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An Empirical Investigation of Bidding Strategies and Their Effects on Online Single-Unit Auctions

Xiling Cui

Vincent S. Lai

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Xiling Cui, Vincent S. Lai
Faculty of Business Administration, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong
Faculty of Business Administration, The Chinese University of Hong Kong Shatin, N.T. Hong Kong
xlcui@cuhk.edu.hk, vslai@cuhk.edu.hk

Abstract

Online bidding strategy is one of the most discussed topics in online auction research. This research aims to empirically confirm online bidding strategies in single-unit auctions and evaluate these strategies in the context of auction winning outcome, final price evaluation, and perceived enjoyment. Both objective and subjective data of online single-unit auctions were collected to validate our postulated hypotheses. Our findings suggest that there are three basic bidding strategies in single-unit auctions and they indeed have different impacts on auction biddings.

Introduction

In recent years, online auctions have received wide acceptance in electronic commerce. This new form of electronic shopping channel offers advantages of flexible pricing, convenient access, time saving, and diversified product offerings [36] that traditional sales channels could not offer. The success and popularity of online auctions have drawn many researchers' interest in this research domain. Many researchers have devoted much to the investigations of such topics as Internet auctions development [11] [46], auction site technology and service [24] [40], bidding behaviour [8] [9] [12] [19] [31], reputation or trust [4] [22] [27] [40] [41], winner's curse [6] [33], mechanisms [16] [23] [25] [28] [39]. Recently, some researchers performed a meta-analysis of eighty-three articles on online auctions and concluded that research on this topic can be categorised into three major areas – facilitating factors, consumer behaviour and auction outcomes [17].

Although much research has been carried out in an attempt to understand online auctions, not much effort has been devoted to investigate bidders' bidding strategies. Of these limited investigations, some researchers [10] have thoroughly studied online bidders using objective bidding data extracted from Yankee auction websites. Through the analysis of these objective data, they found that bidders in Yankee auctions are not homogeneous in terms of their bidding behaviors. They also found that different bidding strategies will generate different auction outcomes, including winning likelihood and consumer surplus extraction.

Undeniably, the findings of Bapna et al. [10] contribute significantly to our understanding of bidding behavior and bidding strategy in online auctions. However, the Yankee auction they studied is one kind of multi-unit auction and another popular auction type in e-commerce is single-unit auction. There are some differences between these two kinds of auctions. For example, in Yankee auctions, bidders do not only bid on prices but also on units (can be more than one, but less than the quantity on auctioned). Bidding takes place progressively on a predetermined starting price and bid increment. Bidders with the highest bids won the auction. If there was a tie on winning bids and there were not sufficient units for all winners, the tie would be broken first by price, second by quantity, and third by time. Single-unit auction, on the other hand, follows English auction's mechanism, which begins with the lowest acceptable price until no bidder will further increase the bid. With this auction mechanism, there is always one unit auctioned at a time and the winning bidder is always the one with the highest bid. Hence, time priority is not a concern in single-unit auctions.

With the difference between single- and multi-unit auctions, it is thus critical to investigate the applicability of bidding strategies identified in multi-unit auctions to single-unit auctions. In addition, findings based on objective data is limited in shedding light on the application rationale of these bidding strategies, their impacts on bidding outcomes, and their applications in fulfilling bidding motivations. An empirical survey of bidders in their adoptions of bidding strategies, thus, may complement and supplement the observations derived from objective data. In this regard, we proposed three research questions to investigate the bidding strategies in single-unit auctions and their impacts on biddings. These questions are:

1. In single-unit auctions, when bidders bid, do they really follow different bidding strategies?
2. What are the bidding strategies these bidders adopt?
3. How do these bidding strategies impact auction winning outcome, final price evaluation, and bidding enjoyment?

Research Background

A bidding strategy represents a series of interrelated types of bidding behaviour that a bidder adopts with a certain purpose or tactic in mind across different phases of an online auction [1]. Bapna et al. [8] [9] [10] have studied bidding strategies using bid time (including the entry and the exit time) and the number of bids as proxies, together with the observation of the bidding price. Based on these criteria, they clustered online bidders into five categories -- evaluators (early or middle), participators, agent bidders, opportunists, and sip-and-dippers. Evaluators refer to bidders who place just one bid at an early stage (or sometimes in middle stages) of an auction; participators are bidders who bid throughout the auction, thus increasing the price by the minimal bid increment; agent bidders use online bidding agents to bid at the minimal level required to outbid the current highest bidder until the bid exceeds the reserve price they set earlier; opportunists are late bidders who act only towards the end of an auction; and sip-and-dippers bid both in the early stage and near the end.

The classification shows that different bidders adopt different bidding strategies. Evaluators "evaluate" the auction through their sole bid that is usually increased by a "jump", bigger than the minimal bid increment. This bidding strategy is called "jump bidding" [12] [19]. Participators follow other bidders and increase their prices by the minimal bid increment. This common strategy is called ratchet bidding (or nibbling) [15] [21]. Agent bidders employ online bidding agents in submitting their bids, which is called agent bidding [19]. Opportunists only bid near the end of auctions. The strategy taken by them is believed to be snipe bidding (or late bidding) [12] [31] [37]. Sip-and-dippers are also believed to adopt snipe bidding except that they have one bid in the early stage that is only for getting the time priority in some multi-unit auctions.

The research of Bapna et al. [10] does not only identify and describe heterogeneous bidder types in Yankee auctions, but also examines the auction outcomes of these bidders. In their study, winning likelihood and consumer surplus extraction are the two auction outcome variables they investigated. First, they found that the probability of winning amongst different bidder types is unequal. Their findings show that opportunists and sip-and-dippers have the highest winning likelihood, followed by participators, evaluators, and agent bidders. They also found that bidders have different ability of extracting consumer surplus, led by agent bidders, and trailed by participators, evaluators, opportunists, and sip-and-dippers.

Research Hypotheses

This study aims to identify the bidding strategies and their auction outcomes in the context of single-unit auctions. Based on literature review, bidders bid differently in Yankee auctions using different strategies. These identified strategies will be re-examined in single-unit auctions and extended to test their impacts on winning outcome, final price evaluation, and perceived enjoyment. Auction winning outcome investigates whether a bidder wins an auction. Final price evaluation is a winners' subjective evaluation of her/his final auction price. Perceived enjoyment assesses the hedonic effect achieved through auction participation.

Bidding Strategies

Bapna et al. [10] have found the heterogeneity of bidders in their investigation of Yankee auctions. These bidders actually take four basic types of bidding strategies, including jump bidding, agent bidding, ratchet bidding and snipe bidding. Although Yankee auction supports multi-unit auction and its rules are different from those of single-unit auctions, we believe that the bidding strategies identified in Yankee auctions could be extended to single-unit auctions as well. Hence, we hypothesize that:

H1a: Online bidders in single-unit auctions, as in multi-unit auctions, are heterogeneous in their bidding strategies.

H1b: Single-unit auction bidders, like their multi-unit auction counterparts, also adopt similar strategies in their biddings.

Winning Outcome

Bapna et al. [10] found that bidders with different bidding strategies have different winning likelihood in Yankee auctions. Opportunists and sip-and-dippers were found to have the highest percentage of winning their auctions, followed by evaluators, participators, and agent bidders. Presumably, it is the bidding strategies that caused a difference in winning likelihood. Opportunists and sip-and-dippers, for example, are more eager to win, thus motivating them to adopt snipe bidding strategy. With this bidding strategy, bidders snipe just before the end of auctions, leaving other bidders little time to response, which highly increases their chance of winning.

Bidders with jump bidding strategy submit bids that are much higher than required, thus intimidating their competitors and creating a better chance for their winning. This strategy has been found to be preferred by experienced bidders [12] and effective in auctions with fewer overall bids [3] [10] [19]. Ratchet bidding, on the other hand, requires bidders to observe and act continuously during auctions, thus increasing their commitment and consequential winning likelihood. Of the four bidding strategies, agent bidding is the most mechanical and the least flexible. This strategy also involves the least commitment, time, and resources from the bidders, which probably could have a reverse effect on winning likelihood. Based on the above findings and discussions, we propose that:

H2: Different bidding strategies have different auction winning outcomes in single-unit auctions.

Final Price Evaluation

Bapna et al. [10] validated that bidding strategies have differential effects on the extraction of consumer surplus. In multi-unit Yankee auctions, the winning bidders pay their own winning prices, which may be higher than the lowest winning price, called marginal price. The loss of consumer surplus is thus the difference of the actual price paid and the marginal price. In single-unit auctions, the winning bidders pay the actual winning prices that may be different from the maximum prices they are willing to pay for the auctions. Therefore, the logic of consumer surplus still exists in single-unit auctions, but is conceptualized and calculated in a different way. If a winning price is lower than what a bidder is willing to pay, this bidder has a positive consumer surplus. Given the findings that bidding strategies have differential effects on the extraction of consumer surplus, it is believed that bidding strategies could also have differential effects on the evaluation of final prices in winning auctions. Hence, we propose that:

H3: Different bidding strategies result in different evaluations of final auction prices in single-unit auctions.

Perceived Enjoyment

Different bidding strategies could have different effects on bidding process and consequence, which may affect the bidders' perceived enjoyment during an auction. For example, sniping other bidders near the end of auctions could be exciting by offering just one bid, which could possibly bring success. Ratchet bidding could also be enjoyable by following the bids of others continuously and closely, which could turn an auction into a game. Jump and agent bidding strategies may also have different intensity of 'fun'. Hence, we propose:

H4: Different bidding strategies result in different extent of bidders' perceived enjoyment in single-unit auctions.

Research Methodology

Instrument Development and Pre-test

This study adopted an online survey approach in data collection. A three-stage validation process was performed to ensure the validity and reliability of our questionnaire. First, whenever possible, previously validated questions and generally accepted instrument construction guidelines [14] [20] [45] were followed. Second, the survey was pre-tested by four business professors with expertise in survey research, IS, and auction; and by six graduate students. The feedback from this phase resulted in some restructuring and refinement of the survey to improve its quality and content validity. Third, a pilot study of the questionnaire was administered to 25 online bidders randomly chosen from Taobao.com – a major online auction website in China. The Cronbach's alphas for all question items in this pilot test were above or near 0.80, suggesting adequate reliability of the questionnaire [32]. The pilot test also resulted in a few changes in wording and sentence structure, which improved the survey's content validity.

Data Collection

Both objective and subjective data in our research were collected from online bidders randomly chosen from the completed single-unit auctions in Taobao.com following a three-stage process. First, auctions completed recently in Taobao.com were randomly selected for our survey. Second, six hundred bidders were randomly chosen from the bidding lists of these auctions. Only validated bidders, whose identities have been validated by Taobao.com, were selected. Third, the chosen participants were contacted through an online instant messenger – WangWang, an online tool provided by Taobao.com to facilitate communications among users. The chosen bidders were sent a brief introduction, including the research objective and requirements, and an invitation to participate in our study. They were also informed of a RMB¥10 reward if they successfully complete an online survey.

A total of 186 bidders responded positively to our invitation. They were asked to complete an online questionnaire hosted in the website of a professional online survey company. The use of this service allowed us to deal with the problems of access control, authentication and multiple

responses associated with web-based data collection [44].
At the end of two months, after two rounds of reminding messages, 179 bidders completed the questionnaire. These respondents' user IDs were then used to match the IDs of their auction information recorded in Taobao.com. Both subjective survey data and objective bidding data were used to evaluate the research hypotheses proposed in our study.

Variable Operationalization

The measure of *winning outcome* was based on Bapna et al.'s [10] winning likelihood. The only difference is that winning outcome measures whether a bidder has won the auction as an outcome; while winning likelihood measures the percentage of winning auctions in one group. *Final price evaluation* was adapted from Padula and Busacca's study [34], which evaluated price from the dimensions of cheapness, fairness and variety. However, their study evaluates products that may have a variety of prices, which differs from our study that each auction has only one final price without any variety. Therefore, price variety dimension was dropped while the other two were kept. The measures of *perceived enjoyment* were adapted from research on hedonic shopping, including adventure perception [2] and joy perception [5].

Data Analysis and Results

Respondent Profile

Among the 179 valid respondents, 77.1% of them are female and 22.9% male. Ninety-five percent of them are in the age range of between 19 and 38. They are mostly college/university educated (81%) and with a monthly income of less than 3000RMB (71.5%). Their occupations are also widely distributed, with government employees, free workers, students, and academics topping the list.

Reliability and Validity Analysis

This study has taken a number of measures to ensure the validity and reliability of the instrument. As far as the instrument's construct reliability is concerned, a reliability test calculating Cronbach's alpha values was performed. The alpha values of final price evaluation and perceived enjoyment were 0.909 and 0.865 respectively, which are significantly above the 0.7 threshold level.

The instrument was further assessed for its construct reliability using exploratory factor analysis (EFA). The initial factoring step involved the application of principal-component analysis to determine the adequate number of factors to explain the observed correlations. Kaiser's rule was then applied to remove the principal components whose eigenvalues were less than one; this resulted in a two-factor solution loaded in accordance with the *a priori* theoretical expectation. Next, a two-factor solution was forced by utilizing orthogonal (Varimax) rotation. Only those items with factor loadings larger than 0.5 were then used in further analyses. The results of this two-step factor analysis are shown in Table 1.

	Perceived Enjoyment	Final Price Evaluation
PE1	**.688**	-.177
PE2	**.711**	-.139
PE3	**.796**	.168
PE4	**.801**	.173
PE5	**.738**	.320
PE6	**.789**	.264
FPE1	.079	**.790**
FPE2	.204	**.821**
FPE3	.123	**.811**
FPE4	.130	**.892**
Cronbach's alpha	.865	.909

Table 1. The exploratory factor analysis results

The convergent validity of our constructs was also evaluated through its average variance extracted (AVE). The AVE values of these two factors are 0.54 and 0.70, all above 0.5, which surpassed the minimal recommended value. Furthermore, they are also higher than their shared variance, 0.11. In conclusion, the tests for both factor loading and AVE do not show any significant violations, thereby demonstrating adequate convergent and discriminant validity of our constructs.

Hypothesis Testing and Discussions

Five hypotheses were postulated in this study. The first two hypotheses on bidding strategies were validated with cluster analysis. The remaining three hypotheses that investigate the effect of bidding strategies on winning outcome, final price evaluation, and perceived enjoyment, were tested with ANOVA.

Cluster Analysis of Bidding Strategies

This study adopted a two-step cluster analysis method to identify the bidding strategies adopted in single-unit auctions. In Bapna et al.'s [10] investigation of bidder types, they selected time of entry, time of exit, and number of bids (NOB) as proxies in their cluster analysis. We adapted their approach and replaced the entry time and exit time with the sequence number of entry (SNOE) and the sequence number of exit (SNOX). The rationale for such changes was due to a large influx of bidders close to the end of auctions, resulting in many bidders having close entry time. The use of entry and exit sequence numbers could eliminate this problem, but still preserved the logic of entry and exit time. In our cluster analysis, we also added a new proxy – number of agent bids (NOAB) – to help identify the frequency of agent use as a strategy. Because our sample auctions have different number of bids from each other, all selected proxies (SNOE, SNOX, NOB, and NOAB) were standardized (divided by the total number of bids in each auction) to eliminate any adverse effect on clustering.

In the first step of deriving bidders' clusters, hierarchical cluster analysis was performed to generate a hierarchical dendogram and an agglomeration schedule table. The results suggest that the percentage of the change of agglomeration coefficients (the value started to decrease instead of increase) from 3 cluster to 2 cluster is the biggest and that of from 4 to 3 is the least, indicating 3 is the most appropriate number of the clustering. This three-cluster solution of bidding strategies confirmed our proposal (H1a) that different bidders use different strategies in single-unit auctions.

Once the optimal cluster number was determined, our next step was to conduct a K-mean cluster analysis to generate this 3-cluster solution. The results, as shown in Table 2, suggest that Cluster 1 has the highest number of agent bids and could be interpreted as agent bidding. Cluster 2 has high SNOE and SNOX and low NOB and NOAB. It seems that bidders in this cluster bid late and infrequently, which are the major characteristics of snipe bidding. Cluster 3 suggests that bidders in this category are using ratchet bidding strategy due to earlier SNOE and more NOB than Cluster 2 but less NOAB than Cluster 1.

	Cluster 1 (n=53)	Cluster 2 (n=88)	Cluster 3 (n=38)	F-value
SNOE	0.314	0.799	0.242	173.79**
SNOX	0.932	0.964	0.450	36.47**
NOB	0.405	0.176	0.197	50.77**
NOAB	0.143	0.014	0.058	241.36**

* Significant at p<=0.1 level

** Significant at p<=0.05 level

Table 2. The Results of the Cluster Analysis

Our cluster analysis suggest that the strategies identified in the three-cluster solution shared similar characteristics with those strategies identified in previous studies [10] [12] [15] [19] [21] [37], thus supporting our hypothesis (H1b) that bidders in single-unit auctions also adopt similar bidding strategies, such as snipe bidding, agent bidding, and ratchet bidding.

Characteristics of Bidding Strategies

ANOVA analysis was then performed to compare the means of winning outcome, final price evaluation, and perceived enjoyment across the bidding strategies. The results suggested that the differences in the means of winning outcome and perceived enjoyment of the three bidding strategies were significant, thus supporting hypothesis (H2) that bidding strategies have differential impacts on auction winning outcome and hypothesis (H4) that bidding strategies have differential impacts on perceived enjoyment. We, however, did not find bidding strategies to have significantly different effect on final price evaluation (H3). Therefore, this hypothesis was not supported in our study.

Conclusions and limitations

This study aims to confirm the research findings of Bapna et al.'s [10] study on bidding strategies in a single-unit auction context and explore the impacts of these strategies on auction outcomes. Our research findings confirm most of our postulated hypotheses, which could shed some light on suggesting avenues for future e-auction explorations. In addition, we improved the cluster analysis by modifying and adding proxies to identify bidder clusters more objectively.

However, this research has its own limitations. First, the data were collected from one online auction website, which may cause a bias in sampling. In future research, data from multiple auction websites have to be collected for theoretical validation and confirmation. Second, our sample size was not large enough for theoretical validation and development. Future studies should generate a larger sample size to validate and extend our research findings.

References

[1] Ariely, D. and Simonson, I. (2003) Buying, bidding, playing, or competing? Value assessment and decision dynamics in online auction., *Journal of Consumer Psychology*, 13, 1&2, 113-123.

[2] Arnold, M.J. and Reynolds, K.E. (2003) Hedonic shopping motivations, *Journal of Retailing*, 79, 2, 77-95.

[3] Avery, C. (1998) Strategic jumping bidding in English auctions, *Review of Economic Studies*, 65, 2, 185-210.

[4] Ba, S. Whinston, A.B. and Zhang, H. (2003) Building trust into online auction markets through an economic incentive mechanism, *Decision Support Systems*, 35, 3, 273-286.

[5] Babin, B.J. Darden, W.R. and Griffin, M. (1994) Work and/or fun: Measuring hedonic and utilitarian shopping value, *The Journal of Consumer Research*, 20, 4, 644-656.

[6] Bajari, P. and Hortacsu, A. (2003) Winner's curse, reserve prices and endogenous entry: Empirical insights from ebay auctions, *Rand Journal of Economics*, 34, 329-355.

[7] Bapna, R. Goes, P. and Gupta, A. (2000) A theoretical and empirical investigation of multi-item on-line auctions, *Information Technology and Management*, 1, 1-2, 1-23.

[8] Bapna, R. Goes, P. and Gupta, A. (2001) Insights and analyses of online auctions, *Communications of the ACM*, 44, 11, 42-50.

[9] Bapna, R. Goes, P. and Gupta, A. (2003) Replicating online yankee auctions to analyze auctioneers' and bidders' strategies, *Information Systems Research*, 14, 3, 244-268.

[10] Bapna, R. Goes, P. Gupta, A. and Jin, Y. (2004) User heterogeneity and its impact on electronic auction market design: An empirical exploration, *MIS Quarterly*, 28, 1, 21-43.

[11] Bichler, M. Field, S. and Werthner, H. (2001) Introduction: Theory and application of electronic market design, *Electronic Commerce Research*, 1, 3, 215-220.

[12] Borle, S. Boatwright, P. and Kadane, J.B. (2006) The timing of bid placement and extent of multiple bidding: An empirical investigation using ebay online auction, *Statistical Science*, 21, 2, 194-205.

[13] Bosnjak, M. Obermeier, D. and Tuten, T.L. (2006) Predicting and explaining the propensity to bid in online auctions: A comparison of two action-theoretical models, *Journal of Consumer Behaviour*, 5, 2, 102-116.

[14] Boudreau, M.-C. Gefen, D. and Straub, D.W. (2001) Validation in information systems research: A state-of-the-art assessment, *MIS Quarterly*, 25, 1, 1-16.

[15] Brint, A. (2003) Investigating buyer and seller strategies in online auction, *Journal of the Operational Research Society*, 54, 11, 1177-1188.

[16] Budish, E.B. and Takeyama, L.N. (2001) Buy prices in online auctions: Irrationality on the internet?, *Economics Letters*, 72, 3, 325-333.

[17] Cui, X. Lai, V.S.-k. and Liu, C.K.W. (2008) Research on consumer behavior in online auctions: Insights from a critical literature review, *Electronic Markets*, 18, 4, 345-361.

[18] David J. Ketchen, J. and Shook, C.L. (1996) The application of cluster analysis in strategic management research: An analysis and critique, *Strategic Management Journal*, 17, 6, 441-458.

[19] Easley, R.F. and Tenorio, R. (2004) Jumping bidding strategies in internet auctions, *Management Science*, 50, 10, 1407-1419.

[20] Fox, R.J. Crask, M.R. and Kim, J. (1988) Mail survey response rate: A meta-analysis of selected techniques for inducing response, *Public Opinion Quarterly*, 52, 4, 467-491.

[21] Friesner, D. Bozman, C.S. and McPherson, M.Q. (2008) Nibbling, sniping, and the role of uncertainty in second-price, hard-close internet auctions: Empirical evidence from ebay, *International Journal of E-Business Research*, 4, 1, 69-81.

[22] Gregg, D.G. and Scott, J.E. (2006) The role of reputation systems in reducing online auction fraud, *International Journal of Electronic Commerce*, 10, 3, 95-120.

[23] Hann, I.-H. and Terwiesch, C. (2003) Measuring the frictional costs of online transactions: The case of a name-your-own-price channel, *Management Science*, 49, 11, 1563-1579.

[24] Hu, X. Lin, Z. Whinston, A.B. and Zhang, H. (2004) Hope or hype: On the viability of escrow services as trusted third parties in online auction environments, *Information Systems Research*, 15, 3, 236-249.

[25] Kauffman, R.J. and Wang, B. (2001) New buyers' arrival under dynamic pricing market microstructure: The case of group-buying discounts on the internet, *Journal of Management Information Systems*, 18, 2, 157-188.

[26] Leloup, B. and Deveaux, L. (2001) Dynamic pricing on the internet: Theory and simulations, *Electronic Commerce Research*, 1, 3, 265-276.

[27] MacInnes, I. Li, Y. and Yurcik, W. (2005) Reputation and dispute in ebay transactions, *International Journal of Electronic Commerce*, 10, 1, 27-54.

[28] Mathews, T. (2004) The impact of discounting on an auction with a buyout option: A theoretical analysis motivated by ebay's buy-it-now feature, *Journal of Economics*, 81, 1, 25-52.

[29] Mathews, T. and Katzman, B. (2006) The role of varying risk attitudes in an auction with a buyout option, *Economic Theory*, 27, 3, 597-613.

[30] Melnik, M.I. and Alm, J. (2002) Does a seller's ecommerce reputation matter? Evidence from ebay auctions, *The Journal of Industrial Economics*, 50, 3, 337-349.

[31] Namazi, A. and Schadschneider, A. (2006) Statistical properties of online auctions, *International Journal of Modern Physics*, 17, 10, 1485-1493.

[32] Nunnally, J.C. and Bernstein, I.H. *Psychometric theory*, (3rd Edition ed.) McGraw-Hill, New York, 1994.

[33] Oh, W. (2002) C2c versus b2c: A comparison of the winner's curse in two types of electronic auctions, *International Journal of Electronic Commerce*, 6, 4, 115-138.

[34] Padula, G. and Busacca, B. (2005) The asymmetric impact of price-attribute performance on overall price evaluation, *International Journal of Service Industrial Management*, 16, 1, 28-54.

[35] Park, Y.-H. and Bradlow, E.T. (2005) An integrated model for bidding behavior in internet auctions: Whether, who, when, and how much, *Journal of Marketing Research*, 42, 4, 470-482.

[36] Pinker, E.J. Seidmann, A. and Vakrat, Y. (2003) Managing online auctions: Current business and research issues, *Management Science*, 49, 11, 1457-1484.

[37] Roth, A.E. and Ockenfels, A. (2002) Last-minute bidding and the rules for ending second-price auctions: Evidence from ebay and amazon auctions on the internet, *American Economic Review*, 92, 4, 1093-1103.

[38] Spann, M. Skiera, B. and Schafers, B. (2004) Measuring individual frictional costs and willingness-to-pay via name-your-own-price mechanisms, *Journal of Interactive Marketing*, 18, 4, 22-36.

[39] Spann, M. and Tellis, G.J. (2006) Does the internet promote better consumer decisions? The case of name-your-own-price auctions, *Journal of Marketing*, 70, 1, 65-78.

[40] Stafford, M.R. and Stern, B. (2002) Consumer bidding behavior on internet auction sites, *International Journal of Electronic Commerce*, 7, 1, 135-150.

[41] Standifird, S.S. (2001) Reputation and e-commerce: Ebay auction and the asymmetrical impact of positive and negative ratings, *Journal of Management*, 27, 3, 279-295.

[42] Standifird, S.S. (2002) Online auctions and the importance of reputation type, *Electronic Markets*, 12, 1, 58-62.

[43] Standifird, S.S. Roelofs, M.R. and Durham, Y. (2004-5) The impact of ebay's buy-it-now function on bidder behavior, *International Journal of Electronic Commerce*, 9, 2, 167-176.

[44] Stanton, J.M. and Rogelberg, S.G. (2001) Using internet/intranet web pages to collect organizational research data, *Organizational Research Methods*, 4, 3, 200-217.

[45] Straub, D.W. (1989) Validating instruments in mis research, *MIS Quarterly*, 13, 2, 147-169.

[46] Townsend, A.M. and Bennett, J.T. (2003) Living and bidding in an auction economy, *Communications of the ACM*, 46, 12, 351-353.

[47] Van der Heijden, Hans (2004) User acceptance of hedonic information systems, MIS Quarterly, 28,4, 695-704.

[48] Zhang, H. and Li, H. (2006) Factors affecting payment choices in online auctions: A study of ebay traders, *Decision Support Systems*, 42, 2, 1076-1088.