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Art auctions on eBay

An empirical study of bidders' behavior on eBay

Master's thesis within Economics and Management of Entertainment and Art Industries

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Jönköping, June 2011

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Date: 2011-05-31

Subject terms: **eBay, auction theory, Late bidding, Sniping, online art auctions**

Abstract

This paper explores the determinants of the number of bidders and final price of 1900s oil paintings auctioned by resellers or dealers on eBay art auctions. We find that starting price has negative effect on bidder's decision whether to enter the auctions or not while seller reputation variables such as seller´s feedback, being top rate seller has a positive effect. Furthermore, auction theory is introduced to study the bidder´s behavior through auction characteristics and final price. We find that, interestingly, the seller´s reputation variables have no significant effect to the final price and the number of bidders has positive effect toward final price of art work. This evidence means that art auctions on eBay has a private value auctions characteristic. However, some specific characteristics of online auctions, which are the last minute bidding and the presence of experienced bidders, significantly affect the final price. Being an experienced winner or using last minute bidding as a strategy substantially pay more than inexperienced winners or winners who do not use last minute bidding in auctioned painting. This could result from different preference of bidders toward auctioned painting or information on which each bidder is holding.

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1. Introduction

A painting is a capital good. A decision to invest is partly based on expectations about the development prices in the future while consumption decision-making is subjected to budget constraint or aesthetic taste. (Andersson & Andersson, 2006)

In the past the methods of display and sales of art pieces were restricted to a few hands. One would have found an interesting art piece through traditional auctions or by a chance at a gallery. Now the scenario has changed. With the creation of online auctions art pieces becomes accessible for an interested people. For example, online auctions give bidders convenience with extensive listing and powerful search engine. This can create a liquid market for paintings expanding the pool of potential sellers and bidders.

The difference in mechanism of traditional auction and online auction may also affect bidders' behavior. Traditional auctions use ascending auction where the price keep rising and winner is the person who admit to offer the highest bid, however online auctions are similar to second-price auctions where the winner pays only the second highest price plus a small increment. In traditional auctions, bidders are aware of the number of others bidders and the highest bid at any point in the auction (Diekmann et al., 2008). In addition, traditional auctions require all bidders to participate at the same time. Hence, there is more flexibility to submit bids in online auctions where bidders can choose the time to participate. This revealed new behavioral patterns such as late bidding, or sniping[1]. Moreover, since transactions mostly happen when bidders and sellers have had little or no previous interaction, this generates risks to both parties. (Houser & Wooders, 2006). Online auction sites encourage sellers to provide adequate information and offer reputation system to reduce this problem.

With the specific characteristics of online auctions, the question arises that what is the behavior of bidders in online auctions. The paper use auction theory to explain this situation. Researcher uses the auction theory to study bidder's behaviors when they bid a piece of art on eBay. eBay is the world largest online auction website offering various categories of items, art works are also included. The huge amount of traffic and potential buyers who regularly visit the site make art auction pretty easier for everyone. Auction theory categorizes an auction into two types which are the private value auction, when the value of item is determined by the bidder herself, and the common value auction, that the value of the item is the same for everyone. Bidders act differently to each types of value.

1.1 Purpose of study

The purpose of this study is to estimate the variables those attract bidders on eBay art auction by using Poisson regression, and to study and to explain the final price of auctions which are affected by auction characteristics such as how bidders react to the final price when there is a new competitor (bidder), how seller's reputation affects the final price and how much the winners who use late bid strategy pay more than the winners who do not use late bid. This is performed by Tobit regression analysis.

[1] Auction sniping or late bidding is the process of placing bids at the very end of auction. This results in an increment higher price than prior bidder does and the auction sniper wins the item with less monitoring.

1.2 Structure of the paper

In the first part, the paper describes the background of eBay auction and eBay art auctions, including the literature related to study.

In the second part, the paper introduces auction theory, which is used in this paper to test the hypothesis.

In the third part, the paper explains data and methods used in the analysis.

The following section, the paper presents the empirical results and the last part concludes the paper and suggests further studies.

2. Historical Background

eBay is an American e-commerce website founded in 1995. At the beginning, eBay was a place to auction collectable items. It gained popularity from being a first marketplace for Beanie Babies[2]. Nowadays, overall only 12% of the listing is auctioned adding up to 9.4 million auctions (Hasket & Sickles 2010). A variety of products is routinely auctioned on the web. The efficiency of the web in matching potential buyers and sellers becomes an alternative way for traditional auction. The auction space provides special opportunities to both buyers and sellers. According to Hasker & Sickles (2010), for sellers, eBay gives an opportunity to sell products in a fast and time-controlled way. In addition, since eBay was the first internet auction site, it has always benefitted from the network economies of a marketplace. Buyers want to go where the most sellers are and sellers want to go where the most buyers are. For buyers, they gain some flexibility on their expense because of the relatively low price and cost of an auction. One can buy anything from antique shops to motors or even real estate. Millions of items are sold for where shipping exceeds the sales price.

Only sellers are responsible for the fee incurred by eBay. Sellers have three different methods to sell their items. They can use an auction, fixed price (Buy it now) which buyers can purchase immediately without putting their bidding (like in the traditional trade), or bargaining (Buy it now or Best offer): when they are selling the items with fixed price (eBay.com, 2011b, 2011c). With best offer option, buyers can offer the sellers the price they want to pay. Seller can accept, reject or make a counteroffer. In an auction, they set a starting bid with/without buy it now option, the duration of the auction, and the shipping cost. In addition, the details of items are described by sellers in the form of texts or pictures with the method of delivery and method of payment. Sellers have an option to set the reserve price which is not publicly shown. The reserve price ensures that sellers receive their satisfied prices. Otherwise, the auction is cancelled. For an auction, there is an insertion fee which is ranged from free when there is no secret reserve price or the starting price starting from $0.01 to $0.99 and up to $2 when the starting price or secret reserve price is equal greater than $200. After sellers had sold the items, they faced fees which were based on the set up price and final price. The final fee charged for auction style is 0 if the item is not sold and 9% of sale price with the maximum charge $50.00 (eBay.com, 2001a). Comparing to the traditional auction house like Sotheby's where the charge on the final sale price can be as high as 35% for seller and buyer is also obligated to pay the fee as auctioneer called a premium.

eBay is now the strongest online auction marketplace in the United States (Hasker & Sickles 2010). eBay is extensively studied within online auction area as eBay provides a rich resource for the auctions. Generally, a number of identical items are listed and auctioned in a specific time with the historical number of bids and historical number of bidder (if any). The information obtained from eBay provides an excellent opportunity to study various topics.

The auctions on eBay come in the form of proxy bidding[3] with an employment of English auction and second-price auction. English auction is the most common type.

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[2]Beanie Babies is a stuffed toy, made by Ty Warner Inc.

[3] An auction with a "robot" or bidding agent that helps bidder to automatically increases bid up to bidder´s predetermined value

Price is continuously rising until only one bidder remains. That bidder wins the object at the final price. The auction can be run by a seller who announces the price or buyers that call out the prices. The price successively rises as bidders gradually leave the auction. Bidders are not allowed to rejoin the auction once they left. An advantage of English auction is that a bidder gain information during the auction. Bidders dropping out, a new incoming bidder, the current high bid can tell a bidder a lot about the valuations of others then bidder uses the bid information to revise her valuation. However, the weak point of English auction is that bidders are likely to bid dishonestly.[4]

Second-price sealed-bid auction help auctioneer to fix the weak point of English auction since bidders individually offer single bid. The winner with the highest bid gets the object. Thus there are more incentives for bidders to summit the true willingness to pay when she just pays for the second-highest bidder's bid.[5] English auctions produce the same revenue to the sellers as a second-price auction, because the price is gradually raised until the second-highest bidder drops out, and that bidder wins the object and pays the price of the second-highest bid plus an increment of fee at final price.

Proxy bidding

The auction starts by having the seller announcing the reserve price (initial price). The bidder, thereafter, submits electronically the absolute maximum that she is willing to bid for an item. Before putting a bid, she knows the current bid, the identity of the seller (using feedback value system), the starting and ending of the auction and the item description. Additionally, she also has the historical bids as the information in case she is not the first bidder. Bidders use historical bids to estimate other's value of the item. eBay places a bid on her behalf and continues to bid whenever she is outbidded by other bidders until the maximum amount that she puts is exceeded or she wins the auction. This function is available for every bidder. eBay calls this the "automatic bidding" function. The positive effects of this technology is to help bidders monitoring the auction with the probability to win the item at a fair market value and helping bidders to win against snipe bids. eBay has no role in the actual exchange of items. The winning bidder and seller complete the transaction by themselves. Table 2-1 demonstrates how the proxy bidding works.

[4]For example, if you value the painting at $1000, and the second-highest bid is now $500, then you will bid just an increment such as $550. You would not bid at $800 when you have a chance to win the item for $550. Hence, in English auction the best strategy is to bid less than you value for the item or "shade your bid".

[5]For example, bidder A's valuation for the item is $10000. Suppose that the competing bid is $7000, bidder A wins the item and earns $3000 as her surplus.

Table 2-1: How does proxy bidding work

Bidder	Maximum willing to pay	Current Price	High bidder
A	30	10	A
B	15	15.5	A
B	35	30.5	B
A	60	35.5	A

From Table 2-1, a bidder is asked to enter the maximum amount she is willing to pay for the item. Suppose the seller sets the minimum bid for a piece of artwork at $10 and a bid increment of $0.5, bidderA enters $30 as her maximum amount. eBay will place a bid just high enough to exceed the reserve price (if any) or make bidderA a high bidder. This means that bidder A might win the auction with less than her maximum bid, so eBay automatically set the current bid to $10. Next, another bidder, let say bidderB, bids this item to $15. Since his maximum amount is less than $30, the current high bidder is still bidder A with $15.5 as a high bid ($15+$0.5 as an increment). BidderB tries again and submits his proxy bid to $35. The situation is changed because bidderA is outbidded. Now bidderB is the high bidder with $30.5 as his bid. eBay will send a notification to bidderA. If bidderA wishes to bid more, she can submit new proxy bid until the listing ends. Suppose that bidderA submits $60 as a new maximum bid, she wins the auction and pay only $35.5. When the auction ends, the winner will be notified about whether she has won and what she can do next.

2.1 eBay art market

There are three categories of art items offered in eBay art auction; "*direct from the artist*", "*wholesale lots*" and "*art from dealers and resellers*". Buyers can choose art works from fixed price option, entering the auction or bargaining with sellers on specific items. Many styles in different date of productions are offered. Buyers can fine an old realism painting from the1900s or 2000s pop art painting. There is an interesting survey about the general characteristics of art eBay in 2003[6]. The research focused on only auctions classified as "paintings" and only classified from 1950 to present. They found that out of the 600,000 post-1950 paintings, more than 90% of the art listing is under the $100 range. After $100, the listing and sales drop off very quickly. Figure 2-1 demonstrates the number of eBay art auctions listed in one month during October and November 2003.

[6]The research was conducted byHttp://www.elise.com

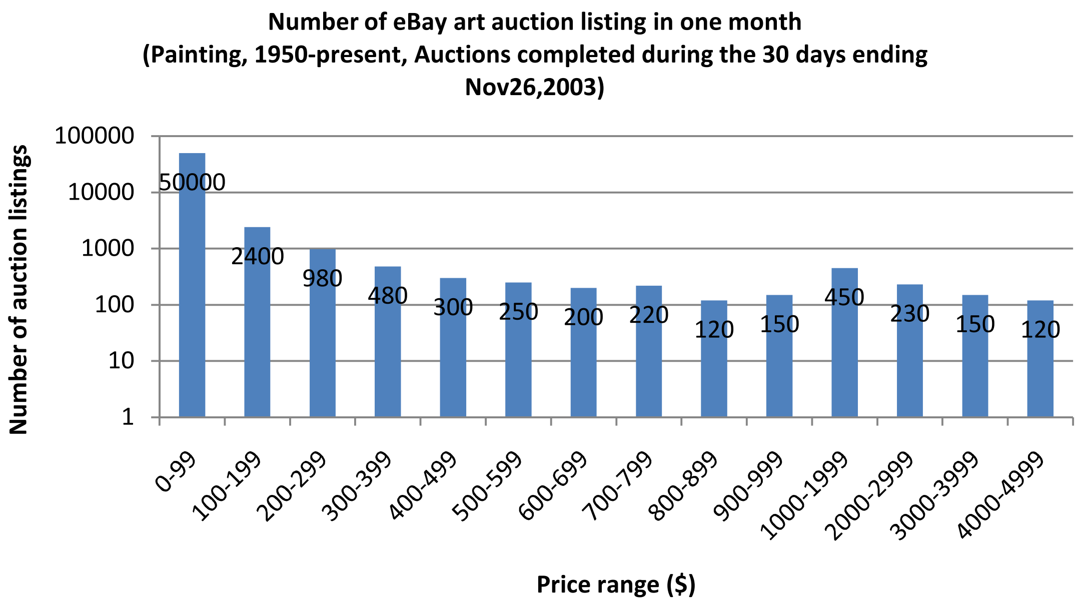

Figure 2-1:eBay art auction listing in one month; Source: http://www.elise.com

The lower the price of the arts, the higher the number of bids and greater percentage of completed sales. From Figure 2-2, approximately 45% of the paintings listed in the $300-$399 range has bids. In addition, the percentage gradually decreases to approximately less than 10% once over $1000 levels.

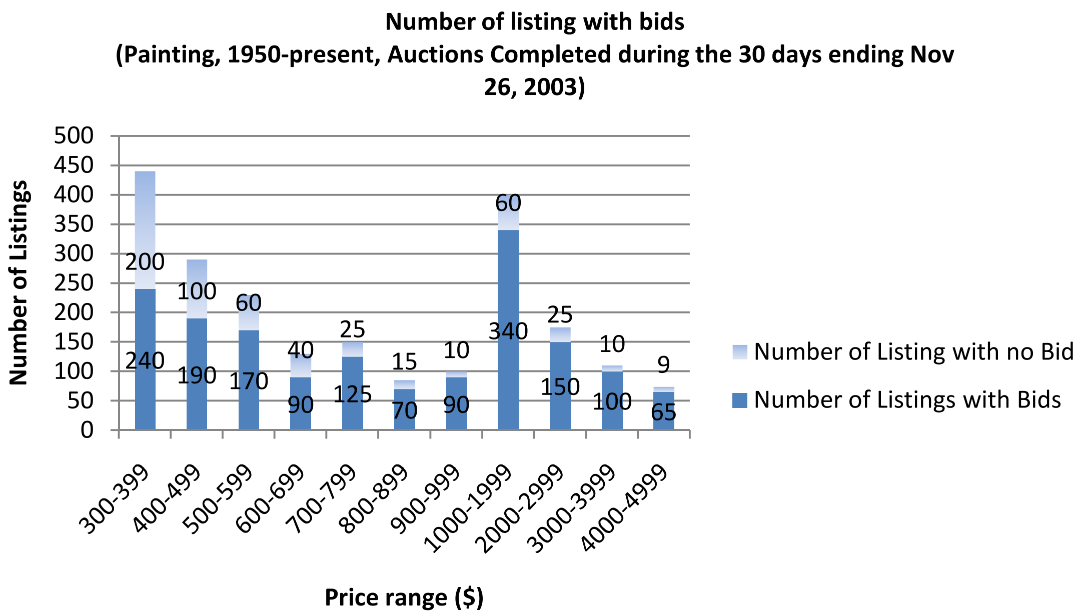

Figure 2-2: The number of listing painting with bids; Source: http://www.elise.com

Sale revenue will usually be divided half-and-half between gallery and artist. Online auctions not only offer low rate of fee, but also the opportunities to represent themselves directly, without going through a gallery. Researchers from elise.com conclude that the biggest risk for an online buyer of a painting is the fraudulent; you might not get what you see. In addition, buyers have to face uncertainty with the quality of the painting because a computer screen might not have the decent resolution to accurately present the true color and aesthetic feeling. It is hard to value what you are buying. On the other hand, the low price of paintings may make buyers more willing to take the chance.

2.2 Related studies

According to Ashenfelter & Graddy (2002), the most of important of art is settled by the public auction. The auction system plays a significant role to determine the incentives for works of art because auction systems work as a tool to transfer public preferences to the value of artistic work. Milgrom & Weber (1982) say that the basic idea is that there are good reasons for auctioneers to signal the truthful information as the information can reduce uncertainty and lead to more aggressive bids which raise the total revenue for auctioneers. With the invention of online auction services such as eBay, The U.S. Commerce Department says online shoppers spent $165.4 billion in 2010 rising 14.8%. Internet auction sales, which are a part of the Ecommerce market such as eBay, the largest online auction company, has 5 year average growth at 15%. eBay's total gross revenue amounted to $9 billion in 2010 (eBay annual report, 2010). Bajari & Hortaçsu (2003) say the rapid development of online auction has three reasons. First, low cost of operation attracts both buyers and sellers to enter the online auction market especially on illiquid markets such as specialized collectibles. The second reason is that online auction sites replace more traditional markets as online auctions extensively use technologies to reduce searching cost e.g. by using powerful search engines. This results in the creation of liquid markets for special categories. Anderson (2006) uses a 'long tail' to explain the phenomena. He argues that if the store or distribution channel is large enough, the collective sale of the products in low demand can make up or exceed the bestsellers. Finally, online auction sites provide the community for buyers. Most online auction sites have an active web board where each buyer can share knowledge globally. This is one of the attractions of online auction. Art products are also included into the line of online auctions. eBay have made art auctions a way not just to only occur with million-dollar works but also into the daily lives of ordinary.

Whether it is traditional auction or online auction, the reasons to enter an auction and the final price of items are influenced by many factors. According to economic and marketing theory, a successful transaction will occur when a seller and buyer trust one another (Swan & Nolan, 1985).

Not only the quality of the items that sellers have more significantly information than buyers, but buyers have to rely heavily on trust to sellers (or dealers). A number of studies on internet auction are related to the reputation system. A good reputation sellers help establish the trust that is necessary for the transaction to take place and affect the price. Trust is required because both parties incur risks. Buyers counter greater risk than sellers since the cost of asymmetric information is higher. They face two types of risks: the transaction risk regarding the seller's honesty and ability to serve the contract, and asymmetric information concerning the quality of the product (Akerlof, 1970).

Sellers bear possibility of none or delayed payment and a lower price in the case of auction (Andrews & Benzing, 2006). Houser & Wooders (2006), McDonald & Slawson (2002), or Melnik & Alm(2002), have consistent finding that, ceteris paribus, positive feedback sellers receive higher auction prices than those who do not. Houser & Wooders(2006) conducted research about Pentium III processors and found that reputation has a statistical significant effect on the price. McDonald & Slawson(2002) found that, in an auction for limited edition Barbie dolls, the higly rate sellers could earn $12 extra per transaction.

Melnik & Alm (2005) who research about coin auction on eBay also add that reputation matters for non-homogenous items which have higher uncertainty about the condition and quality of the items. Negative rating had more significant effects on expensive coins than less expensive ones. Dewally & Ederington (2006) report that a rise in the percentage of negative feedbacks from 0% to 3% lead to 0.15 to 0.18 decrease in the number of bidders. Eaton (2005) studies the effect of items information on the probability of sale and the high bid price (final price) of guitars on eBay. He finds that the lack of physical inspection of items before making a bid raises the uncertainty for bidders. Some information items such as pictures reduce asymmetric information and, interestingly, result in that negative feedback does not have negative impact on high bid. He gives the reasons are that buyers already know that high feedback value of seller might lead to the possibility of high negative feedback , in addition, the existence of negative feedback may inspire buyers to communicate with sellers more.

McDonald & Slawson(2002) and Lucking-Reiley et al. (2000) find that high starting price discourage bidders. However, Li et al. (2004) argue that a high starting price sends a product quality signal to the bidders. The quality signal serves bidders as a pricing indicator, which assumes that the higher the starting price, the higher the quality, thus, it results in a positive relationship between starting bid and final price. Highfill & O'Brien (2007) found that the starting price had a positive effect on the final sale price, but in only marginally. Not only does it have an effect on final price, there is also a significant relation between starting price and the determinant of entry.

Bajari & Hortaçsu(2003) indicate that the starting price has negative effect on the number of bidders ,however it is not significant. They suggest that the seller sets a low starting price to encourage entry. In line with Bajari & Hortaçsu, (2003), Highfill & O'Brien (2009) say that the effect of the starting price on the probability of baseball cards sale. They find that the minimum price of cards mostly represent the card book value. The result is that there is no significant effect from starting price on the probability of sale. Meanwhile, Ku et al.(2006) have an opposite result. They use the term "auction fever" to explain why there is a negative effect of the starting price on the final price. A low starting price attracts bidders to bid more which leads to a bidding war and eventually drives up the item price. The next variable that can affect the determination of entry and final price is the length of auction. Sellers can choose the length of auction from 1 to 10 days. Lucking-Reiley et al.(2000) found that the length of an auction was positively related to price. Highfill & O'Brien(2007) report that the auction length has a significant positive effect on the number of bids. However, there is no significant effect on the final price. Neither, McDonald & Slawson(2002) find a significant relationship between the length of auctions and the final price.

His most relevant for this study using auction theory to determine the number of bidders. Normally, the relationship between the number of bidders and final price is positive as the price rises with an additional bidder (Bajari & Hortaçsu 2003, Dewally & Ederington 2006, Highfill & O'Brien 2007). Auction theory suggests that an item is composed of a private value and/or a common value. The private value is the value that each individual bidder has while the common value is the instinctive value of items that will be equal to everyone. Bidders have a dominant strategy[7] when she has her private value, thus she bids actively until her value. Hence, the value of non-durable consumer goods are mostly explained by the private-value assumption (Milgrom & Weber 1982). On contrary, for a common value, consider the situation in an auction for telecom service rights where the value of the rights depends on expected amount of users, the coverage areas or the length of contract. The value of this auction depends on bidder's private information and the others' valuation of this contract. Bidders, thus, are influenced by other bidders in the evaluation. Studying the effect of an additional bidder on final price could differentiate the private value auction from common value auction.

To be specific, winner's curse is the property of a common value auction when the winner suffers from paying more than the items instinctive value. The winning bidder has higher probability to over-estimates the value of item when the number of bidders increases, thus rational bidders tend to decrease their bid (Dewally & Ederington 2006). Paarsch (1992) points out that more bidders would imply that bidders are optimistic. If the winner's curse exists, bidders will lower their bids in equilibrium. Bajari & Hortaçsu(2003) measure the effect of the winner´s curse, which is the character of a common value auction, and find that bidders lower their bids by 3.2% per each additional bidder. Dewally & Ederinton (2006) examine how the final auction price changes as the number of bidders increases. They find that there are three reasons for why the price increases with the number of bidders. First, the item is a private value auction. Second, some bidders fail to adjust for the winner´s curse. Third, bidders cannot predict the number of total bidders. Yin (2004) finds that the winners of auctions paid more than estimated value in 9% which is the evidence of the winner's curse.

Reddy & Dass (2007) study factors that affect final prices of art objects and related price movements using data from Saffronart.com, the leading online auction house of modern Indian art. They find that the number of bids is highly correlated with the number of bidders which may result in stronger competition and higher prices. In addition, the evidence suggests that the number of bidders has a positive relationship on price level in the beginning of the auction, but then decreases towards the end of the auction. The first article that examines online art auctions by using data from eBay is Highfill & O'Brien (2007). The question of the paper is whether the art auctions on eBay are art for consumption or art for investment. They collected data from eBay and admitted that there is evidence of a positive relationship between the number of bids and final sales price. This generally means that art auctions on eBay are not investment art. In addition, they suggest that an investment art should be, at least, $5,000. However, in their data, only seven sales were in that range.

One interesting bidding behavior in online auctions is late bid or last second bidding. Auctions on eBay have a hard close ending[8] which is different from traditional auction that has soft close ending[9]. Although eBay and sellers advice that bidders

[7] A Strategy is dominant if the strategy earns a player a larger payoff than any other regardless of what any other players do. Hence, a strategy is dominant if it is always better than any other strategy of other players' actions. For example, if she is willing to pay $1000 for painting regardless of other´s value, she has the dominant strategy to other players who are willing to pay less than $1000.

[8] The auctions end at the specific time.

[9] The item will be sold at the highest bid price when auctioneer has confirmed that there are no participating bidders who are willing to make a higher bid.

should submit their maximum willingness to pay when entering the auction[10], bidding in the last minute or seconds in an auction is an optional strategy in online auctions with fixed end-times. Theoretically, late bidding should not be optimal because of eBay's proxy bidding system (Wintr, 2008). Bajari & Hortaçsu (2003) report that more than 50% of final bids arrive after 90% of the auction duration has passed. Moreover, the 25% of winning bids were submitted in the last eight minutes of a three-day auction. Hayne et al. (2010) support that late bidders are overwhelmingly successful at winning auction. The reason is that experienced bidders bid late in order to prevent other bidders to use bid information to update their prior valuations. Roth & Ockenfels (2002) compare the late bidding characteristic on eBay and Amazon. They find that the fraction of late bidding is considerably larger on eBay than on Amazon, which has a soft close ending rule, and more experienced bidders tend to use late bidding on eBay. They explain that late bidding would result in two issues. First, last-minute bidding is an optimal response to the presence of bidders who use incremental bidding[11]. Bidding late deprives the incremental bidder to respond with enough time. Second, late bidding might be an optimal strategy for experienced bidders who want to protect their private information concerning the value of item from others. Bidding just before the end of an auction allows her to profit from her information without leaving sufficient time for other to reexamine the item. However, another possibility of why bidders use late bids is that bidders may not know their personal valuation of an item and, rather than searching for it, they just simply wait until the end of auction and place a late bid. (Bajari & Hortaçsu, 2003).Hasker & Sickles (2010) add another reason that the presence of late bidding may be because the seller may engage in *shill bidding*[12]. Shill bidding is the evidence that there is a third party bid in auction in order to drive up the price and the simple best strategy is to use late bid

[10]"If someone does outbid you toward the last minutes of an auction, you may feel unfair, but if you had bid your maximum amount up and let the Proxy Bidding system work for you, the outcome would not be based on time" (http://pages.ebay.com/aw/notabuse.html, 1999)

[11]Incremental bidderscontinuously raise their bids to maintain thestatus of the currently winning bidder.

[12]A purpose of shill bidding is to find the current high bid. For example, assume that the current price is $30 and the current highest proxy bid is $ 50. If the shill bids are entered $49.19, the current price will be $50 and the shill bidder can stop her bid.

3. Theory/theoretical framework

Auction theory

Auction theory is the study of auctions using principles of economics and game theory. In present time, auctions are implemented to conduct a huge number of economic transactions. Governments use auctions to sell telecommunication rights, treasury bills or including electricity. In addition, firms subcontract or order materials through auction. Art and antiques are commonly sold in auctions.

According to auction theory, most auction models are composed of two elements that are private-value and common-value (Klemperer, 1999). William Vickrey, a pioneer in the economics of incentives and Nobel laureate in 1996 found that in auctions each bidder has his/her own "private value'' which is the individual value of each item for sale. For example, if a Picasso drawing is being auctioned and you want to buy it simply because you like it, then knowing how much others or rivals value it will not affect how much you value it yourself. This might be regarded as buying a work of art for the purpose of private consumption. By contrast, the common-value is the actual value equal to everyone, but each bidder has private information about it. For instance, the value of an oil-leased depends on how much the crude oil underground, and the amount is varying between different geological data that each bidder has access to. In this case, bidders might change their estimated amount (also value) when they know others' information (Klemperer 1999). Wilson (1967) shows that the auction price is a better estimator of the true value of an item when the number of bidders becomes larger.

Private value

When bidders completely ignore their common value signal, the efficient private value auction has occurred (Goeree & Offerman, 2002). Each potential buyer knows the value of the object to herself that is assumed to be independent from others' values then her dominant strategy is to submit the bid equal to that value (Milgrom & webber, 1982). According to the eBay system, Reiley(1999) points out that Vickey auctions ,which is the same as second price auctions, eliminate incentives for sniping and restore the maximum willingness to pay by bidder. Consequence, in auctions of consumer goods, there should be a positive relationship between the number of bidders and the final selling price since an increase in the number of bidders increase the range of minimum prices (or reserve prices) when the bids are drawn(Highfill & O´Brien 2007). In addition, the number of bidders should not have an effect on bids since they will keep bidding their valuation as the dominant strategy (Bajari & Hortaçsu 2003).

Private value in eBay art auctions

According to Milgrom & Weber (1982), bidding pattern differs due to private value and common value assumptions. There are two assumptions. First, in the private value model, one has her private value when she knows her value of the painting and, the second that values are independent.

In addition, the value of a painting is contributed by the assumption that, (1), if the painting could not be resold later for identified price, (2), intangible value such as "prestige value" by owning an admired artist of bidder is independent from others and the authenticity of painting may be difficult to know. The second assumption rules out the evidence that other bidders may have information about that painting or they have the same thinking that the painting is particularly fine then they are likely to value it highly.

The easiest way to determine a private value is given in this example. Assume that a bidder interests only is her private value in consumption art. One of the auctioneers offers an original color lithograph of Picasso for $15,000. Our bidder would be willing to pay up to, for example, $20,000. She does not care if there are no other bidders or if any other bidder is willing to bid over $20,000. She is only interested in whether she can win this auction for $20,000 or less. As a result, keeping bidding until her preserved price.

Common Value

Common value is the key feature of an auction for any investment (Highfill & O´Brien 2007). From Robert Wilson (1967) suggests that when the item has a true value which can not directly observed by the bidders, for example, the item has resale value "V". Each bidder recognizes that she wins the object only when she has the highest value related to her information. By bidding early, a bidder may signal her information which cause other bidders to update their belief about V. This may increase the price that they have to pay. Indeed, lacking of taking others' values into account can lead to an over-payment more than the item is worth. In auction theory, this situation is called "winner´s curse". "Winner´s curse" is a failure in the evaluation of common value auction. In other words, bidders also base their estimation based on their information, the expected value of item, and they know that they can win the auction when their evaluation is the highest. Winning against others who follow a similar strategy means that your estimate is the overestimate of the least conditional on an event of winning. Assume that all bidders receive unbiased estimates of an item´s value, and then bids are an increasing function of these estimates. Thus, the most optimistic bidder is greatly overestimating the value of the item (Wilson, 1967). Rational bidders do not pay too much on average regardless of their information. Milgrom & Weber (1982) say that in order to prevent a winner´s curse, they predict that bidders will rationally be more cautious by lowering their bids, resulting in higher profits for the bidders and less revenue for the seller.

Common value in eBay art auctions

The problem of eBay art auction is that, for most of the art works, estimated value are not given by the auctioneers like in traditional auctions. This creates uncertainty since art evaluation is subjective and the value is unknown to potential bidders. For example, there are three bidders; they estimate the value of the work of art to $4000, $6000 and $8000 respectively when the late resale price of that item has been given a value at $6000. According to the example, the third bidder with the highest positive view by giving the highest offer price towards the item will win the auction. However, the bad news comes after when she finds out later that she paid $2000 more for the item. Winner´s curse results from bidders´ failure to adjust for adverse selection which is the nature of uncertain value item auctions. Inexperienced bidders are vulnerable to the winner´s curse (Kagel et al. 1989)

Bid shading is the strategy for bidders to avoid the winner´s curse. The intuition is that the distributions of their value estimations are probably very spread out when there are many bidders. They reduce the odds of the winner´s curse by placing a bid below what they believe the item is worth based on the number of bidders. However, to predict the number of bidders in online auction is difficult and uncertain. Dewally &

Ederington (2006) and Highfill & O´Brien (2007) separate the number of bidders into predicted and unpredicted number and find that an increase in the number of unexpected bidders has greater impact to the final price than the actual number of bidders. If the art auction on eBay has a common value, the final sale price should not increase with the number of bidders. In addition, the evidence that bidders could not predict the number of bidders is the late bid or sniping. Bidders try to adjust for winner´s curse but do not have full information regarding competitors, thus some bidders wait until the final minute of the auction to submit their bids in order to protect their information. Roth & Ockenfels (2002) and Dewally & Ederington (2006) report that the last minute bidding processes a common value element. Bajari & Hortcsu (2003) explain that bidders are indifferent when it comes to bid timing in a pure private values environment. Thus, bidding in the very last second would be favorable if there were a small element of common value.

To conclude, a bidder tends to win an auction more often if her estimated value is too high rather than too low. Each additional bidder tends to increase the auction final price. However, when the number of bidders increases, the probability that the winning bidder overestimates the item increases. Rational bidders should lower their bids as the number of competitors rises. Thus, if the price increases with the number of bidders, this indicates that

1. The art auction on eBay is a private value auction. An increase of bidders increases the final price regardless of predicted or unpredicted bidders.

2. The art auction on eBay is a common value auction, but bidders fail to adjust for winner´s curse. In order to avoid winner´s curse, bidders use a bid shading strategy. In bid shading strategies, bidders have to predict the number of bidders they are bidding against. If the bidder failed to predict the number of bidders, the final price is a function of unexpected bidders.

4. Methodology and Data

Data were collected from 901 eBay auctions on the "newly list" on Wednesday 13 April 2011 which represent the auction period from 6 April to 20 April 2011 by Java program and edited by hand. In the sample selection, first, we searched which keyword is the most commonly used in eBay art by "What´s hot"[13] service providing by eBay. *Oil painting* was the most popular keyword in the art category. Next, we followed that keyword and chose the *only auction* option in the painting category. We select 1900´s painting with all styles original painting *listed by dealer or reseller*. Since the sellers can mix auction type with fixed price selling, the sample with a "buy it now" option which allows bidders to win the item without entering the auction process was removed. In addition, "reserve not met" items, which represented that the final price did not exceed the secret reserve price, are also removed from sample. 275 items are auctioned in sample representing 30.52 % of the total sample.

4.1Empirical model

We choose to run a Poisson regression. A Poisson regression is suitable for the variable that is a counting number which is assumed to follow Poisson distribution.[14] In the model, we regress the number of bidders with auction characteristics and dummy variables to control the different styles of painting which are impressionism, realism, various types (abstract, modern, etc.) and not specific type (Undefined). In the model, realism is a based group.

$$\begin{aligned}\text{Numbidders} = {} & \beta_1 + \beta_2\text{Start} + \beta_3\text{Logfeedback} + \beta_4\%\ \text{negative} + \beta_5\text{Toprate} \\ & + \beta_6\text{Duration} + \beta_7\text{Impressionist} + \beta_8\text{Various} + \beta_9\text{Undefined} + \varepsilon_1\end{aligned}$$

Next, we obtain the residual from former equation in order to use it in the study of private value auction and common value auction in Model 1 and Model 2. Some auctions result in no sale because no one was willing to enter the auction. In this case, the number of bids is not observed. According to picture 4-1, the percentage of sale is uncertainty; around 25% of the paintings listed among \$0-\$99 have bids, 35% of \$100-\$299, almost 80% of \$300-\$399.

[13]A service that is freely provided for searching the current trend on eBay. (http://pulse.ebay.com)

[14] Poisson regression assumes that the data has a Poisson distribution which we frequently face when we are counting a number of events.

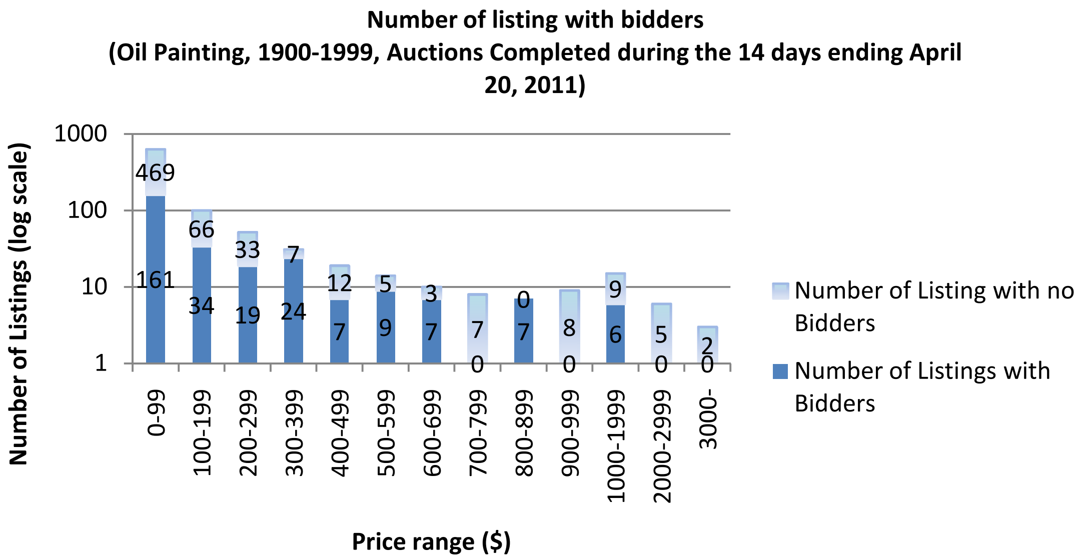

Figure 4-1: Number of listing with bidders

The paper handles this sample selection problem by a Tobit regression with the number of bids as a censoring variable.

- Model 1

$$\mathrm{LogFinal} = \beta_1 + \beta_2\mathrm{Numbidders} + \beta_3\mathrm{Logfeedback} + \beta_4\%\ \mathrm{negative} + \beta_5\mathrm{Toprate} + \beta_6\mathrm{Duration} + \beta_7\mathrm{Winnerexp} + \beta_8\mathrm{Latebid} + \beta_9\mathrm{ExpLatebid} + \varepsilon_2$$

- Model 2

$$\mathrm{LogFinal} = \beta_1 + \beta_2\mathrm{Residual} + \beta_3\mathrm{Logfeedback} + \beta_4\%\ \mathrm{negative} + \beta_5\mathrm{Toprate} + \beta_6\mathrm{Duration} + \beta_7\mathrm{Winnerexp} + \beta_8\mathrm{Latebid} + \beta_9\mathrm{ExpLatebid} + \varepsilon_3$$

4.2 Hypothesis

The purpose of this study is to examine bidders' behavior on eBay art auctions. We begin with an examination how the number of bidders is affected by auction characteristics.

In the final price model, we explore how the final price is determined by auction characteristics, the number of bidders and the number of unexpected bidders which is collected from the number of bidders equation, and then the late bid strategy, which is a specific characteristic of online auction that also affects the final price of item.

The hypotheses and intuitions for the number of bidders are described in Table 4-1 and the hypotheses and intuitions for the final price equation are described in Table 4-2.

- **bidders regression**

Table 4-1: Number of bidders hypothesis

Dependent variable: number of bidders (Numbidders)

Variables	Hypothesis	Intuition
Start	negative	High starting price scares bidders away from entering the auction.
Logfeedback	positive	High seller´s feedback attracts bidders to enter the auction.
%Negative	negative	Negative feedback makes bidders concerned whether the seller will fulfill the agreement. It creates uncertainty. Bidders would prefer not to enter the auction.
Toprate	positive	A good reputation of the seller induces bidders to place bid with confidence.
Duration	positive	Longer auction time persuades more bidders to enter the auction.

- **Final price regression**

Table 4-2: Final price hypothesis

Dependent variable: Log of Final price (LogFinal)

Variables	Hypothesis	Intuition
Numbidders	Positive	An additional bidder will increase the final price of auction.
Residual	Positive	Bidders cannot predict the total competitors. As a result, the number of unexpected bidders has a positive effect on the final price.
Logfeedback	Positive	High seller´s feedback decreases uncertainty, which results in higher price for seller.
%Negative	Negative	Negative feedback lowers bidders willingness to pay.
Toprate	Positive	Top rate sellers are able to earn more revenue than non-top rate sellers because their reputation reduces uncertainty.
Duration	Positive	Longer auction duration gives an opportunity to bidders to enter or raise their bids.
Winnerexp	Positive	Higher winner feedback means she is an experienced bidder. Since she is experienced about art online market, she knows how much she should pay for specific artwork than non-experienced.

Latebid	Positive	Late bidding will increase the final price of auction.
ExpLatebid	Negative	The experience bidders use late bid to conceal their information which results in a lower final price.

4.3Variables

- **Dependent variables**

Final sales price(LogFinal)

Final sales price is the final sale price of an item. For the auctioned items, the final price is greater than the starting price. On the other hand, for the non-auctioned items the final price is the same as the starting price.

Number of bidders (Numbidders)

Number of bidders represents the total number of bidders for each item.

- **Independent variables**

Starting price (Start)

The starting price is the minimum selling price set by the seller. There is no rule about setting price in eBay. Bidders could interpret the signal of the starting price. For example, a low starting price might either imply that the seller wants to attract many bidders or represent the low value of the item.

Log of total seller feedback (Logfeedback)

According to eBay, 2011d, eBay has a system for buyers and sellers to provide feedback on each other after transaction. The system works well if participants think it is working. Thus, buyers and sellers believe that inappropriate behavior will result in negative feedback. Buyers depend strongly on reputation since bad sellers will receive poor feedback and will be deterred. The feedback system roughly represents an eBay member reputation. It´s a result of comments and rating left by counter parties after transactions have occurred. Logsellerfeedback is the logarithm of total seller feedback score. The feedback score also represents the experience of the seller. The higher the score is, the more experienced of the sellers. Buyers can use seller feedback scores to screen the serious sellers who use eBay as their market place.

Percent negative feedback (%negative)

The negative feedback variable is measured as the percentage of negative feedback for a seller. The negative feedback is calculated by taking negative feedback divided by the total feedback times 100. Buyers use negative feedback to reduce uncertainty by looking at the seller´s profile why this seller got negative feedback. Former buyers always leave comments about the service and these comments cannot be removed by the seller.

Toprateseller (Toprate)

Toprate sellers, according to eBay, are power sellers with at least 100 transactions in the past year with a low detail seller rating (DSRs) with U.S. buyers. To be at the lowest level of power sellers need 100 items sold or $3,000 in sales with 98 % positive feedback. Hence, to be a toprate seller is considerably serious seller. In addition, bidders can contact toprate sellers 24/7 by telephone or internet. In this sample, Toprate seller is a binary variable.

Auction length (Duration)

Sellers choose the length of the auction before the auction starts. The days of auction varies from 1 day to 10 days.

Number of unexpected bidders (Residual)

Number of unexpected bidders is collected after running the number of bidders regression. Number of unexpected bidders is the result of the number of bidders minus the number of predicted bidders.

Winner feedback (Winnerexp)

As long as you pay for your item within the required time, sellers can always leave you with positive feedback, but can also leave negative or neutral feedback if you do not pay. We collect winner feedback from each item winner to be a proxy of the winner´s experience. This variable is categorized in two groups, winners with feedback lower than 400 and winner with more than 400 or winner who chooses to conceal the identity by presenting as “private” rather than number.

Last minute bidding (Latebid)

Last minute bidding is constructed as a binary variable when the winning bid is submitted last minutes before the end of auction.

Experienced sniper (ExpLatebid)

The experienced sniper is the interaction of two dummy variables winner feedback and late bidding (Winnerexp*Latebid). It´s introduced to see how much experienced winner who uses late bidding as a strategy pay more than inexperienced winner who does not use late bidding.

5. Empirical result

5.1 Descriptive statistics

Table 5-1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Start	901	171.331	430.349	0.01	7500
Final	901	228.716	540.704	0.01	7500
LogFinal	901	4.471	1.391	-4.605	8.923
%Negative	901	0.433	1.581	0	25
Seller feedback	901	1984.606	4352.957	1	70784
Logfeedback	901	6.369	1.759	0	11.17
Toprate	901	0.292	0.455	0	1
Numbidders	901	1.175	2.610	0	19
Duration	901	7.228	1.470	1	10
Winnerexp	901	0.119	0.324	0	1
Latebid	901	0.129	0.335	0	1
ExpLatebid	901	0.054	0.227	0	1
Impressionism	901	0.315	0.465	0	1
Various	901	0.185	0.389	0	1
Undefined	901	0.259	0.438	0	1
Realism	901	0.241	0.428	0	1

The starting price varies from $0.01 to $7500 with a mean of $171.331 while final prices of total observations are range between $0.01 and $7500 with $228.716 as its mean. The means of the starting price and final price for auctioned items are $64.32 and $248.34, respectively. This can be interpreted as if the auctioned items tend to have slightly lower starting prices and end up with slightly higher final prices compared to the total sample.LogFinal is logarithm of Final. Seller reputation variables compose of % negative feedback, Seller feedback and Toprate. Negative feedback ranks from zero, which means 0 % negative feedback to 25 % with 0.4% negative feedback as its mean. This means that for every 1000 feedback scores, the average negative feedback that sellers have is 4 times. In addition, the seller feedback, which represents the experience of a seller, ranges from 1 to 70784 with 1984.606 as mean. Logfeedback is the logarithm of Seller feedback. Being a toprate seller helps bidders to reduce uncertainty and make bidders bid closer to their valuation. 29% of the sellers in the sample are toprate seller. Next, the number of bidders has the minimum at 0 which means that the item is unsold and maximum at 19 with 1.175 as mean. The average duration of the sample is 7.228 days. In order to evaluate the winners´ experience, the dummy variables Winnerexp is collected. Winnerexp represents 12 %of the sample and 39 % of the auctioned items. We expect that highly experienced bidders will providea better explanation about the private and commonvalue auction. In addition, almost 13% of all paintings have late bids and almost 43% of all auctioned items have late bids submitted in the last minute of the auction. The average time of late bid is 6.50 seconds. According to Figure 5-3, 71% of the late bids is submitted less than 10 seconds before the end of auction.

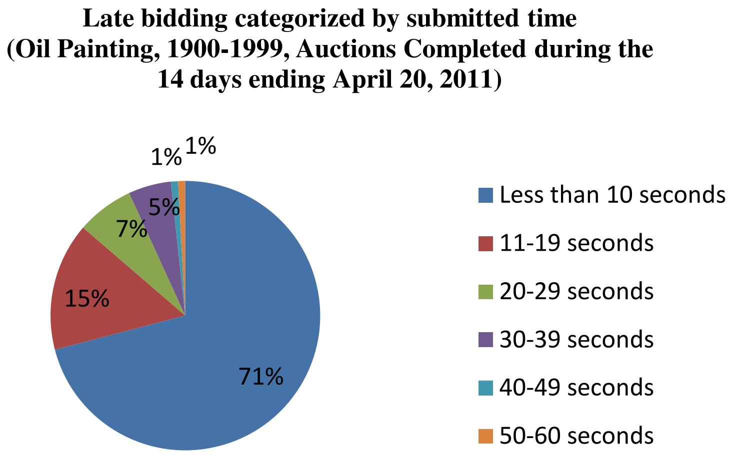

Figure 5-1: Late bidding categorized by submitted time

5.4% of the total sample is auctioned by experienced winners who use late bidding. The last set of variables is the styles art items. We divide the sample into 4 styles of art according to eBay definitions that are realism (Real), impressionism (Impressionism), various styles (Various) such as abstract, landscape, pop art, surrealism and Undefined by sellers (Undefined). Impressionism style is the largest proportion for total sample (around 32 %) while Undefined painting or realism styles make up around 25 % of sample. The rest is Various style.

5.2 The correlation analysis

Table 5-2: Correlation analysis

	Numbidders	Final		Numbidders	Final
Start	-0.1411*	0.7599*	**Winnerexp**	0.3685*	0.0164
Final	0.2532*	1	**Latebid**	0.6194*	0.1121*
%Negative	-0.0599	0.0201	**Impressionist**	-0.0456	-0.0775*
Logfeedback	0.2245*	0.0208	**Various**	0.0774*	0.0478
Toprate	0.1870*	-0.0158	**Undefined**	0.0905*	0.0273
Numbidders	1	0.2532*	**Realism**	-0.1135*	0.0127
Duration	0.2859*	0.1687*	**ExpsLatebid**	0.3553*	0.0661

*Correlation is significant at the 0.05 level

The correlations between the dependent and independent variables that are used in the models are summarized in Table 5-2. The paper provides more detail in the appendix.

From the table, we can observe that the number of bidders (Numbidders) has a negative correlation with starting price (Start) with a 5% significant level. In addition, log of total seller feedback score (Logfeedback) and the top rate seller (Top rate) also have a positive correlation at 5% significant level, while the negative correlation with percent negative feedback (Negative) is not significant. The length of the auction (Duration) also has a positive relationship at 5% level. Finally, the styles of painting (Impressionist, Various, Undefined, Realism), except Impressionist, have a significant correlation with the number of bidders at 5% level, but the correlations are not strong.

For the final price model, we observe that the final price (Final) has very strong relationship with starting price (0.7599), but the reason is that there are many painting ending up without bidders. In the data, eBay shows that final price equals starting price if there are no bidders. In the regression, a sample selection model is introduced. Interestingly, negative feedback (%Negative), log of total seller feedback (Logfeedback) and toprate seller (Top rate) have insignificant correlations with final price. Although, the correlations are not strong, number of bidders (Numbidders) and the length of auction (Duration) also have a positive correlation with final price. Moreover, the experience of the winner (Winnerexp) is not correlated with final price while the last minute bidding (Latebid) has a positive correlation with final price at a 5% significant level.

5.3 The regression analysis

The regression analysis part is divided into 2 parts, the number of bidders and the final price of auctioned item.

In Table 5-3, we use Poisson regression analysis to explore how auction characteristics affect the number of bidders. In table 5-4, we examine how auctions characteristics affect the final price of auctioned item by using Tobit regression analysis

Table 5-3: The Number of bidders result and marginal effect

Dependent variable: Number of bidders

Independent Variables	(1) Poisson regression	Marginal effect Poisson regression
Start	**-0.0092*** **	**-0.0031*** **
	(0.0007)	**(0.0001)**
Logfeedback	**0.183*** **	**0.0612*** **
	(0.022)	**(0.009)**
%Negative	-0.048	-0.016
	(0.061)	(0.021)
Toprate	**0.195*** **	**0.068***
	(0.075)	**(0.028)**
Duration	**0.313*** **	**0.105*** **
	(0.020)	**(0.012)**
Impressionist	**0.515*** **	**0.192*** **
	(0.104)	**(0.046)**
Various	**0.978*** **	**0.464*** **
	(0.106)	**(0.080)**
Undefined	**0.516*** **	**0.198*** **
	(0.102)	**(0.049)**
Constant	**-3.453*** **	
	(0.224)	
Observations	901	
Pseudo R-squared	0.301	
Log likelihood	-1407.7266	

Note: Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

The number of bidders is predicted by a Poisson regression because the number of bidders is count numbers, which are always greater than zero. However, one cannot directly interpret the marginal effect from the Poisson coefficient. The last column of table 5-3 provides the marginal effects from the Poisson regression. The result shows-that the starting price has a very significant negative effect to the number of bidders at 0.1% significant level. $100 increase of the starting price discourages 0.3 bidders to enter the auction keeping everything constant. Many auction starts at very low starting price levels to attract bidders.

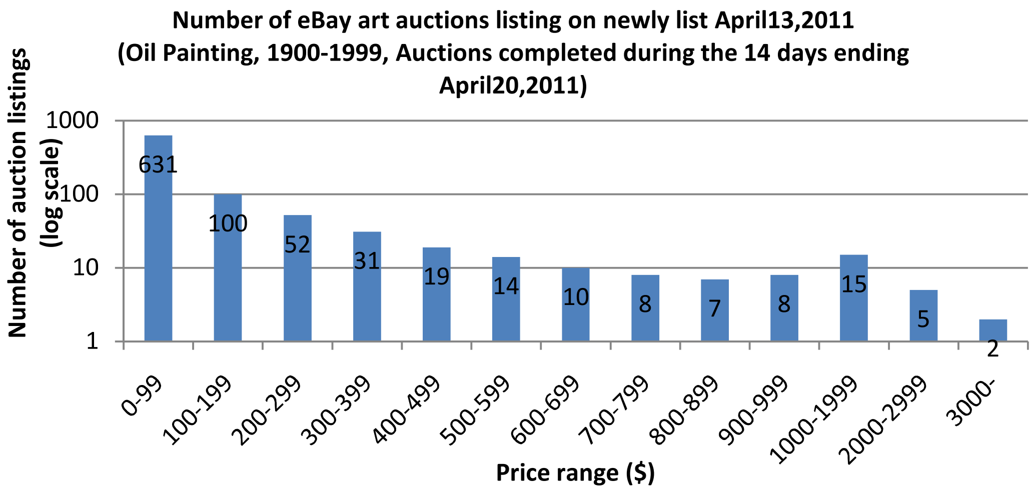

Figure 5-2 Number of listing paintings by start price

According to figure 5-2, for 70% of the sample, the starting price ranges between $0-$99. A $100-$199 starting price accounts for 11% of the sample and gradually decreases with an increase in the starting price. Note that, even though the starting price has a significant effect on the number of bidders it has very small size effect. For the sellers' reputation variables, keeping everything constant, negative feedback has a negative effect on the number of bidders, but it is not significant. A 10% increasing in seller feedback induces more bidders to the auction less than 1%. In addition, at 5% significance level, being a toprate seller leads to an estimated increase of 0.07 the number of bidders compared to non-toprate sellers. Duration also has a significant positive relationship with the number of bidders. 1 day increasing in auction length leads to 0.11 increasing in number of bidders. The longer the period of the auction, the higher the number of bidders keeping everything unchanged. Finally, there are four dummy variables used to categorize the art items. The regression shows that, using realism oil painting as a based group, the rest of styles attract more number of bidders to the auctions keeping every variable constant. Impressionism, Various and Undefined styles attract 0.19, 0.46 and 0.20 more bidders compared to realism style.

We obtain the residual from the Poisson regression in order to use it as number of unpredicted bidders variable (Residual) in the Final price model presented in Table5-4

Table 5-4: The final price result

Dependent variable: Log of final price (LogFinal)

Independent Variables	Tobit Model 1	Tobit Model 2
Numbidders	**0.742*****	
	(0.057)	
Residual		**0.808*****
		(0.070)
Logfeedback	-0.106	0.134
	(0.084)	(0.086)
%Negative	0.021	-0.009
	(0.072)	(0.076)
Toprate	0.182	0.567
	(0.317)	(0.324)
Duration	-0.102	**0.305*****
	(0.087)	(0.086)
Winnerexp	**5.283*****	**5.743*****
	(0.454)	(0.471)
Latebid	**3.802*****	**4.510*****
	(0.471)	(0.481)
ExpLatebid	**-4.800*****	**-5.282*****
	(0.713)	(0.741)
Constant	**-1.561***	**-5.462*****
	(0.818)	(0.842)
Observations	901	901
Pseudo R-squared	0.266	0.252
Log likelihood	-883.514	-900.805

Note: Standard errors in parentheses

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

The model 1, we regress the log of final auction price against independent variables in a Tobit regression. The result shows that *numbidders, winnerexp, latebid and ExpLatebid* are significant at the 0.1% level. In model 2, we use the *Residual* instead of *Numbidders* to explain how much unexpected bidders affect the final price. The result shows that it is significant at a 0.1% level. However, we cannot interpret the coefficients of a Tobit regression in the same manner as an OLS because there are three types of marginal effect possible of interest after a Tobit regression. First, the effect on the expected value of the latent variable. Second, the effect on the expected value of dependent variable conditional on it being larger than the lower bound (in the regression means paintings are being auctioned). Finally, the effect on the probability of being larger than the lower bound (being auctioned). The results of marginal effect are demonstrated in Table 5-5 and 5-6. This paper focuses on the first column which is the marginal effect for the expected value of the final price of paintings conditional on being auctioned.

Table 5-5, 5-6: Marginal effect on Log of Final price from Tobit regression

Predict value and marginal effect, Model 1

Variables	**E(lnFinal|lnFinal>0)**	**Pr(lnFinal>0)**	**E(lnFinal)**
	1.938	0.342	0.6634
	∂y/∂x	∂y/∂x	∂y/∂x
Numbidders	**0.218***	**0.094***	**0.254***
%Negative	0.006	0.003	0.007
Logfeedback	-0.030	-0.013	-0.036
Toprate	0.052	0.023	0.063
Duration	-0.029	-0.013	-0.035
Winnerexp	**2.346***	**0.617***	**3.167***
Latebid	**1.478***	**0.486***	**2.013***
ExpLatebid	**-0.919***	**-0.351***	**-0.730***

Table 5-5

Predict value and marginal effect, Model 2

Variables	**E(lnFinal|lnFinal>0)**	**Pr(lnFinal>0)**	**E(lnFinal)**
	2.007	0.337	0.677
	∂y/∂x	∂y/∂x	∂y/∂x
Residual	**0.228***	**0.098***	**0.273***
%Negative	-0.002	-0.003	-0.003
Logfeedback	0.038	0.016	0.045
Toprate	0.164	0.069	0.200
Duration	**0.086***	**0.037***	**0.103***
Winnerexp	**2.578***	**0.635***	**3.468***
Latebid	**1.819***	**0.540***	**2.474***
ExpLatebid	**-0.985***	**-0.353***	**-0.757***

*** p<0.001, ** p<0.01, * p<0.05 Table 5-6

The marginal effect in Model 1 is presented in Table 5-4. By running the number of bidders and other variables on the log of final price, keeping everything constant, an additional bidder *(Numbidders)* approximately increases the expected final price for the uncensored sample by 21.8%. Surprisingly, *all seller´s reputation variables* are insignificant. There are two possibilities. First, seller´s reputation is a reason to why bidders decide to enter the auction as was found in the number of bidders equation. However, when it comes to final price, bidders are not interest about the reputation of the seller once they decide to enter the auction. They are now focusing on the amount they have to pay if they win the painting. Second, the reputation of the sellers might not be the reason to be included into the factor that can determine the price of a painting because painting characteristics and the individual information might play more important role. The length of the auction *(Duration)* is also insignificant. Finally, the next three variables which explain the experience of the winner and the late bids that normally occurred in internet auction. Keeping everything constant, the experienced winners (*Winnerexp)* approximately pay 234.6% more than the inexperienced winners on the expected final price for auctioned painting. In addition, whether the winner is experienced or not, if the winners use *Latebid* as their strategy, they won the item paying around 148% more than the winners who did not use late bidding, keeping everything constant.

The last variable represents how much the experienced winners who used late bid will pay in final price. Keeping every variable unchanged, they pay almost 300%{(2.35+1.48-0.92)*100} more than inexperienced bidders who does not use late bid.

In Model 2, the residual from the bidder equation is a proxy for unpredicted bidder. Based on auction theory, if bidders are aware of winner´s curse, they would apply a bid shading strategy by predicting the total number of competitors. A large *Residual* means that the bidders could not well estimate the total number of bidders. From Table 5-6, according to the estimated model, keeping every variable unchanged, an additional in *residual* results in an approximate 22.8% increase in final price for auctioned items. Even though this number is slightly greater than the actual bidder effect (21.8%), it means that bidders pay a little bit more when there is a new unexpected competitor or they do not take unexpected competitor effect seriously into account. Similar to Model 1, *all seller´s reputation variables* are insignificant. 1 day increasing in *Duration* results in an 8.6% increase in final price. Three variables that explain the experience of the winners and late bids have following result. Keeping everything constant, 257.8% the winner have to pay more when they are the experienced bidders compared to the inexperienced bidders *(Winnerexp).*182% increasing in final price for the late bid strategy whether the winner are experienced or not *(Latebid*). In addition, 340 %{(2.58+1.82-0.99)*100} increases in final price when the experienced winners used late bidd (*ExpLatebid*) compared to the inexperienced winners who do not use late bidding.

From the result, an increase in the number of bidders raise the final price between 21.8-22.8% for auctioned paintings. Interestingly, using late bidding results in an increase of 140%-180% in final price compare to if late bid are not used. Experience bidders are also willing to pay a considerable amount more than inexperienced ones. In addition, the experienced winner who uses last minute strategy pays relatively more than inexperienced winners who does not apply last minute strategies around 300%.

6. Conclusion

This paper has estimated the impact of various variables on the number of bidders and the final sale price of art auction on eBay. We accept the hypothesis that an increase in starting price discourages bidders to enter the auction. This might be a result of some of the problems that eBay auctions face, such as asymmetric information. Bidders would not willing to enter auctions that starts at a high price level. Seller´s reputation is important for bidders to enter the auctions as high seller reputation for being a toprate seller helps bidders reduce uncertainty and induce bidders to enter the auctions. They might assume that these sellers are serious sellers or dealers who have been doing business on eBay for a long time period. Thus, they are more reliable than the new or lower feedback sellers. In addition, the longer the duration of the auction are attracted more bidders since they have more time to check which items they want to place bids on.

The second set of regressions explores the determinants of the final price of auctioned painting. We find that each additional bidder, both the actual number of bidders and unpredicted bidders, tends to increase the final price by 22-23%. The hypotheses about the seller reputation are rejected as the variables are not significant. This evidence might imply that seller´s reputation does not affect the final price. Bidders are not willing to pay more for good sellers. The reasons might be that for non-homogenous items like paintings, the price could vary based on bidders' preferences or the experience that each bidder has. Moreover, bidders can directly contact sellers in order to ask for more information if they are interested in an item.

One may say that art auctions on eBay can be categorized as art for consumption because the positive relationship between the number of bidders and the number of unexpected bidders to the final price mean that bidders have a private value in to the paintings. In addition, the average price of an auctioned painting, $248.34, is relative low, and probably not for investment purposes. On the other hand, one could not neglect the possibility that art auctions on eBay might process some investment proposes because the relationship between the residual with final price and the evidences of late bidding. Positive relationship between the number of unexpected bidders with final price might say that bidders are aware of Winner´s curse, however they could not predict the total number of competitors before they entered the auction. Because of the experienced bidder and the late bidding impact on the final price, this might be a situation where the information on eBay art auction is not symmetric. Since the experienced bidders or late bidders may have more information about auctioning painting than others, they have a higher willingness to pay. Indeed, an early bid might signal to other bidders the value of the painting. As a result, bidders do not join the bidding war and instead engage in late biding.

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Appendix 1

Correlation Matrix

	Start	Final	%Negative	sellerfeedback	Toprate	Numbidders	Duration	Winnerexp	Latebid	Impressionism	Various	Undefine	Realism	Logfeeback	ExpLatebid
Start	1														
Final	0.7599*	1													
Negative	0.0502	0.0201	1												
sellerfeedback	-0.0528	-0.0286	-0.0539	1											
Toprate	-0.02	-0.0158	-0.1254*	0.2180*	1										
Numbidders	-0.1411*	0.2532*	-0.0599	0.1940*	0.1870*	1									
Duration	0.0514	0.1687*	-0.0181	0.1517*	0.1149*	0.2859*	1								
Winnerexp	-0.0894*	0.0164	0.0408	0.1365*	0.0133	0.3685*	0.0482	1							
Latebid	-0.0876*	0.1121*	-0.0642	0.1329*	0.0885*	0.6194*	0.1187*	0.3608*	1						
Impressionism	-0.0680*	-0.0775*	0.0217	-0.0589	-0.0363	-0.0456	-0.0465	-0.0423	-0.0112	1					
Various	-0.0285	0.0478	-0.0698*	-0.0702*	-0.1115*	0.0774*	-0.0642	0.1339*	0.0554	-0.3236*	1				
Undefine	0.0481	0.0273	-0.059	0.0364	0.0947*	0.0905*	0.1121*	-0.0131	0.0454	-0.4007*	-0.2817*	1			
Realism	0.0505	0.0127	0.1003*	0.0904*	0.0437	-0.1135*	-0.006	-0.0623	-0.0848*	-0.3821*	-0.2687*	-0.3327*	1		
Logfeedback	-0.0227	0.0208	-0.1274*	0.5722*	0.4340*	0.2245*	0.0382	0.0799*	0.1180*	-0.1133*	-0.006	0.0166	0.1116*	1	
ExpLatebid	-0.0552	0.0661*	-0.0459	0.1139*	0.0183	0.3553*	0.0495	0.6533*	0.6239*	-0.0363	0.0871*	0.0037	-0.0435	0.059	1

*Correlation is significant at the 0.05 level