ONLINE AUCTION SEGMENTATION AND EFFECTIVE SELLING STRATEGY: TRUST AND INFORMATION ASYMMETRY PERSPECTIVES

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ABSTRACT

Based on the theory of online trust and information asymmetry, we empirically find structural differences in auction success and price determinants between new and experienced sellers, and between new and used items in online auctions. We classify auction listings into four segments ((new sellers, experienced sellers) × (new items, used items)) and find that sellers in these four segments behave significantly differently. We also discover that, given the same product condition, experienced sellers with unsuccessful auctions can more likely transition to successful auctions (via re-listing) than new sellers with unsuccessful auctions. In addition, trust enhancing strategies are found to be relatively more important than transaction enhancing strategies for auction success. The auction segmentation knowledge attained in this study not only provides the online auction house with solid guidance to customize its services for different groups of market participants, it also helps sellers better position themselves and buyers more intelligently select auction items to bid in online marketplaces.

Keywords: Online trust; Information asymmetry; Auction segmentation; Selling strategy; Trust enhancing strategies; Transaction enhancing strategies

1. Introduction

The fast development of online auctions has drawn significant attention from both practitioners and academics. Modern marketing theory suggests that market segmentation of online auction marketplace could be an important issue to both online auction house and market participants, due to the following benefits:

a) Enhancing market understanding - by segmenting one big market into smaller groups, market participants (auction house, sellers, and buyers) can have a better understanding of the marketplace, which in turn will attract more participants to join;
b) Increasing the effectiveness of online auction house' marketing strategy - online auction house can treat each segment separately with different services. Through customization, the auction house can help sellers in each segment effectively list their products by choosing the right listing options and tools. In addition, by studying the needs and demands of buyers in each segment, the auction house can provide more customized offerings to each group;
c) Improving sellers' competitive position - grouping one online auction market into different clusters enables sellers to better understand which cluster they belong to and who their competitors are. This helps the sellers

formulate the most effective selling strategy to compete with their rivals;

d) Facilitating bidders' decision making process - instead of facing a mass market, buyers with various preferences can choose auction segments that fit their needs to participate in. This can significantly reduce the errors potentially incurred in the bidding decision making process.

Despite extensive literature on online auctions, few conducted auction segmentation and studied the impact of various characteristics in different segments on auction outcome. Literature on economics, marketing, and management information systems point out that seller experience typically serves as a good proxy for ***trust,*** and product conditions such as new or used items imply differences in ***information asymmetry***. In this work, we attempt to segment the online auction marketplace using the two constructs, i.e., ***trust*** and ***information asymmetry***, and study the performance of each segmentation in terms of auction success and final price. As online buyers and sellers are typically unable to physically meet, trust and information asymmetry issues become extremely important in the cyber space [Huston & Spencer 2002]. By using seller experience and product condition, online auctions can be segmented into four groups as shown in Table 1. Each segment cell in the table indicates seller type (new vs. experienced) and product condition (new vs. used) along with dominating issues (underlined) in each segment. For example, the segment of new sellers listing used items poses the most serious challenges on both trust and information asymmetry issues, while the segment of experienced sellers listing new items presents the least problems over the two issues.

Table 1. Proposed Online Auction Segmentation

	New Sellers vs. Experienced Sellers (Trust)	
New Items vs. Used Items (Information Asymmetry)	New Sellers list New Items <u>(Trust Issue)</u>	Exp. Sellers list New Items
	New Sellers list Used Items <u>(Trust and Info Asymmetry Issues)</u>	Exp. Sellers list Used Items <u>(Information Asymmetry Issue)</u>

There exists information asymmetry between consumers and sellers. However, this information asymmetry typically transforms into trust eventually and is also heavily dependent on seller experience according to prior research [Ba & Pavlou 2002; Livingston 2005]. Therefore, in this research we broadly categorize this under the realm of trust. Similarly, trust also exists between consumers and products. However, this is more an indigenous factor. This means the same consumer on the same product but under different product conditions, this type of trust issue diminishes since it's the same consumer on the same product. In addition, segmenting the market in a simple and easily-operational way is expected by marketers. If mingling sellers with information asymmetry and product conditions with trust, we might have more than 10 complicated market segments which might confuse both sellers and buyers on the marketplace.

To overcome the barriers in online auction marketplaces related to trust and information asymmetry, and improve auction performance, sellers can use various auction listing options and tools designed by the online auction house to construct different selling strategies. These auction options and tools can be categorized into two categories (more explanations later): 1) strategies intended to enhance trust from buyers, termed *trust enhancing strategies*; and 2) strategies related to the auction parameters and transaction facilitation, termed *transaction enhancing strategies*.

In practice, both new and experienced sellers (two types of sellers) post their auction listings selling new and used products (two types of product conditions) by utilizing the above two categories of selling strategies. In this 2×2×2 framework, we try to validate our proposed auction listing segmentations by exploring various distinct determinants of auction success and final prices. Our goal in this study is to address the following research questions, which have not been fully explored in the literature:

1. Can seller types (trust) and item conditions (information asymmetry) be used to effectively segment online auction listings?
2. How do sellers in different auction segments behave differently? What strategies are important for sellers to achieve auction listing success: trust enhancing strategies or transaction enhancing strategies?

By analyzing online auction listings in eBay, we find structural differences in auction success and price determinants between new and experienced sellers (related to trust) as well as between new and used items (related to information asymmetry). We then segment online auction listings into four groups by using the trust and information asymmetry dimensions and find sellers in different segments behave notably differently. Using principal component and multi-dimensional scaling analyses, we find trust enhancing strategies are relatively more important for auction success than transaction enhancing strategies. Our findings have significant implications for the online auction house to improve its services. Knowledge about auction segmentation helps the online auction house customize its service and offer new services to different groups of market participants. Auction segmentation also helps sellers seek proper market positioning and construct effective selling strategies for their auction listings, as well as buyers choose the right listings to bid and buy. Online auction house, sellers, and buyers could potentially work together to develop more relevant and effective trust enhancing selling strategies. All these efforts will finally facilitate to create more effective and efficient electronic marketplaces.

Our research contributes to the literature in several fronts. First, unlike many existing studies assuming homogeneity on products (i.e. only new items), we use both seller types and product conditions to better understand the real online auction marketplaces. Second, we segment online auction listings into four groups using the constructs of trust and information asymmetry. We believe this is the first study on online auction segmentation in the literature. Third, we contribute to the theory of trust and information asymmetry by comparing the relative importance of different categories of selling strategies. Our work here calls for the academics and business practitioners to work together to enrich existing online auction theory and provide more effective and efficient selling strategies and tools to market users.

2. Literature Review

Online Seller and Online Trust

For online sellers, a big challenge is to earn trust from online buyers in cyberspace. Analytical and empirical studies on online trust issues abound [Ba & Pavlou 2002; Dellarocas et al. 2004; Dewan & Hsu 2004; Houser & Wooders 2006; Resnick et al. 2006; Resnick & Zeckhauser 2002]. These studies have addressed several aspects of online trust: (1) The definition, dimensions (such as integrity, ability and benevolence), value measure, and role of trust on making transactions [Ba & Pavlou 2002; Ba et al. 2003; Gefen et al. 2003; McKnight et al. 2002; Chang et al. 2015]; (2) The effects of moderators on trust. For example, Gefen and Heart [2006] and Awad and Ragowsky [2008] study the impact of cultures and genders on trust. Gefen [2000] addresses the relationship between trust and personality. Wells et al. [2011] find positive correlation between trust and website quality, and Schlosser et al. [2006] find similar correlation between trust and website investment. Maadi et al. (2016) and Jones and Leonard (2014) identify the key factors to build online trust for e-commerce; (3) Antecedents of trust. McKnight et al. [1998] list the following trust antecedents: personality-based trust, cognition-based trust, knowledge-based trust, institution-based trust, and calculative-based trust. The relationship between trust and IT artifacts has been studied by Wang and Benbasat [2005] and Wixom and Todd [2005]. Chiu et al. [2010] find that bidding justice has a strong positive effect on trust; (4) Feedback systems and trust. This stream of studies mainly addresses the effectiveness of online feedback system and how to better utilize them [Jøsang et al. 2007; Zhang 2006]; and (5) Online trust building. For examples, Pavlou and Dimoka [2006] investigate how texts/comments in feedback influence trust building. Hu et al. [2004] show how the trusted third party can be used to build trust between sellers and buyers.

While the trust issue between online sellers and buyers attracts significant amount of research, the differentiation on sellers is not well addressed. Existing studies on online auctions usually treat sellers as a homogenous group except for the degree of perceived trust to buyers. Literature on sellers' behavior or selling strategy studies can be summarized as follows. Resnick et al. [2006] and Anderson et al. [2007] explore the selling strategies in eBay but discuss only limited selling options available in the past. Lucking-Reiley et al. [2007] and Anderson et al. [2007] study the determinants of bids attracted, auction success, and prices. Gilkeson and Reynolds [2003] demonstrate how a proper starting bid price can attract more bidders and facilitate a successful auction. Tu and Lu [2011] investigate how the past auction listings impact the current ones. Hinz and Spann [2010] explore the selling strategy in reverse auction by utilizing information diffusion. Gregg and Walczak [2008] compare two eBay selling strategies in a lab experiment. Zhou [2012] looks at the best-selling strategy for sellers when bidders share information and cross refer different auction listings. Most of these studies assume sellers as a homogeneous and risk-neutral group. That is, these studies treat all online auction listings as homogeneous ones without carefully addressing the listing differences. However, online auctions are taking place in a dynamic environment and sophisticated auction listings in this environment can cause different sellers to behave differently.

Product Condition and Information Asymmetry

Products in used condition imply a quality uncertainty issue to buyers. In used goods literature, 'lemon' problem is a well-known problem in traditional marketplaces in the area of economics. The classical study of Akerlof [1970] demonstrates adverse selection due to asymmetric information among sellers and buyers of used cars and when taken to the extreme can cause total market failure. In the marketing literature, Brough and Isaac [2012] investigate the ways that buyer usage intent affects the prices of used products. Existing studies, however, do not fully address the impact of product conditions in online auctions. Most studies on selling strategies focus solely on new products except for those emphasizing collectibles [Dewally & Ederington 2006; Kauffman et al. 2009]. In eBay, however, substantial amount of auction items are used ones. For example, on July 8, 2012, there were 113 auction listings for new Sony PlayStation 3 consoles, and 679 listings for used ones; there were 354 auction listings for new Xbox 360 consoles, and 963 listings for used ones; there were 324 auction listings for new Nintendo Wii consoles, and 1098 listing for used ones. While new items are of identical quality, the quality of used items varies depending on factors such as usage time and frequency. When comparing new and used items in online auctions, the fundamental difference is the more pronounced information asymmetry for used items.

Information asymmetry under traditional marketplaces was widely studied in the economics literature following the classic study by Akerlof [1970]. Information asymmetry happens when different people share different information. As some information is private or difficult to convey to others, information asymmetry occurs between one party knowing the information and another party not knowing or fully codifying it [Stiglitz 2002]. Generally speaking, there are two types of information asymmetry regarding market participants: information about quality and information about intent [Stiglitz 2000]. The first one refers to one party being not fully aware of the characteristics of another party, and the second one refers to one party not fully knowing the counter party's behavior or intentions [Elitzur & Gavious 2003]. The information asymmetry regarding market participants is directly related to trust, which has been discussed previously. Information asymmetry regarding products can be divided by pre-purchase information scarcity and post-purchase information clarity [Kirmani & Rao 2000]. Pre-purchase information scarcity happens when a buyer cannot fully access or correctly interpret a product's quality attributes for her purchasing decision making. Post-purchase information clarity arises when a consumer can readily assess the quality of a product immediately after purchase. Among various product categories, experience goods show a high degree of pre-purchase information scarcity, which implies physical experience or other assessment tools should be used for consumers to evaluate product quality [Nelson 1970]. Sometimes, information asymmetry can be used to create values, and therefore there are certain benefits of information asymmetry [Bhargava & Chen 2012].

How to alleviate information asymmetry in the online environment is widely researched in the literature. Clots-Figueras et al. [2016] address trust and trustworthiness building under information asymmetry and ambiguity. The application of signaling theory in reducing information asymmetry is studied by Mavlanova et al. [2012], Gregg and Walczak [2008], and Connelly et al. [2011]. Li et al. [2009] discuss how the Internet auction features can be used as quality signals. Wells et al. [2011] study the way that website quality influences buyers' perceptions of product quality and their purchase intentions. Pavlou et al. [2007] propose several information asymmetry mitigating factors including trust, website informativeness, product diagnosticity, and social presence from the principal-agent perspective.

Potential Contributions and Hypotheses

Most research on trust in online environments focus on seller trustworthiness and trust building. As Ba and Pavlou [2002] point out that this trust framework is valid when dealing with products of the same quality, i.e. new products. However, it is not applicable when dealing with used products with information asymmetry on product quality. Jiang and Benbasat [2004; 2007] find that the trust issues become more problematic when buying and selling products that are difficult to describe or present, such as used ones. Hence, research projects that incorporate seller types with product conditions like this study will help us better understand the real online auction marketplaces.

The existing literature reveals two unexplored areas in online auction research: 1) no studies have combined seller types (related to trust) and product conditions (related to information asymmetry) in the research framework, or explored the auction listing segmentation on the base of seller types and product conditions, which we believe can help get more insights on online auctions; and 2) when addressing selling strategies, existing studies discuss different selling choices, but do not classify them into different categories, or study what categories are dominantly effective. In this study, we try to fill the gaps in the literature. We use seller types and product conditions to segment online auction listings, look at seller behavior, and classify selling strategies to identify what categories are more important under the online environment.

Since new and experienced sellers typically stand at different levels of seller rating/reputation, we believe these two groups of sellers possess significantly different auction success determinants and auction ending price determinants. The above conjecture results in our first set of hypotheses:

Hypothesis 1-1*: The auction success determinants for new sellers are the same as those for experienced sellers.*

Hypothesis 1-2*: The auction price determinants for new sellers are the same as those for experienced sellers.*

As discussed earlier, used items take more share than new ones in electronic marketplaces, particularly in individual-to-individual markets such as eBay. There are potentially significant differences in quality between new and used items. For new items, the quality is virtually identical and information is more likely symmetric between sellers and buyers. On the other hand, the quality of used items can vary greatly and quality information is asymmetric between sellers and buyers. We postulate that new items are significantly different from used items in terms of auction success and price determinants in electronic marketplaces, hence our second set of hypotheses:

Hypothesis 2-1*: The auction success determinants for new items are the same as those for used items.*

Hypothesis 2-2*: The auction price determinants for new items are the same as those for used items.*

3. Categories of Online Auction Selling Strategies

To mitigate the problems associated with trust and information asymmetry in electronic marketplaces, the online auction house along with other parties provides numerous selling options and tools to sellers. These strategies are referred to as *trust enhancing strategies* in this study. For example, a seller can develop her reputation (hence trust) from accumulating positive feedback [Ba & Pavlou 2002; Dewan & Hsu 2004; Houser & Wooders 2006; Livingston 2005; Resnick & Zeckhauser 2002]; choose to offer a warranty or refund guarantee to potential buyers [Balachander 2001]; ask a trusted third party (TTP) to issue quality certification [Anderson et al. 1999]; or release more relevant information by releasing product pictures, descriptions, samples, and specifications [Granados et al. 2004]. Bruce et al. [2004] study how seller ratings with the presence of insurance affect consumer behavior. A third-party trust mechanism such as an escrow service provider can be used to boost online transactions [Hu et al. 2004; Pavlou & Gefen 2004]. Pavlou and Gefen [2004] also investigate the role of credit card guarantee in building effective online marketplaces. Though Roberts [2011] finds that a guaranteed or refund promise does not substitute for reputation in online auctions, sellers still can use these options to improve trust from potential buyers. Balachander [2001] suggests a warranty or refund guarantee be used in online auctions. Anderson et al. [2007] recommend obtaining quality certification from a trusted third party (TTP). Dewally and Ederington [2006] summarize a few of the above trust enhancing strategies in the comic book market in eBay.

In addition to the *trust enhancing strategies*, sellers can also use strategies related to the auction parameters and transaction facilitation, termed *transaction enhancing strategies* in this study. For example, Stanifird et al. [2004] find that Buy-It-Now prices are often ignored by buyers even if they are set below retail prices. But, Popkowski et al. [2009] find that Buy-It-Now prices can be used as the price signal for some products. Existing studies also find the following auction parameters significantly affect online auction success and prices: starting price [Budish & Takeyama 2001; Lucking-Reiley et al. 2007; Stern & Stafford 2006; Waley & Fortin 2005], reserve price [Gilkeson & Reynolds 2003; Lucking-Reiley et al. 2007; Waley & Fortin 2005], payment methods [Bruce et al. 2004], auction ending time [Dholakia & Soltysinski 2001], auction shipping cost, shipping insurance and international shipment [Gilkeson & Reynolds 2003; Lucking-Reiley et al. 2007].

In sum, trust enhancing strategies are those taken by the sellers in an attempt to bolster trust from consumers. For example, offering a warranty or refund guarantee will make a consumer feel the seriousness of the seller with more trust. Posting more relevant information by releasing more product pictures is another example to enhance trust from the buyer on the seller. Auction parameters such as starting bidding price, auction duration, and offering buy-it-now, on the other hand aim to reduce the auction friction and make the transaction smoother are viewed as transaction enhancing. These strategies do not really relate to 'trust' but rather more of action structural parameters. The classification of selling strategy could help seller better understand the role of each category, and guide them to construct the best-selling strategy.

4. Hypothesis Testing

Before testing our research hypotheses, we need to operationally define "new sellers" and "experienced sellers". Dellarocas et al. [2004] uses the feedback score as a proxy for a seller's experience. Following this approach, we differentiate new sellers and experienced sellers by using their feedback scores. We believe that, from the viewpoint of buyers, it is appropriate to use this measure because this is how buyers usually perceive sellers as new or experienced sellers. Higher feedback scores indicate that the seller has more experience. This might also help build buyers' trust in sellers, which in turn affects their purchase decisions and directly determines auction success and ending prices. On the other hand, new sellers need time to accumulate feedback scores through successful auctions. Gaining high feedback scores is typically a lengthy undertaking for sellers. To obtain more robust and general results, we use different feedback threshold levels to define new and experience sellers, i.e., feedback threshold of 0, 3, 5, 7, and 9. That is, when feedback score 7 is used, sellers with scores less than 7 will be treated as new sellers and equal or above 7 will be experienced sellers. We test our hypotheses using each of the threshold values.

We collect data from eBay because it is the largest online auction retailer with over 80% of the online auction market. For this study, 23,355 online auction listings for Sony PlayStation 2 console data points were collected and the data collection spanned three and half months. We choose Sony PlayStation 2 console since it has few standard models (with accessories) and dominates the video game console market which means less interfering noises in our analysis. In addition, Sony PlayStation 2 console has a reasonable market thickness measured by significant number of auction listings and bids every day.

We consider trust enhancing and transaction enhancing strategies along with product attributes jointly to investigate auction success and price determinants. We run multivariate regressions in the study. The relevant dependent variables include reaching a transaction or not (Logit Model)[1] and auction price (Log-linear Model). The independent variables include all legitimate trust enhancing and transaction enhancing strategies that sellers can use, along with some control variables such as product attributes. We outline the multivariate regression models as follows:

Regression 1: *Logit (no transaction=0, transaction=1) = f (the relevant variables in a vector of selling strategies, some control variables)*

Regression 2: *Log (final auction price) = f (the relevant variables in a vector of selling strategies, some control variables*)

Structural Difference between Seller Types: New Sellers vs. Experienced Sellers

Auction Success Determinants: There are studies in the literature discussing the determinants for auction success [Gilkeson & Reynolds 2003; Roth & Ockenfels 2002; Tucker & Massad 2004]. However, they do not distinguish auctions listed by new sellers from those by experienced sellers. In this work, we consider 25 trust enhancing and transaction enhancing variables plus 3 product variables (for a total of 28 variables) that can potentially influence auction success and prices (Appendix 1). We run a regression on overall data without differentiating new sellers and experienced sellers. Subsequently, we run regressions for new sellers and experienced sellers, respectively. We first define sellers with at most 7 feedback scores as new sellers and correspondingly sellers with more than 7 feedback scores as experienced sellers. The regression results are presented in Table 2.

Table 2. Logit Regression Results of Determinants for Auction Success

	All Sellers		**Experienced Sellers**		**New Sellers**	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	-0.5472	0.7075	2.5950	0.1314	-57.1937**	0.0000
ABME	0.0016	0.9759	-0.0103	0.8533	0.8181**	0.0040
ACCS	-0.0270	0.5113	-0.0775	0.0912	0.2191*	0.0238
BRKN	0.3016**	0.0001	0.2726**	0.0013	0.3906	0.0789
BYNW	42.3062	1.0000	42.3374	1.0000	N.A.	N.A.
COND	-0.8491**	0.0000	-0.9377**	0.0000	-0.5564**	0.0000
GAME	-0.1876**	0.0000	-0.0963*	0.0452	-0.6097**	0.0000
GIFT	-0.6760**	0.0001	-0.4865*	0.0198	-1.5062**	0.0000
INSU	0.0947*	0.0210	0.0962*	0.0334	0.1946	0.0645
INTL	0.0999*	0.0163	0.1171*	0.0130	-0.1053	0.2512
LOG(FLSZ)	0.1163	0.3963	-0.2098	0.1359	5.5055**	0.0000
LOG(LNGT)	0.1916**	0.0000	0.2050**	0.0000	-0.0811	0.1829
LOG(#PICT)	0.0689**	0.0001	0.0449*	0.0394	0.01943	0.5224
MEMB	0.0587	0.1193	0.0646	0.1279	0.0623	0.4694
OFFH	0.0185	0.6135	0.0151	0.7124	0.0030	0.9712
PABP	-0.0233	0.6106	-0.0513	0.3036	28.7984	1.0000
PAYP	0.4516**	0.0000	0.6350**	0.0000	0.0553	0.6831
PPFB	0.0010	0.2227	0.0029	0.7420	0.0004	0.7378
PWSL	-0.4277**	0.0000	-0.3820**	0.0000	N.A.	N.A.
PYMT	0.3999**	0.0000	0.4451**	0.0000	0.1940*	0.0289
RETN	-0.2582**	0.0000	-0.3491**	0.0000	-0.1389	0.2111
RSPR	-1.4188**	0.0000	-1.3727**	0.0000	-1.4572**	0.0000
SHIP	-0.1357**	0.0094	-0.0946	0.1162	-0.0518	0.6401
SLFD	0.0001**	0.0000	0.0001**	0.0000	0.0240	0.3344
SLIM	-0.0753	0.1278	-0.0198	0.7185	-0.4362	0.0002
SSPN	-0.6298**	0.0000	-0.5268**	0.0000	-1.5281**	0.0000

Note: In this study, unless stated otherwise, * means significance at 5%; ** means significance at 1%.

[1] Logit model is more appropriate than Probit model for this study. Logit has better interpretation than Probit as it can be interpreted as modeling log odds.

From the result, setting a reserve price is negatively related to auction success, which is comprehensible because setting a reserve price is to impose a minimum final bidding price before an auction can be considered successful. Sellers' feedback scores are positively related to auction success, which partially explains why sellers with low feedback scores have a low auction success rate. The coefficient for the relative positive feedback percentage is positive but insignificant for overall sellers and negative for both new sellers and experienced sellers. About Me is only significant for new sellers. Whether setting a start bidding price is negatively related to auction success for all sellers. Being a power seller, providing gift wrapping services, or offering PayPal Buyer Protection do not seem to help online auctions succeed. Offering Buy-it-now option does not help experienced sellers' auctions succeed (new sellers are not eligible to use the Buy-it-now option). Overall, free shipment is negatively related to, while the number of pictures is positively related to, auction success for all sellers. File size is positively related to auction success for new sellers but not significant for overall and experienced sellers. Shipment insurance helps boost auction success for overall and experienced sellers but the coefficient is positive and insignificant to new sellers. Whether sellers accepting PayPal as a payment method is positively related to auction success for overall and experienced sellers but is not significant to new sellers. Accepting more than one payment method is significantly positively related to auction success in all three regressions. Whether providing a return policy is negatively related to auction success for overall and experienced sellers. Auction length is positively related to auction success for overall sellers and experienced sellers but is negatively and insignificantly related to auction success for new sellers. The accessories attached to the console are not significant for auction success for overall and experienced sellers, but it helps new sellers succeed in online auctions. The significantly negative coefficients for games indicate that games bundled with consoles do not help auctions succeed. In all three regressions, auctions ending time during off-work-hours is not significant for auction success. International shipment helps overall and experienced sellers achieve auction success but fails to do the same for new sellers.

While we observe many differences between new sellers and experienced sellers, we also test whether there is a structure difference in determinants for auction success between new and experienced sellers. The F-test shows that such a structural difference does exist (F-value = 3.32 > 1.49, the critical value at 5% level) when we define sellers with at most 7 feedback scores as new sellers. In Table 3, we list F-test results for **Hypothesis 1-1** under various "new seller" definitions, all of which are high enough to reject the hypothesis. The conclusion obtained is that the determinants for auction success for new sellers are different from those for experienced sellers.

Table 3. F-Values for Different Definitions of New Sellers (CV=1.49)

Hypothesis	**F-values**	**Feedback score criteria for new sellers**				
		=0	**<=3**	**<=5**	**<=7**	**<=9**
H 1-1	F-value for Auction Success (Seller Type)	3.68	6.83	6.11	3.32	1.58
H 1-2	F-value for Auction Price (Seller Type)	2.51	10.61	10.01	9.22	10.59
H 2-1	F-value for Auction Success (Item Condition)	33.36	35.92	36.09	36.02	33.34
H 2-2	F-value for Auction Price (Item Condition)	28.14	28.94	28.29	27.72	27.57

Auction Price Determinants: In a similar fashion, we run the regression for overall sellers regardless of seller experience to investigate the determinants for auction prices. We then categorize sellers with at most 7 feedback scores as new sellers and experienced sellers otherwise. With the auction price as a real number, we run a log-linear regression model. The regression results are presented in Table 4.

The result shows that setting a reserve price is positively related to the final auction price. Also, sellers' feedback scores help increase auction prices. The relative positive feedback rate does not impact auction prices for overall sellers. Yet, if we differentiate sellers as new and experienced sellers, the relative positive feedback rate can help experienced sellers achieve a higher auction price but fails to do the same for new sellers. A power seller has a lower auction price. One possible explanation is that a power seller might have cheaper product procurements than other sellers. The coefficient for PayPal Buyer Protection is insignificant in all three cases. Off-work hours help experienced sellers achieve higher auction prices but not for new sellers. Other trust enhancing and transaction enhancing strategies such as the number of pictures, the file size, gift wrap service, Buy-it-now price, and starting price set by sellers significantly help achieve a higher auction price. Having a return policy and international shipment is negatively related to auction price. Free shipment is not effective in increasing auction prices. Using PayPal as a payment method helps only experienced sellers achieve a higher price but not new sellers. More than one payment methods accepted by sellers does not seem to help experienced sellers collect higher revenue but does help new sellers. The length of eBay membership is negatively related to auction prices for experienced sellers but is the opposite for new sellers.

Table 4. Log-Linear Regression Results of Determinants for Auction Ending Price

	All Sellers		**Experienced Sellers**		**New Sellers**	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	2.1204**	0.0000	0.8520	0.0110	-0.1773	0.8854
ABME	-0.0525**	0.0000	-0.0465**	0.0000	-0.1926**	0.0001
BRKN	-1.0129**	0.0000	-1.0098**	0.0000	-1.0075**	0.0000
BYNW	0.1203**	0.0000	0.1210**	0.0000	N.A.	N.A.
COND	0.2315**	0.0000	0.2262**	0.0000	0.2240**	0.0000
GIFT	0.2058**	0.0000	0.2479**	0.0000	0.0013	0.9891
INSU	0.0931**	0.0000	0.0895**	0.0000	0.0898**	0.0001
INTL	-0.0206**	0.0059	-0.0182*	0.0216	-0.0058	0.7868
LOG(FLSZ)	0.2005**	0.0000	0.1979**	0.0000	0.4061**	0.0004
LOG(LNGT)	0.0351**	0.0000	0.0360**	0.0000	0.0299*	0.0324
LOG(START)	0.0266**	0.0000	0.0231**	0.0000	0.0587**	0.0000
LOG(#PICT)	0.0102**	0.0037	0.0065	0.0869	0.0220*	0.0129
MEMB	-0.0288**	0.0000	-0.0412**	0.0000	0.0423*	0.0350
OFFH	0.0181**	0.0066	0.0267**	0.0001	-0.0416*	0.0345
PABP	0.0073	0.3655	-0.0162	0.0561	0.0957	0.5061
PAYP	0.0312*	0.0207	0.0395**	0.0074	-0.0058	0.8622
PPFB	-0.0002	0.2110	0.0131**	0.0000	-0.0016**	0.0000
PWSL	-0.0475**	0.0000	-0.0482**	0.0000	N.A.	N.A.
PYMT	0.0021	0.7665	-0.0075	0.3319	0.0403*	0.0496
RETN	-0.0360**	0.0001	-0.0415**	0.0000	0.0111	0.6651
RSPR	0.2258**	0.0000	0.2296**	0.0000	0.2358**	0.0000
SHIP	-0.0180	0.0669	-0.0129	0.2177	-0.0323	0.2352
SLFD	0.0000**	0.0000	0.0000**	0.0000	0.0354**	0.0000
SLIM	0.3011**	0.0000	0.3118**	0.0000	0.2309**	0.0000
SSPN	-0.0146	0.2551	-0.0194	0.1292	0.0150	0.8610
#CNTL	0.0488**	0.0000	0.0506**	0.0000	0.0326	0.0941
#GAME	0.0166**	0.0000	0.0151**	0.0000	0.0291**	0.0000
R-squared	0.4442		0.4595		0.4133	
Adjusted R-squared	0.4434		0.4587		0.4078	
F-statistic	580.1903		533.4474		74.5244	

We also test whether a structural difference in auction price determinants exists between new and experienced sellers. Under the case where sellers with at most 7 feedback scores as new sellers, the F-test shows an F-value of 9.22 which is greater than 1.49, the critical value, suggesting that such a structural difference exists. To get robust analysis, we sequentially define new sellers as sellers with at most 0, 3, 5, and 9 feedback scores. The corresponding F-values for Hypothesis 1-2 are presented in Table 3. All tests reject Hypothesis 1-2, indicating that the auction price determinants for new sellers are different from those for experienced sellers.

Structural Difference between Product Types: New Items vs. Used Items

Auction Success Determinants: As mentioned earlier, the information asymmetry regarding product quality is more pronounced for used items than for new items in electronic marketplaces. To discover whether there is a structural difference in auction success determinants between new and used items, we run regressions for both items respectively with the same definitions for new and experienced sellers in the previous sub-section. The regression results are listed in Table 5.

Setting a reserve price or starting price is negatively related to auction success. Bundling games with consoles does not help auction succeed. Sellers' feedback scores, number of pictures, auction length, and multiple-payment methods are positively related to auction success. Being a power seller, providing a gift wrap service, and offering return policy are negatively related to auction success for used items. International shipment helps used items succeed in online auctions. Shipment insurance helps new items succeed. However, slim model or free shipment does not help new items succeed. The following factors have opposite effects on the auction success for new and used items: PayPal, off-work hours, and free shipment. That is, PayPal helps used items succeed but does not help new items. Off-work hours help new item auctions succeed but does not help used item auctions. It seems new sellers (NSEL) have a better likelihood of achieving success with new items and realizing failure with used items.

Table 5. Logit Regression Results of Determinants for Auction Success

	New Items		**Used Items**	
Variable	Coefficient	Prob.	Coefficient	Prob.
C	-0.5533	0.8733	-1.2865	0.4380
ABME	-0.1513	0.2575	-0.0221	0.7164
ACCS	0.1521	0.1362	0.0211	0.6518
BRKN	N.A.	N.A.	0.4943**	0.0000
BYNW	42.7173	1.0000	42.2220	1.0000
GAME	-1.0126**	0.0000	-0.0359	0.4684
GIFT	0.07836	0.8060	-0.9963**	0.0000
INSU	0.4158**	0.0000	-0.0752	0.1107
INTL	0.0787	0.3961	0.1336**	0.0058
LOG(FLSZ)	0.1221	0.7085	0.1607	0.3027
LOG(LNGT)	0.1268*	0.0186	0.0614**	0.0000
LOG(#PICT)	0.2180**	0.0002	0.0663**	0.0004
MEMB	-0.0102	0.9040	0.0556	0.2006
NSEL	0.2700*	0.0341	-0.1713*	0.0124
OFFH	0.4799**	0.0000	-0.1154**	0.0066
PABP	-0.0944	0.3631	-0.1282*	0.0212
PAYP	-0.6198**	0.0001	0.7981**	0.0000
PPFB	-0.0009	0.6522	0.0013	0.2106
PWSL	0.0000	0.9999	-0.4362**	0.0000
PYMT	0.2012*	0.0215	0.4870**	0.0000
RETN	-0.0570	0.5647	-0.2922**	0.0000
RSPR	-0.8872**	0.0000	-1.5654**	0.0000
SHIP	-0.2912*	0.0111	-0.0805	0.1890
SLFD	0.0002**	0.0000	0.0000**	0.0000
SLIM	-0.3041**	0.0004	0.0677	0.2886
SSPN	-1.0806**	0.0000	-0.4302**	0.0000

The F-tests for Hypothesis 2-1 in Table 3 show that there is a structural difference in auction success determinants between new items and used items under different definitions for seller experience. Therefore, Hypothesis 2-1 is rejected by these statistical tests.

Auction Price Determinants: We also run a log-linear model for auction prices for new and used items to investigate any structural difference in auction price determinants. The regression results for new and used items with at most 7 feedback scores as new sellers are listed in Table 6.

The result shows the following factors help both new and used items achieve a high auction price: reserve price, number of pictures, shipment insurance, auction length, Buy-it-now price, number of games and accessories bundled with the console, and starting price. The following two factors are negatively related to auction prices: power sellers and eBay membership length. The following factors are significantly negatively related to auction prices of used items: About-Me, broken items, and e-Bay membership length. Conversely, providing gift wrap service helps increase auction prices for used items. For new items, sellers' feedback scores and multiple payments help increase auction prices, and free shipment decrease prices. Starting prices, file size, and international shipment play opposite roles for new and used items. For example, file size helps used items increase auction prices, but decrease new items' auction prices.

The F-values for Hypothesis 2-2 under different definitions of new sellers in Table 3 suggest rejecting Hypothesis 2-2. This implies that the auction price determinants for new items are, in fact, different from those for used items.

Table 6. Log-Linear Regression Results of Determinants for Auction Price

	New Items		Used Items	
Variable	Coefficient	Prob.	Coefficient	Prob.
C	0.0000**	0.0000	1.1581**	0.0002
ABME	-0.0434	0.1317	-0.0830**	0.0000
BRKN	N.A.	N.A.	-0.9891**	0.0000
BYNW	0.0609*	0.0101	0.1286**	0.0000
GIFT	0.0989	0.1409	0.2388**	0.0000
INSU	0.1045**	0.0000	0.0660**	0.0000
INTL	0.0596**	0.0019	-0.0185*	0.0216
LOG(FLSZ)	-0.3716**	0.0000	0.2954**	0.0000
LOG(LNGT)	0.0889**	0.0000	0.0325**	0.0000
LOG(START)	0.0340**	0.0000	0.0338**	0.0000
LOG(#PICT)	0.0555**	0.0001	0.0121**	0.0009
MEMB	-0.0389*	0.0187	-0.0349**	0.0000
NSEL	0.0484	0.0857	-0.0371**	0.0045
OFFH	0.0387*	0.0157	0.0197**	0.0066
PABP	0.0141	0.5176	-0.0012	0.8906
PAYP	0.0843**	0.0070	-0.0005	0.9702
PPFB	-0.0002	0.5163	-0.0003	0.1701
PWSL	-0.0590*	0.0339	-0.0605**	0.0000
PYMT	0.0649**	0.0002	-0.0114	0.1495
RETN	-0.0096	0.6465	-0.0104	0.2973
RSPR	0.2552**	0.0000	0.2230**	0.0000
SHIP	-0.10269**	0.0001	-0.0043	0.6845
SLFD	0.0000**	0.0000	0.0000	0.1179
SLIM	0.2512**	0.0000	0.2958**	0.0000
SSPN	0.0741*	0.0142	-0.0982**	0.0000
#GAME	0.0228**	0.0000	0.0163**	0.0000
#CNTL	0.0407	0.0770	0.0505**	0.0000
R-squared	0.3791		0.4355	
Adjusted R-squared	0.3731		0.4346	
F-statistic	63.0887		479.5282	

5. Online Auction Segmentation

The above analysis of the determinants for both auction success and prices indicates substantial differences exist between new sellers and experienced sellers (related to trust), and between new items and used items (related to information asymmetry). Based on the theory of trust and information asymmetry along with the empirical support, we divide auctions into four segments: auctions listed by new sellers for new items (NN for short), auctions listed by new sellers for used items (NU), auctions listed by experienced sellers for new items (EN) and auctions listed by experienced sellers for used items (EU). Figure 1 below depicts the perceptual map of online auction listing segmentation.

It is important that we check the effectiveness of this market segmentation. Modern marketing theory suggests using common criteria such as the following to evaluate the effectiveness of market segmentation: homogeneous, heterogeneous, measurable, substantial, accessible, actionable, and responsive [McDonald & Dunbar 2004]. Table 7 offers detailed explanation for our segmentation on each of the criterion. Overall, we believe our auction listing segmentation is effective and valid.

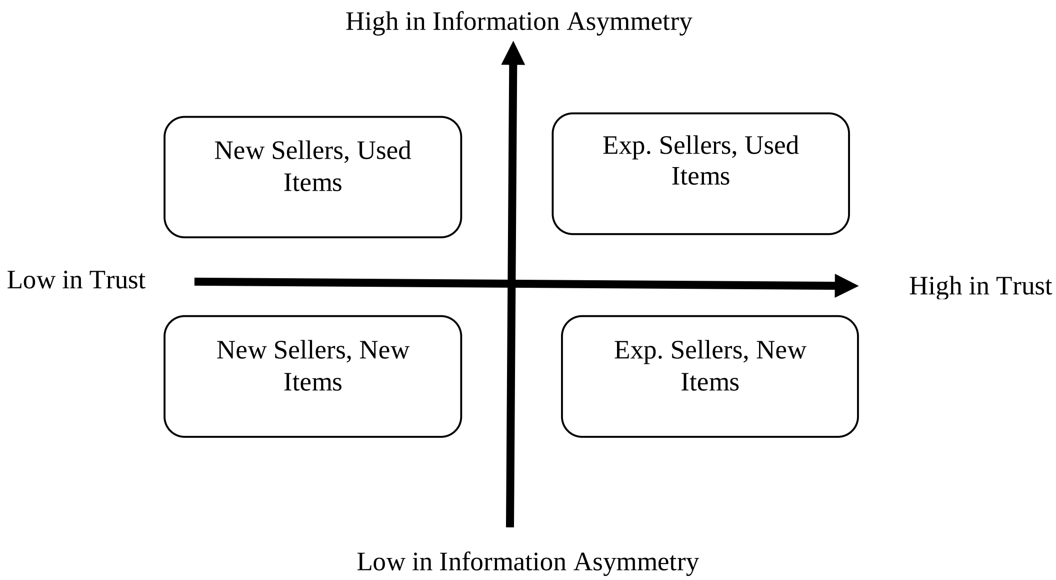

Figure 1. Perceptual Map of Online Auction Listings

Table 7. Effectiveness of Market Segmentation

Evaluation Criteria	Satisfied?	Explanation
Homogeneous	√	For the four segments, each segment shares the commons in trust and information exposure.
Heterogeneous	√	Across different segments, there exist structural differences in determents of auction success and prices.
Measurable	√	Seller types and product conditions are easily identified by the online auction house and market participants.
Substantial	√	Each segment should be large enough in terms of listings to warrant the possible attention of the online auction house and market participants.
Accessible	√	Online auction listings are reachable globally and available 24/7.
Actionable/Practical	√	The online auction house, sellers, buyers and viewers can implement their marketing strategy for each segment.
Responsive	√	Each segment will respond better to specific marketing strategy. In particular, the segment of new sellers and used items (NU) needs more attentions from the online auction house as they might be in a disadvantage.

To understand whether and how sellers in each of the four segments (NN, NU, EN, EU) behave differently, we compare sellers in the following pairs of segments:

1. New sellers with new items (NN) and new sellers with used items (NU);
2. Experienced sellers with new items (EN) and experienced sellers with used items (EU);
3. New sellers with new items (NN) and experienced sellers with new items (EN);
4. New sellers with used items (NU) and experienced sellers with used items (EU).

The first two pairs compare new and used items given the same seller type. The second two pairs are the comparison of new and experienced sellers given the same item condition. Also, from the analysis in Section IV, we identify 15 factors that significantly determine auction success and/or prices. Among these 15 factors, five of them (picture, file size, insurance, return policy, and About Me) are trust enhancing strategies, and the remaining ten factors are transaction enhancing strategies. In Table 8, the t-test for mean value comparison between NN and NU show that 10 of 15 options (reserve price, gift wrap service, files size, shipment insurance, shipment fee, return policy, PayPal, auction length, international shipment, and setting starting bid) are significantly different. F-test show that NN have larger variances than NU in 11 of 15 auction options (gift wrap service, file size, return policy, PayPal, auction length, payment, Buy-it-now, international shipment, free shipment, setting starting bid, and off-working hour). The t-test between EN and EU show that 13 out of 15 options (all except for Buy-it- now and free shipment) are significantly different. F-test show that EN have larger variances than EU in 10 auction options (reserve price, gift wrap service, shipment insurance, return policy, payment, Buy-it-now, international shipment, off-work hours, About Me, and setting starting bid). Given the same item condition, the t-test for NN and EN shows that sellers in NN behave significantly differently from those in EN in 14 out of 15 auction options. The F-test indicates that NN have higher variances in 8 options than EN. The t-test for NU and EU indicate there are 14 different auction options. The F-test demonstrates that NU has higher variances for 7 out of 15 options than does EU. Another observation is that, compared with experienced sellers, new sellers care more about trust enhancing strategies for used items than new items (see NN vs. NU, and EN vs. EU). However, given the same product condition, experienced sellers care more about trust enhancing strategies than new sellers (see NN vs. EN, and NU vs. EU). The above analysis concludes that sellers in the four auction segments do behave differently, and such differences are more significant between new and experienced sellers than between new and used items.

6. Selling Strategies: Trust Enhancing vs. Transaction Enhancing

Primary Analysis: Principal Component Analysis

The individual comparisons for each variable in Table 8 show the detailed differences of seller behavior in all four segments. However, excessive number of factors/dimensions in consideration does not provide a general picture regarding the roles of trust enhancing strategies and transaction enhancing strategies. Principal component analysis (PCA) can help reduce dimensions by defining a new set of dimensions that better explain the variability of the data. In PCA, the first principal component (dimension) counts as much of the variability as possible. The second principal component (dimension) is orthogonal to the first one and captures as much of the remaining variability as possible, and so on for the third principal component [Tan et al. 2006]. By ignoring higher principal components in PCA, we eliminate much of the noise in the dataset and identify the strongest patterns hidden in the dataset in relatively fewer dimensions.

We list the weights for each variable in the first and second principal components in Table 9. The first principal component counts about 61% of the variability and the second principal component counts 28.69% of the variability of the original data. Together, the two components cumulatively account for nearly 90% of the variability of the dataset, suggesting a strong representation power for the original data. We further sum up the weights for trust enhancing and transaction enhancing strategies, respectively. For the first principal component, the total weights for trust enhancing strategies are 0.2924, and total weights for transaction enhancing strategies are 0.0195. Therefore, trust enhancing strategies dominate the first principal component. For the second principal component, the total weights for trust enhancing strategies are 0.0301, and the total weights for transaction enhancing strategies are -0.3693, suggesting transaction enhancing strategies dominate the second principal component. That is, the first principal component can represent trust enhancing strategies, and the second principal component can represent transaction enhancing strategies. Note that the high value in the second principal component means fewer transaction enhancing strategies because the sign of the total weights for transaction enhancing strategies is negative.

Table 8. Pairwise Comparison of Seller Behavior in Four Segments

		Trust Enhancing Strategies					Transaction Enhancing strategies									
		ABME	FLSZ	INSU	PICT	RETN	BYNW	GIFT	INTL	LNGT	OFFH	PYMT	PAYP	RSPR	SHIP	SSPN
NN	Mean	0.033	45.688	0.22	4.003	0.399	0.066	0.034	0.445	4.531	0.498	0.431	0.84	0.202	0.22	0.099
NU	Mean	0.038	44.997	0.258	4.178	0.158	0.056	0.013	0.351	4.851	0.503	0.403	0.907	0.249	0.188	0.007
EN	Mean	0.308	50.792	0.525	4.591	0.217	0.168	0.011	0.369	3.907	0.515	0.573	0.94	0.143	0.165	0.33
EU	Mean	0.227	49.09	0.424	4.937	0.167	0.161	0.006	0.33	4.276	0.556	0.633	0.921	0.123	0.167	0.123
NN vs. NU	t-value	-0.691	3.146*	-2.075*	-1.381	14.489*	0.986	3.894*	4.590*	-2.957*	-0.246	1.337	-5.163*	-2.602*	1.912*	14.230*
	F-value	0.862	1.165*	0.897	0.644	1.804*	1.163*	2.600*	1.085*	1.061*	1.001*	1.020*	1.596*	0.863	1.125*	13.135*
EN vs. EU	t-value	9.980*	8.012*	10.714*	-4.567*	6.921*	0.969	3.183*	4.305*	-7.112*	-4.304*	-6.462*	3.806*	3.114*	-0.196	30.562*
	F-value	1.216*	0.65	1.022*	0.648	1.223*	1.043*	1.811*	1.053*	0.901	1.012*	1.053*	0.772	1.135*	0.994	2.057*
NN vs. EN	t-value	-15.518*	-14.094*	-15.060*	-4.462*	10.216*	-6.859*	4.509*	3.769*	5.762*	-0.821	-6.919*	-9.147*	3.952*	3.491*	-12.489*
	F-value	0.149	0.357	0.69	0.576	1.411*	0.437	2.973*	1.062*	1.017*	1.002	1.003*	2.406*	1.319*	1.247*	0.403
NU vs. EU	t-value	-23.333*	-18.564*	-16.587*	-9.361*	-1.178	-14.565*	3.895*	2.232*	10.371*	-5.186*	-23.263*	-2.565*	17.805*	2.829*	-18.524*
	F-value	0.211	0.199	0.785	0.58	0.957	0.392	2.071*	1.031*	0.864	1.013*	1.036*	1.164*	1.735*	1.101*	0.063

Table 9. First and Second Principal Components

Variable	1st Principle	2nd Principle
PICT	0.2502	0.0165
FLSZ	0.0366	0.0095
INSU	0.0007	0.0027
RETN	-0.0002	-0.0001
ABME	0.0049	0.0013
SSPN	0.0035	0.0002
GIFT	0.0002	0.0001
RSPR	-0.0004	-0.0001
PAYP	0.0003	-0.0002
LNGT	0.0121	-0.3683
PYMT	0.0029	-0.0091
BYNW	-0.0014	0.0151
OFFH	0.0023	0.0017
INTL	0	-0.0058
SHIP	-0.0002	-0.003
Variance	15.5799	7.3289
Variance%	61.0025	28.696
Cum%	61.0025	89.6985
P-value	0	0
Total Weight for Trust Enhancing	0.2924	0.03007
Total Weights for Transaction Enhancing	0.0194	-0.3693
Which One Is Dominant?	**|Trust|>|Transaction|**	**|Transaction|>|Trust|**

We draw the four auction segments with the values of the first and second principal components in opposite values in the coordinates in Figure 2. The horizontal line is the first principal component, representing trust enhancing strategies; and the vertical line is the second principal component, representing transaction enhancing strategies. Figure 2 reveals that experienced sellers use more trust enhancing and transaction enhancing strategies than new sellers because EN and EU are northeastern to both NN and NU. New sellers use more trust enhancing and transaction enhancing strategies for used items than for new items. Experienced sellers use more trust enhancing strategies for used items than for new items, but they use more transaction enhancing strategies for new items than for used items.

To investigate the different roles of trust enhancing and transaction enhancing strategies towards auction success and failure, we further divide each segment into successful (S) and unsuccessful (U) subgroups. We draw the eight subgroups (four successful subgroups and four unsuccessful subgroups) in Figure 3. If we link the unsuccessful point to the successful point (for example, NNU→NNS), we find that all the successful points are to the bottom right of the corresponding unsuccessful points. This pattern indicates that trust enhancing strategies are relatively more important to auction success than transaction enhancing strategies in online auction listings. Trust and information asymmetry problems still exist but can be alleviated by applying trust enhancing strategies in electronic marketplaces. Sellers can improve the auction success rate by building a solid trust enhancing strategy. The auction house should design more tools to enrich trust enhancing strategy.

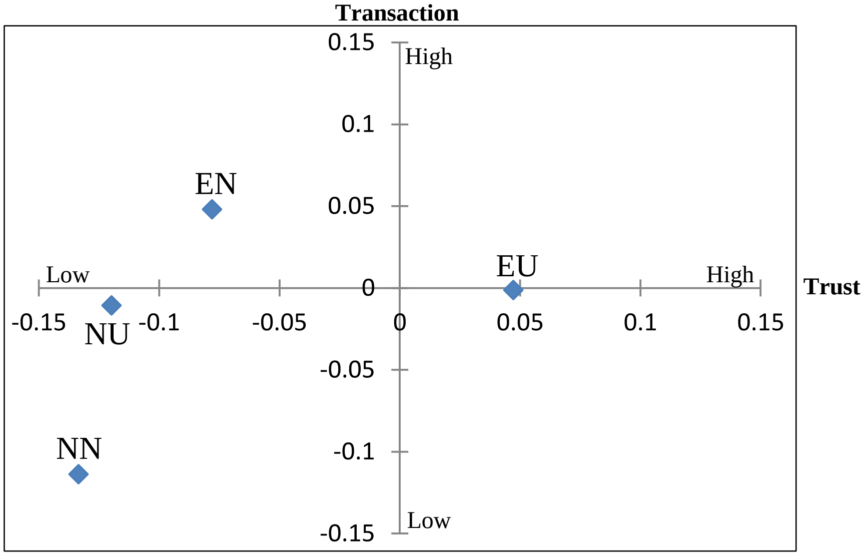

Figure 2. Trust and Transaction Enhancing Strategies for Four Segments

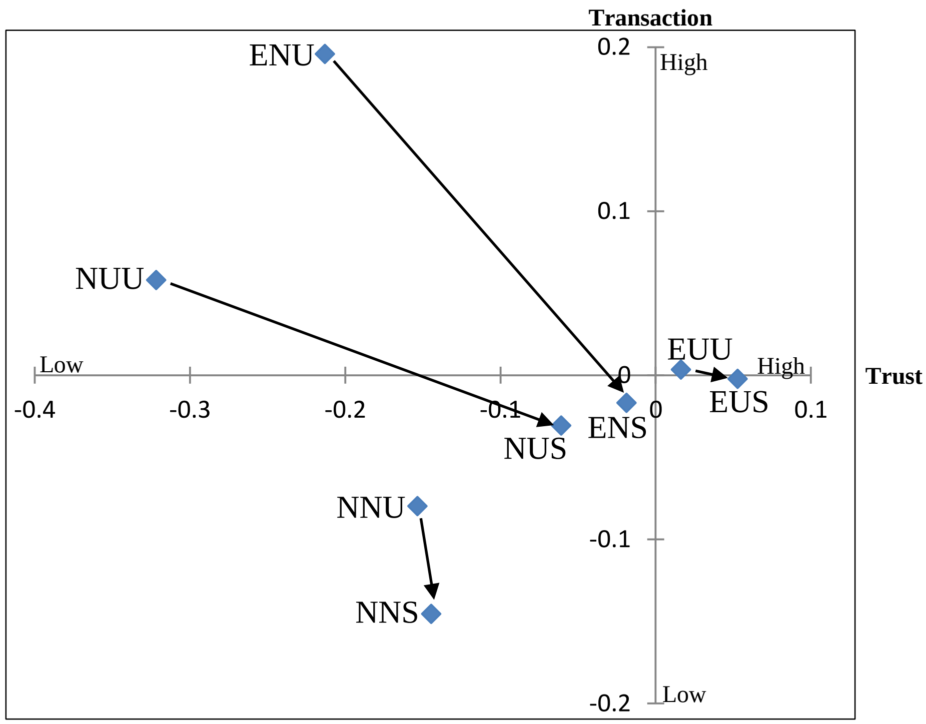

Figure 3. Trust and Transaction Enhancing Strategies for Eight Subgroups

Further Verification: Distance and Multi-Dimensional Scaling Analysis

To explore how different sellers behave differently from each other in the four auction segments, we measure the distance between any two auction segments (*s* and *u*) with fifteen dimensions (*i*=1, 2,…15) listed in Table 8. We apply the Euclidian distance, which is defined as $Eucl(s,u) = \| s-u \| = \sqrt{\sum_{i=1}^{15}(s_i - u_i)^2}$ [Bruno et al. 2002; Tan et al. 2006]. Table 10 shows the Euclidian distances among NN, NU, EN, and EU. NN is close to NU, and EN is close to EU. NN and NU are far distance away from EN. EN and EU are also far away from NU. Thus, we can see for these four auction segments, the auctions with the same type of sellers are closest, and the auctions with different types of sellers are the most extreme in comparison.

Table 10. The Euclidian Distances between Four Segments

	NN	NU	EN	EU
NN	0	0.8345	5.2052	3.5675
NU	0.8345	0	5.9118	4.2213
EN	5.2052	5.9118	0	1.7951
EU	3.5675	4.2213	1.7951	0

To get more insight into the sellers' behavior in different segments, we further divide each of the four segments into successful and unsuccessful subgroups. We list the Euclidian distances among these eight subgroups in Table 11. Successful new sellers with used items (NUS) are close to unsuccessful new sellers with used items (NUU). However, successful experienced sellers with new items (ENS) are close to successful experienced sellers with used items (EUS). Successful experienced sellers with used items (EUS) are close to unsuccessful experienced sellers with used items (EUU). And unsuccessful experienced sellers with new items (ENU) are close to unsuccessful experienced sellers with used items (EUU). Unsuccessful experienced sellers with used items (EUU) are close to successful experienced sellers with new items (ENS). Unsuccessful new sellers with new items are close to unsuccessful new sellers with used items and vice versa. After inspecting the farthest distance for each subgroup, we can see the new sellers with either new items or used items (NNS, NNU, NUS and NUU) are far away from successful experienced sellers with new items (ENS). And experienced sellers with new items (ENS and ENU) are far away from unsuccessful new sellers with used items (NUU), and experienced sellers with used items (EUS and EUU) are also far away from unsuccessful new sellers with new items (NNU). All these demonstrate that sellers in the eight subgroups have different behaviors. We also find that unsuccessful new sellers have a substantially farther distance than unsuccessful experienced sellers. That is, for Euclidian distances, 1.317 for NN > 1.291 for EN and 0.766 for NU > 0.754 for EU. Therefore, unsuccessful experienced sellers are more likely to become successful experienced sellers than unsuccessful new sellers are to become successful new sellers.

Table 11. The Euclidian Distances Among Eight Subgroups

		1	2	3	4	5	6	7	8
		NNS	NNU	NUS	NUU	ENS	ENU	EUS	EUU
1	NNS	0.000	1.317	0.933	1.338	2.106	1.599	1.567	1.640
2	NNU	1.317	0.000	1.246	1.006	2.666	1.473	2.248	1.892
3	NUS	0.933	1.246	0.000	0.766	1.902	1.387	1.275	1.346
4	NUU	1.338	1.006	0.766	0.000	2.625	1.838	2.002	1.716
5	ENS	2.106	2.666	1.902	2.625	0.000	1.291	0.912	1.217
6	ENU	1.599	1.473	1.387	1.838	1.291	0.000	1.201	0.914
7	EUS	1.567	2.248	1.275	2.002	0.912	1.201	0.000	0.754
8	EUU	1.640	1.892	1.346	1.716	1.217	0.914	0.754	0.000

Since the above distances in Tables 10 and 11 are in multidimensional spaces, it is not easy to see their positions intuitively. To solve the problem, one approach is to use multidimensional scaling (MDS) [Cox & Cox 2001], which is an alternative to factor analysis. The advantage of MDS is that we can more intuitively observe the similarities or dissimilarities between the different objects. Figure 4 shows the MDS for four auction segments with the S-Stress of 0.0083 (perfect goodness of fit). In Figure 4, NN is close to NU, and EN is close to EU. EN and EU are located on the right side, and NN and NU are on the left side. Figure 5 shows the multidimensional scaling results after scaling 15 dimensions into 2 dimensions with the S-Stress of 0.02134 (excellent goodness of fit). The advantage of MDS for distance analysis is that the two-dimensional diagrams attain the original distance properties. The disadvantage of MDS is that we need prior information or experience to interpret the meaning of each dimension. With the results of principal component analysis, Dimension 1 can be interpreted as trust enhancing strategies and Dimension 2 as transaction enhancing strategies. Several interesting observations follow. The experienced sellers are distributed on the right side, implying experienced sellers care more about trust enhancing strategies than new sellers. For each segment, the successful subgroup is to the bottom right of the corresponding unsuccessful subgroup, suggesting trust enhancing strategies are relatively more important than transaction enhancing strategies for auction success. This is consistent with the pattern found in the previous principal component analysis. The managerial implication is that sellers can increase the auction success rate by boosting trust enhancing strategy, and the auction house should create more tools to enrich trust enhancing strategy.

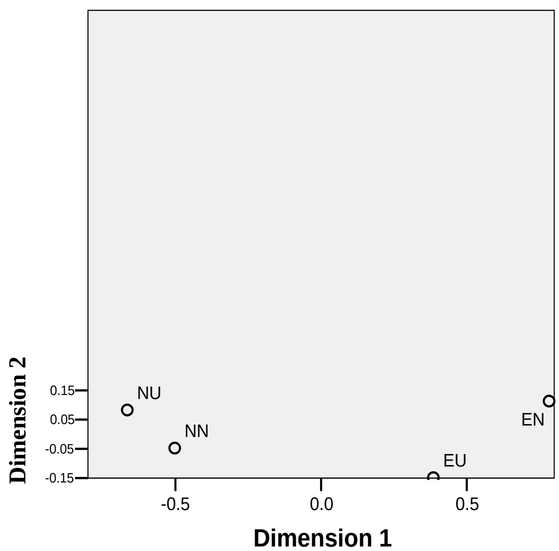

Figure 4. Four Segments Multidimensional Scaling

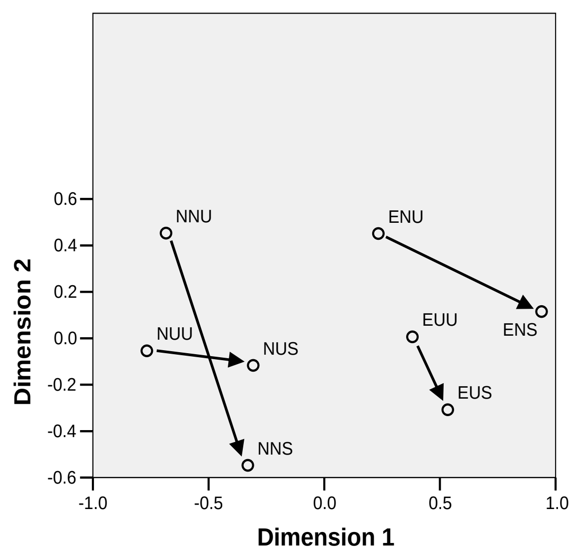

Figure 5. Eight Sub-Groups Multidimensional Scaling

7. Limitations and Discussions

Online Auction Listing Segmentation

The online auction listing segmentation in this study is based on the trust and information asymmetry dimensions and is further validated by the structural differences in auction success and price determinants. We demonstrate that there are significant differences between new and experienced sellers and between new and used items. Based on these findings, we classify online auctions into for segments: NN, NU, EN and EU. As trust and information asymmetry are key issues in electronic marketplaces, and auction success and prices are the primary goals for most sellers, we believe our auction segmentation analysis is very relevant and offers important contribution to the literature.

Buyers and sellers in electronic marketplaces are either individuals or businesses. They typically buy or sell on their own behaves. However, there exists another kind of sellers, i.e. middlemen in eBay (e.g., ISoldIt.com, AuctionDrop.com and QuickDrop.com). These sellers sell items on others' behaves. They take commissions or a percentage from the proceeds for people who might be too busy to sell items or feel selling in eBay is too complicated and costly by themselves. This implies there is a special segment of sellers which should be carefully addressed in eBay. Logically, middlemen have different goals from their clients, thus they might display behavior that actual sellers do not share. For example, unlike normal sellers who most likely care about both auction success and auction prices, middlemen might care more about auction success than auction prices. Therefore, additional segmentation of this type of sellers deserves more research attention. As an extension of this study, we expect more studies to specifically address middlemen in the future.

Product Conditions

Analyzing both new and used items is very important to the understanding of the overall online auction marketplaces. Most prior studies focus only on new products except for limited research on collectibles. At eBay, most auction items are used ones because eBay was initially designed for individuals to dispose of their belongings. Naturally, any research on selling used items is necessary for auction practice and can contribute to the literature. We analyze used items listed both by new and experienced sellers and obtain understanding on the determinants of auction success and prices for these auctions. Further, online auction listing heterogeneity and segmentation provide solid insight for discriminative selling recommendations. Despite our efforts, limitations regarding used items in our study exist. For example, we only distinguish products as new or used but not in more granular sub-categories such as "like new", "very good", "good", and "acceptable" conditions. We believe such sub-divisions will help gain more insights on selling used items in various conditions.

Trust and Information Asymmetry

Electronic marketplaces use the Internet along with other information technologies to match sellers and buyers and significantly reduce their search costs [Bakos 1997]. While technologies serve to facilitate trade, transactions in cyberspace also involve greater uncertainty and more opportunities for fraud than traditional exchanges. It is difficult for online buyers to really know sellers in a virtual environment. They are physically unable to inspect the products for sale and must rely entirely on pictures and descriptions posted by the sellers. As a result, the information advantage of the sellers is more pronounced in online auctions than in traditional market settings. There are two types of information asymmetry in electronic marketplaces. The first is about sellers. That is, the buyers' perceived seller type (e.g., trustful vs. non-trustful) might not be the true type a particular seller belongs to. This type of information asymmetry is highly related to customer trust. The second kind is about products in that a buyer's perceived product information might be different from the actual product attributes and functionality.

We discover numerous trust enhancing strategies that are critical for auction success and prices. Additionally, we also find trust enhancing strategies are relatively more important for auction success than transaction enhancing strategies. The implications of these findings are two-folds. On one hand, we realize that information asymmetry still exists in electronic marketplaces due to their unique market infrastructure. On the other hand, the information asymmetry in electronic marketplaces can be alleviated by adopting effective trust enhancing strategies. Admittedly, the trust enhancing strategies currently available (such as pictures and item descriptions) in electronic marketplaces are still in primitive stages. Many other emerging information technologies such as virtual reality, CAVE automatic virtual environments, and information provider convergence [Haag et al. 2005] can be used to build more effective trust enhancing strategies to improve trust and reduce information asymmetry. We believe that reducing both types of information asymmetry not only help buyers to retrieve correct information for their purchase decision, but also help build trust between buyers and sellers. These efforts will eventually result in more effective and efficient electronic marketplaces.

8. Implications and Conclusions

Theoretical Implications

This study contributes to the literature in three areas. First, while most existing studies assume sellers sell new products, we consider both seller types and product conditions so that we can better understand the real online auction marketplaces. Second, based on trust and information asymmetry, we segment online auction listings into four segments and validate the segmentations by the determinants of auction success and prices. Online auction segmentation provides theoretical foundations and guidance for online auction house to customize its services, for sellers to choose appropriate selling strategies, and for buyers to select proper market counterparts. We believe this study is the first one on online auction segmentation in the literature. Third, we contribute to the theory of trust and information by comparing the relative importance of different categories of selling strategies. Though online auction participants and auction house have done much effort to overcome the barriers of trust and information asymmetry in the online environment, our study shows the trust enhancing strategies are still critical to auction success. This implies both academics and business practitioners need to work together to enrich existing online auction theory and provide more effective and efficient selling strategies and tools to market users.

Managerial Implications

We study different seller types and different item conditions and offer a comprehensive picture regarding auction success and price determinants. The mean value and variance comparison offers a detailed view about seller behavior. PCA and distance analysis reveal that trust enhancing strategies are relatively more important than transaction enhancing strategies for auction success. Based on online auction segmentation and the understanding of sellers' behavior, an online auction house can design specific trust enhancing and marketing tools to each segment. This is important because personalized services can better satisfy each seller group's needs in electronic marketplaces. In particular, the auction house should design more suitable selling tools to new sellers and help them achieve better performances. Recommendations such as an easy and user-friendly listing design, less constraints on some market tools to new sellers, and lower listing fees for the second trial to new sellers should be used to attract more new sellers to use online auctions.

This study also provides some implications to sellers. Our segmentation analysis indicates that different auction segments have different determinants on auction success and prices. This knowledge is important as sellers need to correctly position themselves and adopt the most appropriate and effective selling strategies. PCA and distance analysis suggest sellers should use more trust enhancing strategies than transaction enhancing strategies to achieve desirable auction performances. Buyers can also benefit from auction segmentation. As Kauffman et al. [2009] show that the current online auction market is not efficient, savvy buyers can attain extra surplus by choosing right auction listings to bid.

Conclusions and Future Research

We explore online auction listing segmentation by investigating the differences in determinants of auction success and prices. We find structural differences in these determinants between new and experienced sellers and between new and used items. Based on seller types which are related to trust, and product conditions which are related to information asymmetry, we group auction listings into four segments. We find sellers in different segments behave differently and trust enhancing strategies are relatively more important for auction success than transaction enhancing strategies. The distance analysis shows that given product condition, unsuccessful experienced sellers can more likely transition to successful sellers than unsuccessful new sellers. All these findings have significant implications to the auction house, sellers, and buyers. The segmentation knowledge helps the online auction house customize its services to different groups of sellers; sellers can better position themselves; and buyers can choose the right auction listings to bid.

There are research extension opportunities from this study. We only use one product auction, Sony PlayStation 2 console, in this research. More other items can be used to further validate our findings and generate more insights on seller behavior and segmentation. Using other theoretical foundations to segment online auction listings into smaller clusters is also a valuable topic in the future.

REFERENCES

Akerlof, G.A., "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, Vol. 84, No. 3:488-500, 1970.

Anderson, S.T., D. Friedman, G. Milam, and N. Singh, "Seller Strategies on eBay: Does Size Matter?" *International Journal of Electronic Business*, Vol. 5, No. 6:643–669, 2007.

Anderson, S.W., J.D. Daly, and M.F. Johnson, "Why Firms Seek ISO 9000 Certification: Regulatory Compliance or Competitive Advantage?" *Production and Operations Management,* Vol. 8, No. 1:28-43, 1999.

Awad, N.F. and A. Ragowsky, "Establishing Trust in Electronic Commerce Through Online Word of Mouth: An Examination Across Genders," *Journal of Management Information Systems*, Vol. 24, No. 4:101-121, 2008.

Ba, S. and P.A. Pavlou, "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly*, Vol. 26, No. 3:243-268, 2002.

Ba, S., A.B. Whinston, and H. Zhang, "Building Trust in Online Auction Markets through an Economic Incentive Mechanism," *Decision Support Systems*, Vol. 35, No. 1:273-286, 2003.

Balachander, S., "Warranty Signaling and Reputation," *Management Science*, Vol. 47, No. 9:1282-1289, 2001.

Bakos, J.Y., "Reducing Buyer Search Costs: Implications for Electronic Markets," *Management Science*, Vol. 42, No. 1:1613-1630, 1997.

Bhargava, H.K. and R.R. Chen, "The Benefit of Information Asymmetry: When to Sell to Informed Customers?" *Decision Support Systems*, Vol. 53, No. 2:345-356, 2012.

Brough, A.R. and M.S. Isaac, "Finding a Home for Products We Love: How Buyer Usage Intent Affects the Pricing of Used Goods," *Journal of Marketing*, Vol. 76, No. 4:78 -91, 2012.
Bruce, N., E. Haruvy, and R. Rao, "Seller Rating, Price, and Default in Online Auctions," *Journal of Interactive Marketing*, Vol. 18, No. 4:37-50, 2004.
Bruno, N., S. Chaudhuri, and L. Gravano, "Top-k Selection Queries over Relational Databases: Mapping Strategies and Performance Evaluation," *ACM Transactions on Database Systems*, Vol. 27, No. 2:153-187, 2002.
Budish, E.B. and L.N. Takeyama, "Buy Prices in Online Auctions: Irrationality on the Internet?" *Economics Letters*, Vol. 72, No. 3:325-334, 2001.
Chang, W.L., A.N. Diaz, and P.C.K. Hung, "Estimating Trust Value: a Social Network Perspective," *Information System Frontiers*, Vol. 17, No. 1:1381-1400, 2015.
Chiu, C.M., H.Y. Huang, and C.H. Yen, "Antecedents of Trust in Online Auctions," *Electronic Commerce Research and Applications*, Vol., 9, No. 2:148-159, 2010.
Clots-Figueras, I., R.H. González, and P. Kujal, "Trust and Trustworthiness under Information Asymmetry and Ambiguity," *Economics Letters*, Vol. 147, No. 1:168-170, 2016.
Connelly, B.L., S.T. Certo, R.D. Ireland, and C.R. Reutzel, "Signaling Theory: A Review and Assessment," *Journal of Management*, Vol. 37, No. 1:39-67, 2011.
Cox, T.F. and M.A.A. Cox, Multidimensional Scaling, the 2nd Edition, FL, Boca Raton: Chapman & Hall/CRC, 2001.
Dellarocas, C., M. Fan, and C.A. Wood, "Self-Interest, Reciprocity, and Participation in Online Reputation Systems," MIT Sloan Working Papers, No. 4500-04, SSRN: http://ssrn.com/abstract=585402, 2004.
Dewally, M. and L.H. Ederington, "Reputation, Certification, Warranties, and Information as Remedies for Seller: Buyer Information Asymmetries: Lessons from the Online Comic Book Market," *Journal of Business*, Vol. 79, No. 2:693-729, 2006.
Dewan, S. and V. Hsu, "Adverse Selection in Reputations-Based Electronic Markets: Evidence from Online Stamp Auctions," *Journal of Industrial Economics*, Vol. 5, No. 4:497–516, 2004.
Dholakia, U.M. and K. Soltysinski, "Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions," *Marketing Letters*, Vol. 12, No. 3:225-237, 2001.
Elitzur, R. and A. Gavious, "Contracting, Signaling, and Moral Hazard: A Model of Entrepreneurs," *Journal of Business Venturing*, Vol. 18, No. 6:709-725, 2003.
Gefen, D., "E-commerce: The Role of Familiarity and Trust," *Omega*, Vol. 28, No. 6:725-737, 2000.
Gefen, D., E. Karahanna, and D.W. Straub, "Trust and TAM in Online Shopping: An Integrated Model," *MIS Quarterly*, Vol., 27, No. 1:51-90, 2003.
Gefen, D. and T. Heart, "On the Need to Include National Culture as a Central Issue in E-Commerce Trust Beliefs," *Journal of Global Information Systems*, Vol., 14, No. 4:1-30, 2006.
Gilkeson, J.H. and K. Reynolds, "Determinants of Internet Auction Success and Closing Price: An Exploratory Study," *Psychology & Marketing*, Vol., 20, No. 6:537-566, 2003.
Granados, N., A. Gupta, and R.J. Kauffman, "Transparency Strategy in Internet-Based Selling," in K. Tomak (Ed.), *Economics, IS and E-Commerce*, PA., Harrisburg: Idea Group Publishing, 2004.
Gregg, D.G. and S. Walczak, "Dressing Your Online Auction Business for Success: An Experiment Comparing Two eBay Businesses," *MIS Quarterly*, Vol. 32, No. 3:653-670, 2008.
Haag, S., M. Cummings, and D.J. McCubbrey, Management Information Systems for the Information Age, the 5th Edition, NY., New York: McGraw-Hill/Irwin, 2005.
Hinz, O. and M. Spann, "Managing Information Diffusion in Name-Your-Own-Price Auctions," *Decision Support Systems*, Vol. 49, No. 4:474-485, 2010.
Houser, D. and J. Wooders, "Reputation in Auctions: Theory, and Evidence from eBay," *Journal of Economics & Management Strategy*, Vol. 15, No. 2:353-369, 2006.
Huston, J.H. and R.W. Spencer, "Quality, Uncertainty and the Internet: The Market for Cyber Lemons," *American Economist*, Vol. 46, No. 1: 50-60, 2002.
Hu, X., Z. Lin, A.B. Whinston, and H. Zhang, "Hope or Hype: On the Viability of Escrow Services as Trusted Third Parties in Online Auction Environments," *Information Systems Research*, Vol. 15, No. 3: 236-249, 2004.
Jiang, Z. and I. Benbasat, "Virtual Product Experience: Effects of Visual and Functional Control of Products on Perceived Diagnosticity and Flow in Electronic Shopping," *Journal of Management Information Systems*, Vol. 21, No. 3:111-147, 2004.
Jiang, Z. and I. Benbasat, "The Effects of Presentation Formats and Task Complexity on Online Customers' Product Understanding," *MIS Quarterly*, Vol., 31, No. 3:475-500, 2007.
Jones, K., and L.N.K. Leonard, "Factors Influencing Buyer's Trust in Consumer-To-Consumer E-Commerce," *The Journal of Computer Information Systems*, Vol., 54, No. 4:71-79, 2014.

Jøsang, A., R. Ismail, and C. Boyd, "A Survey of Trust and Reputation Systems for Online Service Provision," *Decision Support Systems*, Vol. 43, No. 2:618-644, 2007.

Kauffman, R.J., T.J. Spaulding, and C.A. Wood, "Are Online Auction Markets Efficient? An Empirical Study of Market Liquidity and Abnormal Returns," *Decision Support Systems*, Vol. 48, No. 1: 3-13, 2009.

Kirmani, A. and A.R. Rao, "No Pain, No Gain: A Critical Review of the Literature on Signaling Unoberservable Product Quality," *Journal of Marketing*, Vol. 64, No. 2:66-79, 2000.

Li, S., K. Srinivasan, and B. Sun, "Internet Auction Features as Quality Signals," *Journal of Marketing*, Vol. 73, No. 1:75-92, 2009.

Livingston, J.A., "How Valuable is a Good Reputation? A Sample Selection Model of Internet Auctions," *Review of Economics and Statistics*, Vol. 87, No. 3:453-465, 2005.

Lucking-Reiley, D., D. Bryanz, N. Prasad, and D. Reeves, "Pennies from eBay: The Determinants of Price in Online Auctions," *Journal of Industrial Economics*, Vol. 55, No. 2:223-233, 2007.

Maadi, M., M. Maadi, and M. Javidnia, "Identification of Factors Influencing Building Initial Trust in E-Commerce," *Iranian Journal of Management Studies*, Vol. 9, No. 3:483-503, 2016.

Mavlanova, T., R. Benbunan-Fich and M. Koufaris, "Signaling Theory and Information Asymmetry in Online Commerce," *Information & Management*, Vol. 49, No. 5:240-247, 2012.

McDonald, M. and I. Dunbar, Market Segmentation: How to Do It, How to Profit from It, UK., Oxford: Butterworth-Heinemann, 2004.

Mcknight, D.H., L.L. Cummings, and N.L. Chervany, "Initial Trust Formation in New Organizational Relationships," *Academy of Management Review*, Vol. 23, No. 3:473-490, 1998.

McKnight, D.H., V. Choudhury, and C. Kacmar, "Developing and Validating Trust Measures for E-Commerce: An Integrative Typology," *Information Systems Research*, Vol. 13, No. 3:334-359, 2002.

Nelson, P., "Information and Consumer Behavior," *Journal of Political Economy*, Vol. 78, No. 2: 311-329, 1970.

Pavlou, P.A. and A. Dimoka, "The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation," *Information Systems Research*, Vol. 17, No. 4:392-414, 2006.

Pavlou, P.A. and D. Gefen, "Building Effective Online Marketplaces with Institution-Based Trust," *Information Systems Research*, Vol. 15, No. 1:37-59, 2004.

Pavlou, P.A., H. Liang and Y. Xue, "Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal–Agent Perspective," *MIS Quarterly*, Vol. 31, No. 1:105-136, 2007.

Popkowski Leszczyc, P.T.L., C. Qiu, and Y. He, "Empirical Testing of the Reference-Price Effect of Buy-Now Prices in Internet Auctions," *Journal of Retailing*, Vol., 85, No. 2:211–221, 2009.

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood, "The Value of Reputation on eBay: A Controlled Experiment," *Experimental Economics*, Vol. 9, No. 2:79-101, 2006.

Resnick, P. and R. Zeckhauser, "Trust among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System," in M.R. Baye (Ed.), *The Economics of the Internet and E-Commerce*, Amsterdam: Elsevier Science B.V., 2002.

Roberts, J.W. (2011), "Can Warranties Substitute for Reputations?" *American Economic Journal: Microeconomics*, Vol. 3, No. 3:69-85, 2011.

Roth, A.E. and A. Ockenfels, "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *American Economic Review*, Vol. 92, No. 4:1093-1103, 2002.

Schlosser, A.E., T.B. White, and S.M. Lloyd, "Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions," *Journal of Marketing*, Vol. 70, No. 2:133-148, 2006.

Standifird, S.S., M.R. Roelofs, and Y. Durham, "The Impact of eBay's Buy-it-Now Function on Bidder Behavior," *International Journal of Electronic Commerce*, Vol. 9, No. 2:167-176, 2004.

Stern, B.B. and M.R. Stafford, "Individual and Social Determinants of Winning Bids in Online Auctions," *Journal of Consumer Behaviour*, Vol. 5, No. 1:43-55, 2006.

Stiglitz, J.E., "The Contributions of the Economics of Information to Twentieth Century Economics," *Quarterly Journal of Economics*, Vol. 115, No. 4:1441-1478, 2000.

Stiglitz, J.E., "Information and the Change in the Paradigm in Economics," *American Economic Review*, Vol. 92, No. 3:460-501, 2002.

Tan, P.N., M. Steinbach, and V. Kumar, Introduction to Data Mining, MA., Boston: Pearson Education, Inc., 2006.

Tu, Y., and M. Lu, "An Empirical Study of Online Auction Dynamics," *International Journal of Electronic Business*, Vol., 9, No. 4:376-388, 2011.

Tucker, J.M., and V.J. Massad, "Effect of Buyer and Seller Experience on Buy It Now Pricing," *Journal of Internet Commerce*, Vol. 4, No. 3:101-115, 2004.

Waley, M.J.C. and D.R. Fortin, "Behavioral Outcomes from Online Auctions: Reserve Price, Reserve Disclosure, and Initial Bidding Influences in the Decision Process," *Journal of Business Research*, Vol. 58, No. 10:1409-1418, 2005.

Wang, W. and I. Benbasat, "Trust in and Adoption of Online Recommendation Agents," *Journal of the AIS*, Vol. 6, No. 3:72-101, 2005.

Wells, J.D., J.S. Valacich, and T.J. Hess, "What Signal Are You Sending? How Website Quality Influences Perceptions of Product Quality and Purchase Intentions," *MIS Quarterly*, Vol. 35, No. 2:373-396, 2011.

Wixom, B.H. and P.A. Todd, "A Theoretical Integration of User Satisfaction and Technology Acceptance," *Information Systems Research*, Vol. 16, No. 1:85-102, 2005.

Zhang, J., "The Roles of Players and Reputation: Evidence from eBay Online Auctions," *Decision Support Systems*, Vol. 42, No. 1:1800-1818, 2006.

Zhou, M., "Reference Price Effect and Its Implications for Decision Making in Online Auctions: An Empirical Study," *Decision Support Systems*, Vol. 54, No. 1:381-389, 2012.

Appendix 1: Summary of Variables

#	Variable	Meaning	Relevance to Strategies
1	**#CNTL**	The Number of Controllers	Transaction Enhancement
2	**#GAME**	The Number of Games	Transaction Enhancement
3	**ABME**	About Me	Trust Enhancement
4	**ACCS**	Have Accessories (Controllers) or Not	Transaction Enhancement
5	**BRKN**	Broken Item or Not	Product Attribute
6	**BYNW**	Buy-it-now Option	Transaction Enhancement
7	**COND**	New Item Or Not	Product Condition
8	**GAME**	Have Games or Not	Transaction Enhancement
9	**GIFT**	Gift Wrap Service	Transaction Enhancement
10	**INSU**	Shipment Insurance	Trust Enhancement
11	**LOG(FLSZ)**	File Size (logarithmic value)	Transaction Enhancement
12	**LOG(LNGT)**	Auction Length (logarithmic value)	Transaction Enhancement
13	**LOG(#PICT)**	Number of Pictures (logarithmic value)	Trust Enhancement
14	**MEMB**	More-Than-One-Year eBay Membership	Trust Enhancement
15	**OFFH**	Off-working-hours Ending Time	Transaction Enhancement
16	**PABP**	PayPal Buyer Protection	Trust Enhancement
17	**PYMT**	More Than One Payment	Transaction Enhancement
18	**PAYP**	PayPal Payment	Trust Enhancement
19	**PPFB**	Percentage of Positive Feedback Ratings	Trust Enhancement
20	**PWSL**	Power Seller	Trust Enhancement
21	**RETN**	Return Policy	Trust Enhancement
22	**RSPR**	Setting Reserve Price or Not	Transaction Enhancement
23	**SLFD**	Seller Feedback Scores	Trust Enhancement
24	**SSPN**	Setting Starting Price or Not	Transaction Enhancement
25	**SHIP**	Free Shipment	Transaction Enhancement
26	**INTL**	Ship to World	Transaction Enhancement
27	**SLIM**	Slim Model	Product Attribute
28	**LOG(START)**	Starting Price set by Sellers(logarithmic value)	Transaction Enhancement