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First Bid Effect in eBay Auctions of New and Used Montblanc Pens

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Abstract: **In this paper, the researcher studied the dynamics of online auctions of Montblanc pens on eBay. The researcher compared two sets of auctions: auctions of new pens and auctions of used pens and concluded that substantial differences seem to exist between the two sets of auctions. The researcher also looked at how the first online bid seems to affect the number of bidders and the number of bids in both auctions and concluded that the first bid in an auction seems to have a very strong influence on the outcome of the auction. The shorter the time between the auction start and the first bid, the higher will be the number of bidders and the number of bids in the auction. The researcher called this the "first bid effect". The research also showed that this phenomenon is more evident in new pens versus used pens. These findings indicate that potential buyers feel more confident in bidding on items on which others have already placed a bid because this ensures to a certain extent that the item sold is genuine and not a replica. This also highlights buyers' perception that used pens are safer to bid on than new ones that nowadays are easily replicated. It is also clear from the research that the relative value of the starting bid has a much higher impact on the auctions for new pens versus auctions for used ones again emphasizing that there are subtle difference in the way buyers approach these two auctions. In this research the researcher used the relative starting bid variable instead of the traditional starting bid variable that was used in previous research arguing that the value of the starting bid is perceived differently based on the perceived value of the item in the auction.**

Keywords: eBay, electronic commerce, trust, Fraud, Bid, Montblanc

I. Introduction

Juda and Parkes [1] observed that only 32.3% of bidders who had more than one auction available bid in more than one auction (bidding in 3.6 auctions on average) and that bidders tend to submit maximal bids to an auction that are $1.22 higher after spending twice as much time in the system, as well as bids that are $0.27 higher in each subsequent auction. This paper attempts to explore how the bidders choose the auction in which they will bid.

Much of the existing literature focused on the feedback rating of the sellers and their reputation, but up to the researcher's knowledge, there is no research so far that studied the relationship between the number of bidders in an auction and bidders' trust in that auction. The researcher believes that trust is contagious, and that the number of bidders is an auction can be seen by a potential bidder as a manifestation of the Trust other bidders have in the auction and in the seller. It would make sense in this case to assume that this already established trust between the seller and the existing bidders will help lower the potential bidder's level of perceived uncertainty and thus help in building trust.

II. Fraud in Online Auctions

Guth, Mengel and Ockenfels [2] reported that "Internet transaction fraud is 12 times higher than in-store fraud." Jin and Kato [3] also believed that "online fraud rate was significantly higher than the fraud rate observed in corresponding offline transactions." This kind of fraud is especially evident in auctions of expensive collectible items like the Montblanc pen. Everyday multiple pens are auctioned on eBay and many of those pens are replicas that are sold as genuine pens. This is such a wide spread phenomenon that a number of guides have already been posted on eBay to help potential buyers differentiate between a fake pen and a genuine one. Because of this, the researcher believes that buyers would normally feel more comfortable bidding on pens that have already been bid on by other buyers because this indicates that the other bidders also believe that the item is genuine and accordingly motivates the potential bidders to participate in the auction and bid for the item.

Chau and Faloutsos [4] studied fraud on eBay and concluded that fraudsters usually aim to gain as much one-time profit as quickly as possible and so they usually sell moderate value or expensive items, but tend not to deliver those items after receiving payment from buyers. To gain credibility though, fraudsters attempt to gain needed reputation on eBay through, a number of strategies:

1. They try to sell or buy cheap items from legitimate users so they can gain ratings at a low cost
2. They sell or buy moderate value and even expensive items from "collaborators", that generally act like legitimate users
3. A mix of both strategies 1 and 2

III. Hypothesis

In this research, the author is introducing the following hypothesis:

- Hypothesis 1: The shorter the time gap between the auction start and the first bid, the more the number of bidders in the auction.
- Hypothesis 2: The shorter the time gap between the auction start and the first bid, the more the number of bids in the auction.
- Hypothesis 3: The smaller the starting bid versus the product's value, the more the number of bidders in the auction.
- Hypothesis 4: The smaller the starting bid versus the product's value, the more the number of bids in the auction.
- Hypothesis 5: there will be no difference between used and new pens in terms of hypothesis 1, 2, 3, and 4.

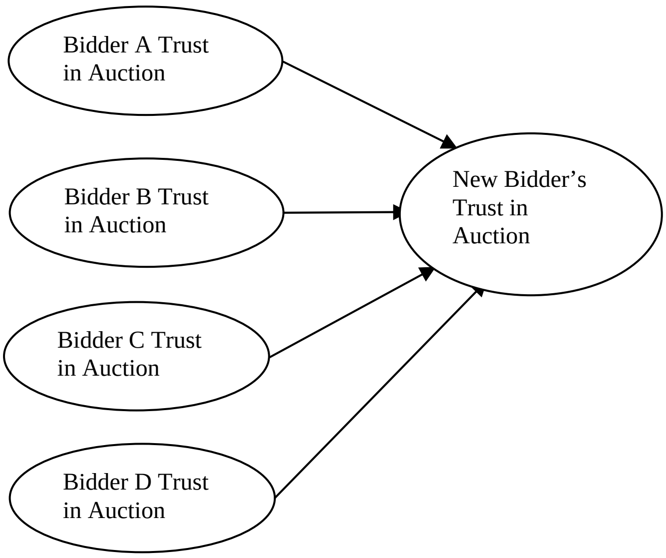


Figure 1. Relationship between existing bidders' trust and a new bidder's perceived trust in auction

IV. Electronic Commerce

Electronic commerce has no settled definition, but at its broadest, it involves conducting business using most modern communication instruments [5]. In 1998, the World Trade Organization (WTO) General Council adopted the view that electronic commerce is the "production, distribution, marketing, sale or delivery of goods and services by electronic means" [5].

Electronic commerce is not only a technological development, but also includes business practices (ex: marketplaces, auctions, etc) built around the transmission of electronic messages between computers. Electronic commerce enables the execution of transactions (exchanges that occur when one economic entity sells a product or service to another entity) between two or more parties using interconnected networks [6]. According to the New Penguin Business Dictionary [7], electronic commerce is "any of a range of activities in different industries and business sectors that focus on commercial exchanges using new, electronic technologies." A typical exchange, the dictionary adds, might entail on-line order-taking, on-line payment, and on-line delivery (as with the purchase and downloading of computer software).

Clarke [8] believes that electronic commerce is a general term for the conduct of business with the assistance of telecommunications, and telecommunications-based tools.

According to the Encyclopedia of Computer Science [6], the goal of most electronic commerce implementations today is to reduce the "friction" in online transactions, where friction is often described in economics as transaction cost. Friction can arise from "inefficient market structures linking buyers, sellers, and intermediaries; inefficient organizational structures (operating units, business processes, and workflows); and inefficient combinations of the technological activities required to make a transaction" [6].

Three factors contribute to the significance of electronic commerce to the world economy today [5]:

1) the rapid growth of the Internet
2) the ability of electronic commerce to facilitate cross-border trade
3) the ability of electronic commerce to reduce transaction costs.

Three forces fuel electronic commerce [6]:

1) economic forces: the need to reduce cost and stay competitive under intense pressure
2) customer interaction forces: to provide marketing channels, to target smaller market segments, and to create new channels of customer service and support
3) technology and digital convergence: convergence of industries such as communications, entertainment, publishing, and computing, is forcing them to compete and cooperate.

Electronic Commerce has emerged from the convergence of several major information technologies and business practices which include: computer networking and telecommunications; client/server computing; multimedia, and hypermedia in particular; information retrieval systems; electronic data interchange (EDI); message handling and workflow management systems; groupware and electronic meeting systems; and public key cryptography.

The growth of electronic commerce was slower though than what many expected, and a number of factors still militate against it replacing traditional non-electronic business models [5]:

1- the security of online payment and information transfer
2- the lack of cost-effective payment methods for low-value transactions
3- Many businesses and consumer still prefer physical presence over electronic transactions (due in part to the threat of fraud) especially to physically inspect the goods before purchase.

V. Trust and eBay

eBay is an online auction house that was launched in 1995 by Pierre Omidyar, to assist his wife in collecting Pez candy dispensers and interacting with other collectors over the Internet [9]. By 2007, more than 4,000 categories of goods were being bought and sold on eBay, providing over 4 million new auctions and 450,000 new items every day to 200 million members worldwide [9].

In order to deal with an uncertain world and to decide to act and pursue our goal without perfect knowledge, we have to take the risk by trusting our information, beliefs, our action, and other agents we are relying upon in order to fulfill our needs [10].

Pavlou et al. [11] define perceived uncertainty in a buyer-seller relationship as the degree to which the outcome of a transaction can not be accurately predicted by the buyer due to seller and product related factors. They then explain that uncertainty consists of seller quality uncertainty (seller making false promises, shirking or defrauding, and hiding its true characteristics), and product quality uncertainty (product condition not being as promise, or product quality being compromised). They then identified four antecedents of perceived uncertainty in online buyer-seller relationships: perceived information asymmetry, fears of seller opportunism, information privacy concerns, and information security concerns and then proposed four uncertainty mitigating factors: trust, website informativeness, product diagnosticity, and social presence.

Trust is defined as the buyer's intention to accept vulnerability based on her beliefs that the transaction will meet her confident expectations [11]. As explained by Ba and Pavlou [12], there are two distinct types of trust: benevolence (the belief that one partner is genuinely interested in the other partner's welfare and has intentions and motives beneficial to the other party even under adverse conditions) and credibility (the belief that the other party is honest, competent and reliable) with the latter being the most prevalent in electronic markets like eBay.

Trust is a very important enabler of electronic commerce, and online auctions like eBay. Liu et al [13] believe that because of the large scale and openness of such systems, one is often required to interact with other agents with whom there are few or no shared past interactions. To help users assess the risk of such interactions, these systems usually offer some trust-management mechanisms.

eBay for example uses a reputation system that provides feedback about users' past behavior and thus help users gain trust. This system also encourages trustworthy behavior, and deters participation by those who are unskilled or dishonest [14].

But eBay's reputation system is not without challenges. Resnick et al. [14] report three problems with soliciting users' feedback:

1- Users might not bother to leave feedback at all
2- It is difficult to elicit negative feedbacks, because it is common for the parties involved to negotiate first before leaving negative feedback
3- The difficulty of ensuring honest reports since some of the users for example collaborate and rate each other positively in order to accumulate positive feedback.

The distribution of feedback can also be challenging since users can change their names (and thus escape from an existing bad reputation), as well as the fact that it is difficult to move one's reputation across systems (for example, eBay, and Amazon). Resnick, and Zeckhauser, [15] concluded that although this reputation system may not work well in the statistical tabulation sense it does seem to work in terms of facilitating transactions and they attributed this to two reasons: 1) even if the system is unreliable or unsound, it might still work if its participants think it is working, and 2) it may function successfully if it swiftly turns against undesirable sellers, a process they called stoning; and if it imposes costs for a seller to get established which they called initiation dues.

Bolton et al. [16] investigated trust among Internet traders in computer-mediated online markets such as eBay and explained some of the challenges in establishing Trust in such markets: transactions on these platforms are characterized by asynchronous actions of anonymous traders, operating at spatially disperse locations. They then explained that in a medium of communication such as Computer-mediated communication it is more difficult to signal trustworthiness and to promote cooperation that richer communication media such as face-to-face communication.

According to Bolton et al. [16] other challenges include the fact that is easier for a buyer or a seller to choose a trader identity other than one's true identity, as well as the fact that lasting personal relationships on Internet market platforms are infrequent. They then concluded that cyberspace makes it particularly difficult to develop social and economic bonding that supports the emergence of trust and trustworthiness in more traditional markets.

Highfill & O'Brien [17] studied Bidding and prices for online art auctions and concluded that a number of variables significantly affected the number of bids: a higher minimum bid decreased the number of bids but the effect was small; availability of the buy-it-now option decreased the number of bids; a longer auction length increased bids; increased shipping and handling fees decreased bids by adding to the overall cost of an item, however, the effect was small. They also concluded that an increase in the number of bids significantly increased the final sales price.

In large scale environments (ex: eBay), there is not sufficient direct experience between agents, and so, prediction is primarily based on the user's "indirect experience" which is obtained from other agents [18, 19, 20]. The Transitive Trust (Web of Trust) model (for example) is based on transitive trust chain. If trustor doesn't know target agent, it asks its neighbors and its neighbors will ask their neighbors if they do not know target agent either, so the trust graph is formed, and so if A trusts B and B trusts C, then A can derive C's trust using B's referral on C and A's trust in B [13].

Song and Baker [21] conducted a field study to elucidate critical factors that determine sellers' net revenue in Internet auctions using two datasets of Internet auctions, one dataset for auctions of a DVD and one for auctions of an MP3 player. They concluded that the buy-now option, number of payment options, number of pictures, and number of delivery methods were found to be significant predictors of outcome for the MP3 player auctions, but not for the DVD auctions. Conversely, auction duration and feedback ratings were found to be significant in DVD auctions but not in MP3 player auctions. They also identified the potential role of the product type in Internet auction research and concluded that "it is conceivable that consumer electronics, collectibles, and commodity-like items—to name only a few types—may have specific sets of variables that influence the final price they bring and the net revenue they are able to generate when auctioned".

VI. Data Analysis

In this research, the researcher collected data from sixty two completed auctions on eBay for Montblanc pens that ended between June 23rd and June 25th, 2009. The sample consisted of 39 auctions for used pens and 23 auctions for new pens (see figure 2). This information is readily available by clicking on the "bid history" for completed auctions on eBay (see figure 8). The following criteria were used to select the sample:

1) The reserve price (if any) was met
2) The auction did not end by a Buy-Now option
3) There was at least one bid on the item and the auction ended in a sale of the item

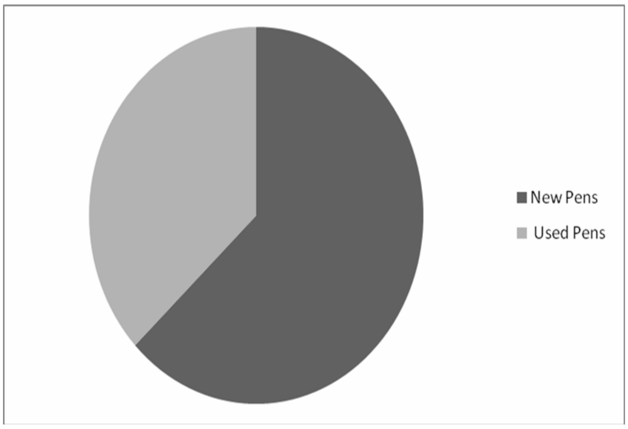


Figure 2. The research sample

The following data was then extracted:

1) Starting bid
2) Winning bid
3) Number of bidders
4) Number of bids
5) Auction start date and time
6) First bid date and time
7) Auction end date and time

The researcher then subtracted the auction start time from the time the first bid was placed and called this variable the "First bid time".

It is important to note that the value of the starting bid in an auction is perceived differently by the buyers according to the perceived value of the product itself. For example, a $10 starting bid for a $10,000 diamond ring is different from a $10 staring bid for a $20 shirt. Accordingly the value of the product needs to be considered when investigating the effect of the starting bid on the auction. To accomplish this, the researcher will divide the starting bid by the selling price in order to create a new variable: the relative value of the starting bid. The higher the value of this variable, the closer is the starting bid from the actual value of the item.

There were a total of 379 bidders in the 62 auctions studied in this research, with an average of 6.11 bidders per auction. The following scatter diagram depicts the distribution of the number of bidders in all the auctions.

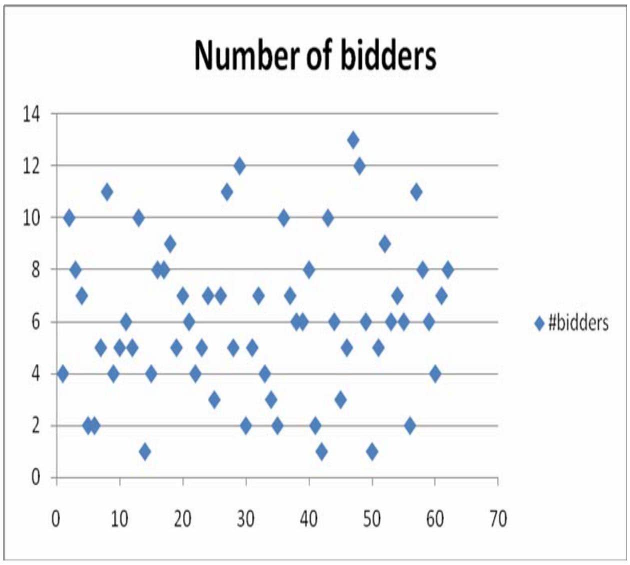


Figure 3. Number of bidders

On the other hand, there were 809 bids in the auctions studied with an average of 13 bids per auction. The following scatter diagram (Figure 4.) depicts the distribution of the number of bids in all the auctions.

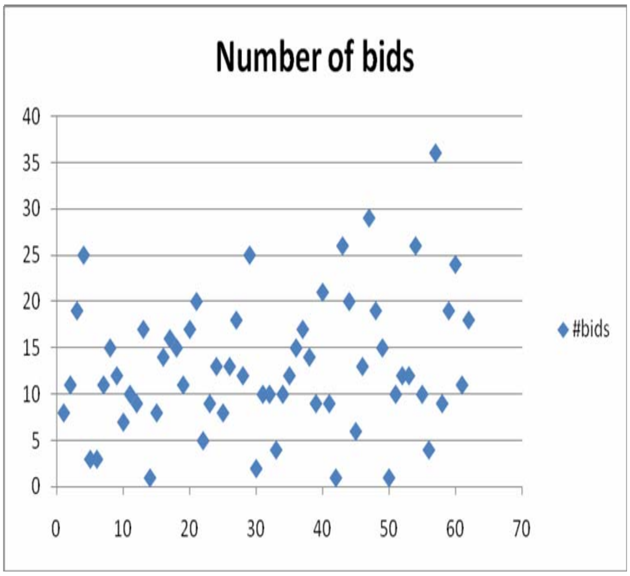


Figure 4. Number of Bids

By plotting the number of bidders versus the number of bids in the auctions, it is clear from the diagram below (Figure 5.) that there is a very strong relationship between the two variables. In other words, the more the bidders in an auction, the higher will be the number of bids in that auction.

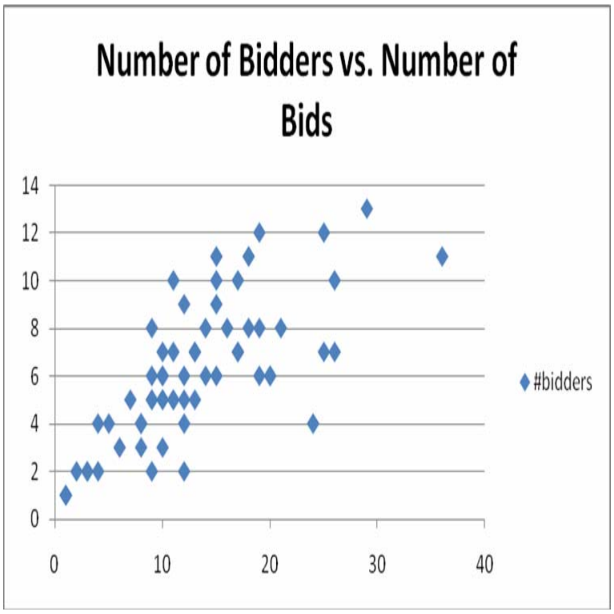


Figure 5. Relationship between number of bidders and number of Bids

The following scatter diagram (Figure 6.) shows the distribution of relative value of the starting bid (calculated by dividing the start price by the sell price). It is clear that only a very few incidents, the selling price was substantially higher than the start price.

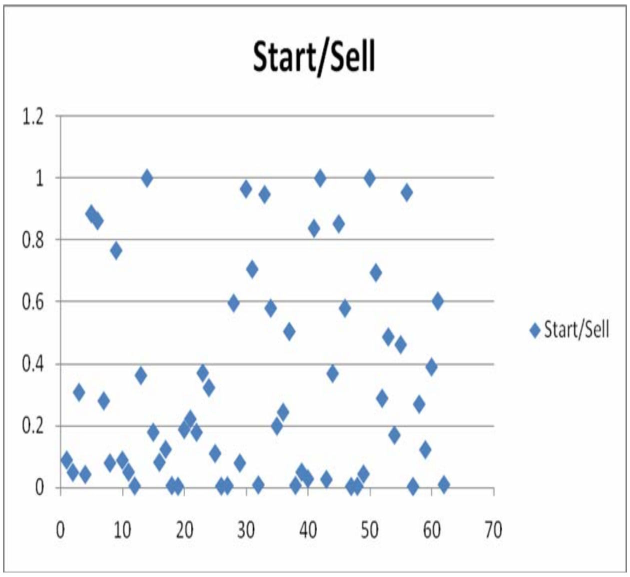


Figure 6. Distribution of the relative value of starting bid

By dividing the sell price by the start price (the inverse of the relative value of the start price), and plotting the scatter diagram for this variable, we can get a better understanding of the distribution of the data (Figure 7.). It is clear from the diagram for example, that only 11 auctions ended with a sell price that was more than 50 times the original start price.

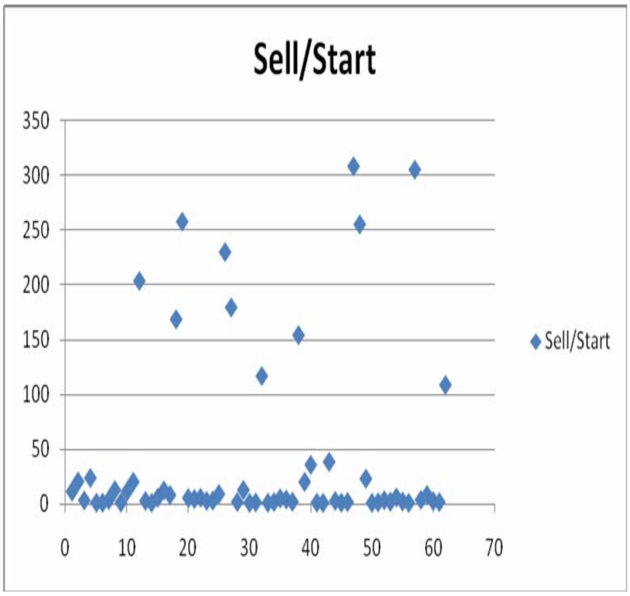
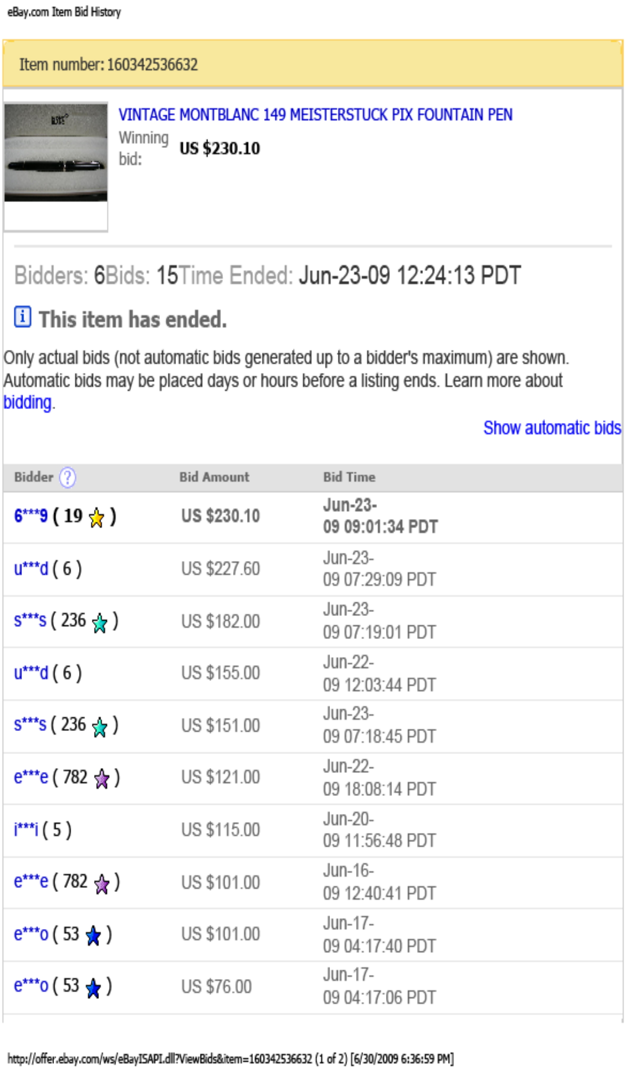


Figure 7. Distribution of sell price divided by start price


eBay.com Item Bid History

Item number: 160342536632

VINTAGE MONTBLANC 149 MEISTERSTUCK PIX FOUNTAIN PEN
Winning bid: US $230.10

Bidders: 6 Bids: 15 Time Ended: Jun-23-09 12:24:13 PDT

This item has ended.

Only actual bids (not automatic bids generated up to a bidder's maximum) are shown. Automatic bids may be placed days or hours before a listing ends. Learn more about bidding.

Show automatic bids

Bidder	Bid Amount	Bid Time
6***9 (19)	US $230.10	Jun-23-09 09:01:34 PDT
u***d (6)	US $227.60	Jun-23-09 07:29:09 PDT
s***s (236)	US $182.00	Jun-23-09 07:19:01 PDT
u***d (6)	US $155.00	Jun-22-09 12:03:44 PDT
s***s (236)	US $151.00	Jun-23-09 07:18:45 PDT
e***e (782)	US $121.00	Jun-22-09 18:08:14 PDT
i***i (5)	US $115.00	Jun-20-09 11:56:48 PDT
e***e (782)	US $101.00	Jun-16-09 12:40:41 PDT
e***o (53)	US $101.00	Jun-17-09 04:17:40 PDT
e***o (53)	US $76.00	Jun-17-09 04:17:06 PDT

http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=160342536632 (1 of 2) [6/30/2009 6:36:59 PM]

Figure 8. Example of bids history for a used Montblanc pen

In this preliminary research, the researcher used the Pearson Correlation Coefficient to measure correlation between the variables. Table 1. shows the correlation between the variables for all the auctions of Montblanc pens.

	First bid time		**Relative value of the starting bid**	
	Pearson Correlation Coefficient (r)	Square of Correlation (R)	Pearson Correlation Coefficient (r)	Square of Correlation (R)
Number of bidders	-0.587	0.344	-.680	.462
Number of bids	-0.527	0.278	-0.602	.362

Table 1. Correlation between variables for all the auctions

As shown in the above table, the first bid time has a high correlation with both the number of bidders and the number of bids. Contrary to the hypothesis, the relative value of the starting bid had a relatively high negative correlation with both the number of bidders and the number of bids.
The researcher then calculated the correlations between the variables for the auctions for used Montblanc pens and the results of the correlation coefficient are shown in table 2.

	First bid time		**Relative value of the starting bid**	
	Pearson Correlation Coefficient (r)	Square of Correlation (R)	Pearson Correlation Coefficient (r)	Square of Correlation (R)
Number of bidders	-0.46409	0.2154	-.57	0..324
Number of bids	-0.4090	0.1673	-.521	.271

Table 2. Correlation between the variables for the auctions for used Montblanc pens

It is evident from the above table that the correlations between the first bid time and the number of bidders and number of bids are still very strong while correlations between the relative value of the starting bid and the same two variables became substantially weaker.
The researcher again repeated the same steps for the auctions for new Montblanc pens and the results of the correlation coefficient are shown in table 3.

	First bid time		**Relative value of the starting bid**	
	Pearson Correlation Coefficient (r)	Square of Correlation (R)	Pearson Correlation Coefficient (r)	Square of Correlation (R)
Number of bidders	-0.7416	0.55	-0.867	0.751
Number of bids	-0.689	0.4747	-0.824	0.679

Table 3. Correlation between the variables for the auctions for new Montblanc pens

It is evident from the above table that the correlations between the first bid time and the number of bidders and number of bids are even stronger in the case of new pens and the same is true for the negative correlations between relative value of starting bid and the same two variables.

VII. Conclusions and Recommendations

This research aimed at validating five hypotheses but after analyzing the data it became clear that although there seems to be a significant correlation between the first bid time (the time the first bid was placed minus the auction start time) and both the number of bidders, and number of bids and again a significant negative correlation between the relative value of the starting bid and both the number of bidders and numbers of bids, the strength of those relationships seem to vary considerably based on the item sold being used or new.
It is evident that the effect of the relative value of the starting bid on both the number of bids and the number of bidders is much weaker in used pens auctions versus new pens auctions, which leads one to believe that in the case of used pens, buyers are less sensitive to the value of the starting bid as long as other bidders have already bid on the item. The same can not be said though with regards to auctions of new pens. It seems that in the latter case, buyers are more cautious and accordingly rely more on the relative value of the start bid and again feel much more comfortable bidding when somebody else has already bid on the item.
Apart from showing the influence of the first bid on the auction outcome (first bid effect), this research also contributes to the literature in terms of clarifying the differences between auctions of used versus new items especially in the case of expensive collectible items that have traditionally been counterfeited.
This research also introduces to the literature the concept of relative value of starting bid which was used in this research instead of the starting bid variable that was constantly used in previous researches.
This research was able to show the very strong relationship between the relative value of the item for sale and the number of bidders as well as the number of bids. The lower

the starting bid (relative to the actual value of the item for sale), the higher was the number of bidders, and accordingly, the higher was the number of bids.

In terms of practical implications, it seems evident that attracting the first bidder should be a major goal for sellers as well as for auction sites and so incentives for first bidders should be provided, for example providing the first bidder with a small discount on the final selling price or even providing small free gifts like a pen box, etc.

IX. Research Limitations and Future Research

There are two primary limitations to this research:

1- In this research the researcher only used sixty two auctions which is considered a small sample size. A larger sample size would be more beneficial.
2- The use of a basic statistical tool like Pearson Correlation Coefficient to measure correlation between the independent variables and the dependent variable is another limitation.

In the next phase of this research, a field experiment will be conducted, in which the researcher will "manipulate the independent variable and measure the effect on the dependent variable" [22]. The experiment will consist of three sets of auctions:

1- In the first auction, the buyers will only be shown the seller's reputation
2- In the second auction the buyers will be shown the number of bidders on the item they want to buy
3- And in the third auction, the buyers will be shown both the number of bidders as well as the seller's reputation.

In each case, the subjects will be asked to choose the auction they will bid on. The experiment subjects will also be asked a number of questions related to the user's trust in the auction they have chosen. The researcher will then use Structural Equation Modeling to discover relationships between the variables and validate the hypothesis. Structural equation modeling (SEM) is a multivariate technique that combines aspects of both multiple regression and factor analysis to estimate a series of interrelated dependence relationships in a simultaneous manner. SEM is very flexible because it can deal with a number of regression equations simultaneously. The same variable may represent a dependant variable in one equation and an independent variable in another equation.

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Author Biography

Ossama Elhadary was born in Cairo, Egypt and he received his Bachelor of Science degree in Communications and Electronics Engineering from the faculty of engineering at Cairo University, and his Masters of Business Administration (MBA) and Doctorate of Business Administration (DBA) from the Maastricht School of Management in Maastricht, the Netherlands. He is currently an assistant professor at the New York City College of Technology at the City University of New York (CUNY). His research interests include B2B Electronic Commerce, online auctions, and best practices in Project Management.