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Determining Price Forming Factors In Online Auctions: A Multiple Product Study

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Abstract

The paper aims to uncover the most significant determinants of the final auction prices on eBay. The paper takes into account three different goods categories which are chosen to be collectibles, consumer electronics and luxury goods. We show that the results vary greatly from one product to another, and no universal set of price determinants was found. We also check the validity of some of the previously published results concerning such auction characteristics as auction length, the item description, auction ending time and other. While some of the findings coincide with those of other authors, for some of them we could not find any overt proof of their verity.

Key words: online auctions, eBay, price determinants, sale probability.

Structure:

1 Introduction

Due to phenomenal achievements in science and technologies as well as the standard of well-being for the past several decades, the classical concept of the world's trade has been changed dramatically. Every year more and more people address online markets in order to shop there instead of dealing with traditional local stores. From this perspective, one of the most successful and innovative ideas was the creation of the online global market places like eBay.

As one the irrefutable benefits, the concept of an online market place provided customers with much more advanced tools and opportunities to seek for the information they need and significantly broadened their overview of the market conjuncture. However, despite all these seemingly ideal conditions for the customers to gain perfect knowledge of the market conditions and prices, eBay is another example of real-time market processes with all the ensuing consequences. Due to numerous distortions, the final auction prices for the identical items vary greatly from one listing to another. This fact gives us grounds to suppose that there is a set of factors that determine those distortions and, consequently, the variation of prices on eBay.

Following economic theoretical statements, it is assumed that the set of price forming factors is not unique and is dependent of the nature of the goods. Hence, the purpose of this paper is to touch both upon theoretical and practical aspects of pricing in online auctions for the goods that have different nature. The paper takes into account three different goods categories which are chosen to be collectibles, consumer electronics and luxury goods. The research is intended to give some additional information to better understand specific features of the real market price formation process for the mentioned categories.

The main our goal is to uncover the most significant factors that influence the final auction prices on eBay. In order to determine those factors, the required information is obtained from the eBay auctions (we take the United States localized website www.ebay.com). As there exist large and barely defined number of factors determining final auction prices (both objective and subjective) we limit our search to those ones which are easily observable and which can be measured or scaled more or less precisely.

To answer all the questions raised, we use methodology of the generalized linear models. The paper deals with variables of different kind, and we run several statistical models so as to compare the product categories mentioned earlier.

Speaking of the practical aspects of the paper, we found that the arguments and conclusions that may be sound for some particular product may appear to be groundless for some other market, and vice versa. The results (at least which obtained from regression analysis) have narrow applicability, and even may be doubtful for a similar product. Thus it is important to be as specific as possible in conclusions concerning online auctions.

2 Literature overview

Web-based auctions started their existence in the mid 1990th when eBay (www.ebay.com), the first web site of the kind, was founded in California in 1995. Among other famous online auction are Amazon.com auctions, Yahoo! auctions, uBid, Overstock.com, Bidorbuy and many others. Nowadays eBay is the largest and one of the fastest growing online auction sites with consolidated net revenues of almost six billion dollars in 2006 [1]. Only in the first quarter of 2007 eBay marketplaces net revenues totaled a record $1.25 billion, a growth rate of 23% over the $1.02 billion reported in the corresponding period in 2006. In addition to this, eBay platform confirmed registered user base totaled 233 million and eBay's users generated a total of 588 million listings, which listings led to eBay gross merchandise volume of $14.28 billion, representing a 14% year-over-year increase from the $12.50 billion reported in the first quarter of 2006 [2].

Since electronic markets continue to grow at a phenomenal rate, their popularity and availability of huge amounts of data attract researchers' attention from different fields such as economics, marketing and some information-related spheres. According to Wood (2004), this research is dedicated to examining how sellers and bidders interact through the online auction market structure and, therefore, typically concentrate on one of the following three auction characteristics: seller behavior, bidder behavior, and auction design. The primary focus of online auction research is given to four main areas. These topic areas are [3]:

- Auction Bids, Winner's Curse, Selling Prices, and Bundling;
- Selling and Buying Strategies and Decision Processes;
- Auction Fraud, Opportunism, Reputation Systems, and Trust;
- B2B Reverse Auction Exchanges.

Wood also points out that there exist many studies dealing with factors that affect auction prices in various contexts. Within the scope of these researches much attention is devoted to a particular problem of determining how important the sellers' feedback is to the buyers and, consequently, how this fact reflects the final auction prices (e.g. Gürtler and Grund 2006; Snijders and Zijdeman, 2004; Melnik and Alm, 2002 and 2003; Livingston, 2002; Lee, Im and Lee, 2000). As a rule, papers revealed that while strong positive feedback increases probability of sale, the negative feedback tends to reduce final auction prices. However, some researchers found no impact of positive or negative ratings on price premiums or found the effect of these ratings statistically insignificant (Ba and Pavlou, 2002; Lucking-Reiley, Bryan, Reeves, 2000) or even come to the conclusion that the negative feedback in some cases may result in increased number of bids or a higher price in the auctions (McDonald and Slawson, 2000; Kauffman and Wood, 2000).

Another common issue in this area is the examination of the effect of a minimum bid in the auctions, that is, how the opening bid and the so called "reserve price" (the minimal price at which the seller agrees to sell the item) affect the auctions' outcomes (Katkar and Lucking-Reiley, 2001; Bajari and Hortaçsu, 2000). The main finding here is that using reserve prices make sellers worse off by reducing the probability of the auction ending with a sale, deterring serious bidders from entering the auction and lowering the expected transaction price of the auction [4].

Among other common factors kept under observation are the length of the auction, Buy It Now option presence in the auctions and buyers' activity during weekends (which is assumed to be much more intense). Some authors also gave some consideration to the matter of the acceptance of the credit cards and some other payment methods by the sellers (Eaton, 2002; Livingston, 2002; Houser and Wooders, 2000).

The authors who aimed to uncover the determinants of the auction prices primarily concentrated their attention on some specific products. Because of theoretical prerequisites, not all the goods being traded on eBay could be chosen for this purpose. In the light of this, single coins had some obvious advantages over other products. They were easy to compare to each other, relatively simple to capture all the major features, and, lastly, they were large in number what provided researchers with enough data. However, some authors proposed to consider some other goods different from the coins. For instance, Eaton (2002) carried out a similar analysis on electric guitars and Kalyanam and McIntyre (2001) examined PDA computers and Andrews and Benzing (2006) analyzed used car auction market. As would be expected, quite often the conclusions made in these papers on some common issues mentioned above do not coincide.

In our belief, these disagreements partly arise from analyzing data taken under different circumstances for variant products. That is, since most products on eBay represent economically specific categories, it is logically correct to surmise that they all have dissimilar price-determinative elements which cause those differences. In fact, researchers themselves agree that their results should be taken with care and consideration since their studies are product-oriented and their conclusions might not apply. That is why we propose to conduct similar theoretical and practical procedures for the products belonging to economically different categories in order to study how our results alter from one product to another. For this purpose, we chose three goods which are traded on eBay and are available in sufficient quantities. These are coins (as collectibles), laptops (as consumer electronics) and prestigious watches (as luxury goods). A detailed description of these products as well as the data collected for them will be given later.

3 Research hypotheses

As it was mentioned earlier, we use generalized linear models procedures in our analysis. The hypothesis tests are conducted in the context of several models. In this section we provide a list of hypotheses we intend to test in our research and a brief explanation to each of them.

First, we expect our results to be noticeably different for all three products. That is, we suppose that the price determinants which have been preeminently discussed in preceding papers on a similar topic (such as feedback, reserve prices, bidders' activity on weekends and some other) will show unlike results towards distinct products. In other words, we contend that the nature of the goods will have its impact on the major price forming factors.

⇒ ***Hypothesis 1*** *(The product's nature hypothesis)*

Economically different products will have dissimilar combinations of major price forming determinants. Conclusions on the influence of a particular factor should be made separately for a certain product and circumstances.

When listing his items on eBay, a seller can choose whether he wants international bidders to participate in the bidding process. In some cases a seller can increase the number of potential buyers greatly by offering their items internationally. eBay gives to a seller opportunity not only to choose the continents where he would consent to ship his item to but also to pick a particular country or multiple countries to deal with. We decide not to make distinction among the regional seller's preferences in case he welcomes overseas bidders, since it would be too complicated to capture them. Instead, we discern whether a seller accepts any none-U.S. bidders for a particular auction in general.

⇒ ***Hypothesis 2*** *(The overseas bidding hypothesis)*

The probability of sale will be higher if a seller accepts bidders from more than one country.

As eBay has been growing exponentially since its very foundation in 1995, today's statistics show that eBay (www.ebay.com) is one of the 20 most visited websites on the web (according to www.alexa.com). eBay services are available 24 hours a day to the people from all over the world living in different time zones. All these facts give us grounds to assume that in today's auctions the consequence of the listing and ending time is diminishing. Although, some earlier McDonald and Slawson (2002) and Andrews and Benzing (2006) showed opposite results, we nonetheless contend that the degree of importance of the time at which an auction ends is gradually decreasing as long as eBay continues expanding.

⇒ ***Hypothesis 3*** *(The auction ending time hypothesis)*

The ending time of the auction will have no effect on the highest bid.

Keeping in mind that the high-priced market for luxury goods should theoretically attract a fewer number of bidders comparing to the lower-priced one, we believe that the former will be insensitive to the auction duration time. We reckon that the importance of the auction length for the luxury products is negligible as compared to the combination of other factors.

⇒ ***Hypothesis 4*** *(The auction length hypothesis)*

Auction length will affect the item's final price for relatively inexpensive goods only.

Earlier it was presumed that the auctions for luxury goods were not sensitive to the auction length and that eBay's high popularity as well as international bidders would smooth participation rates over a week. Combining these comments together leads to the following hypothesis: neither the winning bid nor the auction performance is affected in case the auction ends on a weekend. We admit, however, that previous studies on this issue reported somewhat discrepant results. While some authors showed a weekend effect to be highly significant (e.g. Kaufman and Wood, 2003), others did not find any overt proof of its verity (e.g. Lucking-Reiley, Bryan and Reeves, 2000).

⇒ ***Hypothesis 5*** *(The weekend hypothesis)*

The auction that ends on a weekend will not have higher winning bids comparing to that ending on a weekday.

A large number of papers were and still are being devoted to the particular issue of seller's reputation to a greater or lesser extent. By analogy with traditional markets, seller's feedback is a direct indicator of his experience in online auctions, which is one of the main criteria for a consumer to decide whether he wishes to deal with this seller. We anticipate finding a strong relationship between seller reputation and his successfulness and his ability to attract more bidders on eBay, and vise versa.

⇒ ***Hypothesis 6*** *(The seller experience hypothesis)*

Higher seller reputation will increase both final auction bids and the probability of the item sale.

Although electronic markets provide its participants with a variety of opportunities and benefits, they also have some disadvantages compared to traditional markets. One of the most evident limitations at this point is that online consumers are unable to personally scrutinize the seller or examine the product before purchasing. Hence, online consumers have a higher degree of product and seller uncertainty compared to traditional markets [5]. We hypothesize that by providing more detailed and complete information about his item and his policies in the listing entire description, a seller can reasonably control this uncertainty and thus can bridge a gap between himself and consumers.

⇒ ***Hypothesis 7*** *(The description length and pictures hypothesis)*

The highest bid will be dependent of the item description length and the number of pictures given in the description.

From our point of view, seller's acceptance of various forms of payments in his auctions makes him more 'flexible' or 'convenient' in terms that his prospective customers have more options to pay off the item and hence they do not need to seek for the its substitutes. Pleases note that we do not purport to check which of the payment options suggested by eBay seem to be more attractive to the transactions participants, but instead we want to find out how sellers' payment policies influence buyers' decisions.

⇒ ***Hypothesis 8*** *(The payment methods hypothesis)*

Sellers accepting various payment methods will have higher chances to have their auctions ended successfully.

As to Buy It Now and reserve prices, we expect to come to conclusions similar to those in earlier studies (e.g. Katkar and Lucking-Reiley, 2001; Peeters, Strobel, Vermeulen and Walzl, 2007).

⇒ ***Hypothesis 9*** *(The Buy It Now and reserve prices hypothesis)*

The presence of the Buy It Now option in the auction will result in lower final prices. The auctions with reserve price will have lower probability to be transacted.

And lastly, eBay sellers have means to promote their auctions in a number of ways. According to eBay's own estimates, using certain listing upgrade features appreciably increases final prices or the count of bids. For instance, their Bold and Highlight upgrade was estimated to increase the final auction price by 25%, a presence of a thumbnail picture in the auction should increase the final price by 11% and the Featured Plus! upgrade increases bids by 25% on average [6]. We want to verify if our own estimates will evince the preponderance of these upgrades in our particular cases.

⇒ ***Hypothesis 10*** *(The auction promotion hypothesis)*

The better the auction is promoted the higher is its probability to transact.

4 Data description

As it was mentioned above, one of the main goals of the paper is to disclose the price outlining factors for the three product categories (collectibles, consumer electronics and luxury goods) represented by the following products—coins, laptops and watches. Since all three categories correspond to different types of goods from an economic point of view, it is presumed that they all have specific price determinants in the corresponding auctions. To apprehend distinctly what in fact occasions this unsimilarity if there is any, we compile data on the mentioned merchandise over a four month period from April through July 2007.

Our practical experience shows that capturing the necessary data from eBay by using the so called “spy” or “spider” software programs can result in numerous mistakes and inaccuracies in the collected data. After comparing the upshots provided by some commercial automated data collectors with the original listings we found out that most of the ascertained inaccuracies were due to the divergence between the listings entire description and the information given in item titles mostly used to simplify the process of item search on eBay. Similar findings were also remarked by Andrews and Benzing (2006). The fact is that when listing an item a seller needs to duplicate or provide more specific information at some points and quite often he fails to reenter this information anew what leads to some discrepancies in the auction description. As a rule, the most relevant and detailed information is given in the listing’s entire text description. On the other hand, the software agents capture data from such clearly specified and easy-to-track sources as the listing’s title, accepted payment methods and others rather than from such subjective and tangled enough sources as item text description. Hence, spider programs occasionally obtain inaccurate data concerning shipping information, available payment options and more specific details such as item condition, production date and item’s features.

Therefore, it was decided to collect our data manually, step by step going into particulars of each listing. The three specific products for which the data was captured are the following:

1. American Silver Eagle Dollar coins. To limit our search to the identical items, only the coins produced in the year 2007 were selected. Moreover, the proof coins or any rolls or sets of coins we not considered here. All coins were either

mint (MS) with grades of 69 or 70 or were not graded at all provided that the description clearly stated that the coin came straight from a mint.

2. Dell Latitude D600 laptops. The laptops' configuration we gathered our data on is the following—1.6 GHz Intel processor, 512 Mb of memory, 14" display, CD-RW/DVD combo drive and other standard features. However, in some cases (for instance for refurbished notebooks) this configuration was revised.

3. Rolex Submariner watches. The data was captured for the Rolex Submariner model 16613 watches only. The watches of this model are available in several options—two-tone blue (blue bezel and dial), two-tone black (black bezel and dial), slate serti (slate dial with diamonds and sapphires) and champaign serti (champaign color dial with diamonds and sapphires) watches.

For each listing, some relevant data was collected. In order to reflect the items' particulars, further information was also gathered. The complete list of all the requisites taken from the auctions for three products and a brief description of the corresponding variables is given in Appendix A.

In Table 1 some general information on the collected data is given, illustrating the diversity of our items in many aspects.

As can be seen from the table, the three commodities contrast in various ways. One can observe that for each category and even for each subcategory within the product line sellers employ different tactics. In fact, each category on eBay represents a separate mini-market with its own prices, strategies, peculiarities, rules and conditions. Since the prices at which the items are sold for all the three markets vary greatly, it is of high importance for a seller to correctly determine his selling strategy. As to Rolex watches, experienced sellers prefer not risking and therefore assign a lower price (starting bid) they are willing to sell their item at fairly high. Expectedly, such a strategy leads to a lower rate of auction success but withal assures sellers against unforeseen losses. On the other hand, previous experience prompts coin dealers to let listings go their own way by placing low starting bids and setting no reserve price. Besides that, markets for luxury goods are usually less multitudinous compared to inexpensive ones. As a result, a feedback score of the sellers trading in coins and antiques is times higher compared to those who deal in luxury watches.

Table 1. Descriptive statistics for the collected data

	American Eagle coins	Dell D600 laptops	Rolex Submariner watches
Number of collected listings for a product	544	780	954
Number of listings studied	542	761	905 (94.9%)
Removed	2 (0.37%)	19 (2.4%)	32 (3.4%)
Items sold, %	451 (83.2%)	716 (94.1%)	125 (13.8%)
Price range (of items sold)	\$5.50 - \$217.50	\$175.00-\$660	\$2’325.00-7’995.00
Average price (of items sold)	\$29.86	\$356.54	\$5’197.94
Auctions with no bids received	89 (16.4%)	42 (5.5%)	768 (84.9%)
Average number of bids (of items sold)	7.37	24.59	7.66
Average listing duration, days	4.94	1.86	8.26
Listings available outside the U.S., %	243 (44.8%)	184 (24.2%)	550 (60.8%)
Listings with Buy It Now option, %	39 (7.2%)	33 (4.3%)	576 (63.6%)
Listings with reserve price, %	1 (0%)	61 (8.0%)	22 (2.4%)
Average number of pictures	2.09	3.85	6.83
Count of unique sellers	126	66	146

5 Methodology

To better understand the specifics of our products and to check our hypotheses, we resort to the help of regression analysis. We use four different models that should clarify the price forming processes on eBay. These are exactly the models which were mostly used by different authors in previous studies of this kind. By so doing, we expect to see if we notice some discrepancies or, quite the contrary, attest earlier results.

Before we start, several transformations are required for some variables. First, we eliminate the listings that were not finished. The two most common reasons why the bidding for an item was not finished correctly are 1) the listing was removed by the seller or was no longer available; and 2) according to eBay policies, a seller can finish bidding for his item before the appointed time and sell it at the current bid. The latter was observed more rarely in comparison to the former case. Both events taken together did not exceed 3.4% of the total count of listings for each product (see Table 1).

A large scope of papers that studied seller's experience on eBay suggested that the relationship between the seller's feedback and his reputation was not linear. That is, the first seller's positive or negative feedback scores are much more informative to buyers than the following ones. For example, a seller with a reputation score of 20 would be perceived as having much more experience than a seller with a reputation score of 10 [5], whilst the difference, say, between the scores of 500 and 510 would not be so helpful. It can be explained through the economic theory of marginal utility. The same applies to the number of pictures and the minimum bid amount. By taking the natural logarithms of the initial values we can correct our models with respect to these assumptions. As there can be zero values in the mentioned variables, we add one unit to each variable in order to avoid errors in calculations, that is instead of taking log(number of pictures) we take log(number of pictures+1) and so forth.

The first model implies studying how price premiums are influenced by the various factors. This model is of major concerns for us as it directly highlights the elements, participating in price mechanism on eBay. The dependent variable is the amount of the highest bid obtained in each auction. Some authors (e.g. Lucking-Reiley, 2000 and Houser and Wooders, 2006) suggested taking the natural logarithm of price as a dependent variable; others examined the initial price in their regressions without modifying its value (e.g. Melnik and Alm, 2003). We estimate two models where the dependent variable is both log-transformed (ln_HighBid) and unmodified (HighBid). We also run an additional model for the auctions that ended in transaction to see if the results will be similar to the first two regressions. This is a simple linear regression with HighBid as a response variable (which is known).

While our second model does not answer directly which elements cause changes in auction final prices, it is used as an additional tool to verify the results of other models. It aims to check how the different combinations of independent variables influence the successfulness of an auction. In other words, we want to find out which components have the most considerable effect on the auction sale probability. We apply a binary logit model, where the dependent variable takes a value of 1 or 0 (indicating if a listing results in a sale or not, respectively). The list of the explanatory variables is the same as is used in the first model.

The list of the dependent variables is unique for each product. Where possible, we included all the meaningful variables into a model; however in some cases (due to insufficient observations or model convergence problems) some of the variables were removed from the analysis. The full list of the dependent variables is as follows: auction length, auction ending time, whether an auction ends on a weekend, whether an item is available overseas, whether an auction has the Buy It Now option, whether an auction has a reserve price, the natural logarithm of the starting bid amount, the natural log of the number of pictures, the item description length, the title length, the natural log of the seller's feedback, the log of unique negative ratings, five payment options accepted by a seller and nine promotion upgrades. In addition to this, some other factors were used to capture the product's specifics:

- for the American Silver Eagle coins: whether a coin has a "W" mint mark and whether a coin is graded;
- for the Rolex Submariner watches: the watch type and the watch condition;
- for the Dell D600 laptops: the laptop condition and the hard drive capacity.

As was shown in Table 1, many of the auctions did not receive any bids at all, most often when the starting big was set too high by a seller. In such situations, the price premium is not observable. However, since we do not want to eliminate these listings from the model we assert that the highest bid is below the opening bid but its actual amount is unknown. Since all the independent variables are still observable, we can use a censored regression model, keeping in mind that the level at which the response variable is censored varies across observations. The same censored normal-likelihood estimation procedure was used by Lucking-Reiley et al. (2000).

Table 2 summarizes the information on the models and lists all the variables to be used there. Please note that a brief description for the corresponding variables is given in Appendix A.

Table 2. Models description and variables used in the study

Model 1 and 2	Model 3	Model 4
Model type		
Censored regression	Linear regression	Logistic regression
Dependent variable		
The natural logarithm of the highest bid amount in an auction (*ln_HighBid* and *HighBid*)	Actual price paid for an item (*HighBid*)	Whether an auction ends in a sale (*Sale*)
Independent variables		

For all products:	
Duration	auction length in days (available options include 3, 5, 7 and 10 days);
EndTime	the time at which an auction ends (categorical variable; one of the four time intervals);
Weekend	whether an auction ends on a weekend (dummy);
USdelivery	whether an item is available outside the U.S. (dummy);
BuyItNow	whether an auction has a Buy It Now option (dummy);
Reserve	whether an auction has a reserve price (dummy);
ln_MinBid	opening bid amount;
ln_Pictures	natural logarithm of the number of pictures in the item description;
TitleLength	the title length;
DescrLength	description length (categorical; four categories);
ln_Feedback	natural logarithm of the seller's feedback score;
ln_Negative	natural logarithm of the number of the seller's unique negative ratings;
Payment (5 variables):	
PayPal	whether a seller accepts PayPal (dummy);
BankCheck	whether a seller accepts bank or cashier checks (dummy);
PersCheck	whether a seller accepts personal checks (dummy);
Card	whether a seller accepts credit or debit cards directly (dummy);
Other	whether a seller accepts other payment methods (dummy);
Upgrade (8 variables):	
FeatPlus	whether an auction is upgraded with FeaturedPlus! feature (dummy);
Highlight	whether an auction is upgraded with Highlight feature (dummy);
Border	whether an auction is upgraded with Border feature (dummy);

Bold	whether an auction is upgraded with Bold feature (dummy);
Gallery	whether an auction displays a picture next to its title (dummy);
GallPlus	whether an auction is upgraded with GalleryPlus feature (dummy);
Subtitle	whether an auction has a subtitle (dummy);
SuperSize	whether an auction has any super sized pictures in the description (dummy);
For the American Silver Eagle coins only:	
W_mark	whether a coin has the "W" mark (dummy);
Certification	whether a coin is graded (dummy);
For the Rolex Submariner watches:	
WatchType	the watch type (categorical; four types);
WatchCondition	how many years of warranty is given to a watch;
For the Dell D600 laptops:	
LaptopCondition	the watch condition (categorical; two options);
LaptopHD	the capacity of a hard drive of a laptop.

6 Models estimation

In this section we go through the stages of our analysis. As our estimation procedure is similar for the three selected products, below we describe the analysis process for the Rolex watches only, taken as an example. For the other two products, only relevant major statistics are presented as well as the discussion of the obtained results.

Before we start estimating our models, we first want to escape the problems with overfitting or instability of the parameter estimates in our analysis. For that reason, we check the correlation coefficients between variables for all the three products. The correlation matrix for the Rolex watches data indicates that the highest correlation coefficient does not exceed 0.7 in absolute value. In general, only two coefficients are larger than 0.6 and five are larger tan 0.5 what can be reckoned as a positive sign, taking into account that the total number of the between-variables correlation coefficients for 28 variables equals 28*(28+1)/2=406. Such a result is a good indicator that our data suites for modeling.

The brief description of our data, given in Table 1, displays that less then 14% (125 out of 905) of the observed listings were sold. Eliminating the listings which did not receive any bids would be quite incorrect, since those auctions contain important information about causes of such outcomes. Obviously, the two main reasons why an auction is not completed are 1) the opening bid was set too high so that no buyer agreed to pay such amount of money for the item, and 2) the highest bid amount did not reach the hidden reserve price set by the seller. If an auction did not result in a sale because of the reserve price, we still have the records for the number of bids and the highest bid. On the other hand, when the starting bid was set too high and the auction did not receive any bids at all, the only information we have is that the would-be price for this item lies below the opening bid value. We can say that this latent price is censored from below, or left-censored at the minimum bid amount of that auction. With this assumption, we can analyze our data using the Tobit model methodology.

We assume that the variable that stands for the price premiums in the auctions is normally distributed. The maximum-likelihood estimation procedure is used to obtain the parameter estimates for this regression. After removing the cases with the missing values from our dataset and also listings the format of which did not imply bidding (you buy or not at a set price), we get 905 observations. A censored regression is built, keeping in mind that unlike in a standard Tobit model, the censoring point (minimum bid amount) is unique for each listing. Having done some simple data transformation, we run the model. The following table contains a summary for this procedure (column 1).

INSERT TABLE B.1 (APPENDIX B) HERE

The table shows that our model, as a whole, is statistically significant. By testing the difference between our model and the null model, the likelihood-ratio chi-squared test shows that the model fits well (chi-squared=639.89, df=35). Since the R^2 statistic in not available, we can use some pseudo-R^2's statistics as a measure of the goodness of fit of the model. McFadden's pseudo-R^2 suggests that one can obtain the measure of fit of a model by computing the expression 1-Loglikelihood(model)/Loglikelihood(null model). In our case, this statistic equals 1-694.8/1014.7=0.315. Others recommend considering a value of a squared covariance coefficient between the predicted and observed values. By computing it we get a value of 0.507, what indicates that our predictors account for around a half of the variability in the outcome variable.

The table also shows that only some of the entered variables are statistically significant in the model. The intercept term, Reserve, ln_MinBid, and Highlight appear to be significant at the 0.1% level; USdelivery, Gallery and GallPlus are at the 1% level; BankCheck and FeatPlus parameters are significant at the 5% level.

However, whilst some of the estimates have a predictable influence on the auction prices, others do not. As we expected to see, hidden reserve price in an auction adversely affect final prices. Minimum bid tends to increase the auction price, and a 1% change in its value accounts for 0.23% increase in the amount of the highest bids. Three of five coefficients for the payment methods appear in the model with a negative sign, though only one of the estimates (BankCheck) is significant at the 5% level. In addition to this, three listing upgrades estimates are below zero. One of the four estimates, which are significant at different levels, is negative (Gallery). Some additional analysis is required to understand what cause such results.

Column 2 presents summary for an identical model with the only exception that the response variable is non log-transformed. As we can see, the results differ greatly. Nonetheless, we should not forget that less than 14% of watches were sold, and thus the outcomes of censored regression for all 905 observations are doubtful and spurious to some extent.

To check the validity of these two models, we provide another regression, which only includes the auctions where the listed item was sold (column 3). With 125 such listings, we further investigate the effect of the selected variables on the auction premiums.

It is not a surprise that the results of this model do not coincide with the previously mentioned regressions. When dealing with such little number of actually recorded bids (there are 137 listings which received at least one bid), the estimates suggested in Tobit-type models should be taken very carefully. Speaking of the model itself, the high value of F-statistic (11.82 on 34 and 90 degrees of freedom) displays that our model is statistically significant and the adjusted R^2 (0.748) indicates good fit, suggesting that the selected predictors explain around 75% of the variance of price. The estimates of the model will be discussed later in the text.

As regards our logistic model, the dependent variable here is a factor which indicates whether an auction resulted in a sale or not. The matter of interest is if, given a certain combination of variables, we can predict how successful that combination might be for a seller in terms of probability of sale. Column 4 in the above table demonstrates the logit regression results for 905 listings.

Although the model fits well (deviance/df ratio is 488.56/869=0.562), most of its parameters are statistically insignificant. At the same time, some of the parameters are significant at the 0.1% level (BuyItNow), at the 1% level (ln_MinBid, Gallery) and some are at the 5% level (Duration, PayPal, Highlight and Gift).

We could try to improve our model by thoroughly examining which factors would be left in the model and which ones would be removed from it or by introducing some interaction terms to the model. However, this part of analysis is out of the scope of this paper. We only note that the forward selection/backward elimination procedures suggested that the following variables might be left in the model—Duration, BuyItNow, ln_MinBid, Highlight, WatchType, Gallery, Paypal and PersCheck. All these variables are significant at least at the 5% level provided that all these terms are included in a separate model.

By exponentiating the regression coefficients of the logit model, we can obtain the odds ratios. For instance, the odds ratio for the BuyItNow is exp(-1.119)=0.327 which means that the odds of the auction that has a Buy It Now price to result in a sale is 0.33 times the odds of the auction success that has no such option, *ceteris paribus*. In other words, the presence in an auction of the Buy It Now option significantly reduces its chances to end in a sale. For the rest of the significant estimates, the odds ratios are as follows—Duration 0.8 (at the 5% level), PayPal 2.51 (1%), ln_MinBid 0.74 (1%), Highlight 7.3 (1%), Gallery 0.11 (1%), Gift 0.06 (1%).

Some results are fairly unexpected. While the Highlight upgrade should considerable increase the seller's chances to sell his item, the availability of a picture for a listing or gift services significantly reduce them. After examining the observations closely, we noticed that the Highlight tool was mostly used to attract buyers' attention when the starting bid was set quite low. Further, in some cases sellers did not provide any pictures at all when listing an item with a low opening bid. For such expensive products as Rolex watches, this fact augments the level of buyers' uncertainty about the item and their valuation of the item declines. As a result, the final price for the majority of the listings that did not have a listing picture was much lower compared to those with a picture.

Speaking generally, the starting bid estimate, significant at 1% level, suggests that increasing the minimum bid value will lower probability for an item to be sold. However, by including the natural logarithm transformation of the opening bid values in our model we made it more difficult to interpret the meaning of that estimate. We also ran a similar model with the initial values of this variable instead of its logarithmic transformation, and its estimate appeared to be even more significant (at 0.1% level) with the estimate itself of around zero. This is caused by the large starting bid amounts for the Rolex listings, indicating that each additional dollar would not make any difference in auction sale odds. The interpretation of the ln_MinBid estimate might be easier in lower-priced auctions.

7 Results

To begin with, we advance some remarks regarding the study as a whole. First of all, regression analysis as such has limited applicability in studies connected with human choices. It is very unlikely that we can use it to explain or predict human action, whose preferences change greatly according to the situation he is in. When making a decision, a man bases his choices on individual and often hardly interpretable tangled grounds. Speaking of eBay, it is pretty difficult to realize what a buyer is guided by when preferring one item to another and so forth, not to mention attempts to "model" the behavior or hundreds and thousands of such buyers.

Secondly, even if we imagine that someone could uncover the key components of people's preferences, it is likely that their interactions would be so perplexed that today's knowledge in regression analysis would not be enough to construe them. When running different regression models, we concentrate our attention on the simplest and most evident constituents of some phenomenon, rarely even studying their second- or higher order interactions. All our models in this study examined the most straightforward properties of online auctions, and therefore the results should be taken with a proper degree of skepticism.

And finally, the experimental design of our study is based on examining the actual auction outcomes and thus does not stipulate answering the "what would have been if" questions. The obtained estimates merely retain and reflect *facts* of the real-life events, rather then indicate how a certain auction *should be* held to return the highest benefits to a seller. The results can not point to the best selling tactic since the best strategies might not have been observed in our cases.

In general, most of the models we tested appeared to be well fitted and the dependent variables to be quite reasonably explained by the chosen predictors. In some cases due to convergence difficulties some of the variables were not included. Appendix B displays results for the examined models for each product. In this section we analyze and provide interpretation of these results based on the hypotheses which were formulated earlier in the paper.

Hypothesis 1 *(The product's nature hypothesis).* Each product proved to have distinct elements of the resulting price premiums. Please note that here we refer not to such individual features as item condition or its color, but rather to the components which are mostly believed to influence final prices and so are frequently studied (seller's feedback, reserve prices and so forth).

In some cases, the parameters that appeared to be significant in models for different products, turned out to have opposite sign of their estimated coefficients and some of them could be hardly interpreted. However, we note that due to the different prevailing seller strategies on each product market, we could not check the significance of some of the components because of lack of data. For instance, the auctions with reserve prices are highly unpopular in the lower-priced coin market, so we excluded the corresponding variable from our model. Nonetheless, we contend that the preferred sellers' tactics are foremost determined by such products' essentials as price, target group, purpose of use, availability and other. Any changes in auction format are caused by these particulars first of all.

One of a few price components that showed quite similar results across our models is the amount of the log-transformed starting bid. It is statistically significant in most regressions, mainly having a negative effect on the price. It appears significant with a positive sign (0.23) in the censored regression for the Rolex watches only. We can explain it by reminding that sellers prefer setting a somewhat high opening bid what leads to a low transaction ratio (13.8%). But in cases where the auction starting bid amount was set low, the final price rarely reached that high starting bid for obvious reasons. That is why the regression suggests a positive relation between the opening bid and price. Secondly, in the absence of a large count of watches with a low opening bid, some buyers agree to pay more making their choice in favor of initially high priced items. In fact, 67 of 125 (53.6%) watches that were sold received one bid only. From that point of view, the following logistic model would give an answer how the minimum bid affects the sale probability of an auction. With 99% confidence interval, we conclude that a unit change in the log-transformed minimum bid amount leads to almost 25% (exp(-0.3)=0.74) decrease in sale probability. It is difficult to interpret a unit change in a log-value of the starting price, but we can have an idea of how much this change is by calculating the price levels that that are equivalent to a unit change starting from 1 dollar:

exp	0	1	2	3	4	5	6	7	8	9
Price ($)	1	2.7	7.4	20.1	54.6	148.4	403.4	1'096.6	2'981	8'103.1
Increase($)	-	1.7	4.7	12.7	34.5	93.8	255	693.2	1884.4	5122.1

Hypothesis 2 *(The overseas bidding hypothesis)*. Unexpectedly, none model suggested overseas shipping increase final prices or sale probability. On the contrary, in the models where the corresponding estimates were statistically different from zero, the results were opposite. In the Tobit-type censored regressions for Rolex watches and the American Eagle coins, the related parameters are 0.129 and 0.108 (at 5% and 1% significance level). Since our response is log-transformed, interpreting these outcomes is straitened. But, applying a similar model with the original value of the price as a response variable, we find that for the auctions where the international bidders were not accepted, the price was $129.5 and $6.157 higher respectively, on average (the same significance level remained). As the average price for the watches was $5'197.94 and for the coins was $29.86, such an increase accounted for 2.5% and 20.6% growth in the average price, respectively. We can see that the effect is much higher for the coins. Further, the logistic model indicates that the odds of sale for the auctions that accepted bidders from the U.S. only are 2.28 times the odds for the auctions opened to both U.S. and international bidders.

The reader should note that we made no distinction between the continents or countries which sellers would agree to ship their products to. Tracking this information would considerably complicate the models, and it was decided to only indicate if a seller was willing to deal with international customers. The obtained results suggest that international bidders (any) influence neither the final auction prices nor the odds of sale.

Hypothesis 3 *(The auction ending time hypothesis)*. The significance/insignificance of the ending time effect is not easy to establish since the results differ across the models. While the Rolex watches market seems to be indifferent to this parameter, the other two do not show identical outcomes. In the censored model for the Dell laptops, the coefficient for the 12 A.M.-6 P.M. time interval is significant and negative (-0.038), thus reflecting an average decrease of $14.49 in price for the auctions finished within this interval comparing to that from 0am to 6 A.M. The latter estimate is taken from the non log-modified model, which also recommends the fourth time interval 6 P.M.-12 P.M. have a lower price ($12.11 drop) in regards to the first one (10% significance level). The only product where the fourth interval showed higher bids compared to the others is the coins. Significant at the 5% level, its estimate is 0.201 which is equivalent to $9.2 average increase in price.

To further test the importance of the ending time on the auction outcomes we substitute the related variable with the dummy variable which indicates if an auction ends after 5 P.M. in order to compare the results to those given in Andrews and Benzing (2006). No direct evidence that the ending time had any positive or negative effect on the auction price was found for the watches and laptops. For the coins, although the estimate for the entered dummy variable was significant at the 10% level in the logit model only (estimate=0.67, p=0.058, exp(estimate)=1.956), the chi-squared test for independence test indicated that whether or not a coin was sold depended on whether the listing ended after 5 P.M. (chi-squared=5.909, p=0.015) However, the ending time did not have any effect on the final price amount.

We conclude that the auction closing time does not affect the final prices but may increase the probability of sale for some lower-priced products provided the latter are salable. Similar to Andrews and Benzing (2006) who studied the used car market, we found that ending an auction between 5 P.M. and midnight does not generate more sales or higher prices for the items where a single bid can be decisive. Though, we do not decline the idea that "an auction that ends when buyers are more likely to be available (i.e., not at work or asleep) may tend to generate more bids and higher bids" [10].

Hypothesis 4 *(The auction length hypothesis).* The chi-square test suggests sale probability be not independent of the length of the auction for all three products. After reviewing the results of our models and building some additional regressions, this relationship was found rather negative for Dell D600 and American Eagle coins. The relationship seems to be positive for the Rolex watches, but not significant. Thereafter, we conclude that the auction duration does not affect either odds of sale or price premiums. Thus the conclusion made in Lucking-Reiley et al. (2000) that the longer auctions provide higher prices with the elasticity of auction price with respect to number of days of +0.06 was not verified.

Hypothesis 5 *(The weekend hypothesis).* Neither could we find any proofs that the seller was better off if his listing ended on a weekend. The only model where the estimate related to whether an auction finished on a weekend was significant at the 5% level, was negative. The so called "weekend effect" had no any signs of its presence in the studied auctions. Kauffman and Wood (2003) have come to an opposite conclusion, but their interest was "to examine individual bidders' utilities and independent private valuations for specific items" [5] rather than the price determinants themselves, and the implemented model differed from the ones used in our analysis. Thus, the comparison of the results would be theoretically incorrect.

Hypothesis 6 *(The seller experience hypothesis).* In most censored regressions, the parameter estimates reflecting the influence of the count of negative ratings received by a seller were negative, but were different in value and insignificant. At the same time, the estimate of the seller's feedback score was mostly positive. With 90% confidence interval, a 1% increase in the seller's positive feedback score in the auctions for the Rolex watches yielded a 0.035% increase in the auction price, which is very similar to the estimates of Lucking-Reiley et al. (2000). The logistic regression outcomes are somewhat unclear. The model displays that in case of the watches and coins the higher seller's feedback score increase seller's chances to sell his item, and negative ratings decrease them, though the estimates were not statistically different from zero. The latter appeared significant for the Dell laptops, but with the opposite signs for both feedback score and negative ratings. As Eaton (2002) points out "the negative feedback is acting as a proxy for more experienced sellers" and that "negative feedback is more likely to occur for those who are active traders on eBay" [11]. Thus, negative feedback is rather an indicator of the seller's experience and does not necessarily mean his unsuccessful trade activity. Higher feedback score's resulting in less sales is more difficult to explain. But since our estimates are very unstable, our conclusions are by no means clear. Therefore, we suggest relying on the results of the studies which examine this topic in more detail (e.g. Melnik and Alm, 2002, McDonald and Slawson, 2000). As was mentioned before, this topic is extremely popular in the literature dedicated to online auctioning.

Hypothesis 7 *(The description length and pictures hypothesis).* After thorough analysis of the effects of the description length and number of pictures in auctions, it becomes obvious that these descriptive constituents affect each product in a different way. As for the expensive watches, while additional pictures seem to affect positively both prices and sales (although no significant effect was found), the length of the description seem to increase prices but not the probability of sale (no significant effect either). For the laptops, we found no evidence that availability of a larger number of pictures influenced final prices but discovered that more pictures meant less sales (each additional pictures gave 0.326 times odds of sale). On the contrary, prices tend to decrease as entire description grows, but sales are not affected. For the coins, where sellers usually provide no more than two pictures we found that each additional picture added another $1.6 to the price, but had no effect on sales. Similar to the Dell laptops, size of the item description brought negative effect on final prices (price dropped by around $12.7 and $21.5 if the description length was about 500-1’000 and 1’000-2’000 words respectively), having no statistically significant effect on sales.

Summing up, we can say that providing pictures is not a burden and by giving more information about his item one can benefit from higher premiums. It is especially true in cases, where pictures can show whether or not the item has any special features. For instance, the presence of the “W” mark on a coin (reflecting their striking at the mint at West Point, New York) considerably increased its value for bidders. A single picture displaying this mark could say much more than words. In this sense our results are similar to those of Melnik and Alm (2005) who found that presence of images reduces uncertainty about the product when the quality of the product is less easily established. On the other hand, in some cases pictures could also uncover a product’s flaws. This is how a negative effect on laptops’ prices can be explained. Similar effect was also found in the study of Andrews and Benzing (2006).

Unlike Kauffman and Wood (2003), we did not reveal any proof of the importance of the description length. Perhaps surprisingly, the relationship is rather negative for the laptops and coins and is not statistically different from zero for the watches auctions. We conclude that in the studied cases the description length played little role in either establishing higher prices or sale occurrence.

Hypothesis 8 *(The payment methods hypothesis).* Several previous papers have attempted to study how methods of payment influence buyers’ willingness to pay. Melnik and Alm (2003) found that seller’s acceptance of personal checks has a statistically positive effect on coin prices. Furthermore, similar to Houser and Wooders (2003) and Kauffman and Wood (2003), they also showed that bidders were not significantly influenced by the whether the seller accepted credit cards. In our case, although the coefficient on personal checks is significant and positive in coin auctions, it did not have such an effect for other products. Similar to Eaton (2002), the coefficient related to credit cards is unstable and sometimes indicates a negative influence on price or sale.

Taking PayPal and bank/cashier checks also tends to have positive effect on prices. However, their estimates appear with a negative sign in the censored regressions for the

Rolexes but if we consider that only less than 14% of watches were transacted, we should rely more on regression results for the transacted watches and the logit model, which show positive effect, though insignificant.

Generally, we did not notice any indisputable evidence of the importance of any of the payment method in our study. The results vary from product to product, and even significance of some of the estimates is hardly interpretable or dubious.

Hypothesis 9 *(The Buy It Now and reserve prices hypothesis)*. From the models we can see that the listings for the Submariner watches with Buy It Now prices were harder to sell (the corresponding odds ratio is 0.327 at the 1% level) but higher prices were fetched (+$593.27); the estimates for the reserve prices are more than contradictory. While the censored regressions give a highly significant estimate (equivalent to $1'796.6 drop in price) the linear model for the listings that received at least one bid indicates that prices were higher for the listings with reserve prices. The presence of a reserve price in the Dell auctions added about $11.1 to the laptop price while Buy It Now added nothing. Auctions with reserve prices are extremely unpopular in lower-priced auctions, and so we could not examine the importance of reserve prices in the coins listings. The price of the American Silver Eagle coins seems to be indifferent to the presence of the Buy It Now price.

The results are inconclusive and deeper analysis is required to test their validity. To determine the effects of starting bids and reserve prices on auction outcomes, Katkar and Lucking-Reiley (2001) empirically established that reserve prices lowered the expected transaction price of the auction and reduced the probability of the auction resulting in a sale. We suggest relying on these results; however, we also note that there is no guarantee that the results would be alike had they run the experiment with diverse goods (they studied Pokemon cards on eBay). Hence, we contend that the effect of both Buy It Now and reserve prices greatly depends on particular circumstances and details of the auction format.

Hypothesis 10 *(The auction promotion hypothesis)*. As we noted earlier, according to eBay's own estimates, using their Bold and Highlight upgrade was estimated to increase the final auction price by 25%, a presence of a thumbnail picture in an auction should increase the final price by 11% and the Featured Plus! upgrade increases bids by 25% on average. None of these statements was clearly verified in our study, at least in the examined models. If any of the parameters is significant in one of the models, it is difficult to acknowledge its verity in a corresponding model for a different product.

If not taking generally, the thumbnail picture (Gallery) in the auctions for the coins increased both prices and probability of sale. FeaturedPlus! and Highlight upgrades also caused increase in prices for the Rolex Submariner watches. Providing the title of a listing in bold (Bold) increased its visibility enough to increase prices in laptop auctions. However, these all are particular cases for each product, which do not imply the expected systematic yields for sellers.

8 Conclusions

Summing up, we once again emphasize that regression analysis has a limited application in studies connected with human preferences. Fairly often, the list of determinants that influence this or that phenomenon and the interactions between them might be far beyond the assumptions needed for statistical analysis. As a rule, the analysis comes to examining the most visible and comprehensible occurrences of the events, leaving behind more tangled relationships and thus causing difficulties in interpreting the parameters of a model.

As our study demonstrates, results differ from one model to another, and that is why drawing conclusions regarding such intricate subject as human choices from a single model is inadmissible. Reasonable meaning should be present in each stage of modeling, otherwise the analysis turns into mere playing with numbers.

As regards analysis and the established results, we found that different products traded online represent separate mini-markets with their own rules, determinative constituents and consequences. The interactions that seem to be important in coin market may appear groundless in the auctions of a pricier product, and vice versa. Therefore, one should be very careful and as specific as possible in his conclusions concerning online auctions.

Below we provide a brief list of the key findings of our study:

1. As it was already mentioned, nature and peculiarities of a good determine auction format and seller strategies and hence each product has its specific price determinative elements;

2. We found no evidence that the auctions where international bidders are accepted by the seller the final prices or the probability of sale should be higher;

3. The time when auction ends seem to have no effect on the prices but may increase the probability of sale for some products provided they are salable;

4. The assumption that the longer auctions tend to provide higher prices was not verified;

5. Neither could we verify that the seller would get higher bids if his listing ended on a weekend;

6. In the examined cases the description length played little role in either establishing higher prices or sale occurrence;

7. No certain evidence of the substantial importance of any of the payment method in our study was found since the results vary from product to product;

8. Using eBay listing upgrades may be an advantage, however the expected systematic yields for sellers from certain upgrades were not found.

Our findings are by no means conclusive and further, narrower and detailed analysis is required to study the price formation processes in online auctions, with implementation of various techniques and approaches. Auctions on eBay are never static and we do not deny that other researches would come to different findings, had they studied all three products again. As our own experience suggests, the better a seller or buyer knows the specifics of a particular auction market the easier for him to find his own set of factors of his success in online trade.

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Appendix A

Factors	Variable description
Data collected for each listing	
Auction highest bid	The highest bid at the end of an auction, which is calculated regardless of whether an auction ended in a sale.
Auction length	Measured in days. Available options—three, five, seven and ten days.
Auction ending time	eBay official time (Pacific daylight time) is taken into account as one of the four time intervals—from 0.00 to 6.00, from 6.00 to 12.00, from 12.00 to 18.00, from 18.00 to 0.00.
Auction ending on a weekend	Takes a value of one if a listing ended during the weekend and zero otherwise.
Item sold	Equals one if an auction successfully ended in a sale; zero otherwise.
Shipping destination	Takes a value of one if a listing implied delivery within the U.S. only; else zero.
Shipping/handling costs	Applicable if an auction was intended for the U.S. customers only and the costs were clearly stated in the item description. In case a listing was for the U.S. only but there were several shipping options (e.g. when the shipping costs depended on the auction highest bid progressively or there were several options to choose from) the amount of these costs was not taken. Measured in dollars.
Buy It Now option presence	Takes a value of one if a listing involved a preset Buy It Now price at which buyers could finish the auction at any time; zero otherwise.
Buy It Now price	If a listing had the Buy It Now option, its price was taken.
Reserve Price presence	Equals one if a seller set a hidden reserve price at which he was willing to sell his item; zero if he did not.
Starting bid value	The price at which a seller wanted bidding to begin for his item (in dollars).
Title length	The length of the listing's title in characters (according to eBay policies, it cannot exceed 55 characters).
Number of pictures in description	The number of distinct pictures of the actual item that are provided by a seller in the entire description.
Item description length	Approximate length of the item description. It was decided to break the length interval into four categories—up to 500 words,

	from 501 to 1000, from 1001 to 2000 and above 2000 words.
Seller's Feedback Score	A number used to measure a seller's reputation on eBay. Members receive points for ratings as follows: +1 (positive), 0 (neutral), or -1 (negative). The Feedback Score is the sum of all the ratings a member has received from unique users [7].
Number of unique positive ratings	The number of unique members who have given this member a positive rating. If the same member leaves more than one positive rating, it will only count once [8].
Number of unique negative ratings	The number of unique members who have given this member a negative rating. If the same member leaves more than one negative rating, it will only count once [8].
All positive feedback	The total number of positive Feedback received for all transactions, including repeat customers [8].
Positive Feedback	The percentage of positive ratings left by members. This is calculated by dividing the number of unique positive ratings by the sum of unique positive and negative ratings [8].
Payment options	A set of five dummy variables to indicate which of the following payment methods were accepted by seller in his listing—PayPal, Money orders/Cashier checks, Personal checks, Credit/Debit card and Other options.
Auction promotion features	A set of ten dummy variables to capture some special promotional features for an auction (if there are any): Home Page features, Featured Plus!, Highlight, Border, Bold, Gallery, Gallery Plus, Item Subtitle, Gift Services, Supersize pictures.
Specific data: American Eagle coins	
The presence of the "W" mark	Starting from June 13, 2007, the American Eagle Silver Uncirculated Coins carry the "W" mint mark, reflecting their striking at the United States Mint at West Point, New York [9]. Previously, the coins did not have such a mark. Dummy variable records if a coin has the "W" mark.
Grading	Indicates whether a coin was graded by any of the companies offering such services.
Specific data: Rolex Submariner watches	
Watch type	Factory Rolex Submariner model 16613 watches come in four options—two-tone blue, two-tone black, slate serti and champaign serti dial watches.
Watch condition	Since it is difficult to compare such subjective categories as 'pristine' or 'as new' or 'excellent', we consider all the watches of this kind as worn. The watch is reckoned as unworn only if

	such was clearly mentioned in the item description.
Specific data: Dell D600 laptops	
Laptop condition	A variable describing laptop condition—brand new, used, refurbished, repair/parts or other.
Hard drive capacity	The capacity of the hard drive of a laptop in gigabytes.

Appendix B

Table B.1. Regression estimates for Rolex watches (standard error is given in parentheses)

	(1)	(2)	(3)	(4)
	Model type			
	Censored (Ln_HighBid)	**Censored (HighBid)**	**Linear (HighBid)**	**Logit**
(Intercept)	6.808*** (0.358)	3710.9*** (955.054)	4334.625*** (1017.028)	-0.156 (2.27)
Duration	0.025 . (0.015)	92.2 *** (19.086)	15.917 (46.157)	-0.224* (0.1)
USdelivery1	0.129** (0.05)	129.5* (64.099)	321.928* (143.864)	0.514 . (0.311)
BuyItNow1	0.04 (0.051)	317.4*** (64.339)	602.422*** (149.165)	-1.119*** (0.338)
Reserve1	-1.84*** (0.129)	-1796.6*** (164.589)	206.676 (242.852)	-0.708 (0.673)
ln_MinBid	0.233*** (0.016)	249.7*** (20.287)	66.944* (25.655)	-0.3** (0.102)
WatchCondition2	-0.07 . (0.04)	-1024.8*** (51.414)	-952.025*** (165.197)	0.241 (0.304)
DescrLength2	-0.032 (0.055)	51.9 (69.935)	282.926 (176.214)	-0.466 (0.376)
DescrLength3	0.08 (0.068)	234** (87.18)	121.254 (379.873)	-0.893 (0.58)
DescrLength4	0.004 (0.318)	-448.6 (404.553)	-	-12.968 (509.371)
PayPal1	-0.014 (0.058)	60.4 (73.519)	34.951 (222.17)	0.919* (0.416)
BankCheck1	-0.134* (0.059)	-129.7 . (74.937)	315.505 . (171.405)	0.095 (0.39)
PersCheck1	0.085 . (0.046)	292*** (58.06)	-17.937 (147.662)	-0.348 (0.296)
Card1	0.069 (0.07)	173.9* (88.66)	440.8 (272.713)	-0.106 (0.553)
Other1	-0.042 (0.053)	41.9 (68.039)	-18.245 (156.132)	0.094 (0.319)
FeatPlus1	0.184* (0.078)	461*** (99.075)	244.209 (245.54)	0.845 (0.534)
Highlight1	1.191*** (0.161)	759.5*** (205.345)	26.037 (243.808)	1.989* (0.991)
Border1	0.057 (0.154)	-58.3 (196.262)	-145.091 (322.379)	-0.525 (0.885)
Bold1	-0.133 . (0.074)	231.7* (95.188)	-5.922 (159.782)	0.288 (0.381)
Gallery1	-0.441** (0.163)	213.8 (208.033)	784.533* (300.361)	-2.219** (0.855)
GallPlus1	0.28** (0.096)	12.7 (122.109)	156.326 (229.361)	0.915 (0.574)
Subtitle1	0.064 (0.048)	56.9 (60.85)	-119.59 (152.263)	0.215 (0.328)
Gift1	-0.059 (0.118)	-195.8 (150.205)	2156.84** (745.104)	-2.801* (1.256)
SuperSize1	0.055 (0.052)	188.6** (65.993)	62.467 (146.366)	0.46 (0.373)
EndTime2	-0.136 (0.101)	71.5 (128.295)	-2.864 (417.139)	1.091 (0.803)

EndTime3	-0.061 (0.099)	274.1* (125.74)	210.661 (409.294)	0.954 (0.789)
EndTime4	-0.081 (0.099)	213 . (126.638)	-12.3 (426.448)	0.824 (0.802)
ln_Feedback2	0.035 . (0.018)	55.7* (23.007)	88.617 . (45.374)	0.012 (0.11)
ln_Negative2	0.013 (0.035)	96 (44.341)	-197.866 . (110.307)	-0.267 (0.24)
ln_Pictures	0.081 (0.059)	-62.5 (74.794)	80.877 (195.938)	0.663 . (0.375)
Weekend1	0.018 (0.039)	10.7 (50.045)	-62.93 (127.297)	-0.346 (0.274)
WatchType1	-0.116 (0.094)	-1102*** (119.649)	-2529.919*** (641.488)	0.575 (0.85)
WatchType2	-0.154 (0.098)	-1160.3*** (124.226)	-2704.674*** (651.447)	-0.402 (0.877)
WatchType3	0.037 (0.096)	172.1 (122.818)	-1859.625** (679.637)	-0.974 (0.917)
WatchType4	0.043 (0.098)	315* (124.869)	-1474.779* (710.213)	-0.711 (0.95)
TitleLength	-0.002 (0.004)	-116 (227.425)	24.446* (11.636)	0.042 . (0.025)
Log(scale)	-0.651*** (0.024)	6.5 (0.024)	-	-

Signifinance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Models summary:

Censored (Ln_HighBid)	Scale= 0.521 Gaussian distribution Loglik(model)= -694.8; Loglik(intercept only)= -1014.7 Chisq= 639.89 on 35 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 5 n= 905
Censored (HighBid)	Scale=664 Gaussian distribution Loglik(model)= -7165.5; Loglik(intercept only)=-7797.4 Chisq=1263.74 on 35 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 5 n=905
Linear (HighBid)	Residual standard error: 587.9 on 90 degrees of freedom Multiple R-Squared: 0.817, Adjusted R-squared: 0.7479 F-statistic: 11.82 on 34 and 90 DF, p-value: < 2.2e-16 n= 125
Logit	(Dispersion parameter for binomial family taken to be 1) Null deviance: 726.79 on 904 degrees of freedom Residual deviance: 488.56 on 869 degrees of freedom AIC: 560.56 Number of Fisher Scoring iterations: 13 n= 905

Table B.2. Regression estimates for Dell laptops (standard error is given in parentheses)

	(1)	(2)	(3)	(4)
	Model type			
	Censored (Ln_HighBid)	**Censored (HighBid)**	**Linear (HighBid)**	**Logit**
(Intercept)	5.616*** (0.128)	259.26*** (45.469)	294.15*** (47.992)	31.25 (4139)
Duration	-0.005 (0.004)	-1.51 (1.275)	-1.549 (1.3)	-0.384 . (0.203)
USdelivery1	-0.036* (0.016)	-10.37 . (5.822)	-8.081 (5.911)	-0.291 (1.085)
BuyItNow1	0.029 (0.033)	7.92 (11.688)	28.303* (14.184)	0.065 (1.653)
Reserve1	0.029 . (0.016)	11.14* (5.636)	10.965 . (5.662)	-2.779 (1.699)
ln_MinBid	-0.016*** (0.003)	-5.02*** (1.044)	-3.774*** (1.094)	-1.336*** (0.404)
LaptopCondition2	-0.064 (0.065)	-26.33 (23.088)	-31.214 (22.879)	-1.491 (3766)
LaptopCondition3	-0.02 (0.064)	-11.08 (22.587)	-13.086 (22.365)	-7.283 (3766)
LaptopHD	0.003*** (0)	1.33*** (0.165)	1.27*** (0.167)	0.01 (0.033)
DescrLength2	0.009 (0.018)	5.16 (6.442)	4.041 (6.544)	-
DescrLength3	0.031 (0.021)	12.87 . (7.293)	15.291* (7.359)	-
DescrLength4	-0.227 . (0.117)	-80.63 . (41.468)	-	-
PayPal1	0.131* (0.055)	42.39* (19.712)	26.474 (23.118)	3.352 (4.324)
BankCheck1	0.071** (0.022)	21.65** (7.683)	26.102** (8.102)	2.736 (1.672)
PersCheck1	0.032 (0.034)	6.27 (12.079)	-0.19 (12.314)	-
Card1	-0.062*** (0.018)	-14.53* (6.323)	-14.892* (6.465)	-1.054 (1.839)
Other1	0.051** (0.019)	17.37* (6.791)	21.094** (7.284)	-0.711 (1.273)
FeatPlus1	0.019 (0.017)	3.97 (5.977)	-0.288 (6.008)	1.771 (1.418)
Highlight1	-0.025 (0.084)	-8.18 (29.733)	-11.734 (29.481)	-
Border1	-0.03 (0.054)	-11.79 (19.354)	-10.249 (19.183)	-
Bold1	0.052* (0.026)	20.12* (9.163)	16.666 . (9.311)	5.754** (2.175)
Gallery1	-0.004 (0.036)	2.54 (12.851)	1.51 (12.849)	-10.57 (1719)
GallPlus1	-0.182** (0.065)	-38.35 . (23.024)	-48.658* (23.019)	-
Subtitle1	-0.005 (0.016)	-3.34 (5.557)	-1.56 (5.752)	0.091 (1.165)
SuperSize1	-0.011 (0.054)	-11.3 (19.375)	-14.868 (19.199)	-
EndTime2	-0.018	-7.26	-6.863	-2.876

	(0.017)	(6.03)	(5.994)	(3.383)
EndTime3	-0.038* (0.017)	-14.49* (6.117)	-14.653* (6.086)	-3.262 (3.447)
EndTime4	-0.033 . (0.017)	-12.11 . (6.191)	-12.519* (6.145)	0.172 (3.301)
ln_Feedback	0.017* (0.007)	5.75* (2.559)	5.133 . (2.636)	-1.466* (0.632)
ln_Negative	-0.013 (0.008)	-5.91* (2.917)	-6.205* (2.964)	1.02. (0.559)
ln_Pictures	-0.01 (0.015)	-6.66 (5.255)	-6.884 (5.52)	-5.209*** (1.448)
Weekend1	-0.017 . (0.009)	-6.14 . (3.29)	-7.582* (3.308)	-0.435 (0.797)
TitleLength	-0.002 (0.002)	-0.48 (0.596)	-0.599 (0.607)	0.088 (0.133)
Log(scale)	-2.273*** (0.026)	3.6*** (0.026)	-	-

Signifinance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Models summary:

Censored (Ln_HighBid)	Scale= 0.103 Gaussian distribution Loglik(model)= 601.6; Loglik(intercept only)= 337.6 Chisq= 527.96 on 32 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 5 n=761
Censored (HighBid)	Scale= 36.6 Gaussian distribution Loglik(model)= -3622; Loglik(intercept only)= -3868.6 Chisq= 493.14 on 32 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 5 n= 761
Linear (HighBid)	Residual standard error: 37.05 on 684 degrees of freedom Multiple R-Squared: 0.4398, Adjusted R-squared: 0.4144 F-statistic: 17.32 on 31 and 684 DF, p-value: < 2.2e-16 n= 716
Logit	(Dispersion parameter for binomial family taken to be 1) Null deviance: 341.802 on 760 degrees of freedom Residual deviance: 70.204 on 736 degrees of freedom AIC: 120.20 Number of Fisher Scoring iterations: 17 n= 761

Table B.3. Regression estimates for American Eagle coins (standard error is given in parentheses)

	(1)	(2)	(3)	(4)
		Model type		
	Censored (Ln_HighBid)	**Censored (HighBid)**	**Linear (HighBid)**	**Logit**
(Intercept)	1.274*** (0.314)	-48.144** (17.707)	-35.923 . (20.399)	-2.351 (3.119)
Duration	0.014 (0.009)	0.534 (0.494)	0.808 (0.53)	-0.052 (0.103)
USdelivery1	0.108** (0.036)	6.157** (2.015)	6.573** (2.138)	0.089 (0.407)
BuyItNow1	-0.103 (0.085)	-8.642 . (4.713)	-3.909 (6.199)	-0.849. (0.498)
ln_MinBid	0 (0.01)	-1.133 . (0.579)	0.649 (0.655)	-1.335*** (0.183)
DescrLength2	-0.2*** (0.042)	-12.731*** (2.396)	-12.001*** (2.524)	-0.822 (0.653)
DescrLength3	-0.437*** (0.119)	-21.492** (6.718)	-21.402** (6.895)	10.81 (736.8)
PayPal1	0.171 (0.199)	9.157 (11.345)	3.969 (13.943)	2.013 (2.402)
BankCheck1	0.104 (0.086)	-0.448 (4.835)	4.504 (5.251)	-0.184 (0.702)
PersCheck1	0.126** (0.038)	8.77*** (2.17)	7.23** (2.345)	0.933* (0.445)
Card1	0.004 (0.065)	-2.543 (3.675)	-3.177 (3.914)	0.021 (0.869)
Other1	-0.012 (0.041)	1.036 (2.284)	1.823 (2.444)	-0.487 (0.516)
Gallery1	0.182* (0.074)	9.692* (4.191)	1.193 (5.199)	2.759*** (0.651)
Subtitle1	0.076 . (0.045)	6.681** (2.516)	5.186 . (2.714)	0.485 (0.549)
EndTime2	0.131 (0.083)	6.054 (4.716)	7.398 (5.169)	-0.26 (0.685)
EndTime3	0.109 (0.08)	4.56 (4.51)	5.29 (4.946)	-0.063 (0.641)
EndTime4	0.201* (0.082)	9.202* (4.652)	8.774 . (5.063)	0.329 (0.666)
ln_Feedback	0.028 (0.018)	1.145 (0.996)	0.46 (1.131)	0.209 (0.177)
ln_Negative	-0.004 (0.025)	-0.021 (1.418)	0.267 (1.636)	-0.09 (0.231)
ln_Pictures	0.112* (0.057)	8.356** (3.216)	9.236** (3.43)	0.039 (0.205)
Weekend1	0.045 (0.035)	1.837 (1.989)	1.236 (2.123)	-0.012 (0.416)
TitleLength	0.006 (0.004)	0.163 (0.226)	0.161 (0.25)	0 (0.034)
W_mark1	0.527*** (0.041)	19.811*** (2.288)	20.12*** (2.497)	0.871* (0.416)
Certification1	0.466*** (0.045)	11.31*** (2.522)	11.161*** (2.848)	1.05* (0.445)
Log(scale)	-1.095*** (0.033)	2.942*** (0.033)	-	-

Signifinance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Models summary:

Censored (Ln_HighBid)	Scale= 0.334 Gaussian distribution Loglik(model)= -183.8; Loglik(intercept only)= -421.5 Chisq= 475.4 on 23 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 6 n= 542
Censored (HighBid)	Scale= 19.0 Gaussian distribution Loglik(model)= -2015.4; Loglik(intercept only)= -2160.4 Chisq= 290.06 on 23 degrees of freedom, p= 0 Number of Newton-Raphson Iterations: 5 n= 542
Linear (HighBid)	Residual standard error: 19.32 on 427 degrees of freedom Multiple R-Squared: 0.3964, Adjusted R-squared: 0.3639 F-statistic: 12.19 on 23 and 427 DF, p-value: < 2.2e-16 n= 451
Logit	(Dispersion parameter for binomial family taken to be 1) Null deviance: 490.55 on 541 degrees of freedom Residual deviance: 253.32 on 518 degrees of freedom AIC: 301.32 Number of Fisher Scoring iterations: 15 n= 542