Selling Online Versus Offline: Theory and Evidences From Sotheby's

Eiichiro Kazumori* California Institute of Technology

ABSTRACT

We consider a recent business and policy question of "how and why does a firm use online markets versus traditional offline markets ?" using a unique dataset of more than 3000 auctions held by Sotheby's online at eBay and offline at New York in June-July2002. We find robust empirical regularities in our dataset about the use of online markets. First, the average transaction price is more than 10 times higher in offline markets. This fact strongly suggests that the seller is not simply randomly assigning assets between online and offline markets. Second, the higher the mean and spread of pre-auction estimates of an asset, the more likely seller is to sell the asset in offline markets. Third, the transaction rate is higher in offline markets. Next, we build a simple model of offline and online markets to identify the business logic behind these empirical regularities. We model offline markets as an auction with endogeneous entry a la McAfee and McMillan (1987) where the traders pay transaction costs to hold transactions. We model online markets as standard ascending auctions. In online markets, the seller can save transaction costs and entry by bidders is easy, but the seller cannot reveal much information, leading to higher valuation risk and severe winner's curse. The seller sells the asset with high valuation risk in offline markets to alleviate winner's curse. In order to compensate for the transaction costs, the expected value of the asset sold in offline markets is higher. Since the seller's profit is equal to social surplus in offline markets due to entry costs, the seller is more eager to sell assets. Finally we provide a simple maximum likelihood estimation of transaction costs and information revelation effects based on discrete choice models.

*This paper is based on a joint project with John McMillan. I thank Takeshi Ameiya, Susan Athey, Alan Sorensen, and Robert Wilson for helpful conversations. We thank seminars participants at Stanford GSB, Toulouse IDEI, and SWET for their useful feedbacks. We are grateful for Stanford GSB CEBC for financial assistances. The full version of the paper, with proofs, is available at http://www.hss.caltech.edu/ kazumori

EC'03, June 9–12, 2003, San Diego, California, USA.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Sciences - Economics

General Terms

Aucions, Electronic Commerce

1. INTRODUCTION

Due to recent developments of Internet-based transaction technologies, online markets are increasingly important in our economic activities. According to the US Census Bureau, the estimate of U.S. retail e-commerce sales for the second quarter of 2002, not adjusted for seasonal, holiday, and trading-day differences, was $10.243 billion, an increase of 24.2 percent from the second quarter of 2001. In 2000, in the manufacturing industry, ecommerce accounted for 18.4% (777 billion dollars) of the total value of shipments.

Still we have not yet reached a consensus about potentials and limitations of online markets. In this paper, we try to answer business and policy needs for more precise understandings of online markets by studying how a firm uses online markets in practice and what metrics will influence its behavior.

We briefly review previous results in four areas: Internet auctions, comparisons between online and offline markets, and art auctions.

First, we explore Internet auctions, especially eBay markets. Bajari and Hortacsu (2002a) discovered last minutes bidding phenomena and presented the first structural estimation of eBay markets. Bajari and Hortacsu (2002b) summarized results in this area up to early 2002.

Second, we look at competitions in online markets. Baye, Morgan, and Scholten (2001) studied price dispersion among online sellers. Ellison and Ellison (2001) focused on price search engines. Goolsbee and Chevalier (2002) examined sales ranks and prices in online bookstores.

Third, comparisons between online and offline market user behavior. Goolsbee (2000) studied consumers' computer purchases. Brown and Goolsbee (2000) studied insurance policy prices and consumer surplus. Choi, Laibson, and Metrick (2001) compared online traders with phone-based traders. Carlton and Chevalier (2001) studied consumer free-riding by online retailers.

Finally we review art auctions. Ashenfelter (1989) presented a systematic description of art auction markets including the discussion on unbiasedness of sales estimates and declining price anomalies.

Our dataset records the result of 3000+ auctions held by Sotheby's online and offline in June and July 2002. This dataset includes all sales activities by Sotheby's on the Internet and almost all activities at Sotheby's New York, which used US dollars during that period. We collected the auction data from the Internet using Perl codes.

We identified three empirical regularities. First, the mean sales price in offline auctions is more than 10 times higher than that in online auctions. This result strongly suggests that the seller is not assigning assets randomly between online and offline markets. Then how does the seller choose between online and offline ? We went on to study pre-auction estimates provided by the seller. We noticed that, higher the estimate dispersion or higher the estimate mean of an asset, more likely the seller is to sell the asset offline. Third, the transaction rate offline is higher than that online. Anecdotal evidence from eBay's art auctions in 2000 suggests robustness of the finding.

We formulate a simple microstructure model of online and offline markets. We model online markets as standard ascending auctions: The bidders estimate the value of the asset from the description in eBay web page and compete in an ascending auction. We model offline markets as auctions with endogenous entry where the potential bidders pay participation costs (e.g. flying or sending bidding agents to New York) to obtain an estimate at the preview and compete in the auction. These differences in market structures highlight trade-offs: In online markets, the seller can save transaction costs, and there is more competition due to low participation costs. However, the seller cannot reveal much information, so the bidders face high valuation uncertainty and severe winner's curse.

Third, we study a business logic behind these empirical regularities.

Suppose an asset has high valuation uncertainty. Take an example of a classical watch created in 1725 (which was on sale and purchased in an offline auction.) If the seller sells the asset online, bidders only receive information from the webpage, so they are uncertain of the value of the asset. Thus, bidders will bid cautiously to avoid winner's curse. Then the seller cannot get high sales prices. On the other hand, if the seller sells the asset offline, the seller can hold the preview and bidders can inspect the asset by themselves. Then, being sure of the value of the asset, bidders will bid more aggressively. Thus the seller will get higher prices. Also, if an asset has higher valuation uncertainty, then bidders will bid cautiously, so they can get the asset with lower price,and receive higher expected profit ex ante. Thus, more bidders will enter the auction, so the competition advantage of online auctions will decrease. Therefore, for both reasons, the seller will choose to sell the asset in offline auctions if the expected value of the asset is high enough to cover the transaction costs.

Next, we consider the transaction rate. In online markets, the seller wishes to exclude some bidders whose marginal revenue is less than zero. But in offline markets, since the bidder has zero expected profit under free entry equilibrium, the seller's expected profit is equal to social surplus, so the seller does not exclude bidders.

In conclusion, online markets have the potential of low transaction costs and easiness of entry, and the limitation of low information revelation and winner's curse. The seller should weigh carefully these advantages and disadvantages paying attention to metrics such as the number and information processing ability of potential customers, the valuation characteristics of the asset, and transaction costs and informational revelation in the offline transaction process.

For contributions, this paper first presents empirical regularities and theoretical reasoning behind the use of online markets by an asset seller. In previous studies, the data on the firm's activities between online and offline markets are mostly anecdotal.

Second, we contribute to a study of comparative statics of auctions. We use mean-dispersion family distributions for underlying signals. Mean-dispersion family covers wide range of distributions such as Gaussian, Uniform, and Log-normal. Mean-dispersion distributions are tractable because the expectation of the order statistics and hazard rate can be expressed by those of the baseline distribution. Since the bidder's expected profit in the auction is expressed using the expectation of order statistics and hazard rate, we can compute quantitative comparative statics.

2. OFFLINE AND ONLINE MARKETS

In this section, we provide institutional descriptions of offline and online market structures used by Sotheby's.

2.1 Offline markets

Sotheby's offline markets have four steps: consignment, cataloguing, exhibition, and sale. After a prospective seller contacts Sotheby's, its specialists check the asset's authenticity and appraise its value. The owner then consigns the asset to Sotheby's, which puts it in an upcoming auction. Sotheby's auctions usually have a theme, such as "20th Century Works of Art" or "Egyptian, Classical, and Western Asiatic Antiques," so the sale is delayed until there is an auction that it fits. The auction catalog, which is available about one month ahead of the auction, contains a description of the asset, its exhibition history, and reference notes with an upper and lower-bound estimates. The seller mounts an exhibition of the assets to be sold a few days before the auction. The exhibition is open to the public, and Sotheby's specialists are on hand to answer questions. Finally there is the auction itself, run with open ascending bidding. Major sales are social events for the glitterati. Space in the auction room is scarce so seats are rationed, the most desirable seats (Watson(1992)) being assigned to clients who have spent heavily in the recent past.

2.2 Online markets

Sotheby's online markets have a checkered history. Sotheby's began online operations in January 2000 as a joint venture between Sotheby's and Amazon.com. This alliance was dissolved after nine months. (The end came five days after Sotheby's pleaded guilty to colluding with Christie's to fix fees in their offline auctions.) The seller operated the online markets on its own from October 2000 to June 2002. During this time it sold goods worth over $100 million in a period when the art market in general was depressed, but it lost money because of the web site's high set-up costs. Then Sotheby's formed a joint venture with eBay. The joint venture replaced eBay Premiere, eBay's own site for high-end auctions, while Sotheby's online business moved to eBay's web site, allowing Sotheby's to cut staff and expenditures in its online division. Our dataset comes from eBay auctions held by Sotheby's.

2.3 Comparison between two markets

The online markets differ from the offline markets in four respects.

First, rather than large auction events with specific themes at discrete times, miscellaneous assets are continuously on offer via the web site.

Second, the auction is run by eBay's rules; in particular, each auction has a fixed end-time, and Sotheby's is subject to the seller rating system.

Third, the offline markets have higher transaction costs. In offline auctions the sale must wait until a suitable auction is scheduled, bringing costs of delay for the seller. The seller incurs costs in mounting the exhibition and in running the theatrical performance that makes up an offline auction. The bidders incur travel costs and other costs of participating; the seller bears these costs indirectly via lower bids and fewer bidders (McAfee and McMillan (1987)). In online markets, the seller pays the cost of producing the website descriptions, though these are presumably no larger than the offline-auction costs of catalog preparation. Bidders' costs of participating online are negligible.

Finally, the offline auctions generate more information for bidders than the online markets. In an offline auction, bidders inspect the asset at the preview exhibition and can ask questions of the art experts present. In an online auction, bidders get only what information is posted on the web page, which is similar to what we have in catalog, including auction estimates by the experts[1].

3. DATA AND EMPIRICAL REGULARITIES

We now report the result of the examination of the data.

3.1 Data

We collect data on offline markets from Sotheby's website[2] and data on online auctions from eBay website[3] using Perl codes running on Unix servers. The data are collected for online transactions where the seller is Sotheby's at eBay between June 26 and July 23, 2002. The data are collected for offline transactions closed from June 1 to June 30, 2002, at New York Sotheby's using the US dollar. Why the difference in dates ? Sotheby's started selling at eBay from June 13, 2002, and we wanted two weeks' adjustment periods before starting the collection of the data.

In our dataset, there are 1890 offline auctions and 1300 online auctions. The basic summary statistics follows:

	offline markets	online markets
Number of auctions	1890	1300
Ended in sale	1213	517
Total Sales	23572639	682845

Table 1. Summary Statistics

[1]What are the examples of these information which can be acquired in the previews? A catalogue states, " Neither we nor the Consignor make any warranties or representations of the correctness of the catalogue or other description of physical condition size, quantity, rarity, importance, medium, provenance, exhibitions, literature or historical relevance of the property and no statement anywhere, whether oral or written, shall be deemed such a warranty or representation. Prospective bidders should inspect the property before bidding to determine its condition, size or whether or not it has been repaired or restored. "(Sotheby's (1988))

[2]http://search.sotheby's.com/liveauctions/

[3]http://pages.ebay.com/search/items/basicsearch.html

It is difficult to classify the assets objectively into categories. For offline auctions, we simply use the title of auctions as a proxy of categories. There were eight auctions in June of 2002 at Sotheby's New York: Old Masters Paintings on June 5; 20th century Works of Arts on June 7; Important Jewels on June 12; Arcade Jewelry on June 13; Egyptian, Classical and Western Asiatic Antiques and Islamic Works of Art on June 13; Fine Books and Manuscripts on June 16; Masterpieces from the Time Museum on June 19; and Important Watches, Wristwatches and Clocks on June 20.

In online markets, we use the categorization by eBay. In their categories, there are ancient and ethnographic art; Asian art; Books and Manuscripts; Ceramics and Glass; Collectibles and Memorabilia; Furniture and Decorative Arts; Jewelry; Paintings-Drawings -Sculpture; Photographs; Prints; Silver and Vertu; Stamps, Coins, and Medals; and Watches and Clocks.

Auctions	Offline	Online
Jewelry	278	73
Art	361	0
Clocks, Time Museum	562	41
Exotic Antiques	286	0
Books, Prints	283	37
Painting	152	113
Furniture	0	233
Silver, ceramics	0	259
Photo, stamps, coins	0	272
Collectibles	0	356

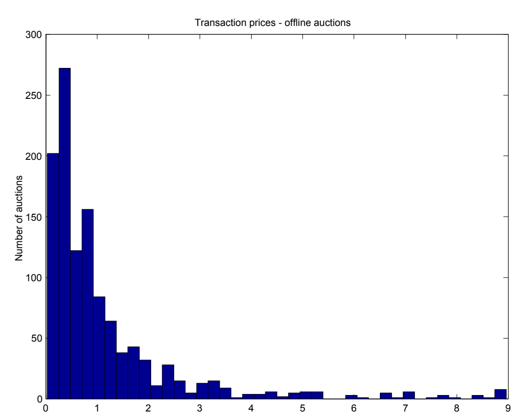
Table 2. Comparisons between two markets

We now begin our examination of the data. First, we look at the transaction price.

3.2 Findings 1.

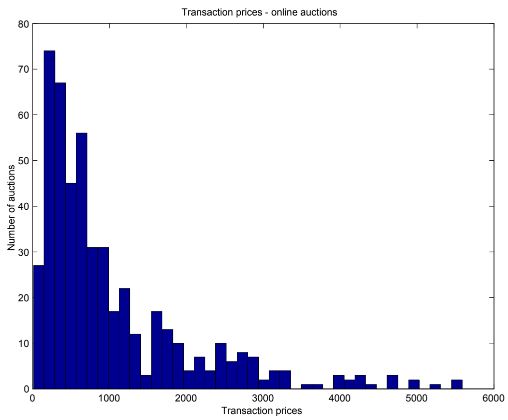
The transaction price is higher in offline markets.

First, the mean sales price is 18801 dollars in offline markets and 1483 in online markets. We provide histograms[4] and summary statistics below. The first histogram records the distribution of sales prices for offline markets. The first histogram records the distribution of sales prices for offline auctions. It shows that the distribution of the sales prices is quite skewed.



[4]When we draw histograms, we removed upper 3% of the samples to improve the graphics.

The next histogram shows the distribution of sales prices for online auctions. The distribution is again skewed. The distribution of the sale price in online auctions is similar to that in offline auctions, except for the fact that the price is measured in terms of 10K in the offline aucions.



The summary statistics of the sales price in offline auctions and online auctions is recorded below. The number of sales observations in offline markets, 1213, is smaller than the number of total observations in offline markets, 1890, since there are 587 auctions which ended in nonsale. For the highest price in offline markets, it was George Graham's timepieces with 1,219,500 dollars. In online markets, it was a Frank Lloyd Wright Copper Weed Holder with 83,750 dollars. For the lowest price, in offline markets, it was a Cartier 1995 watch with 358 dollars. In online markets, it was a Nicole Hornby Magnol with 11.5 dollars.

	Obs	Mean	Std dev	10%	50%	90%
Off	1213	18801	70563	1912	7170	32682
On	517	1483	4136	202	690	2815

Table 3. Transaction Prices

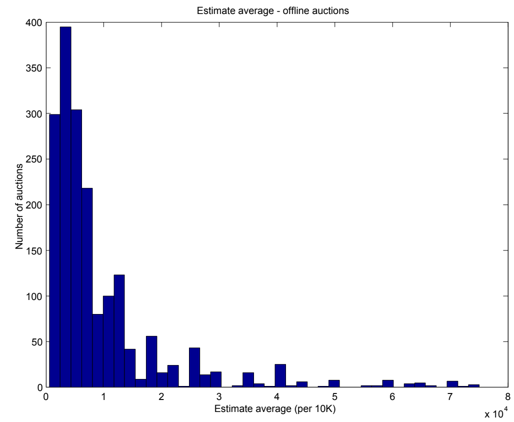
These data shows that the average sales price in offline market is We interpret this difference as a strong evidence that the seller sells different assets in online and offline markets. One possibility is that the difference in the number of bidders between offline and online auctions is a cause of the difference in the sale prices for an identical object. But if it were true, then, since the entry cost in the online auctions is lower than in the offline auctions, the number of potential number of bidders will be larger in online auctions than in offline auctions, so the average price of the online auctions would be higher than that of the offline auctions. But this contradicts with the data.

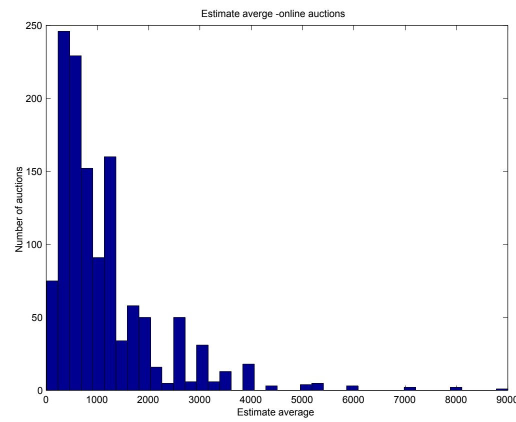
Now let us explore how the seller allocates an asset between online and offline markets. We will examine the pre-auction estimate.

3.3 Findings 2.

The seller sells assets with higher estimate means (= (the lower estimate + the higher estimate)/2) in offline markets.

First, the estimate mean is 13174 in offline markets and 1592 for online markets.





	Obs	Mean	Std dev	10%	50%	90%
Off	1890	13174	27018	1750	6000	25000
On	1300	1592	3392	250	825	2775

Table 4. Distributions of Estimates mean

For the highest estimate mean in offline markets, it is a Pierre Frederich Ingold timepiece with 375000 dollars (sold). In online markets, it is Norma Jeane Baker's Wedding Gown with 60000 dollars (unsold). For the lowest estimate means in offline market, it is 1995 Cartier travel watch with 600 dollars (sold). In online market, it is a Lee Tanner's photograph of John Coltrane with 15 dollars (unsold).

We run a probit regression on 3190 samples. The coefficients are statistically significant from zero. We express EstAvg in terms of 100 dollars.

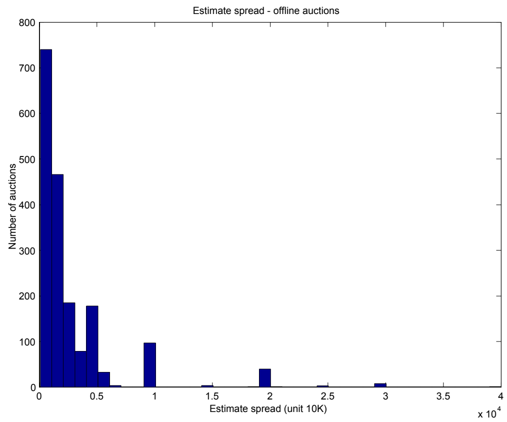
	Coefficient	Standard Error
Estavg (per 100 dollars)	.0158555	.0065756
Const	-.4413621	.0317562

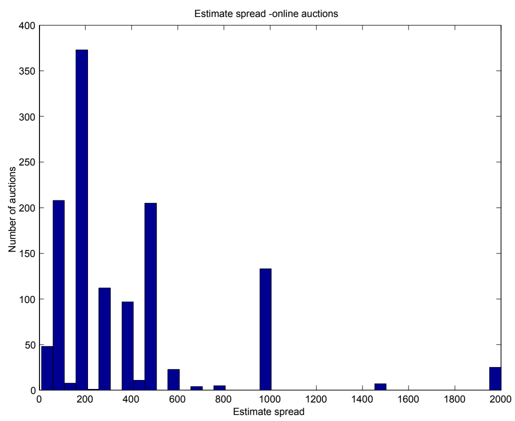
Table 5. Effect of Estimate Average on the Channel Choice

We observe a similar regularity for estimate dispersion (the upper estimate - the lower estimate).

3.4 Findings 3.

The seller sells assets with higher estimate dispersions in offline markets.





	Obs	Mean	Std dev	10%	50%	90%
Off	1890	4492	12347	500	2000	10000
On	1300	523	1141	100	300	1000

Table 6. Distributions of Estimate dispersions

For the highest estimate dispersions, in offline, it is a Pierre Ingold timepiece with 250000 dollars (sold). In online, it is a Norma Jean Wedding Dress with 20000 dollars (unsold). For the lowest estimate dispersion, in offline, it is a 'Fouga' wristwatch with 100 dollars (sold). In online, it is Lee Tanner's photo with 10 dollars (unsold).

The result of a probit regression is given below.

	Coefficient	Standard Error
EstDiff (per 100 dollars)	.05531648	.00199457
Const	-.4832916	.0333872

Table 7. The effect of estimate difference

Both coefficients are statistically significant from zero.

3.5 Findings 4.

The transaction rate (the rate at which an auction ended in sale) is higher in offline auctions.

First, in offline markets, the transaction rate is 64.1% and in online markets, the transaction rate is 39.7%. The breakdown of the sales among categories are given below.

Offline	Online
Master Paintings 0.98	Coins 0.8
Time Museum 0.97	Furniture 0.66
20th Century Art 0.67	Watch 0.63
Watches 0.66	Paintings 0.55
Antique Jewels 0.64	Silver 0.47
Books 0.57	Ceramics 0.46
Arcade Jewels 0.58	Prints 0.33
Jewels 0.49	Collectibles 0.28

Table 8. Transaction rates: category comparison.

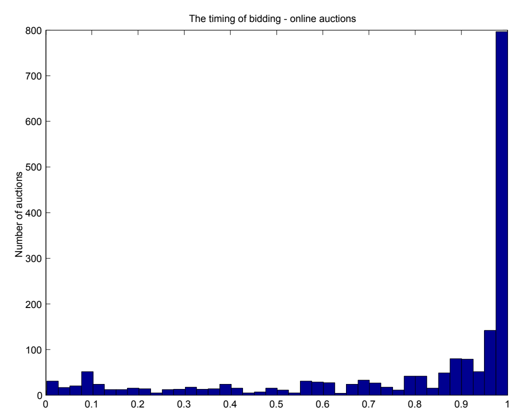
In addition, there is evidence to suggest robustness of the difference in transaction rates. In 2000, eBay held auctions of arts, calling it the Great Collection Auction. Guzman, an eBay representative mentioned the difference in transaction rates: "... (A)approximately 48 percent of the lots offered by GC result in a sale. That figure is rather impressive by online standards but pales when compared to offline auctions, in which rates of 70 percent sold and higher are not uncommon. At Christie's Manhattan headquarters in 1999, for example, the mean sale rate for lots offered in categories ranging from antiquities to Impressionist paintings was 89 percent. " (Tully (2000))

Finally, we note 'last-minutes bidding' phenomena in online auctions.

3.6 Findings 5.

In online auctions, bidders submit bids at the very close to the end of the auction.

Bajari and Hortacsu (2002) discovered last-minutes bidding phenomena: the bids are concentrated at the end of the auction. We confirm their findings in our data of online auctions. In online markets, the mean bid is made in 0.78403 of the length of the auction. The median is 0.956.



Obs	Mean	Std dev	10%	50%	90%
1860	.784	.302	.205	.956	.999

Table 9. Timing of Bidding

4. THE MODEL

In this section we present our formulations and derive an equilibrium in each market. First, we present our formulation of players.

4.1 Players

First, the seller is defined by a unit endowment of an asset with zero valuation and uncertainty neutral preferences.

Second, bidder i =1,...,N is defined by a scalar signal x_i; the payoff function $u_i(s,x) - p$ where $x = (x_i, x_{-i})$ is the vector of signals, s is the information variable, and p is the payment; and uncertainty-neutral preferences. We assume u_i is symmetric, nondecreasing, continuously differentiable.

We model offline markets with endogenous entry.

4.2 Offline markets

First, the seller provides information on the asset in the auction catalogue. The information revelation is truthful[5].

Second, each potential bidder decides whether to enter the auction. At the time of the choice, each potential bidder reads the catalogue. Each bidder learns the number of bidders who have already showed interests and entered the auction[6].

Third, if potential bidder i decides to enter, bidder i spends a participation cost $c \in (0, C)$ for some $C \in \mathbb{R}_{++}$.

Fourth, each bidder attends the preview and estimate the signal x_i^{off} from the distribution F^{off}.

Fifth, the bidders compete in an ascending auction with a secret reserve price r^{off}. The seller pays a cost c to hold an auction.

There are three comments on the formulation.

First, bidders learn the signal *after* the entry decision. In an actual auction process, the bidders have to arrange the visit to the preview in New York before the inspection of the asset.

Second, potential bidders decide entry sequentially a la McAfee and McMillan (1987). Here we generalize McAfee and McMillan model to allow for more general value structures. Levin and Smith (1994) modeled simultaneous entry. There are no essential differences between two formulations since both of the analysis are driven by bidder's zero profit conditions.

Third, every bidder has to pay the participation cost. Bidders with telephone bidding will be at informational disadvantage and may not earn positive expected payoffs[7].

In contrast, we model online 'frictionless' markets as standard ascending auctions.

4.3 Online markets

First, the seller reveals information on the asset on the webpage. The seller reveals information truthfully because of its guarantee[8] and the eBay's feedback rating system.

Second, each bidder $i = 1, ..., N$ enters the auction.

Third, bidder $i = 1, ..., N$ obtains the signal x_i^{on} from the distribution F^{on}.

Fourth, bidders compete in an ascending auction. The seller put the reserve price $r^{on} \in \mathbb{R}$.

We now explain the distributional assumptions.

4.4 Distributional assumptions

First, each of X_i^{off} and X_i^{on} belongs to a mean-dispersion family with a mean zero base random variable z with a distribution function F^Z and continuously differentiable density f^Z and with mean and dispersion parameters $(\mu^{off}, \sigma^{off})$ and (μ^{on}, σ^{on})[9].

Second, each signal $(X_1^j, ..., X_N^j)$, j =on, off is independent.

Third, S and X^j, j =on, off are 'uniformly strictly affiliated' (USA) i.e. there exists $m > 0, M < \infty$ such that for all x,

$$m \le \frac{\partial}{\partial x_i} E[u_i(s,x)|X = x] \le M$$

This assumption is satisfied in many standard functional forms such as the mean common value $u_i(s,x) = \sum x_i/N$ and Wilson (1998) log normal model of $u_i(s,x) = sx_i$. Recall affiliation already implies that $E[u(s,x)|X = x]$ is nondecreasing in each arguments.

Fourth, both of X_i^{off}, and X_i^{on}satisfy increasing hazard rate condition[10].

Fifth, offline markets provide more precise signals $\mu^{off} = \mu^{on}$ and $\sigma^{off} = k\sigma^{on}$ for some $0 < k < 1$. k is the parameter measuring the reduction in dispersion in offline auctions. $k = 0$ implies complete reduction in dispersion and $k = 1$ implies zero reduction.

5. EXPLANATIONS OF EMPIRICAL REGULARITIES

In this section, we give a heuristic explanation of these empirical regularities based on the model presented in the previous section. The full analysis of the model is delegated to Kazumori and McMillan (2003).

5.1 The effect of the estimate dispersion

In section 2, we found that higher estimate dispersion leads to the choice of offline markets. The argument is as follows: The higher estimate dispersion implies severe winner's curse. It will lead to more cautious bidding, lower sales price, and higher bidder profits.

Now suppose the seller chooses offline markets. First, by selling in offline markets, the seller can provide better information to the bidders. The bidder will then bid more

[5]An offline auction catalogue states, " We guarantee the authenticity of Authorship of each lots contained in this catalogue... 'Authorship', locations the identity of the creator, the period, culture, source of origin of property, as the case may be, as set forth in the Bold Type Heading of such catalogue entry."(Sotheby's (1988))

[6]This information which might be available from the conversations with Sotheby's specialists when the potential bidders try to arrange a visit to preview.

[7]For example. Milgrom and Weber (1982), theorem 7.

[8]"Each seller guarantees that the authorship, period, culture or origin of the lot is as set out in the Guaranteed sections of the View item page in the description of the lot." and this guarantee is valid for three years for the bidder who purchases the asset. http://pages.sothebys.ebay.com/help/rulesandsafety/guarantee.html

[9]The assumption implies

$$F^{on}(x) = F^Z(\frac{x - \mu^{on}}{\sigma^{on}}), F^{off}(x) = F^Z(\frac{x - \mu^{off}}{\sigma^{off}})$$

Intuitively, a member of location-scale family is obtained by a shift in mean μ and dispersion σ of the base distribution.

[10]The hazard rate of the random variable x is $h(x) = f(x)/(1 - F(x))$.

aggressively, creating a higher sales price for the seller. This effect is larger as the initial estimate dispersion. Second, the higher estimate dispersion implies more serious winner's curse, which will imply higher bidder's rent. Thus more bidders will enter the auction even after the information revelation. This will diminish the competition advantage in online auctions.

5.2 The effect of the estimate mean

The arguments in the previous sections do not immediately suggest that the seller sells the expensive asset in online auctions. A shift in the mean value of the asset, given that the asset has the same dispersion, does not affect the bidder's expected profit in standard models. As a result, the comparison between online and offline auctions is independent on the shift in the mean value. Then why do sellers choose to sell the expensive art assets in offline auctions ?

First, in offline auction, the seller has to pay transaction costs for the seller itself and the entry cost of the bidders indirectly. If the expected sales price from an offline auction does not cover these transaction costs, the seller will not hold an offline auction.

Second, the seller does not want to sell the asset with lower expected value because it usually implies that the asset has lower dispersions.

Third, in the case of art assets, expensive assets have large valuation uncertainty, and the gains from information revelation in the offline trading processes are larger. On the other hand, in case of financial assets such as equity and bonds, offline transaction does not affect the valuation uncertainty of these assets. As a result, there are no merits in trading these assets offline given the transaction costs saving in online trading. Another piece of indirect evidence is that an expensive asset with a small valuation uncertainty can be successfully sold in online auctions. An example of this successful auction of a copy of the Declaration of Independence for 8.14 million at Sothebys.com in 2000. On the other hand, Marylin Monroe's wedding dress, offered on sale on the Internet was not purchased.

5.3 The difference in the sale rate

In section 2, we saw that the offline auction has the higher sales rate. We can evaluate as follows: in offline markets, since the seller's profit is equal to social welfare, the seller always sells the asset. On the other hand, in an online auction, since it is a standard ascending auction, the seller sets the positive reserve price to increase the sales price[11].

6. EXAMPLE

We now provide a simple numerical example to illustrate the point.

Suppose the seller has an asset and wonders whether to sell the asset in online auctions or offline auctions. There are three bidders interested in the asset, and each bidder values the asset as an mean common value model $\sum x_i/3$.

(1) Suppose the seller estimates that the bidders will have signal distributed unif [2000, 18000] based on the information the seller provides on the Internet. On the other hand, the seller has the option to hold an offline auction. In the offline auction, the bidders need to pay 100 dollars to attend the preview. The seller expects that the information will be more accurate so that the bidders will have signals from uniform [8000, 12000]. Should the seller hold an offline auction ?

(2) Suppose the seller estimates that the bidder will have signal distributed unif [9200, 10800] based on the information on the Internet. The seller can reduce the dispersion to [9800, 10200]. Should the seller hold an offline auction ?

(3) Suppose the seller estimates that the bidder will have signal according to [0,16000]. Should the seller hold an offline auction ?

Solution. (1) First, compute the seller and bidder profit from online auctions. In expectation, bidder 1 has the signal of 14000, bidder 2 has the signal of 10000, and bidder 3 has 6000. Bidder 3 will drop out at 6000 (this simplification is not without loss of generality due to linear structure of the model.) Consider a symmetric equilibrium where each bidder drops off at the price equal to be value of the asset given the signal of the bidders who have already dropped out, and assuming all other remaining bidders having the same signal with that bidder. Bidder 3 will drop out at 6000. Bidder 2 will drop out at (6000+10000*2)/3=8667. The seller's expected price is 8666 and bidder's ex ante expected profit is (10000-8667)/3=433.

Second, compute the profits from offline auctions. Suppose all three bidders choose to enter the auction. In expectation, bidder 1 has the signal of 11,000 dollars; bidder 2 has 10,000 dollars; and bidder 3 has 9,000 dollars. Bidder 3 should drop out at 9,000 dollars. Then bidder 2 drops out at (9,000+10000*2)/3=9666 dollars. That is, bidder 2 shades the bid with 333 dollars. The seller's revenue is 9666 dollars. The bidder's ex ante expected payoff is 334/3=111 dollars. Given that, each of three bidders will decide to enter the auction, since the ex ante expected profit of 111 is higher than the entry cost of 100.

Third, compute the seller's decision. In an online auction, the expected price is 8667. In an offline auction, the expected price is 9667-100=9556. Thus the seller will hold an offline auction.

(2) First, compute the equilibrium payoffs. Fourth, consider the asset with the signal in online [9200, 10800]. On mean, bidder 1 will have 10400, bidder 2 will have 10000 and bidder 3 has 9600. Bidder 2 drops out at (9600+20000)/3=9867. Thus the seller's expected price is 9867 and the bidder's ex ante profit is 133/3=43.

Second, compute payoffs from offline auctions [9800, 10200]. On mean, bidder 1 has 10100, bidder 2 10000 and bidder 3 9900. Bidder 3 will drop out at (9900+10000*2)/3 = 9966. The seller's expected price is 9966 and the ex ante profit of the bidder is 34/3=11. Given this profit, the third bidder will not enter. Then will the number of bidder be 2 ? The price is 9933, and the expected profit of each bidder is 67/2=34. Thus the second bidder will not enter. Thus only one bidder will enter the auction, and he may bid the asset with ε (depending on the formulation of bargaining between the seller and the bidder).

Third, compute the seller's choice. The seller's price from online auction is 9867 and ϵ from offline auction. Thus the seller sells in online auctions.

The conclusion of this example is that the dispersion of the estimation has an important effect on the profit of the

[11]The model assumes that the seller has zero value of the asset. As a result, the sales rate in the offline auction is 100% in the model. A modification of the would be to assume that the seller has the value of the item equal to the estimate mean.

seller in common value auctions. If the dispersion is large, the seller may wish to hold an offline auction with some participation costs. But if the dispersion is small, it may not pay to hold an offline auction.

7. ESTIMATION

In this section, we start the estimation of transaction costs and information revelation by formulating the qualitative response models.

7.1 A qualitative response model

We consider the decision of the seller regarding whether to sell the asset in online markets or in offline markets. We assume that the seller's utility associated with the choice of the market is the expected profit from selling each markets π_S^{off} and π_S^{on} plus an additive error term ϵ^{off}, and ϵ^{on}. The data is the upper and the lower bound of the estimate x. The parameters are the transaction costs c_{seller} and c_{bidder}, and efficiency improvement k. Let $\theta = (c, k)$. Let U^{off} and U^{on} be the seller's expected utility: $U^{off} = \pi_S^{off}(x,\theta)+\epsilon^{off}$ and $U^{on} = \pi_S^{on}(x,\theta) + \epsilon^{on}$.

The basic assumption is that the seller sells the asset in offline markets if $U^{off} \geq U^{on}$. Thus defining $Off = 1$ if the seller sells the asset in offline markets, we have

$$P(Off = 1) = P(U^{off} \geq U^{on}) = F(\pi_S^{off}(\underline{x},\overline{x}) - \pi_S^{on}(\underline{x},\overline{x},\theta))$$

where F is the distribution function of $\epsilon^{off} - \epsilon^{on}$. The log likelihood function is

$$\begin{aligned} \log L &= \sum_{i=1}^{n} Off_i \log F(\pi_S^{on}(\underline{x},\overline{x}) - \pi_S^{off}(\underline{x},\overline{x},\theta)) \\ &\quad + \sum_{i=1}^{n}(1 - Off_i)\log(1 - F(\pi_S^{on}(\underline{x},\overline{x}) - \pi_S^{off}(\underline{x},\overline{x},\theta))). \end{aligned}$$

The maximum likelihood estimator $\hat{\theta}$ is defined by $\frac{\partial \log L}{\partial \theta}|_{\theta=\hat{\theta}} = 0$. Given the smoothness, the consistency and asymptotic normality of maximum likelihood estimator is standard (Amemiya (1985), Section 9.2.2.)

7.2 An estimation

First, in this draft, we use a very simple parametrization. Z=uniform $[-0.5, 0.5]$, $X = \mu + \sigma Z$, $u_i(s,x) = \sum x_i/n$ where n is the number of bidders.

Second, compute the functional form of the discrete choice model give above. In online auction[12], since $H(w,m) = F(w)^{n-1}$,

$$\begin{aligned} \pi_B &= \frac{1}{n}(EY_{1,n} - EY_{2,n}) = \frac{\sigma}{n}(EY^Z_{1,n} - EY^Z_{2,n}) = \frac{\sigma}{n(n+1)} \\ \pi_S &= \mu - n\pi_B = \mu - \frac{\sigma}{(n+1)}. \end{aligned}$$

Note the simple comparative statics result: the seller's expected payoff is decreasing in the dispersion and increasing in the number of bidders. Now in in offline auctions, the number of bidders is determined by $k\sigma/n(n+1) = c$. For simplicity, we approximate[13] the solution of this equation by $n = (k\sigma/c)^{0.5}$ to make a model linear in parameters. We set the number of bidders in the online market be 2. Note 1860/1300=1.43 was an mean number of bidders for online auctions. Thus we obtain

$$\pi_S^{on}(\underline{x},\overline{x}) - \pi_S^{off}(\underline{x},\overline{x},\theta) = c_{bidder}^{0.5} k^{0.5} \sigma^{0.5} + c_{seller} - \frac{\sigma}{3}.$$

Note that in this model, we cannot separately estimate k and c_{bidder}.

Third, we report the result of an estimation. For the probit model of 3190 samples, assuming $\epsilon^{off} - \epsilon^{on} \tilde{} N(0, 400^2)$,

off	Coefficient	Standard Error	z	P>|z|
$c_{bidder}^{1/2} k^{1/2}$	3.011	.7443	4.05	0.000
c_{seller}	222.2	22.80	9.74	0.000

Table 7: Estimates of Costs and Information Revelation Parameter

A possible value of c is 90 for $k = 0.1$. There are 200~300 auctions in one day for offline auctions, so if they bid for 10 assets, the total bidding cost will be around 1000 dollars. The threshold value where the bidder's rent from selling online is equal to that from selling offline is 942.3 dollars.

8. CONCLUSION

In this paper, we studied the seller's choice between online and offline markets. We examined the dataset from Sotheby's and identified robust empirical regularities concerning the transaction price and the transaction rates. We built a simple microstructure model of online and offline markets that emphasized the trade off between information revelation and participation costs to explain these empirical regularities.

9. REFERENCES

[1] Amemiya, Takeshi (1985), *Advanced Econometrics*, Harvard University Press.

[2] Ashenfelter, Orley (1989), How Auctions Work for Wine and Arts, *Journal of Economic Perspectives* 3(3), 23-36.

[3] Ashenfelter, Orley and Katheleen Grady (2002), Art Auctions: A Survey of Empirical Studies, CEPR Discussion Paper 3387.

[4] Bajari, Patrick and Ali Hortacsu (2002), The Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions, forthcoming, *Rand Journal of Economics.*

[5] Bajari, Patrick and Ali Hortacsu (2002), Cyberspace Auctions and Pricing Issue: A Review of Empirical Findings, preprint, Chicago GSB.

[6] Barber, Brad M., and Terrance Odean (2000), Online Investors: Do the Slow Dies First ?, forthcoming, *Review of Financial Studies.*

[7] Barber, Brad M., and Terrance Odean (2001), The Internet and the Investor, *Journal of Economics Perspectives.*

[12] We do not consider reserve prices in this estimation and simulation. It is easy to compute Bulow and Klemperer (1996) bounds.

[13] For reasonably large k, the differences between the solution of $x^2 = k$ and $x^2 + x = k$ is small, for $k = 10$, the solution is 3.16228 and 2.70156.

[8] Baye, Michael, John Morgan, and Patrick Scholten (2001), Price Dispersion in the Small and Large: Evidence from an Internet Price Comparison Site, preprint, UCB Haas.

[9] Brown, Jerry and Austan Goolsbee (2000), Does the Internet Makes Markets More Competitive ? Evidence from the Life Insurance Industry, preprint, *Journal of Political Economy.*

[10] Bulow, Jeremy and Paul Klemperer (1996), Auction versus Negotiations, *American Economic Review* 86(1), 180-93.

[11] Bulow, Jeremy and John Roberts (1988), The Simple Economics of Optimal Auctions, *Journal of Political Economy.*

[12] Carlton, Dennis and Judith A. Chevalier (2001), Free Riding and Sales Strategies for the Internet, *Journal of Industrial Economics.*

[13] Choi, James, David Laibson, and Andres Metrick, How Does the Internet Affect Trading, Evidences from Investor Behavior in 401(k) Plans, forthcoming, *Journal of Financial Economics.*

[14] David, Herbert (1981), *Order Statistics,* Wiley.

[15] Ellison, Glenn, and Ellison, Sara F., Search, Obfuscation, and Price Elasticities on the Internet, preprint, MIT.

[16] Goolsbee, Austan (2000), Competition in the Computer Industry: Online versus Retail, preprint, Chicago GSB.

[17] Goolsbee, Austan and Judith Chevalier (2002), Measuring Prices and Price Competition Online: Amazon and Barnes and Noble, preprint, Chicago GSB.

[18] Kazumori, Eiichiro and John McMillan (2003), Selling Online versus Live, mimeo.

[19] Levin, Dan and James Smith (1994), Equilibrium in Auctions with Entry, *American Economic Review* 585-599.

[20] McAfee, Preston and John McMillan (1987), Auctions with Entry, *Economic Letters* 23, 343-47.

[21] Milgrom, Paul and Robert J. Weber (1982), A Theory of Auctions and Competitive Bidding, *Econometrica* 50(5), 1089-1122.

[22] Sotheby's (1988), *Contemporary Prints: New York, Saturday, November 5, 1988*, Sotheby's.

[23] Tully, Judd (2000), Upmarket eBay and Cyber Sotheby's: Bidding on fine-art auction Web sites is taking an increasingly larger slice of the auction pie, http://www.cigaraficionado.com

[24] Wilson (1998), Sequential equilibria of asymmetric ascending auctions: the case of log-normal distributions, Economic Theory.