Preliminary. Do not cite without the authors' permission

What Determines a Nice Auction Page?

July 30, 2012

Gabriella Bucci and Rafael Tenorio * Department of Economics DePaul University 1 East Jackson Blvd. – Suite 6200 Chicago, IL 60604

* Corresponding author

I. Introduction

Over two million people visit Internet auction giant eBay each day.¹ The number of products offered on the site is astonishing, with total product listings at any given point in time in the vicinity of sixty to seventy million.² Depending on the product category, eBay users searching for specific items often have hundreds, even thousands of auctions to choose from. Given the potentially large number of available auctions of substitutable products, a buyer's decision about what auction to bid in may be affected by the packaging or visual appeal of an auction page. In principle, the presence of photographs, detail of the description, and other cosmetic characteristics of the auction listing will likely affect bidder traffic, and potentially affect both the likelihood that an item will sell, and the final price the item will fetch. However, a routine visit to eBay reveals that the degree to which sellers elaborate their product listings varies widely, not only across product categories, but also within individual categories. On one end, some sellers build fancy and elaborate pages with multiple pictures, animations, colorful fonts, and detailed explanations of the attributes and condition of their product, whereas, on the other extreme, some sellers build very simple pages, with minimal explanation and no picture of the item. In between, there is a spectrum of intermediate cases where the page listing is neither very elaborate nor very simple, with some dimensions of heterogeneity standing out more prominently than others.

The empirical literature on auction page characteristics has focused primarily on the impact of the display of product pictures and other page attributes on bidder traffic and the

¹ Author's estimate based on various Internet sources.

² Authors' estimate based on eBay average daily listings over a one-week period in July of 2012.

final auction price. Among others, Eaton (2002), Hou (2007), Lewis (2011), Melnick and Alm (2004), Snijders and Zijdeman (2004), find that the inclusion of product pictures or scans increase the expected winning bid in the auction. A smaller subset of studies (e.g., Drake (2007), Snijders and Zijdeman (2004)), also show that more product information, as included in the detail provided in the page listing, has a positive impact on the final auction price. In addition, Jin and Kato (2006), and Lewis (2011), find that specific quality claims made by sellers are also likely to impact the final auction price. There may be two types of mechanisms behind the listing attribute-auction price relationship. The first one is a *marketing* or informative advertising mechanism, by which potential bidders increase their willingness to pay for the product when more detail is provided in the auction page. More information disclosure lowers the bidders' information gathering costs and thus increases willingness to pay. The second one is a *signaling* mechanism, by which bidders increase their willingness to pay for products offered by sellers willing to incur costs to assemble better listings. Given the inherit asymmetric information present in online markets, these costs may constitute a credible signal of both seller and product quality. Whether the page building costs are significant enough to allow for clean separation is an empirical matter (see Dewally and Ederington (2003), and Lewis (2011)).

Since auction listing characteristics are likely to positively influence winning bids, we expect that rational sellers will account for this when deciding how much effort and resources to expend in building their auction pages. As a result, there may be a causality problem in the aforementioned relationship: Listing characteristics influence auction price, but at the same time expected auction price may influence listing characteristics. However, the page attributesitem price relationship may be subject to significant intra and inter-product variation arising from both idiosyncratic (seller and buyer) as well as product-specific features (e.g., the degree of commoditization of the product). In other words, there must be factors other than the expected price that influence the various characteristics of eBay auction listings.

The main questions we tackle in this paper are: (a) What determines the optimal amount of resources sellers expend in building their auction pages,? (b) What determines inter-product variation of auction listing characteristics,? and (c) If the attributes of an auction listing potentially impact both the probability of selling and the final auction price, why do we observe significant intra-product variation in auction listings? We will examine these questions using a simple model of seller listing expenditures based on buyer, seller and product characteristics, and we will then test the implications of this model using a panel of data from various products sold on eBay.

II. A Simple Model

Our goal is to model the amount of resources that sellers will devote towards increasing the visual appeal or degree of niceness of an internet auction page. Auction pages include information about the product being auctioned and the seller offering the product in various degrees of detail. A description containing basic product information is standard to every page. The first question we tackle is what may induce a seller to expend more to voluntarily include information beyond this basic description, such as photographs, fine details, or fancier packaging through special fonts, colors, animations, or video. Some sellers also provide information about their eBay storefronts or additional products they offer. Milgrom and Weber (1982) showed that auctioneers have the incentive to truthfully disclose all available information to prospective bidders. This result, known as the *linkage principle*, simply establishes that the seller's disclosure of information will lower the value discovery costs of the bidders, thus inducing them to bid higher. As we stated before, there are various degrees of detail the seller may decide to voluntarily disclose in an auction page. The richer the explanation and presentation details, the more precise the bidders' value estimates are likely to be. Let us call this mechanism the *marketing* or informative advertising mechanism. However, as originally stated, the linkage principle does not account for the cost the seller herself must incur in order to supply various amounts of information. Providing a better explanation and packing the presentation with more details involves higher resource usage, and thus it is costlier to the seller, so that she must trade-off the benefits and costs involved in this activity. This costly information disclosure may introduce a second mechanism by which bidders' valuations for a particular item may be higher when there is more page detail. Since bidders know less about the item than sellers do, they view this costly effort sellers exert in building the page as a signal of seller and product quality. This is known as the signaling mechanism (Spence, 1973).

In what follows we present a simple model of the expenditure a seller will choose to incur in building an auction page and thus providing more detailed and nicely packaged information to prospective bidders.

<u>Cost</u>

Le *R* be the amount of resources a seller puts into building an auction page. These are the resources associated with writing a detailed product description, taking and posting photographs of the product, and using other informative and persuasive aids to increase the appeal of the product. Each seller is endowed with a degree of experience *E*, which will affect her ability to build an auction page. More experienced sellers on auction sites such as eBay, have been transacting for a longer time, are more familiar with the listing process, and, in many cases, have made investments in software or subscriptions to special sites or services that allow them to generate auction pages with multiple features in a more efficient way. ³

Based on this, we propose the following cost function:

$$C(R; E) = \rho(E)R^{2}; \rho' < 0$$
 (1),

where the negatively sloped scaling function $\rho(E)$ reflects the fact that, for a given resource level, more experienced sellers are able to generate nicer pages at a lower marginal cost. Like every standard cost function, both the first and second derivatives with respect to *R* (*C_R* and *C_{RR}*) are positive; i.e., the cost function is increasing and convex in resources. ⁴

<u>Revenue</u>

We assume that prior to visiting the auction page, each potential bidder holds a value estimate for the object they target to buy, and that they will update or refine this estimate with information provided by the seller in the auction page. Since this information is directly related

³ The following article describes fifteen such listing tools: <u>http://www.ecommerce-</u> <u>guide.com/article.php/3924176/15-EBay-Listing-Tools-to-Make-Selling-Online-Easier-Faster.htm</u>

⁴ These resources can be purely monetary (e.g., paying for a photo service), or the monetary value of time and effort spent in the listing process.

to the resources the seller devotes to building the auction page, the updating factor, and thus the seller's expected auction price, depends on the resource expenditure R. Assuming, for simplicity, that the auction is of the second-price variety, ⁵ we define the seller's expected price P as:

$$P(R; V) = V + \gamma(R)V, \gamma' > 0 \text{ and } ; \gamma'' < 0$$
(2),

where V is the second-highest value estimate among all bidders prior to visiting the auction page. Bidders update their value estimates according to the function $\gamma(R)$, which we assume to be independent of the bidder identity to preserve symmetry. We also assume that the updating function $\gamma(R)$ is positive for all possible *R*'s (sellers would not reveal costly adverse information), as well as increasing and concave, indicating diminishing returns to the resource expenditure associated with building a page.

Equilibrium Effort

Assuming E and V are predetermined, the optimal resource expenditure devoted towards building an auction page is given by:

$$C'(R) = P'(R)$$
, or
 $2\rho(E)R = \gamma'(R)V$

(3)

From (3), we obtain two basic comparative static results:

⁵ Formally, eBay auctions are not exactly second-price auctions, because bid increments are coarse and bidding takes place sequentially over a fixed time interval.

 (i) The optimal resource expenditure devoted towards building an auction page increases with the seller's experience:

$$\frac{\partial R}{\partial E} = -\frac{2\rho'(E)R}{2\rho(E) - \gamma''(E)V} > 0 \tag{4}$$

 (ii) The optimal resource expenditure devoted towards building an auction page increases with the value of the object:

$$\frac{\partial R}{\partial V} = \frac{\gamma'(R)}{2\rho(E) - \gamma''(E)V} > 0$$
(5).

Product Type

Suppose there are two types of products, standard (*S*) and unique (*U*). Standard products are basically undifferentiated and commodity-like, and there is no significant variation in attributes within a specific item category. Examples of standard products are a specific movie DVD, a hardback or paperback edition of a book, and a given model of a digital media player. Unique products are more differentiated and one-of-a-kind, and there may be meaningful variation in attributes within an item category. Examples are collectible coins, rare baseball cards, vintage designer items, and retail items offered in many different styles, trims, or colors.

Based on these definitions, information about a standard product is more readily available outside of the auction page/site; while information about a unique product is more specific to the auction page. For instance, if a bidder wants to buy a new or like-new copy of the first edition of the latest Michael Crichton book, she pretty much knows what to expect before visiting the auction page. In contrast, if a bidder wants to buy a pair of discontinued vintage *Air Jordan* shoes, she must visit the page to get information about the color, condition, and other attributes of the shoe. Thus, to a bidder, holding everything else constant, the marginal value of the auction page information is higher for a unique product than for a standard product, i.e., $\gamma'|_U > \gamma'|_S$. Further assuming that the marginal cost function of building a page is the same for both product types, i.e., that the function ρ does not depend on product type, ⁶ we get our third comparative static result:

(iii) The optimal resource expenditure devoted towards building an auction page increases with the marginal impact it has on the bidders' valuation or willingness to pay, and is larger for unique than for standard products:

$$\frac{\partial R}{\partial \gamma'|_{U}} > \frac{\partial R}{\partial \gamma'|_{S}} > 0 \tag{6}$$

This follows from (3) and the assumption that $\gamma'|_U > \gamma'|_S$.

Bidder Expertise

Suppose now that after deciding on an item to buy, and forming an initial value estimate ("I think I'd pay at most \$10 for the latest Michel Crichton paperback"), a prospective bidder has the option of gathering preliminary information outside of the auction page. This

⁶ It is reasonable to assume that it takes the same marginal amount of resources to write a description or to take/post a photograph for a unique or a standard product.

information, which we denote by *I*, may allow for a more precise updating of the bidder's initial value estimate. ⁷

Based on this, the modified expected price is:

$$P = V + \gamma(R; I)V; \gamma_R > 0, \gamma_{RR} < 0, \gamma_I ?, \gamma_{RI} ?$$
(7)

The sign of the cross-derivative γ_{Rl} depends on whether the information the seller provides in the auction page acts as a substitute or as a complement to the information acquired by the bidder prior to visiting the page. Will the auction page information be basically the same as the outside information and thus weakly substitute for it, or will it be specific enough to complement what the bidder already knows about the product?

From (3) and (7), we get:

$$\frac{\partial R}{\partial I} = \frac{V \gamma_{RI}}{2\rho} < 0, \text{ if } R \text{ and } I \text{ are substitutes}$$
(8a)

$$\frac{\partial R}{\partial I} = \frac{V \gamma_{RI}}{2\rho} > 0 \text{, if } R \text{ and } I \text{ are complements}$$
(8b)

Intuitively, whether a seller chooses to expend more resources in building a page as a function of *I*, will depend on how informed she expects her average or typical bidder to be, which in turn may depend on the type of product being sold. In the case of a standard product, because more precise information is available outside the auction page, we speculate that *R*

⁷ Although this information is readily –and freely- available on various merchant and product review sites or publications, a bidder would actually have to know that it exists to be able to use it.

and *I* are more likely to be substitutes. Thus the expected presence of more informed or more expert bidders may prompt a seller to expend fewer resources toward providing information within the auction page, i.e., $\gamma_{RI} < 0$ and $\frac{\partial R}{\partial I} < 0$. Conversely, we speculate that, in the case of a unique product, information outside the auction page is coarser and less specific to the product, and therefore *R* and *I* are more likely to be complements. In this case, the expected presence of more informed/expert bidders may likely induce a seller to expend more resources toward providing information and building a nicer auction page, i.e., $\gamma_{RI} > 0$ and $\frac{\partial R}{\partial I} > 0$. These are only speculations or hypotheses, however. Whether *R* and *I* are substitutes or complements is ultimately an empirical matter, and will depend on the interaction of product type and expected bidder expertise. We will get back to this issue and address it in the empirical section.

III. Data

Item Descriptions

To test some of the implications of the theory, we collected data on 2000 eBay auctions for ten items (200 per item). Five of these items belong in the *unique* category, and the remaining five in the *standard* category. We selected these items with the goal of having enough variation both in terms of average value and degree of commoditization or uniqueness. Below is a description of each item.

<u>Unique</u>

a. Barry Bonds Rookie Topps Baseball Card

There are five existing varieties of this card:

- 1986 Topps Traded
- 1986 Topps Traded Tiffany
- 1987 Topps
- 1987 Topps Tiffany
- 1987 Topps Glossy

The value of each card is determined by its scarcity (i.e., how many were originally issued), and physical condition (i.e., centering, edge and corner crispness, and clarity of surfaces). If the card rates highly on these dimensions, an owner may decide to get it professionally graded by a premier service, like PSA (Professional Sports Authenticators or BGS (Beckett Grading Services). A high rating (roughly 9 or better) considerably increases the value of the card, and constitutes a credible signal of quality. In our sample, the mean opening bid was \$8.50 but the standard deviation was \$12.75. The minimum opening bid was \$0.01 and the maximum was \$79, pointing out to the heterogeneity of the card value.

b. One Ounce American Eagle US Silver Dollar

American Eagle Silver Dollar coins have been produced each year by the United States Government since 1986. Some people consider them among the most beautiful American coin designs. Each official U.S. American Silver Eagle Dollar coin contains one troy ounce of 0.999 pure silver and is 40.6 mm. (about 1.6 in.) in diameter. The value of the coin may depend on year of issue, condition, and packaging (i.e., whether they come in a special or custom-made case).

c. Oakley Half-Jacket Sunglasses

These sunglasses are among the best-selling in the market due to their versatility (lenses and frames are interchangeable) and the myriad of options they provide. There are twenty-two possible frame colors (from jet black to powder blue to pink), two lens shapes (oval and rectangular), and thirty two different lens colors (twenty two regular, ten polarized, and two transition ones). This creates a tremendous array of possible combinations, which results in a large variety of auction offerings on any given day. Additional heterogeneity may be introduced by the condition (new or like new) of the sunglasses, and by the inclusion of the original box, case, and warranty papers.

d. Jordan Retro XI Shoes

These shoes, from the Nike Air Michael Jordan series, were originally released in 1995, and remain one of the most popular Air Jordan shoes ever released, especially among shoe collectors. They are the lightest Air Jordan's ever made, and feature distinctive contrasting patent leather inserts. There are three versions of the Air Jordan XI, low, mid, and high tops. Accounting for the number of color combinations they come in, there are fifty four possible Air Jordan XI shoes on the market (excluding any special or limited editions). We limited our sample to men's sizes from 9 to 12 to avoid any possible market anomalies associated with either too small or too large sizes, which tend to be more heavily discounted.

e. Tiffany Bowl

Established in 1837, *Tiffany and Co*. has been one of the premiere designers of jewelry, watches, and fine table items in the world. Tiffany Bowls are made from several materials, and come in various styles and sizes. Each item features a distinctive seal certifying its authenticity. Due to market thinness for individual designs and sizes, we included both crystal and sterling silver candy dish size bowls (between 5"-9" in diameter). Compared to some of our other products, there is fairly sizable price dispersion here, mainly due to a difference in the mean price of sterling and crystal bowls. In addition, although eBay does its best to limit the listing of counterfeit items, there is a well-established market for fake Tiffany products. This may add some uncertainty to the bidder's perception of the value of some of these bowls.

<u>Standard</u>

a. Office Space DVD

This feature comedy film was originally released in 1999 and did not do very well at the box office (it barely recouped costs). However, it racked fantastic sales on video and DVD, and some people consider it a cult classic. The wide screen DVD edition was released in August of 2000, and the full screen edition was released in August of 2002. Special editions, with several extra features, were released in November of 2005, after the DVD data for this project was collected. Thus the only heterogeneity in this product category arises from the full vs. wide screen.

b. Apple 4 Gigabyte iPod Mini (First Generation)

This digital audio player was released in February of 2004 and discontinued in February of 2005. It was first replaced by a second generation model, which was also later discontinued (in September of 2005). The iPod Mini was ultimately replaced by the iPod Nano. Other than the colors (gold, silver, blue, green, and pink) there are no elements of heterogeneity within this product category.

c. Nintendo Entertainment System

This is an 8–bit video game console originally released in 1985. At the time, it was considered a revolutionary system and it quickly became the best-selling video game platform to that date. In terms of game design and controller layout, it set the standard for subsequent consoles. Along with this system, Nintendo introduced the model of software licensing for third party developers. All of the systems in our sample are used but in fine working condition (the system was discontinued in 1995), and included the controllers, the power source, and the A.V. outlet plug. Other than some possible cosmetic and wear-and-tear differences, there are no sources of heterogeneity. We excluded refurbished systems, and also systems that were bundled with anything but a basic set of generic games (three games at the most).

d. Mac OS X v. 10.5 (Leopard) for Desktops

This is the sixth major release of Apple's operating system for Macintosh computers. It was released in October of 2007, and it replaced v. 10.4, also known as Tiger. This OS retails both as a single use and as a family pack (five installs). We included both retail packages in our sample (there is a more or less constant and consistent price gap of around \$25 between both versions). Other than the retail type, there is no variation across products in our sample.

e. Lot of One Hundred Used Tennis Balls

Other than the brand of the balls, which is sometimes homogeneous and sometimes varies within a lot, there is nothing that separates one lot from another. Obviously, when it comes to used tennis balls, the brand is most likely not important.

Auction Information

For each auction, we collected the opening and winning bids (if applicable), number of posted bids, seller feedback scores, and buyer feedback scores. We also created dummy variables for four listing characteristics; (i) the presence of a single picture, (ii) the presence of multiple pictures, (iii) whether or not there was a detailed description of the item, and (iv) any other special page attributes such as fancy or colorful fonts, animations, or videos. The divide between single and multiple pictures is important because, at the time we collected the data, sellers could post one picture free of charge, while incurring a marginal charge for each additional picture. The seller feedback score usually signals seller reputation, but we also use it as a measure of experience (it has to be strongly correlated with cumulative number of items sold). We also calculate the average bidder (not just winning bidder) feedback score for each item and use that to proxy average bidder experience within each item category (i.e., experience-wise, what types of bidders are attracted to the item in question).

We use the information on listing attributes to calculate a *Page Niceness* index:

Niceness = Single Picture + Multiple Picture + Detailed Description + Other Attributes, where the listing attributes are all dichotomous dummy variables (1 if present, 0 if absent). The niceness index ranges from zero to four and we use it as a proxy for the resources a seller devotes to designing the auction page. For example a listing that includes only the name and basic condition of the item being auctioned would receive a niceness index of zero, indicating minimal resources expended. On the other hand a listing that includes three pictures, a detailed description, and special fonts would have a niceness index of four, naturally requiring more resources from the seller. Table 1 shows mean values of descriptive statistics for each product as well as the combined sample.

Standard Products				Unique Products						
	DVD	Ipod	Nintendo	Leopard	Tennis	Bullion	Rookie	Tiffany	Oakley	Jordan
Open	6.23	77.43	16.07	26.63	7.72	7.43	8.50	39.24	44.27	47.05
Bid	(4.93)	(104.76	(18.79)	(34.47)	(6.51	(3.74)	(12.75)	(88.94)	(48.51)	(75.09)
Win	9.31	247.21	46.67	88.82	20.25	10.31	46.73	57.49	85.38	138.41
Bid	(2.73)	(24.94)	(44.24)	(16.56)	(9.19)	(1.92)	(309.17)	(80.33)	(23.91)	(81.24)
# Bids	4.56	20.58	11.59	12.55	7.19	3.01	5.82	4.23	11.94	14.23
	(4.02)	(14.93)	(9.07)	(7.45)	(4.87)	(2.96)	(5.64)	(5.43)	(10.31)	(10.60)
Seller	6228	1317	1747	1122	704	1426	1609	2100	1858	686
Feedback	(22186)	(5914)	(8363)	(5520)	(1436)	(1861)	(1989)	(4908)	(4907)	(4493)
Bidder	132	77	154	500	275	175	344	282	91	98
Feedback	(239)	(112)	(640)	(569)	(673)	(237)	(404)	(432)	(84)	(252)
Niceness	1.98	2.72	2.33	1.81	1.22	3.19	3.26	2.85	2.98	2.97
Index	(1.23)	(1.22)	(1.14)	(0.90)	(0.54)	(1.02)	(0.93)	(1.02)	(0.94)	(0.79)

Table 1: Mean Values of Descriptive Statistics (standard deviations in parentheses)

	All Standard Products	All Unique Products
Opening	26.88	29.30
Bid	(56.63)	(59.27)
Winning	84.81	67.09
Bid (\$)	(91.53)	(158.94)
# Bids	11.3	7.84
	(10.48)	(8.78)
Seller	2223	1536
Feedback	(11382)	(3915)
Bidder	227	199
Feedback	(520)	(322)
Niceness	2.01	3.01
Index	(1.15)	(0.96)

 Table 1: Mean Values of Descriptive Statistics (standard deviations in parentheses)

On average, the auctions of the standard products in our sample have more bids and a higher winning bid than our unique products. The iPod Nano is an expensive standard product which increased the average winning bid for standard products in our sample. As expected, auction pages for standard products have lower average niceness indexes. The exception to this is the iPod, which has an average niceness index very close to that of Oakley sunglasses and Air Jordan shoes, which are unique products.

IV. Results

To estimate the determinants of page niceness and test the predictions of our model, we first estimated logistic regressions of each of the four defined page attributes on auction characteristics, product characteristics, and buyer and seller characteristics (Table 2). Detailed descriptions and a single picture are the two most commonly observed auction page attributes. The frequency of multiple pictures and other attributes is only about half as large.

Table 2: Logistic Estimation of Page Attributes

Attribute of Auction Page				
Variable	Picture	Multiple	Detailed	Other Attributes
		Picture	Description	
Intercept	1.0338 ^a	-1.4333ª	0.1972	-0.7033ª
	(0.1593)	(0.2065)	(0.2046)	(0.1593)
Average Winning	0.00470 ^ª	0.00544 ^ª	0.00402 ^a	0.00355 ^a
Bid	(0.000983)	(0.000829)	(0.000952)	(0.000737)
Unique Product	1.4772 ^ª	1.1621 ^ª	0.9345 ^ª	-0.2619
	(0.3985)	(0.2164)	(0.2648)	(0.1894)
Seller	0.000104 ^a	4.5E-5 ^a	0.000239 ^ª	0.000205 ^a
Feedback	(0.000033)	(1.3E-5)	(0.000054)	(2.7E-5)
Seller Feedback	-388E-12	-137E-12	-1E-9	-944E-12 ^ª
Squared	(3.89E-10	(9.15E-11)	(1.336E-9)	(1.51E-10)
Avg. Bidder	-0.00432 ^ª	-0.00304 ^a	0.00387 ^ª	-0.00158 ^ª
Feedback	(0.000476)	(0.000716)	(0.000752)	(0.000489)
Unique*bidder score	0.00581 ^ª	0.00659 ^ª	-0.00249 ^b	0.00336 ^ª
	(0.0018)	(0.000980)	(0.00122)	(0.000801)
Auctions w/with Attribute	1578	894	1692	850
-2 log Likelihood	1490.768	2079.318	1635.558	2544.329
Percent Concordant	84.8	81.0	62.8	67.4

(standard errors in parentheses)

- a = significant at the 1% level Chi-square test
- b = significant at the 5% level Chi-Square test

The results show that auction pages are more likely to contain pictures and a detailed description if the object is more valuable (average winning bid is higher), if the product is unique, and if the seller is experienced. We include the average winning bid as sort of a (value) fixed effect for each product. Obviously, the winning bid is not exogenous to page niceness, but averaging across all auctions in that product category should mitigate this problem. To deal with this possible endogeneity, we also ran all of the above logistic regressions using the opening bid for each product instead of the average winning bid. In general, the opening bid is a noisier indicator of value (many auctions are listed at very low initial price), but is exogenous to page niceness. The opening bid coefficient has the correct sign and is statistically significant, though not as strong as the average winning bid.⁸ Regarding bidder experience (as measured by the average bidder feedback), we find that if sellers expect their typical bidder pool to be more experienced, auction pages are less likely to have pictures and other attributes, and more likely to have detailed descriptions. This suggests that sellers expect that experienced bidders rely more on the information contained in item descriptions than they do on any accompanying pictures or any bells and whistles on the page. In fact, when bidders are experienced, the presence of pictures on a page appears to be driven by the uniqueness of the product. This is shown by the positive coefficient of the (unique*bidder) interaction term. This is not surprising because pictures of standard, well-known products, contain little information beyond that included in the item description. For unique products, on the other hand, a picture can provide additional important information about the condition of the merchandise. Sellers of unique products who attract more experienced bidders are less likely to have detailed item

⁸ Results are available from the authors. Our next set of regressions will include the opening bid.

descriptions on their page. This is shown by the negative sign of the (unique*bidder) variable. This result is consistent with the fact that these specialty bidders have honed their knowledge of these unique products and rely more on their knowledge than on details the seller provides. The presence of pictures for these unique products provides more information to the experienced bidders than the remaining page attributes.

Next, we estimated an ordered logistic regression of the page niceness index on the same explanatory variables. By construction, a higher niceness index corresponds to higher seller effort. The results are shown in Table 3.

Table 3: Ordered Logistic Regression of Page Niceness

Intercept 4-2.6161-2.3058-1.7199Intercept 3-1.08410.1445)b(0.1215)aIntercept 3-1.0841-0.7397-0.1769Intercept 20.05330.42460.9563Intercept 20.05330.42460.9563Intercept 12.70653.10943.6076Intercept 10.00460.015230.1758)aBid0.00460.005211Depening Bid0.0006)a0.00064)a0.00226Inique Product1.75230.62590.6392Seller Feedback0.00010.000013a0.000013aIndex squared-432 E-12-44 E-12-171 E-12Avg. Bidder-0.00064-0.002310.000418aInique*avg bidderI.00034)c0.000403a0.000418aInique*avg bidderI.0.005620.00330Inique*avg bidderI.0.005620.00330Inique*avg bidderI.0.005620.00330Inique*avg bidderI.0.005620.00330Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique*avg bidderI.I.I.Inique		-	-	
Intercept 3-1.0841-0.7397-0.1769(0.1286)a(0.1347)a(0.1122)dIntercept 20.05330.42460.9563(0.1258)(0.1344)a(0.1153)aIntercept 12.70653.10943.6076(0.1735)a(0.1853)a(0.1758)aBid0.00460.0052-Bid(0.0006)a(0.00064)a-Dpening Bid1.75230.62590.6392Unique Product1.75230.62590.000847)aSeller Feedback0.00014)a(0.00097)0.000861)aFeedback squared-432 E-124-4 E-12171 E-12Avg. Bidder-0.00064-0.002310.000418)Feedback0.00034)c(0.000403)a0.000418)Huique*avg bidder5.00034)c0.0005620.00330	Intercept 4	-2.6161	-2.3058	-1.7199
Intercept 2(0.1286)a(0.1347)a(0.1122)dIntercept 20.05330.42460.9563(0.1258)a(0.1344)a(0.1153)aIntercept 12.70653.10943.6076(0.1735)a(0.1853)a(0.1758)aAverage Winning0.00460.0052.Bid(0.0006)a(0.00064)a.Dpening Bid0.00061a0.00226.Intique Product1.75230.62590.6392Seller Feedback0.00014a0.000017a0.000863Feedback squared4.32 E-124.4 E-12.171 E-12Avg. Bidder-0.000640.002310.00013aFeedback0.000640.00033a0.000418)Inique *avg biddetI.Terter0.0005620.00330		(0.1388)a	(0.1445)b	(0.1215)a
Intercept 20.05330.42460.9563Intercept 10.1258)(0.1344)a(0.1153)aIntercept 12.70653.10943.6076(0.1735)a(0.1853)a(0.1758)aAverage Winning0.00460.0052.Bid0.0006)a(0.00064)a.Opening Bid0.00226Unique Product1.75230.62590.6392Seller Feedback0.00010.000970.00086Feedback squared.432 E-12.44 E-12.171 E-12Avg. Bidder-0.000640.002310.00051Avg. Bidder0.00034)c(0.000403)a(0.000418)Huique*avg bidder0.005620.0330	Intercept 3	-1.0841	-0.7397	-0.1769
Intercept 1(0.1258)(0.1344)a(0.1153)aIntercept 12.70653.10943.6076(0.1735)a(0.1853)a(0.1758)aAverage Winning0.00460.00527Bid(0.0006)a(0.00064)a7Dpening Bid770.00226Unique Product1.75230.62590.6392Seller Feedback0.00010.1666)a0.1663)aFeedback squared-432 E-124-4 E-121.71 E-12Avg. Bidder-0.000640.002310.00051Feedback0.000640.002310.00051Avg. Bidder-0.000640.000430a0.000418)Huique*avg bidderI.0.005220.00330		(0.1286)a	(0.1347)a	(0.1122)d
Intercept 12.70653.10943.6076Intercept 12.70653.10943.6076(0.1735)a(0.1853)a(0.1758)aAverage Winning0.00460.0052Image WinningBid(0.0006)a(0.00064)aImage WinningDopening BidImage Winning0.002260.000847)aOpening BidImage Winning0.62590.6392Unique Product1.75230.62590.6392Seller Feedback0.00010.0000970.00086Gonoon110.000014)a0.0000970.000086Feedback squared-432 E-12-4-4 E-12-171 E-12Avg. Bidder-0.000640.002310.00051Feedback(0.00034)c(0.000403)a0.000418)Huique*avg bidderImage Windig Wi	Intercept 2	0.0533	0.4246	0.9563
No.01735)a(0.1853)a(0.1758)aAverage Winning0.00460.0052IBid(0.0006)a(0.00064)aIOpening BidII0.00226Opening BidIIIUnique Product1.75230.62590.6392Seller Feedback0.000110.0000970.000867)aFeedback squared432 E-12I-44 E-12I-171 E-12Avg. Bidder-0.000640.002310.00051Feedback0.000640.002310.00051HeighbackIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII		(0.1258)	(0.1344)a	(0.1153)a
Average Winning0.00460.0052IBid0.0006)a0.00064)aIDpening BidII0.00226Opening BidIIIUnique Product1.75230.62590.6392Bill0.00011a0.0000970.000847)aSeller Feedback0.00010.0000970.000086Feedback squared-432 E-12-4-4 E-12-171 E-12Avg. Bidder-0.000640.002310.00051aFeedback0.00034)c0.0002310.00051aHunique*avg bidderII0.005620.00330	Intercept 1	2.7065	3.1094	3.6076
Bid(0.0006)a(0.00064)aOpening Bid(0.00064)a0.00226Opening BidII(0.000847)aUnique Product1.75230.62590.6392(0.0905)a(0.1666)a(0.1663)aSeller Feedback0.00010.0000970.00086Feedback squared-432 E-12-4-4 E-12-171 E-12Avg. Bidder-0.000640.002310.00051Feedback(0.00034)c(0.000403)a(0.000418)Unique*avg bidderII0.005620.00330		(0.1735)a	(0.1853)a	(0.1758)a
Opening BidIIIOpening BidI0.00226Unique Product1.75230.62590.6392(0.0905)a(0.1666)a(0.1663)aSeller Feedback0.00010.0000970.00086(0.000014)a(0.000013)a(0.000013)aFeedback squared-432 E-12-4-4 E-12-171 E-12(8.09 E-11)a(8.07 E-11)a(8.47 E-11_b)Feedback-0.00064-0.00231-0.00051Feedback(0.00034)c(0.000403)a(0.000418)Unique*avg bidderIII	Average Winning	0.0046	0.0052	
Lunique Product1.75230.62590.6392(0.0905)a(0.1666)a(0.1663)aSeller Feedback0.00010.0000970.00086(0.000014)a(0.000013)a(0.00013)aFeedback squared-432 E-12-4-4 E-12-171 E-12(8.09 E-11)a(8.07 E-11)a(8.47 E-11_b)Feedback-0.00064-0.00231-0.00051Feedback(0.00034)c(0.000403)a(0.000418)Unique*avg bidderI.0.005620.00330	Bid	(0.0006)a	(0.00064)a	
Unique Product 1.7523 0.6259 0.6392 (0.0905)a (0.1666)a (0.1663)a Seller Feedback 0.0001 0.000097 0.000086 (0.000014)a (0.000013)a (0.000013)a Feedback squared -432 E-12 -4-4 E-12 -171 E-12 (8.09 E-11)a (8.07 E-11)a (8.47 E-11_b) Feedback -0.00034)c -0.00231 -0.00051 Inique*avg bidder I. 0.00562 0.00330	Opening Bid			0.00226
NomeNomeNomeNomeSeller Feedback0.00010.0000970.000086(0.000014)a(0.000013)a(0.000013)a(0.000013)aFeedback squared-432 E-12-4-4 E-12-171 E-12(8.09 E-11)a(8.07 E-11)a(8.47 E-11_b)(8.47 E-11_b)Avg. Bidder-0.00064-0.00231-0.00051Feedback(0.00034)c(0.000403)a(0.000418)Unique*avg bidderImage: Second Seco				(0.000847)a
Seller Feedback 0.0001 0.000097 0.000086 (0.000014)a (0.000013)a (0.000013)a Feedback squared -432 E-12 -4-4 E-12 -171 E-12 (8.09 E-11)a (8.07 E-11)a (8.47 E-11_b) Avg. Bidder -0.00064 -0.00231 -0.00051 Feedback (0.00034)c (0.000403)a (0.000418) Unique*avg bidder Image: Marce	Unique Product	1.7523	0.6259	0.6392
k k		(0.0905)a	(0.1666)a	(0.1663)a
Feedback squared -432 E-12 -4-4 E-12 -171 E-12 (8.09 E-11)a (8.07 E-11)a (8.47 E-11_b) Avg. Bidder -0.00064 -0.00231 -0.00051 Feedback (0.00034)c (0.000403)a (0.000418) Unique*avg bidder - 0.00562 0.00330	Seller Feedback	0.0001	0.000097	0.000086
Avg. Bidder -0.00064 -0.00231 -0.00051 Feedback (0.00034)c (0.000403)a (0.00034)c Unique*avg bidder - 0.00562 0.00330		(0.000014)a	(0.000013)a	(0.000013)a
Avg. Bidder -0.00064 -0.00231 -0.00051 Feedback (0.00034)c (0.000403)a (0.000418) Unique*avg bidder 0.00562 0.00330	Feedback squared	-432 E-12	-4-4 E-12	-171 E-12
Feedback (0.00034)c (0.000403)a (0.000418) Unique*avg bidder 0.00562 0.00330		(8.09 E-11)a	(8.07 E-11)a	(8.47 E-11_b
Unique*avg bidder 0.00562 0.00330	Avg. Bidder	-0.00064	-0.00231	-0.00051
	Feedback	(0.00034)c	(0.000403)a	(0.000418)
(0.000712)a (0.000785)a	Unique*avg bidder		0.00562	0.00330
			(0.000712)a	(0.000785)a
-2 log likelihood 5339 5275 5335	-2 log likelihood	5339	5275	5335

a = significant at 1% level chi-square test c = significant at 10% level chi-square test

b =significant at 5% level chi-square test d = significant at 15% level chi-square test

The intercepts are the estimated log odds of having a niceness index equal to or lower than the indicated value when the independent variables are evaluated at zero. They tell us the expected cumulative distribution of page niceness for auctions of standard items with all other independent variables (average winning bids or opening bids, seller score, and buyer score) evaluated at zero. The expected cumulative probability of each niceness index can be calculated from the intercepts. One such calculation is provided in Table 3a and shows that the cumulative probability of higher niceness indexes becomes smaller and smaller. All the regression specifications in Table 3 have expected cumulative distributions comparable to those shown in Table 3a.

Table 3a: Expected Cumulative Probability of Niceness Index for base group

(standard product with bid=0, seller feedback=0, and buyer feedback=0)

Nice Index	4	3	2	1
Intercept	-2.6161	-1.0841	0.0533	2.7065
Cumulative Odds	0.073	0.338	1.055	14.977
Cumulative Probability	0.068	0.253	0.513	0.937

(Calculated from Table 3, column 1)

The parameter estimates in Table 3 confirm that unique products are more likely to have nicer auction pages. Seller experience, as measured by the seller feedback score, has a positive but concave effect (diminishing returns) on seller resources spent across all of our specifications. Bidder experience, on the other hand, has a negative impact on increasing levels of page niceness. This is consistent with the fact that more experienced bidders rely more on their own knowledge about the product when participating in auctions. As discussed before, we used two alternative measures of item value; the average winning bid for each product category (somewhat endogenous), and the individual item's opening bid (exogenous but noisy). As we see in the table, both measures indicate that higher valued objects induce more resources spent in building auction pages.

Finally, we address the question of whether page niceness and expected bidder expertise are substitutes or complements. We hypothesized that the two are more likely to be substitutes for standard products because less page-building effort is needed if bidders are more experienced and thus better informed about the products. On the other hand, accurate information about more unique products is difficult to obtain anywhere other than on the auction page for that particular item. Thus sellers of unique products will expend more resources and include more details on their auction page when they expect more experienced or expert bidders. In this case, seller-provided detail and bidder expertise are more likely to be complements. The results are consistent with our hypotheses. The parameter estimate on bidder experience is negative and statistically significant, indicating that seller will expend fewer resources in building pages if they expect more knowledgeable bidders, *unless the item is unique*. The positive and significant parameter estimate for the (unique*bidder) interaction term indicates that when bidders are experienced, a unique product is more likely to exhibit increasing levels of page niceness. This suggests that page niceness and bidder experience are complements for unique products. Combining this result with that obtained in Table 2, we can suggest that sellers of unique products should devote most of their effort and resources to taking multiple high quality pictures of their unique products rather than to writing detailed descriptions.

A criticism of the page niceness index is that it assigns equal weight to all of the identified dimensions of the auction listing. As a robustness test, we redefined our niceness index as a dichotomous variable in which the page was nice if it had multiple pictures and a detailed product description, and not nice otherwise. ⁹ The results shown in Table 4 are very similar to the results of our earlier regressions. ¹⁰

⁹ We computed raw correlations and simple OLS regressions to gain an idea of which of the page niceness components were more strongly related with the item's winning bid. Consistently, we found that multiple pictures and detailed description were the stronger attributes.

¹⁰ We also recalculated the niceness index using higher weights for the more important page attributes (multiple pictures and detailed descriptions). The regression results for these different definitions of the niceness index are available upon request and are very similar to the results on table 3.

Table 4: Logistic Estimation of Nice Page vs. Plain Page

Explanatory Variable		
Intercept	-1.4095 ^a	-0.6430 ^a
	(0.2086)	(0.1656)
Avg. Winning Bid	0.0050 ^a	
	(0.00083)	
Opening Bid		0.00139 ^d
		(0.000889)
Unique Product	0.7865ª	0.5298 ^b
	(0.2132)	(0.2127)
Avg. Seller feedback	0.00006ª	0.000046 ^a
	(0.000013)	(0.000013)
Feedback Squared	-192E-12 ^a	-156E-12 ^c
	(8.79E-11)	(8.84E-11
Avg. Bidder Feedback	-0.00326 ^a	-0.00492 ^a
	(0.00074)	(0.000791)
(Unique*Bidder)	0.00722 ^a	0.00784 ^a
	(0.000971)	(0.00103)
-2 Log Likelihood	2143.268	2177.645
Percent Concordant	78.7	78.0

(Nice Page = 1 if there are multiple pictures and a detailed product description, 0 otherwise)

a = significant at 1% level chi-square test c = significant at 10% level chi-square test

b =significant at 5% level chi-square test d = significant at 15% level chi-square test

V. Conclusion

The existing literature on online auctions has found that the attributes of auction pages may positively impact both bidder participation and auction prices. We claim that auction page attributes cannot be treated as exogenous in explaining auction outcomes. Rational sellers should be aware that nicer pages will positively impact the expected profitability of their auctions. Therefore the effort and resources sellers devote to building auction pages should be based on the tradeoff between this expected profitability and the cost involved in expending more effort to build auction pages.

In this paper, we have modeled the optimal amount of resources that sellers devote to increasing the visual appeal or degree of niceness of internet auction pages. We accounted for both product-specific, and trader (seller and buyer)-specific attributes that may impact this decision. Our model predicts that sellers will devote more resources toward building an auction page if (a) the product is unique, as opposed to standard or commoditized, (b) the product is more valuable, and (c) the sellers are more experienced. The model also yields an ambiguous prediction about the impact that expected buyer experience or expertise has on the seller's page-building effort. This impact depends on whether the product is unique (more resources spent) or standard (fewer resources spent). We collected data from 2000 eBay auctions to empirically explore the predictions of our model. Our results lend support to all of the model's predictions under alternative logistic specifications. With respect to the impact of expected bidder expertise, we find that sellers of standard products who attract experienced buyers can afford to devote less effort to pictures and the overall niceness of the auction page,

but should write clear and detailed descriptions for their products. However sellers of unique products who attract more experienced buyers should devote more resources to designing their auction page and should devote most of this effort to taking multiple pictures of their product.

Our results also suggest that existing empirical work which finds a positive impact of page attributes on bidders' participation and auction prices may have empirically misspecified this relationship. If a seller anticipates that a nicer page will fetch a higher price, the amount of resources she devotes toward building a page is not exogenous with respect to the item's (expected) value. We explore this issue in a companion paper.

References

- Dewally, Michael, and Louis Ederington (2006), "Reputation, Certification, Warranties, and Information as Remedies for Seller-Buyer Information Asymmetries: Lessons from the Online Comic Book Market," Working paper, Towson State University - Department of Finance.
- Drake, John (2007), "Important Auction Characteristics in e-Marketplace Decisions: An Exploratory Look at Auction Selection and Product Valuation," Proceedings of the Southern Association for Information Systems.
- Eaton, David (2002), "Valuing Information: Evidence from Guitar Auctions on eBay," Working paper, Murray State University.
- Hou, Jianwei (2007), "Price Determinants in Online Auctions: A Comparative Study of eBay China and US," *Journal of Electronic Commerce Research*, 8 (3), pp. 172-183.
- Jin, Ginger Zhe, and Andrew Kato (2006), "Price, Quality and Reputation: Evidence from An Online Field Experiment," *RAND Journal of Economics*, Winter 2006, 37(4), pp. 983– 1005.
- Lewis, Gregory (2011), "Asymmetric Information, Adverse Selection and Seller Disclosure: The Case of eBay Motors," *American Economic Review*, 101 (4), pp. 1535-1546.
- Melnik, Mikhail, and James Alm (2005), "Seller Reputation, Information Signals, and Prices for Heterogeneous Coins on eBay," Southern Economic Journal, 72(2), pp. 305-328.
- Milgrom, Paul, and Robert Weber (1982), "A Theory of Auctions and Competitive Bidding," *Econometrica*, 50 (5), pp. 1089-1122.
- Snijders, Chris, and Richard Zijdeman (2004), "Reputation and Internet Auctions: eBay and Beyond," *Analyse & Kritik*, 26, pp. 158-184.
- Spence, Michael (1973), "Job Market Signaling," *Quarterly Journal of Economics*, 87 (3), pp. 355–374