profile conjoint model reflecting the impact of 3 product features – price, brand and bundling – but with no consideration about the channel-specific attributes of demand. Under the contemporary diverse channel environment, it may involve the limitation to cover all kinds of channels and to structure the complete demand curve. Bank et al.'s approach [13] identified the demand curve which is consistent with the observed expenditure patterns of individuals. His model used the quadratic engel curves, however in the managerial perspective it also involves the limitations both in the cost of data collection and in timely analysis. Compared to other demand estimation studies concentrating on the testing and demonstrating the accuracy of models with the empirical data, our model more focuses on giving the practical guidelines to managers - how to collect the data and implement the potential abilities of the models by introducing the data from e-auction. Once we construct the partial demand curve in e-auction, the following process of our framework is to estimate full demand curve just using the partial one based on censored regression model. Furthermore, once we complete the demand curve of total population, we can also divide it to sub curves of separate channels (i.e., one of offline channel, e-posted-price shop, and e-auction). Through this reverse analysis, our model supports managers specific channel strategy of new product and yield management for the optimal pricing and production level.

3. RESEARCH DESIGN

3.1 Conceptual Foundations

Most of high-tech products are dealt with in e-auction market, which again shows the value of auction as a right test marketplace for high-tech products. Besides the abundant quantity of data, auction mechanism also has an economic efficiency for researchers studying demand estimation. The first requirement for our model is accessing more accurate data in a more time competitive way. Compared to other survey methods which have little incentive for the customers to reveal their true Willing-To-Pay (WTP) and consume lots of time for data collection, utilizing e-auction data has much superior attributes in both way – the saved cost and high data quality. Once a customer joins a bidding event, they call the bidding price from the lowest to their highest reserved price, generally several times. The true WTP is naturally revealed through this process regardless of being a winner in that bidding. It means e-auction may be the unique source where we can scan not only actual buyers' but also potential ones' WTP. The last prices called by bidders can be each one's WTP for that item when they purchase in e-auction. In this reason, e-auction can draw every bidder's WTP which couldn't be easily observed from other channels and provide us partial demand curve in that limited channel.

Generally, one online bidding process takes 3 to 15 days to be completed, which means the candidates of winner should pay some extra cost of monitoring all the bidding progression, which is not required to the customers of other channels who prefer the immediate purchasing thus have higher WTP for the identical product. From this, we can easily conjecture that various WTP among different channels is originated from the different transaction costs and expected prices of each channel. In our research, we first identify the critical factors determining customers' transaction cost and demonstrate that those factors finally determine consumer WTP in a specific channel. Hence, we set up demand (WTP) estimation model using these factors as explanatory variables.

3.2 Research Framework

Firstly, in order to identify the determinants of customer channel preference, we need to understand customer purchasing behavior. When a customer decides to purchase a product, she encounters situations involving qualitative or discrete choices in addition to the continuous choices. For example, she should decide which channel to participate and how much money to pay for the product. In most cases, the optimal discrete choice – which channel she will visit – depends on the outcome of the continuous choice – the price and transaction cost for the product. Similarly, the continuous choice - WTP - also depends on the outcome of discrete choice of channel. We consider transaction cost as the most important factor affecting customers' channel preferences as well as WTP. Because a rational customer would consider the trade-off between the expected price and expected transaction cost of each channel, she will choose the channel which has lowest total cost: sum of item price and transaction cost other than that. Hence the revealed WTP in a selected channel can be her valuation depreciated by channel specific transaction cost. However channel specific transaction cost alone does not affect the size of WTP. We conclude individual specific transaction cost is more critical on individual WTP. In our model, these factors are identified as the sensitivity of time and the skill level for internet usage – we take the notations for these as '**time_sensitivity**' and '**iskill**'. If she feels high disutility from long transaction time, it means she is willing to pay little transaction cost even though purchasing at a higher price, thus would choose the channel with lower transaction cost instead of e-auction. In case of **iskill**, the experienced one would perceive relatively low transaction cost compared to the inexperienced one in electronic channel. Hence we employ these two as explanatory variables for WTP estimation. The estimation model and the definitions of variables are as follows.

$$WTP = \beta_1 + \beta_2 \times iskill + \beta_3 \times time\_sensitivity$$

iskill : the level of internet usage expertise such as internet connection, web searching, ordering, payment.

time_sensitivity : the level of disutility perception when a consumer spend time on a transaction.

For this estimation, the firms need to identify customers' attributes like **time_ sensitivity** and **iskill**, which could be indirectly accessed by utilizing accumulated enterprise CRM database. However the WTP data for dependent variable can be acquired only from e-auction. Because of this limitation in the dependent variable, we use the censored regression model. Based on this estimation process, our DSS framework can be organized in 2 phases. First it constitutes demand curve according to the process explained above. In the second phrase, it utilizes this estimated demand curve in the decision making processes of new product planning.

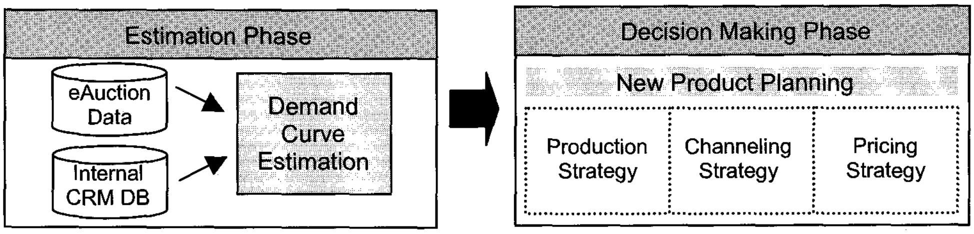

Figure 1. DSS Model based on Demand Estimation

In order to illustrate how online auction data can be capitalized to estimate consumers' willingness-to-pay of various channels, we generate data using Agent Based Modeling (ABM) simulation. There are several reasons why ABM simulation is employed for validation of our concept. Since it is impossible to know the 'true' demand ex ante, for empirical validation, we may apply our method presented in this paper and use other traditional estimation methods for demand estimation. Then we compare the results with the realized demand ex post. While the empirical approach may provide richer information and the base of judgment on the quality of our approach, on the same time, there may be much risk of estimation errors. Therefore, in terms of local validity, simulation method has some advantages. Especially we can start with the known 'true' demand. Then, we test how statistical methods can be applied to produce demand curves for various channels from the partial one obtained from online auction data.

4. MODEL AND RESULT

4.1 Agent-Based-Model

The purpose of ABM is to simulate heterogeneous customers' purchasing behavior and collect the data set for WTP estimation. Because our model is based on a limited data from a specific market to estimate the market demand curve including all kinds of channels, we are especially concentrating on identifying one's channel determinants and the relationship of it and WTP in that channel. We consider 3 representative channels – offline shop, e-posted-price shop, e-auction – and the sample product for our simulation is iriver MP3 player (model no: iFP 890) from e-auction market. The expected price in channels is increasing from e-auction to the offline channel which is based on the survey of sample product price. The net price of iriver iFP 890 in the offline channel is 280000₩ ($1 ≒ 1000₩), but many internet shops posted its price 260000-270000₩, and in the e-auction, it is transacted 240000-260000₩, thus we set investigated average price from real world as the expected price for each channels in the simulation. Agents have 3 attributes – WTP for the product, **time_sensitivity, iskill. time_sensitivity** is randomly distributed between 0-1 and **iskll** is also randomly distributed between 1-5. The larger value of these means higher level of them. WTP follows normal distribution between 250000₩ and 320000₩ and the CDF of which has the identical shape with common demand curve. During the simulation process, the agent chooses his best market based on the combination of her transaction cost and expected price at each market. If she gets negative utility of purchasing cause of her WTP is lower than the sum of expected price and transaction cost in her best market, she gives up the purchasing. This process is as follows.

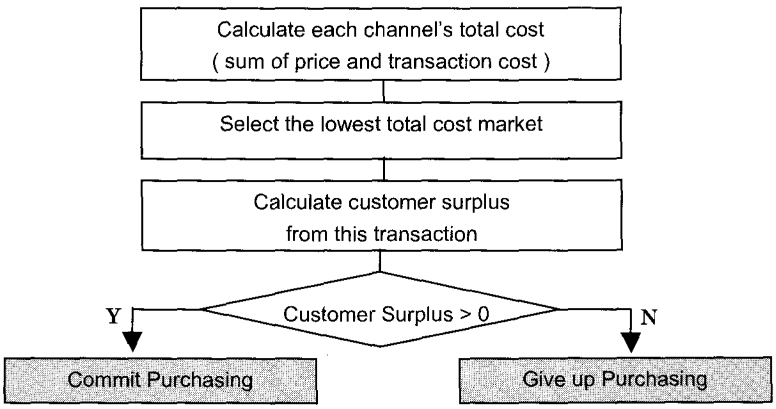

Figure 1. Customer Channel Choice Process

The transaction cost can be represented as a function of **time_sensitivity** and **iskill**. According to Hann and Terwiesh's paper (2003), the transaction cost of electronic channel reaches to about 3% of the price in that channel. The transaction mechanism in their paper is even simpler than the e-auction mechanism thus we set their transaction cost is similar to that of our e-posted-price shop. Firstly we assume the agent of neutral attributes is indifferent to channel type because her total costs are similar through all channels. In our model, we set each channel's transaction cost based on the offline net price. We assume, for the agent of neutral attribute, offline channel's transaction cost charges 1% of the price, and in case of e-posted-price shop and e-auction, it charges 5% and 10% of offline price respectively. Transaction cost can be happened in the 3 phases. First, during pre-purchasing process such as search, transportation, second during purchasing process itself like ordering and payment, and finally during the post purchasing process such as delivery and service. The risk and complexity of transaction involved every phrase can be increased as the market moves to electronic channel, dynamic pricing mechanism and customer-to-customer transactions like e-auction. In this reason we set more weight of transaction cost on the electronic channel, especially e-auction channel, but in the total cost perspective, we make a neutral agent indifferent to any channel as explained. One more important thing is an agent of low time_sensitivity wouldn't feel as much transaction disutility as an agent of high time_sensitivy, and iskill also can be an important factor affecting the weight of net transaction cost in the electronic channels, hence we can say the formula for transaction cost as following equation.

$$transaction\_\cos t_{n,i} = 3(iskill)^{-1} \times 2time\_sensitivity_i \times price_{off} \times a_n$$

$a_n = 0.01,\ iskill_i=3,$	*if n=offline channel*
$a_n = 0.05$	*if n=e-posted-price channel*
$a_n = 0.1$	*if n=e-auction channel*

The subscript '*n*' and '*i*' mean each channel type and individual. '$Price_{off}$' means the expected price from offline channel, which is used for standard price for calculation. By multiplying this with a_n, we can get the neutral transaction cost of each channel. By 3 times of $(iskil_i)^{-1}$ and 2 times of *time_sensitivity*, we can make the agent with neutral attribute, whose *iskill* is 3 and *time_sensitivity* is 0.5, indifferent to any channel in the total cost perspective. To reconcile the iskill effect on the offline channel, we set it '3' for all agents in offline channel.

4.2 Estimation and Results

We generated the data of 1000 agents with WTP, iskill, time_sensitivity from simulation, 20% of which showed negative utility for purchasing and not available for our estimation model, 23% selected e-auction and 27% selected e-posted-price shop, and the rest 30% selected offline channel, thus we used 800 data set of 226 uncensored WTP from e-auction and 574 censored WTP from other channels. Our objective of estimation is to find out the demand function for all 800 customers just using the 226 uncensored, unlimited demands from e-auction channel. When we estimate the limited dependent variable based on continuous exogenous variables, we can employ several approaches. One of them is to use Ordinary Least Squares (OLS) estimations and estimate the demand with separated estimation equations for each group – limited and unlimited. An alternative way for entire sample is using dummy variables for a single estimation equation. Another approach of qualitative analysis models only determines whether to visit one special market or not, which can be accomplished with a linear probability model, a Probit model or a logit model. With this method, we can know the probability of a given customer's being a user of e-auction, but cannot find out the demand function. However, like ours, typical sample is comprised of the ones who visited various channels, thus we should consider the joint determination of whether or not to visit a specific channel and how much to spend there. The above approaches considered only one part of this complete model and OLS estimator can be a biased one because of the simultaneity between the WTP and the channel choice model. For our joint determination of which channel to visit and how much to spend, we employ the censored regression model which has developed by James Tobin (1958). This handles many complicate situations such as estimation of labor supply curves or housing demand problems. Our framework also depends on the limited dependent variable – individuals demand information from e-auction. In our estimation model, we also assume we can identify individual channel preferences or the indicators for these latent variables, thus all the independent variables are observable and WTP is the only limited variable for estimation. While original Tobit model have left censoring point like above example, our model has right censoring point because we cannot obtain the WTP values larger than a certain censoring point. Our estimation result is as represented.

Table 1. Estimation Results

Left censored obs	0	Right censored obs		574
Uncensored obs	226	Total obs		800
	Coefficient	Std. Error	z-Statistic	Prob.
C	27.57050	0.159243	173.1353	0.0000
ISKILL	-0.708892	0.034017	-20.83937	0.0000
TIME_SENSITIVITY	9.041827	0.218403	41.39983	0.0000

The P-values are showing the strong significance of each coefficient. From the result we can gain the demand estimation model as following.

$$WTP = 27.57 - 0.71 \times iskill + 9.04 \times time\_sensitivity$$

The model shows WTP has negative correlation with individual skill of internet usage and positive correlation with individual disutility level from time consumption. Internet skill means the web browser or site specificity and personal specificity of using electronic channel, thus more experienced person with electronic channel would try to search lower price and has lower WTP. In case of time_sensitivity, it means a customer seeking more convenient and low risk purchasing would pay more money instead of paying more transaction cost for saving money.

Because we can analyze the demand from unobservable channels as well as observable one through censored regression, we estimate not only the full demand curve but also divide it to partial demand curves for each channel. Through the following graphs, we can compare the actual demand curves and estimate ones. Left part of Figure 2 shows actual and estimated full market demand curves including all kinds of channels. Right part of Figure 2 shows the classified demand curves by channels. Initially, we could gain the e-auction demand curve – a bold line of right part – and we can also gain all other channels' demand curves through our estimation model – 3 fine lines based on this. Under the contemporary multi-channel environment, taking into account both full market demand curve and classified ones of channels are strongly required for firms' decision making process of accurate product planning, forecasting and balanced channel strategies

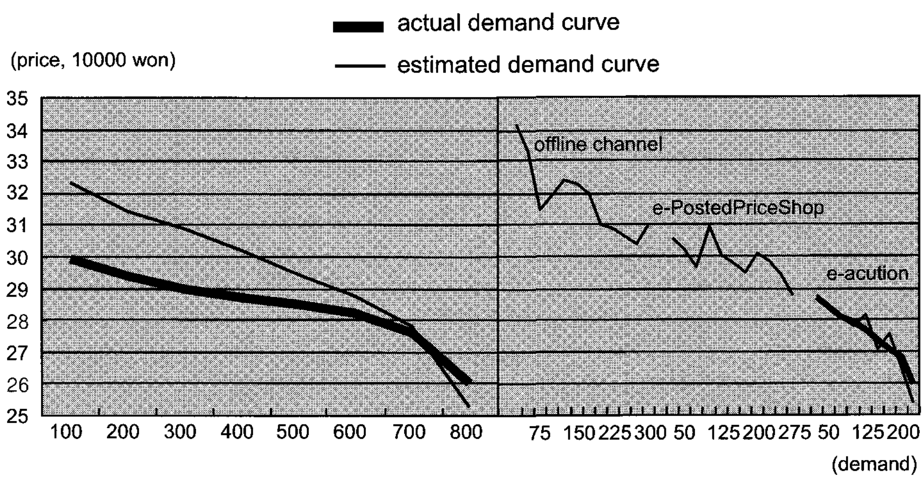

Figure 2. Actual and Estimated Demand Curve

5. DISCUSSION AND CONCLUSIONS

This research showed new ideas for estimating a demand curve suggesting applicable data sources and a statistical analysis method. This idea can be applied to many smart strategies of firms struggling to gain competitive advantages for their products. Using the idea and methodology in this paper, it is possible to develop new e-intelligent system which scans relevant data and uses it for various analyses focusing on marketing interests. In case of producing high-technological goods, a firm can take the monopolistic position in the market at the introduction period of the product. Furthermore, its very short product life cycle urges the firm to rapidly response to the changing demand side. Using an e-commerce site is such a good method to obtain valuable information with easiness and speed, almost simultaneously when an event takes place. Especially, an auction site may be the unique place where buyers interact directly with sellers by publicly representing their WTP, thus it can play an important role as the abundant data source for analyzing various economic agents' behavior. In this reason, we propose taking our approach for a yield management methodology of various channels. By utilizing our framework, a firm can identify right price and quantity of its product which is required in separated channels. We argue that the purpose of this strategy is not in the sales with the higher price, but in the sales with the right price fitting customers' demands well, which is greatly critical for the time-based competition of firms and finally brings the largest profits for firms.

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