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GENERAL RESEARCH

Online auction: the effects of transaction probability and listing price on a seller's decision-making behavior

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Abstract This study seeks to the answer the question of how an individual would trade off between listing fee (i.e., cost of listing an auction item) and transaction probability (i.e., the chance that a product will be sold). Applying the trade-off decision-making paradigm into the auction context, we examine a seller's choice of online auction outlet and subsequent starting price strategies when facing the trade-off between transaction probability and listing fee. Results from a set of laboratory experiments suggest that a seller would be willing to incur a high cost in exchange for a higher transaction prospect. Furthermore, if the expected transaction probability is high, a seller is more likely to set a high starting price despite incurring a high listing fee. The implications for theory and practice are discussed.

Keywords Online auction · Decision-making · Seller behavior

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Introduction

With more online auction websites entering the electronic market, competition for sellers and bidders intensifies (Kalyanam and McIntyre 2002; Kim et al. 2002). Consequently, it is critical to know how to attract sellers to auction their products and buyers to bid (Antony et al. 2006). Although the auction theory is now relatively well-established (Klemperer 1999) and increasing research attention has been paid to studying online auctions (Luckling-Reiley 2000), our understanding of online auctions is incomplete for two reasons. First, significant amount of traditional auction studies have focused on studying the impact of different auction types, e.g., ascending-bid and descending-bid auctions, on market performance (see Klemperer 1999 for a complete review). It is often assumed that sellers and bidders trade in a single auction house, leaving limited knowledge on how the different auction websites affect a seller's behavior for instance. Second, although many online auction studies have examined bidders' behaviors in response to online auction features, such as auction duration, starting price and reserve price (Dholakia and Simonson 2005; Yokoo et al. 2004; Bapna et al. 2003, 2001a, b), less attention has been paid to understand sellers' behaviors. To this end, two sequentially related predicaments facing a seller, i.e., 1) which auction website to list his/her products, and 2) how to price the product, are inadequately examined.

A seller's decision on the source of auction website is complex for he/she could be compelled to make explicit trade-offs, e.g., listing fee (i.e., cost of listing an auction item) and transaction probability (i.e., the chance that a product will be sold). To illustrate, consider this scenario: there are two auction websites, namely website A and website B, which differ in terms of the listing price (i.e., cost of listing an auction item), and transaction probability (i.e. the chance that a product will be sold). Website A, (e.g., eBay), charges sellers both a listing fee and a percentage commission of the item sold. Website B, (e.g., Yahoo!Auction), offers free listing. However, website B suffers from a much lower successful transaction probability than website A. How would a seller choose? Would one simply focus on one attribute and maximize it (e.g., choosing the auction website with the lower transaction cost)? In other words, how would a seller trade off between the attributes explicitly to balance his/her utility for lower cost against the utility for higher transaction probability?

Along the same vein, suppose the seller has chosen an auction website, how would he/she derive the pricing strategy? If the seller sets a lower starting price, the product would enjoy a higher probability of being auctioned off (i.e., higher transaction probability). However, if the seller delineates a higher starting price, he/she could earn higher returns but at the expense of lower probability of the product being auctioned off and higher probability of losing the non-refundable listing fee. The two questions, i.e., the choice of auction website and the starting price strategy, manifest the typical dilemma of a seller's decision on where and how to auction his/her items. The objectives of this paper are hence two-fold. First, it seeks to examine how sellers choose a website in the online auction market through controlled experimentation. In our knowledge, many extant online auction studies have focused more on a bidder's behavior rather than that of a seller's. Furthermore, significant amount of empirical studies have been conducted based on the secondary field data (see Pinker et al. 2003 for the review), making it more challenging to dichromate the impact of single or small set of auction factors on an individual behavior, e.g., the seller's. Leading from this, the second objective of this study is hence, to observe how sellers set the starting prices for their products in the chosen auction website. Each of these problems involves a trade-off of factors: the first involves a seller's trade-off between transaction probability and cost; the second involves a seller's trade-off among payoff, transaction probability and cost. Essentially, by examining the two issues, we seek to provide and test a more nuanced theoretical understanding of a seller's behavior in an online auction decision-making environment.

Conceptual background and hypothesis development

Since the appearance of the seminal work of Luckling-Reiley (2000), online auction research has made significant progress in the past one decade (Ariely et al. 2005; Park and Bradlow 2005). Despite the widespread research interests, many of the extant studies focus on essentially similar issues of examining the effects of some traditional institutional parameters (e.g., reserve price) in the new online context and/or newly implemented institutional mechanisms (e.g., reputation feedback mechanism and auction-ending rules) with a view toward understanding bidders' behaviors and increasing sellers' revenues (Bapna et al. 2001a, b; Pinker et al. 2003).

While the existing literature has enhanced our understanding of the impact of online auctions on market performance (i.e., bidders' and sellers'), little attention has been paid to understanding how sellers choose an auction website to put their products on offer, and the starting-price strategy given the inherent properties of the website. We contend that given the increasing numbers of auction websites available on the Internet and their variations/ properties, sellers are now required to make strategic decisions of where and how products should be put on offer. Hence, it is imperative to take into considerations of the "where" and "how" components of decision making when examining sellers' behaviors. In the next two subsections, we will anchor on the individual judgment and decision-making literature on trade-off to unveil how a seller cogitate the auction conditions to derive decisions.

The "where"—choice of auction source

Sellers, on the online-auction market, are not only disposing their products, but also playing the role of customers who choose different brands of auction services on the Internet. Indeed, with more online auction websites appearing in the market, sellers are spoilt with choices, which often could be difficult to decide. One real-life example illustrating the seller's choice of auction source predicament is the battle between eBay and Yahoo!Auction. In October 1998, Yahoo!Auction, decided to enter the auction market to compete with eBay. Yahoo!Auction closely approximated the design of eBay, with similar categories of goods, similar auction bidding rules (e.g., proxy bidding) and similar auction-listing procedures. Yahoo!Auction, which boasted millions of regular users at its parent site, sought to leverage the existing user bases and offer the service for free to create the critical mass to compete with eBay.

However, the result of the "free" strategy, which was meant to increase auction traffic and generate additional advertising revenue for the site, was disappointing. Yahoo! Auction managed to achieve only a much smaller transaction scale and a significantly lower auction transaction probability compared to eBay. In January 2001, Yahoo! Auction began charging sellers a listing fee in an attempt to reposition itself. Two weeks later, eBay, the website with the higher successful transaction probability and higher fees, announced an increase in listing fee for some categories of items by as much as 65%. There were very few seller defections. However, when Yahoo!Auction started to charge a transaction fee, there were significant defections of sellers. Furthermore, the number of listings plunged by 82% compared to previous months. On June 6, 2005, Yahoo!Auction revised its fee charging policy again; offering auction services to all sellers free. As a seller, should he/she auction on a website with higher listing fees and higher successful transaction probability (e.g., eBay) or one with lower listing fees and lower successful transaction probability (e.g., Yahoo!Auction)?[1]

To answer this question, we anchor on the theoretical lens of trade-off decision-making literature (Anderson et al. 1993; Green et al. 1991; Meyer and Kahn 1991). Research on trade-offs between attributes has offered insights into an individual's values for various attributes, for example, the relative importance of different attributes such as price versus safety in selecting a car (Luce et al. 1998), and price versus flight delay in selecting an airline (Jaideep and Tellis 2000; Meyer and Shi 1995). Such knowledge about an individual's values is used to understand how an individual would react when confronted with trade-offs among attributes like probability, gain and loss, for some time. Research on trade-off has advocated that an individual's judgments could be influenced in the manner in which the attributes for considerations are presented (Luce et al. 1998). For instance, the same circle appears larger when surrounded by small circles and smaller when surrounded by large ones. Likewise, the same auction website may appear attractive on the background of less attractive websites and unattractive on the background of more attractive websites.

In relation to our context, the first task that a seller has to do after deciding to liquidate products through the online auction is to compare and contrast the different auction services available. A typical seller's choice, such as the simplified auction website choice task illustrated in Table 1, involves a set of alternatives, each described by some attributes or consequences. The set of alternatives can vary in size from one choice to the next, with some choices involving as few as two options (in some cases, the two options may be simply to either accept or reject an alternative), and others potentially involving many more. The attributes may vary in their potential consequences, the desirability to the seller, and the seller's willingness to compensate the loss of one attribute with more of another. For instance, a seller may be certain about the values of an attribute (e.g., service) but more uncertain about another (e.g., transaction probability). The seller may not have the information on all of the options of some attributes (e.g., service information may not be available for a new entrant auction website). Making decisions in situations involving uncertainty often requires one to accept loss in one attribute, with potentially threatening consequences. For example, the trade-off between price and safety in selecting a car (Luce et al. 1998) and price for probability of flight accident in selecting an airline (Jaideep and Tellis 2000) could all have monetary and well-being consequences.

In this paper, we define sellers' subjective transaction probabilities as the combination of all attributes other than the transaction costs that make an auction website desirable (e.g., traffic intensity, number of items being sold at the site, number of bidders participating in an auction, reliability, and brand reputation). In other words, we believe transaction probability embodies a standard measuring the service quality, which an auction website provides. Prior evidence suggests that quality tends to be a more prominent attribute than others (Bettman et al. 1998). Indeed, according to the concept of inter-attribute correlation (Luce et al 2001), the more negative the correlations, the more one has to accept less of one attribute in order to get more of another attribute (Bettman and Sujan 1987). Inter-attribute correlation is also related to notions of dominance; when the number of attributes is small, removing dominated options leads to more negative inter-attribute correlation for the remaining options (Curry and Faulds 1986).

Table 1 Simple example of a decision matrix: choosing an auction website

Auction website	Successful transaction probability	Listing fee
A	High	High
B	Average	Average
C	Low	Free

[1] Luckling-Reiley (2000, p. 249), who collected data on Yahoo! Auction, eBay and Amazon separately in 1999, observed "difference in fees appears to have an important effect on sellers' incentives and behavior. With fees (even small ones) for auction listings, a seller has more incentive to make sure that her auction results in an actual transaction. Indeed a quick check revealed that most Yahoo!Auction had very high minimum bids or reserve prices, with the sellers apparently hoping for someone to come along and be willing to pay their high prices. By contrast, at eBay and Amazon, sellers knew that they would incur a listing fee whether the item sold or not, so they had an incentive to set reasonably low reserve prices to increase the probability of an actual transaction. Our summer 1999 data confirmed the existence of this effect: eBay had 54% of all auctions result in a sale, Amazon's fraction was 38%, while Yahoo!'s fraction was only 16%. With five-sixths of its auctions failing to receive any acceptable bids, Yahoo! had a significantly lower auction transaction rate than either eBay or Amazon. Thus incentives may be working in the predicted direction: the higher the listing fee, the more careful sellers are to design an auction listing which actually results in a transaction."

Relating the concept of inter-attribute correlation (Luce et al. 2001) to our context, we could speculate that decision makers might be more resistant to trading off quality (e.g., transaction probability) for a better price than accepting a higher price for better quality (Nowlis and Simonson 1997; Hardie et al. 1993; Simonson and Tversky 1992; Blattberg and Wisniewsi 1989; Heath and Chatterjee 1995). Choices between alternatives defined by unfavorable quality values apparently generate negative emotion, resulting in emotion-focused coping behavior; choosing the higher quality alternative (i.e., maximizing the quality attribute in choice) appears to be a coping mechanism in these situations (Luce et al. 2001). Carmon and Simonson (1998) also argued that quality is generally over-weighted relative to price in choice tasks because quality attributes are generally associated with more loss aversion. Furthermore, empirical electronic commerce studies suggested that whether bidders purchase online is determined by a combination of quality factors, such as the ability of the site to load quickly, the availability of familiar brand names and a clear return policy, and not by factors such as pricing or cost (Becker-Olsen 2000). Applying these results to our study, we propose that sellers are more concerned with transaction probability rather than costs such as listing fee and final price commission. We believe sellers would choose an auction website with a high transaction probability despite the high cost that may be incurred. This is because sellers might want to avoid having to cope with the negative emotions of a failed transaction. We thus hypothesize:

H1: Online sellers exhibit the tendency of attributing more weight to transaction probability than cost, preferring an auction website that has a high transaction probability and charges a high cost over one with a lower transaction probability and charges a lower or no cost.

The "how"—starting price strategy

Once a seller has decided on the auction website, the next decision to make is how should the item be priced, i.e., the delineation of the starting price. The conventional wisdom on sellers' starting-price strategies tends to favor a low starting price: a high starting price has a higher tendency to deter potential bidders, which may result in the item not being sold at all (Bapna et al. 2001a, b; Vakrat and Seidmann 2000). In contrast, a low starting price could attract more bidders to participate in the auction. In general, most sellers would think that an item with a low starting price would lead to a higher probability of a successful transaction and vice versa. While there is a general consensus that a high starting price would deter potential bidders' entries, there is an explicit divergence of views on the relationship between starting prices and final seller payoffs. Several researchers suggested that the starting price is critical: too high and few people would participate; too low and the final payoff may be low (Vakrat and Seidmann 2000). Yet, there are others who argued that a low starting price (with a high secret reserve price) could grease the wheels of bidding to build up bidding "momentum" to propel the price higher (Malhotra and Murnighan 2000).

The question to ask is how would a seller go about delineating the starting price? We posit that when a seller chooses a starting-price strategy, he has to deal with uncertainty and the possibility of loss. Particularly, he has to decide whether to selectively maximize or satisfice on payoff, i.e., trade-off transaction probability and cost when maximizing all three attributes is impossible. Prior studies on experimental psychology have suggested high positive or negative payoffs are likely to be associated with very low probabilities while mediocre or zero payoffs are typically related with high probabilities (Shafir et al. 1993). We thus assume that sellers may intuitively believe a high starting price would lead to a low transaction probability and a high payoff while a low starting price would result in a high transaction probability and a low payoff. This form of decision making under risk could be explained by means of the mixed choice problem described by the advantage model (Shafir et al. 1993). A mixed lottery means either a less-than-certain probability p to win a specified sum of money d or a $1–p$ probability to lose a specified sum of money l. In our research on the seller's strategy choice, we simply regard listing fees as transaction cost without taking into account percentage commission. This simplification is reasonable because any percentage commission could be deducted directly from the final payoff by the seller. Therefore, we can refer to a seller's choice of a starting-price strategy as a mixed lottery. That is, the seller has either the transaction probability of p to sell his product and gain the earning e (when the listing fee l has been deducted), or a probability of $1–p$ of losing the non-refundable listing fee l.

Shafir and his colleagues (1993) suggested that probability advantage is qualitatively different from payoff advantage or loss advantage. To compare these qualitatively different advantages, the unitless parameters k_G (in the case of gains) and k_L (in the case of losses) representing the relative weight of payoffs and probabilities, and the relative weight of losses and probabilities respectively, are introduced into the model. Empirical analyses have verified the parameters k_G and k_L to be less than unity for most people, meaning that people generally give more weight to probabilities than payoffs and losses when choosing between lotteries. In the seminal paper by Slovic and Lichtenstein (1968), the authors noted that the prices participants gave for bets were highly correlated with bet payoffs, but the choices were more highly correlated with probabilities. They concluded that if people are offered two bets, one with a high probability and low payoff (a "P-bet") and the other with a low probability and high payoff (a "$-bet"), they might choose the high-probability P-bet but price the high-payoff $-bet higher. Given these findings, we hypothesize:

H2: Online sellers show aversion to the risk of possible failure and loss incurred in a high starting price strategy with a low transaction probability, preferring a low-starting price strategy with a high transaction probability to other starting-price strategies.

Research method

Experimental design

To validate the two hypotheses, we followed the principles of experimental economics (Smith 1982) to design and conduct an auction-website-cum-starting-price choice game as a function of three interactive task parameters (see Table 2): successful transaction probabilities (p), listing fees (l) and earnings (e). We deliberately manipulated the three parameters by converting all expected monetary values of the corresponding strategies in one product category into an approaching value 0.3, and all expected monetary values of the corresponding strategies in another product category into an approaching value of 0.1. The expected monetary value (EMV) of each alternative was computed as: $EMV = (e - l) \times p - l \times (1 - p)$. The EMV gained by a seller was a function of the probability of a successful transaction (p) multiplied by the payoff (subtracting earnings, e, by listing fee, l), and reduced by the probability of an unsuccessful transaction ($1–p$) multiplying the listing fee (l). In other words, EMV was the difference between transactions in which items were auctioned off (earnings minus listing fees) and transactions in which the items were not auctioned off (i.e., the seller incurs listing fees).

Table 2 depicts three treatments in our experiment. The participants in each treatment focused on the comparison of two auction websites with different attributes. Treatment 1 was between "a high transaction probability and a high listing fee" auction website and "a low transaction probability and no listing fee" auction website. Treatment 2 was between "a high transaction probability and a high listing fee" auction website and "a medium transaction probability and medium listing fee" auction website. Treatment 3 was between a "medium transaction probability and a medium listing fee" auction website and a "low transaction probability and no listing fee" auction website.

For each auction website, we also designed three starting price strategies (High, Medium and Low). Each treatment had two product categories (operationalized through EMV) with different categories of transaction probabilities (i.e., high EMV meant a higher transaction probability and low EMV meant a low transaction probability). Each participant went through two rounds of decision making (one for each EMV manipulated by different product categories) involving the choices of either Auction Website A or B for each product category. In each product category, the EMVs were manipulated to be the same for each starting price strategy because if the EMVs were different, the participants might choose the strategy with the highest EMV, and therefore confound the results. Hence, in this repeated-choice experiment, if participants were to choose one auction website and an associated starting price strategy randomly, the EMV would be the same. This implies that our experimental results could be compared with a random choice model in which an auction website and all strategies can be chosen equally in each period. If our experimental results were significantly different from the random choice model, they would lend support to our hypotheses that participants give more weight to transaction probability and choose starting-price strategies that are associated with high transaction probabilities. Moreover, the use of three treatments, in which there was a paired comparison of different auction websites under different EMVs (product categories), adds robustness to our results.

The values 0.3 and 0.1 were chosen for the EMVs for three reasons. First, we wanted to approximate the listing fee and the transaction probability used in the experiment with those in real markets. For auctioning a product with a starting price or a secret reserve price below $25, eBay and Yahoo!Auction charge a listing fee ranging from $0 to $0.55. In addition, at the time when our sample data was collected, the successful transaction probability in the category of 35 mm Single Lens Reflex (SLR) cameras was 60% for eBay and 16% for Yahoo!Auction; the successful transaction probability in the category of DVD was 45% for eBay and 7% for Yahoo!Auction. Based on these figures, we thus had EMVs 0.3 and 0.1 in our two product categories. Second, we had to consider the experiment budget. In our 20-periods repeated experiment, we gave participants the initial capital and real money incentives. We must therefore keep the expected payoff in each round at a relatively low level. Third, we wanted to avoid those transaction probabilities that were too close to 0 or 1 (e.g., 97% or 2%) as they would render the experimental tasks meaningless for participants.

Experimental system

We developed a computer-based market game to provide a static context in which participants could make choices

Table 2 Experiment design

Auction website		Treatment 1			Treatment 2			Treatment 3		
		Listing fee	Earning	Prob	Listing fee	Earning	Prob	Listing fee	Earning	Prob
	EMV 0.3									
A	High starting price	0.50	2.50	0.32	0.50	2.50	0.32	0.25	2.50	0.22
	Medium starting price	0.50	1.50	0.53	0.50	1.50	0.53	0.25	1.50	0.37
	Low starting price	0.50	1.00	0.8	0.50	1.00	0.8	0.25	1.00	0.55
B	High starting price	0.00	2.50	0.12	0.25	2.50	0.22	0.00	2.50	0.12
	Medium starting price	0.00	1.50	0.2	0.25	1.50	0.37	0.00	1.50	0.2
	Low starting price	0.00	1.00	0.3	0.25	1.00	0.55	0.00	1.00	0.3
	EMV 0.1									
A	High starting price	0.50	2.50	0.24	0.50	2.50	0.24	0.25	2.50	0.14
	Medium starting price	0.50	1.50	0.4	0.50	1.50	0.4	0.25	1.50	0.23
	Low starting price	0.50	1.00	0.6	0.50	1.00	0.6	0.25	1.00	0.35
B	High starting price	0.00	2.50	0.04	0.25	2.50	0.14	0.00	2.50	0.04
	Medium starting price	0.00	1.50	0.07	0.25	1.50	0.23	0.00	1.50	0.07
	Low starting price	0.00	1.00	0.1	0.25	1.00	0.35	0.00	1.00	0.1

over time (see Fig. 1). In each period, participants chose one auction website and an associated starting-price strategy for their products. After each period, participants knew immediately if the product was auctioned off. If the product was indeed auctioned off, the payoff was added to the participants' accounts. Otherwise, the listing fee of the auction would be deducted from their assets for that period. The participants then received an update of their cumulative

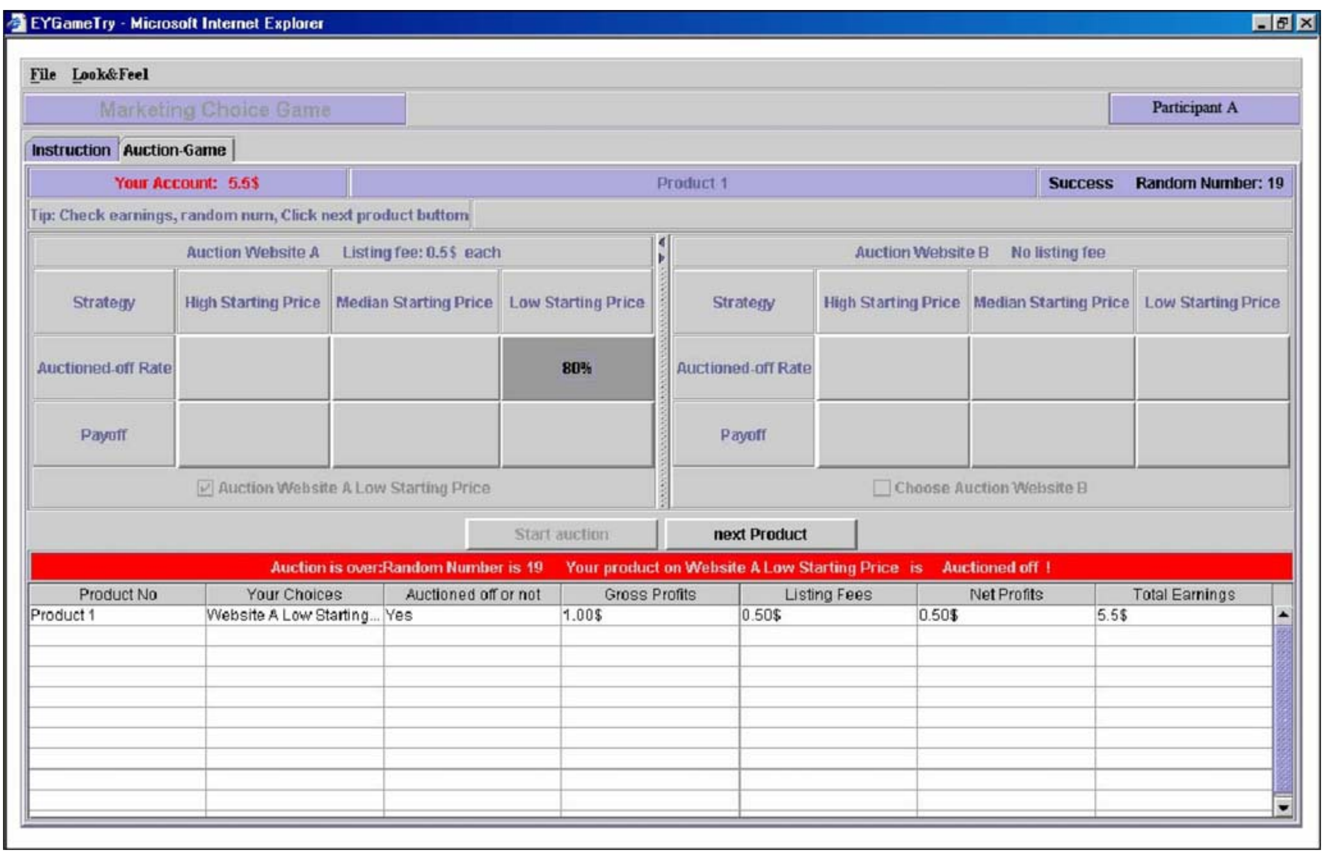

Fig. 1 Sample computer interface used in the experiment

rewards up to that period. They were told to maximize their profit.

Experiment procedures

Ninety third-year undergraduate students enrolled in a public university participated in the repeated-play version of the auction-website-choice game on the computer, motivated by a cash incentive. Neither special skill nor experience was required of the participants. They were told during recruitment that the experiment was on individual decision making, that they would be paid in cash for participating, and that the minimum payment would be $10 for about half an hour of their time. It was also pointed out that higher payments according to performance were possible but not guaranteed. The participants were informed of the time and location of the experiment.

The participants took part in the experiment on an individual basis in a designated laboratory at a specified time. Upon arrival, the participants were seated by the experimenter at terminals distributed throughout the room. They received all detailed instructions through the terminal. They were told that they would play the role of a seller making choices from a pair of auction websites to auction an item in two sessions (see Fig. 1). In each session (each product (EMV) category), the participants would auction off an item for 20 periods. For each auctioned item, the participants would choose the auction website and set the starting price, choosing one of three given strategies (high, medium and low starting price strategies). The use of the computer prevented any asymmetry in presentation.

Prior to the start of the experiment, the participants were encouraged to deliberate as much as possible before making their decisions and to make as much money as they could. In the first session, the participants were randomly assigned to any treatment with 0.3 EMV, and they would receive $5 as their initial capital. After the participants input their choice for each auction, the computer system would simulate a random auction buying procedure. Based on the payoffs and the listing fees, the computer calculated the reward or loss depending on their conditions, and displayed this information as feedback for the period. For example, with an EMV of 0.3, the mean payoff would be the initial deposit plus the variable returns of 0.3 * 20 periods, which was approximately $11 ($5+$6). Table 3 depicts the mean payoffs for the three treatments.

Upon completion of their 0.3 EMV treatment, the participants were again randomly assigned to any treatment with 0.1 EMV for the second session. They received $5 again. Other conditions were similar to the first session. The participants generally spent 35 min completing the whole experiment. Throughout the experiment, no communication was allowed among the participants. After the experiment, the participants were required to complete a simple feedback questionnaire designed to identify the cues and rules they had used in making their choices during the experiment. Total realized payments to participants varied between $12.00 and $24.00 ($18 in average). Table 3 presents the descriptive statistics of the payoffs obtained by the participants in the three treatments.

Table 3 Descriptive statistics of payoff in the three treatments

	EMV 0.3		EMV 0.1	
	Mean	Std	Mean	Std
Treatment 1				
Payoff ($)	11.16	3.31	8.16	3.29
Treatment 2				
Payoff ($)	11.96	3.66	7.16	3.51
Treatment 3				
Payoff ($)	11.01	2.71	6.76	2.05

Results

We first examined the average propensity of the participants to choose an auction website (test of Hypothesis 1), followed by an analysis of their choices of starting-price strategies (test of Hypothesis 2). To minimize end-game effect, we removed the last two periods' transactions and analyzed the data from the first 18 rounds.

Choice of auction websites (test of Hypothesis 1)

Although the EMV from the choices of any auction websites (for 20 rounds) in each of the three treatments was actually the same to the participants, the participants showed strong preferences for the auction website with the higher transaction probability despite the higher listing fee charged. In Treatment 1, as we expected, the participants were more likely to choose Auction Website A (with a high transaction probability and a high listing fee of $0.50). Only 126 of 540 (23.3%) choices were for Auction Website B (with a low transaction probability and no listing fee) in the session of EMV 0.3; the choice percentage was even lower (16.1%) in the session of EMV 0.1. This means that the participants showed a strong aversion to the extremely low transaction probability (4%, 7% and 10% respectively). In Treatment 2, most choices were still for Auction Website A (with a high transaction probability and a high listing fee of $0.50); only 20.7% of the choices were for Auction Website B (with medium transaction probability and a medium listing fee) in the sessions of EMV 0.3, and 32.1% in the sessions of EMV 0.1. This increase in choice percentage suggests that the low level of transaction probability in both websites made the effect of a listing fee more salient for the participants. In Treatment 3, the transaction probabilities of both websites were manipulated to be relatively low, compared to those in Treatment 1 and 2. The participants only showed weak preferences for Auction Website A (with a relatively higher transaction probability of 56% in the session of EMV 0.3 and 63.7% in the session of EMV 0.1). Compared to the other two treatments, more choices were for Auction Website B (with relatively lower transaction probabilities). It appears that when the transaction probabilities of both websites were low, the listing fee charged became more salient to the participants.

Figure 2(a) and (b) graphically depict the choice percentages of auction websites made by the participants in the three treatments in the session of EMV 0.3 and in the session of EMV 0.1 respectively. A visual comparison shows that despite different trade-off contrasts, the participants generally chose auction websites with relatively higher transaction probabilities regardless of the cost incurred. Since the EMV of any choice of auction websites was the same, the differential preferences provide robust evidence that the participants consistently gave more decision weights to transaction probability than listing fee. Additionally, a post-experiment survey also reveals that 76% of the participants deemed transaction probability to be the most important factor in their decisions compared to only 16% and 9% for payoff and listing fee respectively.

Choice of starting price (SP) strategy (test of Hypothesis 2)

Table 4 summarizes the choice percentages of SP strategies for each session in all three treatments. Similar to Hypothesis 1, the EMV of randomly choosing any of the six SP strategies in any one session would be the same for each period. We compared the participants' choices of SP strategies with a random choice model in which all strategies could be chosen equally in each period. In Treatment 1, the result shows that the participants' choices were significantly different from the random choice model (χ^2=39.76, p<0.001 in the session of EMV 0.3; and χ^2= 76.58, p<0.001 in the session of EMV 0.1). In the session of EMV 0.3, the choices were surprising because they did not conform to our prediction: most choices (36.3%) were for the medium SP strategy for Auction Website A. In the session of EMV 0.1, as expected, most choices were for the low SP strategy (45.2% for Auction Website A, and 11.9% for Auction Website B).

In Treatment 2, the comparison of the participants' choices of SP strategies with a random choice model yielded χ^2 value=45.42 (p value <0.001) in the session of EMV 0.3, and χ^2 value=75.99 (p value <0.001) in the session of EMV 0.1. As in Treatment 1, in the session of EMV 0.3, the choices of SP strategies were inconsistent with our prediction: most choices (37.0%) were for the medium SP strategy, not the low SP strategy. In the session of low transaction probability (EMV 0.1), as expected, most choices for the low SP (32.6% for Auction Website A with a high listing fee, and 21.3% for Auction Website B with a medium listing fee). The participants generally gave more weights to transaction probability in the session of low transaction probability (EMV=0.1), showing strong risk aversion.

Different from Treatments 1 and 2, the choices of SP strategies in Treatment 3 show the participants' strong preferences in the session of EMV 0.3 (χ^2=17.49, p< 0.003). The χ^2 value in the session of EMV 0.1 was 48.45 (p<0.001). The choices of SP strategies in both sessions, however, were consistent with our prediction. In the session of EMV 0.3, most choices were for low SP (30.7% for

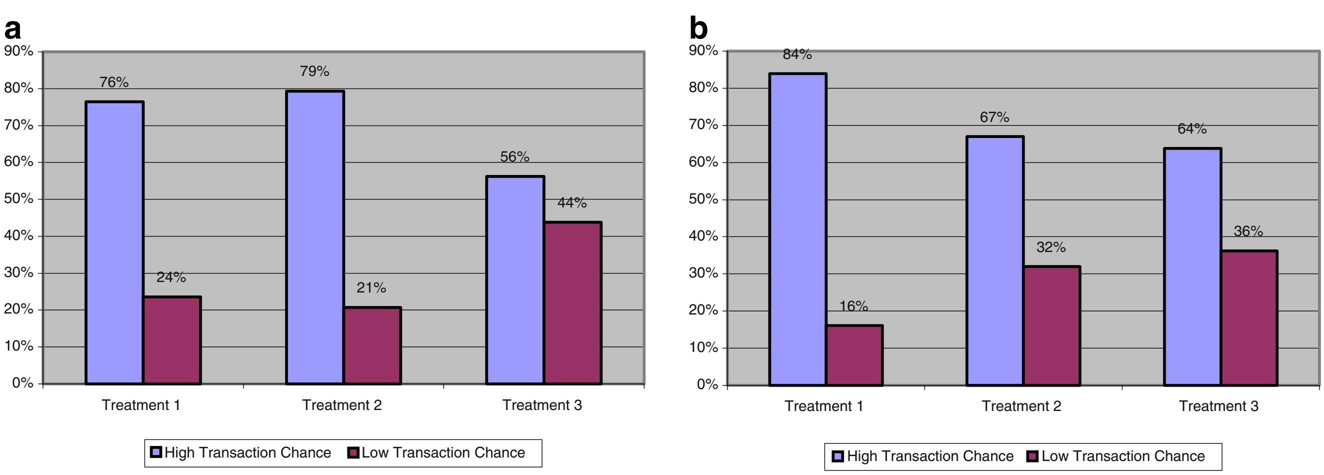

Fig. 2 **a** Choice percentage of auction website in three treatments (EMV 0.3). **b** Choice percentage of auction website in three treatments (EMV 0.1)

Table 4 Choice percentages of starting price strategy in three treatments

	Treatment 1 (n=540)					
	Auction website A			Auction website B		
	l=\$0.50			l=\$0.00		
	e=\$2.50	E=\$1.50	e=\$1.00	e=\$2.50	e=\$1.50	e=\$1.00
EMV 0.3	p=0.32	p=0.53	p=0.80	p=0.12	p=0.20	p=0.30
SP strategy	High	Medium	Low	High	Medium	Low
Choices	102	196[a]	116	43	26	57[a]
Percentages	18.9%	36.3%	21.5%	8.0%	4.8%	10.6%
EMV 0.1	p=0.24	p=0.40	p=0.60	p=0.04	p=0.07	p=0.10
Choices	98	111	244[a]	12	11	64[a]
Percentages	18.1%	20.6%	45.2%	2.2%	2.0%	11.9%
	Treatment 2 (n=540)					
	l=\$0.50			l=\$0.25		
	e=\$2.50	e=\$1.50	e=\$1.00	e=\$2.50	e=\$1.50	e=\$1.00
EMV 0.3	p=0.32	p=0.53	p=0.80	p=0.22	p=0.37	p=0.55
SP strategy	High	Medium	Low	High	Medium	Low
Choices	124	200[a]	104	33	28	51[a]
Percentages	23.0%	37.0%	19.3%	6.1%	5.2%	9.4%
EMV 0.1	p=0.24	p=0.40	p=0.60	p=0.14	p=0.23	p=0.35
Choices	89	102	176[a]	28	30	115[a]
Percentages	16.5%	18.9%	32.6%	5.2%	5.6%	21.3%
	Treatment 3 (n=540)					
	l=\$0.25			l=\$0.00		
	e=\$2.50	e=\$1.50	e=\$1.00	e=\$2.50	e=\$1.50	e=\$1.00
EMV 0.3	p=0.22	p=0.37	p=0.55	p=0.12	p=0.20	p=0.30
SP strategy	High	Medium	Low	High	Medium	Low
Choices	71	66	166[a]	56	71	110[a]
Percentages	13.1%	12.2%	30.7%	10.4%	13.1%	20.4%
EMV 0.1	p=0.14	p=0.23	p=0.35	p=0.04	p=0.07	p=0.10
Choices	44	83	217[a]	38	44	113[a]
Percentages	8.1%	15.4%	40.2%	7.0%	8.1%	20.9%

N sample size of each treatment; *l* listing fees for each auction; *e* earnings if the item were auctioned off; *p* successful transaction rate of each starting-price strategy

[a] denotes the most choices of starting price (SP) strategy given to the treatment. Note: The choices of the six SP strategies would add up to 100%. Choice of the website and SP strategy was performed simultaneously

Auction Website A with a medium listing fee and 20.4% for Auction Website B with no listing fee). In the session of EMV 0.1, most choices were still for low SP (40.2% for Auction Website A with a medium listing fee and 20.9% for Auction Website B with no listing fee).

Figure 3(a)–(d) graphically depict the choice percentages of SP strategies made by the participants in the two different websites in the three treatments for each EMV (product category). A visual comparison would suggest that the data partially support our Hypothesis 2: the participants generally chose the low SP strategy, showing risk aversion. Most choices were for the low SP strategy for the session of EMV 0.3 in Treatment 3 and for all sessions of EMV 0.1 in all the three treatments. However, in the sessions of EMV 0.3 under Treatments 1 and 2, most choices were for the medium SP strategy instead.

Discussions

This study has been undertaken to understand sellers' choices in auction websites and their starting-price strategies in the online auction market context. A highly stable pattern of results was observed: participants in our experiment consistently gave more weights to transaction probability than listing fee. This observation contradicts a fundamental normative assumption of the trade-off literature in which trade-off between (or preference for) attributes, such as price and quality in prior research as well as transaction probability and listing fee in this study, is not stable (Simonson and Tversky 1992). Particularly, prior research highlights that any change in factors such as the values of attributes, framing of attributes and options, and inclusion of a dominated alternative, could result in different decisional choices (Bettman et al. 1998, 1991;

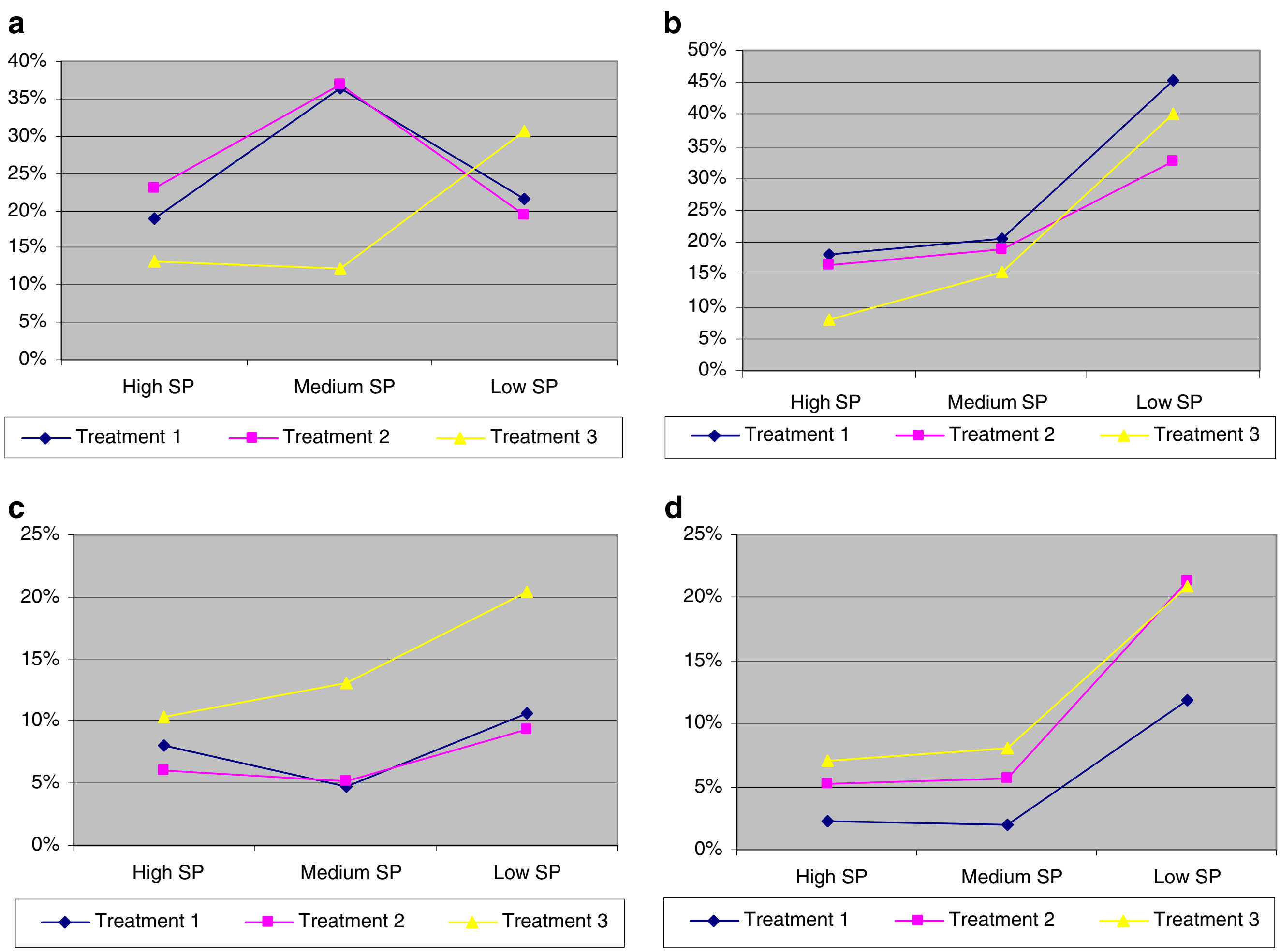

Fig. 3 **a** Choice share of SP strategy with high listing fee charged (EMV 0.3). **b** Choice share of SP strategy with high listing fee charged (EMV 0.1). **c** Choice share of SP strategy with no/low listing fee charged (EMV 0.3). **d** Choice share of SP strategy with no/low listing fee charged (EMV 0.1)

Luce et al. 2001; Bettman and Sujan 1987). In contrast to this assumption, our results demonstrate that more sellers would opt to auction at a website of high transaction probability irrespective of what the listing fee is. We recognize that a transaction probability threshold could exist and it might alter the observation we have made in this study. However, to the extent that our operationalization of the transaction probability covers a wide probability spectrum of 0.04–0.8, such a possibility is relatively low. One plausible reason is that transaction probability is a strictly dominating attribute that suppresses other competing attributes (e.g., price) during evaluation. This is in accordance with the strictly dominated alternative notation in economics theory (Heath and Chatterjee 1995).

The results on choice of starting-price strategy are also noteworthy. For websites with a low level of transaction probability, the participants tended to choose the low starting-price strategy, showing risk aversion. For websites with a high transaction probability, the interactive effect of payoff and transaction probability led the participants to choose the medium starting-price strategy, as they sought to attain higher payoffs in the game. The participants exhibited extreme aversion to the choice with an extremely low transaction probability in spite of the possible highest payoff and zero cost incurred. The partial support of Hypothesis 2 is interesting and counter-intuitive. We note that the transaction probability of the medium SP strategy under Treatments 1 and 2 is close to 0.5. One probable explanation can be derived from the Venture Theory (Hogarth and Hillel 1990), which models how decision weights are affected by the psychological constructs of emotion (e.g., caution) and cognition (e.g., imagination). The Venture Theory predicts that in the domain of gains, the effects of payoffs on risk attitudes are larger for medium-sized probabilities, thus leading to strong preference for the medium SP strategy (payoff=\$1.5, transaction probability=53% and cost=0.5). According to the theory, participants in the experiment could use a simple heuristic by ignoring the cost factor and focusing on a comparison of the medium SP and the low SP: "Try the medium SP twice, I can win $1.50; try the Low SP, and I need at least three probabilities to win $1.50."

The result on choice of starting-price strategy is quite interesting. According to Luckling-Reiley (2000), sellers could set very high starting prices or reserve prices for their items in Yahoo!Auction due to the zero or low listing fees charged; at eBay, sellers know that they would incur a listing fee regardless of whether the item is sold or not. Therefore, they should have the incentive to set reasonably low reserve prices to increase the probability of an actual transaction. The data in our experiment, however, shows that if the expected transaction probability is sufficiently high, sellers might set a relatively high starting-price strategy to seek a relatively high payoff in spite of a high and non-refundable listing fee. As for choices for an auction website with lower or no listing fee charged, sellers may set a reasonably low starting price strategy to increase the probability of a successful transaction. Our experimental findings are counter-intuitive to Luckling-Reiley's (2000) rational economic assertion.

Before we discuss the implications of the research, we consider some of its limitations, which offer several opportunities for future research. First, the laboratory experiment method was limited to a static task environment, where there was no opportunity to simulate complicated learning conditions. Furthermore, the study involved induced gambles for small stakes that might limit the interpretation of the results. Adding to this, the payoff in the experiment was manipulated as a controlled value. However, in the real online auction world, the payoff related to the choice of starting-price strategies is always dynamic (e.g., Luckling-Reiley 2000), and it is impossible for sellers to predict their final payoff unambiguously. These limitations, however, may not be that severe, as we have manipulated factors in the experiment such as transaction probability (high or low), listing fee (high, low or no listing fee) and payoff (high, medium or low). Towards this end, this research complements the extant field investigations (e.g., Luckling-Reiley 2000) by offering a more fine-grained understanding of a seller's behavior.

Second, in this research, we have tested our hypotheses only in simplified situations. Specifically, we assumed that there were only two key attributes (i.e., transaction probability and listing fee). In reality, auction websites could differ in some other features, such as eBay's Feedback Forum to promote trust (Kim and Ahn 2007; Ba and Pavlou 2002). Moreover, other market level factors, such as product supply and the cost of holding on to the products by the sellers, could affect the results. In our experiment, we did not consider the effect of these conditions. Future research should examine how these differences affect auction sellers' choice behavior.

Third, in this study, we focus solely on a seller's decision-making behavior in the choice of auction source and the starting price strategy. Research on online auctions could be categorized into three types, namely bidder factors, seller factors, and auction institution (Stern and Stafford 2006; Luckling-Reiley 2000). Furthermore, behavior could be influenced by cognitive and emotional factors, such as trust. The current study focuses on a seller's decision-making behavior without considering the other factors and hence, future studies could be conducted to extend this research by considering them. Adding on to this, it is imperative to note that we simplified the definition of a seller's subjective transaction probability by defining it as the function of all attributes related to the attractiveness of a website, e.g., the brand recognition, except for the transaction cost. The rationale is that it is less feasible to consider all or many multiples of possible attributes of the transaction probabilities, within an experiment. It is through this study that we hope to ignite researchers to examine the seller's decision-making behavior further.

Despite the limitations, this research adds to the literature in two main ways. First, this study extends the work by Luckling-Reiley (2000) by demonstrating that more sellers would choose auction websites of high transaction probability irrespective of the listing fee. This, in our view, could suggest that the transaction probability attribute dominates the listing fee attribute. More importantly, it could suggest that selective bias on one attribute (i.e., transaction probability) could lead to systematic disregard for other competing attributes (i.e., listing fee) that would have direct and consequential impact on surplus. In other words, the present study complements prior trade-off research (Bettman et al. 1991) by suggesting the possibility of a dominating attribute. Second, our results on the choice of starting-price strategy indicate that sellers are more likely to exhibit risk aversion by choosing a low starting-price strategy in a low transaction probability condition but are inclined to choose a medium starting-price strategy in a high transaction probability condition. The less systematic exhibition of risk aversion in the results contradicts what Luckling-Reiley (2000) has speculated. Future research is needed to further investigate our observations for boundary conditions.

The current research is also of important practical implications. From a loss aversion perspective, eBay, being the first mover in the online auction market, has the advantage of establishing itself as the first brand, thus becoming the reference brand for sellers in the online auction market. Any subsequent brand, such as Yahoo! Auction, which is not a dominant new entrant, would hence suffer a disadvantage: at least one of its attributes would be a loss relative to the first entrant. While a full analysis of competitive entry from a loss aversion perspective is beyond the scope of this paper, it is clear that such an analysis would suggest that the later entrant should consider the relative loss aversion of the attributes that define the online auction market. Efforts to minimize the difference between the new entrant and the pioneering brand should concentrate on those attributes with the highest degree of loss aversion. In our research, we have found this attribute to be the transaction probability at the auction website, and not listing fee.

Since sellers give more weights to successful transaction probabilities, owners of online auction websites may utilize various means, such as a tutorial on B2C auctions, auction advertising on prominent websites, thematic auctions (e.g., an electronic celebrity auctioneer) and "buy-it-now" choices, to deepen sellers' perspectives on transaction probability. Providing help-guides to novices and strengthening search and personalization functions at the auction website could also serve such purpose. Towards this end, auction websites should also consider which of their product categories attracts the heaviest traffic and with the highest successful transaction probability. With such information, auction websites could then publicize the product categories and leverage the traffic to raise the transaction probability of other product categories.

Market researchers have also strongly advocated that a new brand should try to introduce some new attributes to shift the bases of competition. These new attributes might then deprive the pioneering brand of its status as a reference brand if the new attributes become important (Hardie et al. 1993). This implies that Yahoo!Auction should introduce new features into the online auction market. For example, Yahoo may combine its strong advertising, search engine, free email and personalization services to maximize the exposure of sellers' auction listings at Yahoo!Auction. As this study has suggested, the effect of listing fees could be salient to some sellers when transaction probabilities in the competing websites are low. Yahoo!Auction could compete with eBay more aggressively in some product categories where the average transaction probabilities of both sites are low, such as real estate, automobiles and some other products with high prices and low transaction probabilities.

Conclusion

With more auction websites emerging on the market, sellers are facing a great dilemma in deciding on which website to auction a product. This study took a modest step toward contributing to the existing knowledge about online auctions by investigating the issue on how an individual would trade off between listing fee (i.e., cost of listing an auction item) and transaction probability (i.e., the chance that a product will be sold). In doing so, we hope to help auction sellers and bidders to gain maximum value from online auctions and thereby contribute to the growth of this type of electronic commerce.

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