An economic analysis of consumer learning on entertainment shopping websites

Jin LI
Xidian University

Zhiling GUO
Singapore Management University, ZHILINGGUO@smu.edu.sg

Geoffrey K.F. TSO
City University of Hong Kong

6-2016

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Zhiling GUO
Singapore Management University, ZHILINGGUO@smu.edu.sg

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Citation

LI, Jin; Zhiling GUO; and TSO, Geoffrey K.F.. An Economic Analysis of Consumer Learning for Online Entertainment Shopping. (2016). *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS).* 1-14. Research Collection School Of Information Systems.
Available at: https://ink.library.smu.edu.sg/sis_research/3429

AN ECONOMIC ANALYSIS OF CONSUMER LEARNING FOR ONLINE ENTERTAINMENT SHOPPING

Jin Li, School of Economics and Management, Xidian University, Xi'an, Shaanxi, China, jinli@xidian.edu.cn

Zhiling Guo, School of Information Systems, Singapore Management University, Singapore, zhilingguo@smu.edu.sg

Geoffrey K. F. Tso, College of Business, City University of Hong Kong, Hong Kong, msgtso@cityu.edu.hk

Abstract

Entertainment shopping supported by pay-to-bid auction is an emerging online business model in recent years. Consumers expect both entertainment value and monetary return from their participation in entertainment shopping. We propose a dynamic structural model to study consumers' online shopping behavior. We analyze the learning process of consumers from two perspectives based on the Bayesian updating framework: (1) consumers update their beliefs about the entertainment value through their repeated personal participation experiences, and (2) consumers infer the expected monetary payoffs on the website by observing the publically available auction ending price information. We estimate the model using a large dataset from an entertainment shopping website. The results show that consumers generally show risk-seeking preferences. They significantly overestimate the entertainment value but underestimate the level of competition at the beginning of their participation, which helps to explain the observed decreasing participation rate over time. Through counterfactual policy simulations, we discuss the website design implications and recommend strategies to create a sustainable business model.

Keywords: E-Commerce, Entertainment Shopping, Dynamic Structural Model, Consumer Learning, Bayesian Statistics.

1 INTRODUCTION

The proliferation of e-commerce has inspired many new forms of online selling mechanisms. For example, Madbid.com, claimed as the number one fun shopping website, is a fast-growing entertainment shopping site that has attracted over 1 million users over Europe and across the world. Other well-known websites, such as DealDash.com, Bidcactus.com and QuiBids.com, sell goods using a similar mechanism called penny auction. Penny auction, also known as pay-to-bid auction or bidding fee auction, is a special form of all-pay auction which requires all participants to pay a non-refundable bidding fee to place each small incremental bid. Economists have suggested that all-pay auction can generate greater revenue than the standard auctions such as those used by eBay, representing a 3 billion industry today (Easley et al. 2011; Krishna and Morgan 1997). Despite the great promise, many of the new sites, such as Swoopo.com and BigDeal.com, have failed after a short period of operation. Decreasing consumer confidence leads to decline in the overall growth of the industry, casting doubts about whether entertainment shopping represents a sustainable business model.

Pay-to-bid auction differs from the traditional auction in several ways. In traditional auctions, if a bidder wins, he gets the product with a price close to its market value; if the bidder loses, it does not cost him anything. In pay-to-bid auction, if a bidder wins, he can achieve huge savings; if the bidder loses, he gets nothing after spending a lot of money in bids. The auctioneer collects revenue from the bidding fees paid by all participants. The huge revenue potential for the auctioneer and the high return for the winner have great appeal for both entrepreneurial start-ups and consumers.

Because it is possible that consumers pay a large amount of bidding fees and still lose an auction, some analysts have criticized the business model as a type of gambling, similar to lotteries. However, the industry defends itself differently and brands itself as entertainment shopping. The selling mechanism turns shopping into a competitive bidding game, while the winning bidders get the merchandise with substantial savings and all losing bidders get exciting experiences, which may worth the bidding fees they pay in the auction games. Proponents view it as a “game of skill” that “allows the most skilful to get amazing bargains.”

The above debate motivates us to look at the business model from the lens of participating consumers. First, we are interested in understanding consumers’ participation incentives. What major motivations attract consumers to the website and play—bargain hunting or just for fun? By effectively combining consumers’ utility derived from both entertainment and monetary payoff, we are able to better understand their preferences toward specific types of product auctions. Second, we aim to understand how consumer learning occurs over time, and how the learning affects their incentives to continually participate on the website. In the following sections, we review the relevant literature, describe our data, present our model and discuss our findings.

2 LITERATURE REVIEW

Online auction is a popular selling mechanism used in many e-commerce websites such as eBay. Different from traditional fixed price purchase environment, decision dynamics is very complicated in online auctions. Because auctions take over time and bidding has a context effect (Simonson 1999), consumers may emotionally respond to environmental stimuli during the auction process, such as excitement, impulse buying (Adam et al. 2012), escalation of commitment (Malmendier and Lee 2011; McGee 2013), strategic late bidding (Caldara 2012), and strategic exit through “Buy-Now” option (Angst et al. 2008; Reiner et al. 2014), etc. The decision making complexity makes it challenging to fully understand consumers’ behavior in online auctions.

Because the implementation of pay-to-bid auctions in e-commerce is new, only a small number of studies have examined this type of auction from a theoretical perspective. Hinnosaar (2013) shows that high variance of outcomes is common for such auction mechanism. Platt et al. (2013) incorporate risk-loving preferences to explain the excess revenue in the auctions. Byers et al. (2010) show that information asymmetries across participants can increase the auction duration and thus produce excess profits. Augenblick (2014) considers regret over the past bidding costs. Reiner et al. (2014) analyze how the "Buy-Now" feature available on the pay-to-bid auction site helps reduce bidders' churn rate.

Most empirical research in online auctions focuses on the traditional types of eBay auction (Bockstedt and Goh 2012; Easley et al. 2011). There are only few empirical works on pay-to-bid auctions. Wang and Xu (2012) find that such auction websites may lose money to sophisticated participants, but profit from most inexperienced bidders who quit quickly after losing some money and realize it is actually hard to win the auctions. This suggests that players do learn through repeated participation.

Prior research shows that learning naturally occurs in various complex decision making environments (Dey et al. 2013; Geng et al. 2009). Erdem and Keane (1996) consider consumers' use experience and advertisement as two noisy signals to learn a new product's attribute. Erdem et al. (2008) further incorporate the product price and advertisement frequency to enrich the consumer learning model. In the context of targeted marketing, Narayanan and Manchanda (2009) use a Bayesian learning model to account for the heterogeneous learning rates of individual physicians for new prescription drugs. Iyengar et al. (2007) provide a consumer learning framework to study both service quality and usage quantity learning in the service industry. More recently, Zhao et al. (2013) examine how learning through readers' own reading experience and others' online reviews affect consumer buying behavior. Ghose and Han (2011) develop a dynamic structural model of consumer learning to understand user content generation and consumption behavior in the mobile channel. Huang et al. (2014) apply the structural Bayesian modeling method to analyze consumer learning on a crowdsourcing platform. Adding to this line of research, we propose a dynamic structural model with Bayesian learning to study consumers' participation behavior in the entertainment shopping e-commerce environment.

Various studies in consumer research confirm that shopping experiences can produce both utilitarian and hedonic value (Angst et al. 2008; Holbrook and Hirschman 1982). Hedonic value refers to the enjoyment users derive from the process of participating in the system, apart from its utilitarian values that directly related to the shopping outcome (Babin et al. 1994). It is an important design factor in the online entertainment community (Liu et al. 2007). Recent research suggests that perceived enjoyment is very important in web systems, games, and systems for home and leisure purposes (Van der Heijden 2004). In the auction environment, Adam et al. (2012) find evidence that consumers derive a hedonic value from auction participation that makes exciting auctions more attractive and possibly induces bidders to stay active in the auction for a longer period. In our research context, we not only consider tangible values such as goods and services acquired, but also examine intangible and emotional costs and benefits. We simultaneously account for both hedonic and utilitarian values in consumers' decision making.

3 DATA

We collected data from an entertainment shopping website in China. The website sells a large number of consumer electronics, as well as other popular products found in typical online retail stores. Our data set includes 23,884 auctions from September 26, 2011 to January 21, 2012. During this time period, the website provided a relatively stable number of auctions, and attracted a steady stream of newly registered users to the site every day.

Based on the website navigation, we aggregate and classify auctions into three general categories: Virtual Products (e.g. top-up cards, bidding tokens etc.), General Merchandise (e.g. home daily supplies, electronic appliances etc.) and Digital Products (e.g. tablets, mobile phones etc.). First, we separate virtual products from physical products as we believe these two types of products have distinct features that might lead to different consumer behavior. Second, we further separate digital products from the physical product auctions because digital products are the most popular and most profitable. The remaining physical product auctions are included in the General Merchandise category. This results in a relatively balanced sample of 5000~7000 auctions in each category.

The website rewards users in different ways by offering free tokens. For example, new users get free tokens upon registration and existing users can earn free tokens by posting pictures of winning products and participating in online discussion. The free tokens can be used in free auctions, such as the small value top-up card auctions. Because free auctions restrict bidders to use free tokens, rather than paid tokens, to place the bids, we treat free auctions separately as the fourth auction type. Overall, there are 21,463 auctions provided in the three-month period, among which 3,533 are free auctions. Table 1 reports the descriptive statistics for the three types of paid auctions and free auctions.

Product Categories	**Virtual Products**	**General Merchandise**	**Digital Products**	**Free Auctions**
Total number of auctions	5,488	5,154	7,288	3,533
Total number of profitable auctions	3,976	1,611	2,431	6
% of profitable auctions	72.45	31.26	33.36	0.17
Average retail price / ¥(s.d.)	50.45(26.42)	220.49(134.84)	442.03(710.70)	31.18(40.00)
Average ending price / ¥(s.d.)	2.29(3.26)	2.12(3.32)	7.73(29.65)	5.16(7.30)
Average duration / minutes (s.d.)	33.35(128.61)	28.31(109.38)	69.35(227.96)	7.30(21.36)
Average website profit / ¥(s.d.)	181.17(318.59)	-6.66(312.10)	338.54(2550.18)	-26.02(38.73)

Table 1. Summary Statistics for Auctions

We see that Digital Products have higher average retail price, higher auction ending price, longer duration, and higher website profit than other categories. Apparently, this category has attracted a lot of bidders who contributed significantly to the website revenue. The large average auction ending price of Digital Products indicates intense competition in the auctions. Longer auction duration implies higher cognitive cost and time cost. Accordingly, a large amount of bidding fees will be sunk, resulting in large sunk cost. The large variance indicates that the auction outcomes are highly uncertain, which also makes it difficult for users to estimate the auction ending prices and thus infer expected payoff from the auctions accurately. Comparing the Virtual Products with General Merchandise categories we see that the average auction ending prices and auction duration are similar. However, the average retail price for Virtual Products is smaller than that for General Merchandise, while the average website profit for Virtual Products is higher than that for General Merchandise. This shows that Virtual Products and highly popular Digital Products have higher demand than General Merchandise. We believe the website provides auctions for General Merchandise in order to add variety of product choices. A wide range of product selection may attract new users to come and existing users to revisit the website.

There are 32,070 active bidders during our observation period. Our data shows that most registered users are only active for a very short period of time. It is possible that users who registered early can obtain more information than those who registered late. To eliminate such concern, we sample users who registered on the same day in our analysis. We randomly select 241 unique users who registered on a typical weekday in September 2011. (We have tested other samples in our model robustness check.) On one hand, these users have the same prior information set. On the other hand, the observation period for the sample users is long enough to reveal users' learning process.

Variables	**Mean**	**S.D.**	**Min**	**Max**
Total number of auctions	5.89(5.21)	18.66(10.79)	1(1)	822(77)
Number of paid auctions	4.12(3.36)	16.23(8.43)	0(0)	749(66)
Number of free auctions	1.78(1.85)	3.53(5.50)	0(0)	150(76)
Number of winning auctions	0.50(0.33)	2.82(1.39)	0(0)	61(11)
Number of days the bidder is active	2.24(2.32)	3.56(3.40)	1(1)	69(25)
Days between first and last bidding	4.53(7.66)	12.14(18.12)	0(0)	91(85)
Numbers inside the parentheses are for the selected 241 users, and numbers outside the parentheses are for all 32,070 users.				

Table 2. Summary Statistics for Registered Users

Table 2 shows the descriptive statistics for the participation behavior of the sample users. The average number of winning auctions is very small, indicating high competition and low probability of winning. The mean duration of user participation (the average number of days between the first and last participation of a registered user) shows that users only stay active for a few days, which reflects the lack of participation on the website. Because the amount of free bidding tokens awarded to or earned by each user is limited, the mean and variance of participation in free auctions are relatively smaller than the paid auctions.

4 THE MODEL

4.1 Utility Function

Because entertainment effect is a key feature in entertainment shopping, we assess consumers' shopping experience along two important dimensions: utilitarian and hedonic values. As such, we incorporate both the perceived non-monetary entertainment value and the expected monetary return in the bidder's utility function. We also consider the risk attitude in the structural model.

Let U_{ijt} be the utility bidder i obtained from participating in a category j auction on day t. We define the utility function as

$$U_{ijt} = E_{it}^{e} + \beta_j + \alpha P_{ijt}^{o} + \alpha r P_{ijt}^{o2} + \lambda' S_{it} + \varepsilon_{ijt} \quad (1)$$

The first term E_{it}^{e} represents the user's entertainment value through personal experience (denoted by the superscript 'e'). The second term β_j is auction type-specific, non-monetary entertainment effect. The third term P_{ijt}^{o} captures the effect of auction competition by observed auction price signals (denoted by the superscript 'o'). The fourth squared term P_{ijt}^{o2} measures the bidder's risk preferences in response to auction competition. The fifth term S_{it} is a vector of bidder and time-specific covariates. In the following, we describe each term in the utility function in detail.

Because E_{it}^{e} is the website entertainment value bidder i experienced at time t, it reflects the bidder's overall evaluation of the entertainment shopping environment. The auction rules, the number of products and variety of product selection, the shopping convenience, and other aspects of the website design may affect the website entertainment value. We assume each registered user derives his own entertainment value from the entertainment shopping site with its true mean drawn from a normal distribution. Initially the user has a prior belief about his entertainment value. After participating in an auction, the user updates his belief about the entertainment value based on his own in-auction experience. If the user has participated sufficient number of auctions on the website, he will eventually learn the true entertainment value the website brings to him. We will present the detailed entertainment belief update process in the next section.

In addition to the general website entertainment value a bidder perceives, different types of auctions may bring different entertainment experiences to users. For example, the auction for virtual products such as the top-up telephone cards can be immediately cashed out upon winning. Unlike other physical products that have to be shipped to the winners, immediate gratification of the virtual products may bring high excitement for bidders in this type of auctions. One the other hand, an auction for popular digital products such as iPhone may take hours, even a day, to complete, so it incurs high time cost and cognitive cost for the bidders. We thus use β_j to denote the auction type-specific entertainment value, where a positive value can be understood as the non-monetary, psychological benefit and a negative value the participation cost incurred in different types of auctions.

Bidders may infer the level of competition from the observed historical auction ending prices. The mean auction ending price represents the expected return, and the variance of the auction ending price captures the uncertainty involved in the expected return. Because P_{ijt}^{o} denotes the mean ending price of type j auctions observed by bidder i on day t, we focus on auction ending prices at category level rather than individual auction level. The reason for this modelling choice is that we are mainly interested in understanding the bidders' participation in different types of auctions instead of any individual auctions. The parameter α is the coefficient measuring the effect of the expected monetary return, and r captures bidders' risk preference toward uncertainty in the auction outcome.

Finally, S_{it} contains bidder- and time- specific covariates, including the bidder's earning in the previous period, his cumulative wealth up to time t, and a loss indicator capturing his continuous auction failures. The parameter vector λ is used to measure how the covariates affect the utility. Finally, the error term ε_{ijt}, which is unobservable to the researcher but is known to the bidders, captures the bidder choice-specific random shock in period t. For example, these errors can be any promotion activities or reminder emails that are unknown to researchers but can influence bidders' choice of participation.

4.2 Learning of Entertainment Value

We assume that bidders have a prior belief E_{i0} for the entertainment value when they first register on the website. The prior belief is normally distributed with mean E_0 and variance σ_{E0}^2 as

$$E_{i0} \sim N(E_0, \sigma_{E0}^2). \tag{2}$$

After registration, bidders can access to both free and paid auctions provided by the website. Bidders learn the entertainment value through experiencing both types of auctions. We hypothesize that the free auction experience signal is more precise than the paid auction signals, because the free auction does not involve real money bidding, which helps quickly discover the true entertainment value a bidder can enjoy from participating in the auctions.

Let μ denote the true mean entertainment value, we define bidder i's direct experience through the s^{th} paid auction and m^{th} free auction on day t as $E_{its}^{p} = \mu + \delta_{its}$, where $\delta_{its} \sim N(0, \sigma_\delta^2)$, and $E_{itm}^{f} = \mu + \eta_{itm}$, where $\eta_{itm} \sim N(0, \sigma_\eta^2)$, respectively. Here δ_{its} and η_{itm} measure the deviation of bidder i's received entertainment signal at time t from the true mean entertainment value, and σ_δ^2 and σ_η^2 are bidding experience variances, which measure the precision of signals. Accordingly, bidder i receives the experience signal only when he bids in one auction, and the signals follow a Normal distribution: $E_{its}^{p} \sim N(\mu, \sigma_\delta^2)$, and $E_{itm}^{f} \sim N(\mu, \sigma_\eta^2)$.

Assume bidder i participates in a total of n_{it} paid auctions and f_{it} free auctions on day t. The series of observed signals can be aggregated, which have the following Normal distributions respectively: $E_{it}^{p} = \frac{\sum_s E_{its}^{p}}{n_{it}} \sim N\left(\mu, \frac{\sigma_\delta^2}{n_{it}}\right)$, and $E_{it}^{f} = \frac{\sum_m E_{itm}^{f}}{f_{it}} \sim N\left(\mu, \frac{\sigma_\eta^2}{f_{it}}\right)$. Conditional on the signals obtained on day t, bidders update their posterior belief according to the Bayes' theorem (DeGroot 1970) as follows:

$$b_{it}^{E}(\mu) = N(E_{it}, \sigma_{Eit}^2), \tag{3}$$

where $E_{it} = \frac{\sigma_{Eit}^2}{\sigma_{Ei,t-1}^2} E_{i,t-1} + n_{it}\frac{\sigma_{Eit}^2}{\sigma_\delta^2} E_{it}^{p} + f_{it}\frac{\sigma_{Eit}^2}{\sigma_\eta^2} E_{it}^{f}$, and $\sigma_{Eit}^2 = \frac{1}{1/\sigma_{Ei,t-1}^2 + n_{it}/\sigma_\delta^2 + f_{it}/\sigma_\eta^2}$. Here $E_{i,t-1}$ is the mean and $\sigma_{Ei,t-1}^2$ is the variance of the entertainment belief at the beginning of day t, which are the same as the posterior ones at the end of day $t-1$. The prior belief on day 1 is specified as $E_{i0} = E_0$ and $\sigma_{Ei0}^2 = \sigma_{E0}^2$. Based on the Bayesian update, bidders place a relatively higher weight on more precise signals (i.e., the signals with a lower variance).

4.3 Learning of Auction Ending Prices

Based on the auction rules, the higher the ending price for an auction, the lower the expected revenue (which equals to the retail price subtracts the auction ending price), and thus the more intense the competition. Because the retail prices are fixed on the website, consumers observe the historical auction ending prices as proxy signals based on which they form expectations about the monetary return for different types of auctions. Simple regression reveals that the number of bidders is significantly and positively correlated (p-value < 0.01) with the auction ending price for all three types.

We assume that bidders have a prior belief for the average auction ending price when they joined the website: $P_{ij0} \sim N(P_{0j}, \sigma_{P0}^2)$, where P_{0j} is the prior mean and σ_{P0}^2 is the prior variance. This can be obtained by historical price information available on the website. In addition, bidders update their beliefs about future auction ending prices as new auctions are completed on the website. We assume that bidders update their ending price beliefs on a daily basis. All auctions' ending prices for a specific type are aggregated into one signal as $P_{ijt}^o = P_j + \zeta_{ijt}$, where $\zeta_{ijt} \sim N(0, \sigma_{\zeta j}^2)$ and $\sigma_{\zeta j}^2$ is the ending price variance for type j auctions. Thus, the observed ending price signal can be expressed as $P_{ijt}^o \sim N(P_j, \sigma_{\zeta j}^2)$. Conditional on the daily ending price signals obtained, bidders update their posterior belief accordingly:

$$b_{it}^O(P_j) = N(P_{jt}, \sigma_{Pjt}^2), \tag{4}$$

where $P_{jt} = \frac{\sigma_{Pjt}^2}{\sigma_{Pj,t-1}^2} P_{j,t-1} + \frac{\sigma_{Pjt}^2}{\sigma_{\zeta j}^2} P_{ijt}^o$ and $\sigma_{Pjt}^2 = \frac{1}{1/\sigma_{Pj,t-1}^2 + 1/\sigma_{\zeta j}^2}$. Here $P_{j,t-1}$ is the mean and $\sigma_{Pj,t-1}^2$ is the variance of the prior ending price belief for type j auctions at the beginning of day t, which is the same as the posterior belief at the end of day $t-1$. Considering the significant ending prices differences among three types, we specify the type-specific ending price prior beliefs as $P_{ij0} = P_{0j}$ and $\sigma_{Pj0}^2 = \sigma_{P0}^2$.

4.4 Monetary Gain and Continuous Loss

In the utility function, we define S_{it} as a vector of bidder- and time-specific covariates. We include such monetary terms as the bidder's earning in the last period M_{it}^l and his cumulative wealth up to time t, M_{it}^c. The last period earning is calculated as the total revenue (retail prices minus auction ending prices for winners and zero for losers) subtracts sunk cost in the previous day. The cumulative wealth is the bidder's account balance at time t. We take the log transformation of the revenue (similarly, for sunk cost and cumulative balance) plus 1 to rescale the measure and to avoid infinitely negative values.

We also include a continuous loss factor. Escalation of commitment (Staw 1976) and sunk cost fallacy have been used to justify people's increased investment such as money and time in a decision. In the pay-to-bid auction games, bidders incur some sunk costs (the non-negligible biddings fees) each time they lose an auction. In order to evaluate whether the bidder may make poor decisions by using past failures to justify continued involvement, we use a loss indicator L_{it} to indicate whether the bidder has lost a fixed number of auctions continuously or not. For example, if the bidder loses 15 auctions continuously, then the indicator is 1, otherwise it is 0. A significant and positive estimate of the coefficient for L_{it} will confirm escalation of commitment. The values for M_{i1}^l, M_{i1}^c and L_{i1} at the beginning of day 1 are all specified as zero.

4.5 Expected Utility and Likelihood

Bidders make bidding decisions based on their expected utilities. Bidder i holds an information set I_{it} containing all received auction-related signals up to day t. Conditional on the information set, the expected utility for bidder i from bidding in type j auctions at time t is

$$E[U_{ijt} | I_{it}] = \widetilde{U}_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where

$$\widetilde{U}_{ijt} = E[E_{it}^e | I_{it}] + \beta_j + \alpha E[P_{ijt}^o | I_{it}] + \alpha r E[P_{ijt}^{o2} | I_{it}] + \lambda' E[S_{it} | I_{it}]. \tag{6}$$

For the entertainment value, we have $E[E_{it}^{e}|I_{it}] = E[\mu|I_{it}] = E_{i,t-1}$. Similarly, the expected ending price is $E[P_{ijt}^{o}|I_{it}] = E[P_j|I_{it}] = P_{j,t-1}$. Furthermore, we can write $P_{ijt}^{o} = P_{j,t-1} + (P_j - P_{j,t-1}) + \zeta_{ijt}$ and derive the conditional expectation $E[P_{ijt}^{o2}|I_{it}] = P_{j,t-1}^{2} + [(P_j - P_{j,t-1})^2|I_{it}] + \sigma_{\zeta j}^{2}$. Therefore, the conditional expected utility for bidder i is expressed as:

$$E[U_{ijt}|I_{it}] = E_{i,t-1} + \beta_j + \alpha P_{j,t-1} + \alpha r P_{j,t-1}^{2} + \alpha r E[(P_j - P_{j,t-1})^2|I_{it}] + \alpha r \sigma_{\zeta j}^{2} + \lambda_1 M_{it}^{l} + \lambda_2 M_{it}^{c} + \lambda_3 L_{it} + \varepsilon_{ijt}. \quad (7)$$

Bidders' participation probability for a specific auction type is based on the bidders' expected utility. We assume that ε_{ijt} follows a Type I extreme value distribution. The probability of observing bidders' bidding action A_{ijt} can be specified as

$$Pr(A_{ijt}) = \left(\frac{exp(\tilde{U}_{ijt})}{1+exp(\tilde{U}_{ijt})}\right)^{A_{ijt}} \left(\frac{1}{1+exp(\tilde{U}_{ijt})}\right)^{(1-A_{ijt})}. \quad (8)$$

where A_{ijt} denotes bidder i's participation variable, which equals 1 if bidder i bids in type j auctions at time t and 0 otherwise. We further assume that bidders' bidding decision for each type of auctions is independent. The joint likelihood for the sample bidders' bidding series can be specified as

$$Likelihood(A) = \prod_{i=1}^{N} \prod_{j=1}^{J} \prod_{t=1}^{T} Pr(A_{ijt}). \quad (9)$$

where A is the bidding decisions matrix for all N bidders for J types of auctions over the entire observation period T.

5 EMPIRICAL RESULTS

The likelihood function in Equation (9) is jointly determined by the perceived entertainment effect and the perceived auction ending prices, means and variances, and bidder- and time-specific covariates in each time period. Although the ending price signals can be observed, the entertainment signals through bidding are unobservable. From the researcher's point of view, we only know the distribution of the signals. Considering the infeasibility of high dimensional integration for the likelihood function in closed form, we use simulated maximum likelihood (McFadden 1989) as an approximation method to compute the likelihood function.

Table 3 summarizes the estimation results. The three β values are negative, which reflect the average cognitive cost for bidders to participate in a specific type of auction. We see that the absolute values for Type 1 (Virtual Products, 4.930) and Type 2 (General Merchandises, fixed at 5) are smaller than the Type 3 (Digital Products, 6.307) auctions. This seems reasonable because the average durations for Type 1 and Type 2 auctions are relatively short and auctions usually end very quickly from a few minutes to a few hours. But Type 3 products generally have higher retail prices and bidders who participate in such auctions may persist for a long time. For example, the popular Apple product auctions may last for more than one day, pausing at 00:00 am and restarting at 9:00 am. The time cost and cognitive cost associated with this type of auctions are higher than other types of auctions.

The entertainment value measures the average overall effect of the entertainment shopping environment on bidders' utility, such as the bidders' general attitude toward enjoyment of playing the online auction games. The prior entertainment belief E_0 (6.935) is significantly higher than the true mean entertainment value we estimated (4.677). It indicates that bidders overestimate the entertainment benefit they can obtain at the beginning of an auction they participate. Recall that bidders experience the entertainment effect by their own participation in both paid and free auctions. The results show that the natural logarithm variance for the free auctions (1.541) is smaller than that from the paid auctions (5.216). Thus, the signal from free auctions is more precise because bidders have no monetary sunk cost for free auctions and can obtain more accurate entertainment valuation through participating in free auctions.

Parameters		Estimates	Std. Error
β_1	Type 1 (Virtual Products) auction cognitive cost	-4.930	0.155***
β_2	Type 2 (General Merchandise) auction cognitive cost	-5	-Fixed
β_3	Type 3 (Digital Products) auction cognitive cost	-6.307	0.616***
μ	Mean website entertainment value	4.677	0.625***
α	Sensitivity to auction competition	-4.219	0.384***
r	Risk preference	-0.071	0.002***
λ_1	Past monetary gain	-0.455	0.049***
λ_2	Cumulative monetary gain	0.307	0.057***
λ_3	Continuous bidding loss	0.796	0.394**
E_0	Prior belief about website entertainment value	6.935	0.563***
σ_{E0}^2	Variance of prior belief about entertainment value	10	-Fixed
$ln\sigma_\delta^2$	Log variance of paid auction participation signal	5.216	0.296***
$ln\sigma_\eta^2$	Log variance of free auction participation signal	1.541	0.160***
P_{01}	Prior belief for Type 1 auction ending price	1.814	0.101***
P_{02}	Prior belief for Type 2 auction ending price	1.831	0.108***
P_{03}	Prior belief for Type 3 auction ending price	5.462	0.392***
σ_{P0}^2	Variance of prior belief about auction ending price	10	-Fixed
P_1	Mean ending price for Type 1 auction	2.346	0.070***
P_2	Mean ending price for Type 2 auction	2.195	0.061***
P_3	Mean ending price for Type 3 auction	8.441	0.556***
$ln\sigma_{\zeta 1}^2$	Log variance of Type 1 auction ending price signal	-0.799	0.147***
$ln\sigma_{\zeta 2}^2$	Log variance of Type 2 auction ending price signal	-1.064	0.147***
$ln\sigma_{\zeta 3}^2$	Log variance of Type 3 auction ending price signal	3.371	0.147***
Note: *** denotes significant at 0.01; ** denotes significant at 0.05.			

Table 3. Parameter Estimation

We see that the initial ending price beliefs are 1.814, 1.831 and 5.462, which are smaller than the true means, 2.346, 2.195 and 8.441, respectively. This indicates that bidders underestimate the auction ending prices for all three types of auctions. Bidders' overestimation of entertainment value and underestimation of auction competition together explain the observation that many bidders participate in a lot of auctions at the beginning and then the number of participated auctions decreases over time. As to the auction ending price signal precisions, Type 1 and Type 2 auctions show more precise signals as the natural logarithm of variances are very small (-0.799 and -1.064). However, the signals' variance for Type 3 auctions is relatively large (the natural logarithm of variance is 3.371). These results suggest that learning of the auction ending price in Type 3 auctions is more difficult than learning in the first two types of auctions.

The parameter α for the perceived auction ending price is negative (-4.219). It indicates that auctions with higher ending price may reduce bidder's utility, which leads to a lower participation probability. This is intuitive because higher auction ending price implies intense competition in the auction, which reduces bidders' incentive to participate in the auction. However, the risk preference parameter r is also negative (-0.071). Together with the negative value of α, we conclude that bidders show risk-seeking preference.

The parameter for bidders' past gain is negative (-0.455). While a loss in the recent past increases the probability of participation in the next time period, a win in the recent past reduces the participation interest in the following time period. Therefore, the payoff in the previous time period has a negative impact on utility.

In contrast, the effect of cumulative balance on utility is positive (0.307). It implies that losing too much money cumulatively on the entertainment shopping website has a large negative effect on the utility and bidders may quit the website without bidding anymore. On the other hand, there may be few game-addicted bidders. The coefficient for the continuous loss indicator is positive (0.796), which is statistically significant at 0.05 level. In our estimation, we set the threshold for continuous auction loss at 15, which is relatively a large number. The positive coefficient indicates that bidders become more addicted after losing many auctions, reflecting the gambling effect inherent in the entertainment shopping mechanism. This is consistent with the prior findings on escalation of commitment that has been widely discussed in the psychology literature on lottery and gambling.

6 POLICY SIMULATIONS

A key advantage of structural model is to allow for counterfactual analyses. We conduct a set of policy experiments aiming to provide business insights and marketing strategies for building a more sustainable business model. For all simulations, we evaluate each policy change by making 2000 iterations using the estimated parameters. We then use the average performance measures to assess the effects of policy changes.

6.1 Entertainment Value

A lot of entertainment shopping websites go bankrupt after a short period of operation. The problem is the quickly decreasing rate of active users. Because consumers have to pay for the "fun" each time they place a bid on the website, the website needs to find ways to improve the overall consumer experience in the entertainment shopping environment. For example, bidders incur high cognitive cost during the last 10-second bidding wars. Automatic bidding can dramatically lower the cognitive load and the monitoring cost of the bidders, thus increase bidder utilities. The website may consider providing automatic bidding tools to allow bidders to customize their bidding strategies. In addition, the website can provide more auctions in the Virtual Product category where the auction-specific cognitive participation cost is the lowest. All these efforts will help increase the participation rates.

Our simulation procedure is to increase the true entertainment value μ by 20% (50%) while other parameters remain the same as the estimated values. Hence, the entertainment signals obtained through participating in paid and free auctions follow the Normal distributions with changed means. Table 4 reports the percentage of active bidders on different days after registration when we increase the mean entertainment value by 20% and 50%, respectively. Because bidders' participation on the registration day is based on their prior entertainment beliefs, there is no significant change on the first day. During the following days, the percentage of daily active bidders for all three types of auctions increases. For example, comparing with the current level 0.25%, the percentage of active bidders for Digital Products (Type 3) on day 11 increases to 0.32% (0.56%) if the mean entertainment value improves by 20% (50%). There is a large increase in the percentage of bidders' participation in the first month. The percentage of active bidders on day 91 when the mean entertainment value increases 50% is 0.28%, significantly higher than the current level 0.12%. The results clearly show that more bidders will stay active after the policy change.

Active Bidder Percentage	Day 1	Day 11	Day 21	Day 31	Day 61	Day 91
Type 1: Virtual Products						
Current Policy	17.56%	0.81%	0.56%	0.31%	0.08%	0.04%
Ent. Value increased by 20%	17.66%	1.02%	0.75%	0.42%	0.11%	0.06%
Ent. Value increased by 50%	17.62%	1.67%	1.22%	0.64%	0.17%	0.09%
Type 2: General Merchandise						
Current Policy	15.44%	0.35%	0.15%	0.10%	0.08%	0.05%
Ent. Value increased by 20%	15.52%	0.45%	0.20%	0.16%	0.11%	0.07%
Ent. Value increased by 50%	15.49%	0.76%	0.32%	0.23%	0.17%	0.11%
Type 3: Digital Products						
Current Policy	13.87%	0.25%	0.26%	0.31%	0.10%	0.12%
Ent. Value increased by 20%	13.97%	0.32%	0.35%	0.42%	0.12%	0.18%
Ent. Value increased by 50%	13.92%	0.56%	0.58%	0.64%	0.20%	0.28%

Table 4. Percentages of Active Bidders by Increasing the Mean Entertainment Value

6.2 Bidder Learning

Our base model results show that initially bidders overestimate the entertainment value. They update their beliefs about the entertainment value after participating in some auctions. Therefore, offering newly registered bidders with free bidding tokens would enable them to participate in more free auctions, which helps them to quickly discover the true entertainment value and lower their bidding utility. This may have a negative revenue impact on the website. Table 5 shows that removing free auctions can help increase the expected percentage of active bidders on the website. The policy simulation suggests that alternative strategies, such as offering discounted paid bidding tokens (e.g., bidding token with a discounted prices) rather than free bidding tokens, should be provided to bidders at the time of registration.

Active Bidder Percentage	Day 1	Day 11	Day 21	Day 31	Day 61	Day 91
Type 1: Virtual Products						
Current Policy	17.56%	0.81%	0.56%	0.31%	0.08%	0.04%
No Free Auction Training	17.66%	2.01%	1.47%	0.85%	0.22%	0.11%
Type 2: General Merchandise						
Current Policy	15.44%	0.35%	0.15%	0.10%	0.08%	0.05%
No Free Auction Training	15.52%	0.88%	0.38%	0.31%	0.22%	0.16%
Type 3: Digital Products						
Current Policy	13.87%	0.25%	0.26%	0.31%	0.10%	0.12%
No Free Auction Training	13.97%	0.63%	0.69%	0.84%	0.25%	0.41%

Table 5. Percentages of Active Bidders by Removing Free Auctions Training

7 CONCLUSION

The recent proliferation of many entertainment shopping websites worldwide has attracted both consumers and businesses. Despite the huge revenue potential, a lot of websites have ceased operation in a short period of time, casting doubt on the entertainment shopping concept and sustainability of its business model. This study proposes a dynamic structural model to understand consumers' participation behavior on such a website. We conduct policy simulations to evaluate the potential impact on consumer participation. We offer several policy recommendations to increase consumers' lifetime value on the website.

Specifically, our model captures consumers learning from both their own participation experience and observational learning on the website. We find that both types of learnings are important to influence consumers' participation behavior. In particular, consumers significantly overestimate the entertainment value but underestimate the level of competition at the beginning of their participation, which explain the observed decreasing participation rate over time. We further find that consumers generally show risk-seeking preferences. Some heavily-addicted users are more willing to participate in new auctions after experiencing continuous and significant loss. We find evidence of escalation of commitment from these heavily-addicted bidders.

Through counterfactual policy simulations, we have discussed several website design implications to create a more sustainable business model. First, we recommend the website to use automatic bidding tools to increase user experiences. Second, the website can influence consumer learning by reforming the free auction mechanism and free bidding token reward policies. Our policy simulation results indicate that these changes can induce users to stay active for a longer time. This is important for the online entertainment shopping websites to retain consumers.

Our current model has several limitations. First, because our focus is on consumers' learning across different bidding games, we do not incorporate consumers' in-game experience. That is, we do not explicitly model consumers' bidding strategies in each stage of the auction bidding game. A possible future direction is to build a micro-level behavior model to study consumers' bidding strategies. Second, consumers are heterogeneous in nature. They may have different budget constraint, risk attitude, and shopping interests. Because we do not have access to consumer characteristics data, our model cannot capture such heterogeneity. Future research may use survey and lab experiments to collect such behavior data. An enriched model can offer more valuable insights that are unavailable from this study. Finally, we consider the consumer's participation decision as a myopic decision problem based on the consumer's current information set, his belief about the entertainment value and perception about auction competition. Future research may build a dynamic optimization model to study consumers' forward-looking behavior in managing a portfolio of their auction participations subject to their own budget constraints.

Acknowledgement

This research was supported by the Chinese fundamental research funds for central universities under grants No.JB160611 (20101166317) and No.XJS16026 (20103166317).

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