An Investigation of Price Dispersion in Internet Auctions

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Abstract

It can be observed that in consumer-to-consumer on-line auctions, there is a strong degree of price dispersion, even in liquid markets with a large number of bids per auction item. This Thesis research strives to quantify such dispersion and present explanations for the key findings on the nature of price dispersion in on-line auctions of like goods:

Although contrary to common sense and public opinion, I found no significant correlation of winning bid price with feedback rating. This is true for low, medium-high and high value goods and for both new and used goods. This observation holds for all ranges of feedback ratings.

Of all of the other variables of an auction listing: (shipping costs, amount of opening bid, number of bids, accepted payment types, picture in listing, and the use of reserve prices), only picture in listing and use of reserve prices are correlated with winning bid price. This observation holds for all types of goods examined. However, correcting for these variables does not significantly reduce price dispersion.

The majority of the dispersion in winning bid prices of same-good auctions can be explained by the unique ability of the on-line auction process to obtain the reservation prices of buyers in the market, through its use of maximum bid amounts and proxy bidding. An auction winning bid curve for a good can be constructed by aggregating the winning bid prices of all auctions of that good over a period of time. The downward sloping and isoelastic nature of this curve can be explained in part by the downward sloping demand curve for that good, made up by the range of premiums buyers are willing to pay in order to increase their chances of winning the auction, and getting the item sooner. The exact shape of the curve can be further explained and in fact reconstructed by an examination of the statistics of grouping bids in auctions.

Arbitrage to take advantage of the dispersion of winning bid prices can be shown to be possible, and in theory it appears to be surprisingly profitable. This suggests that on-line auction markets are only weakly market efficient. Several explanations were explored as to why arbitrage has not been pursued, thereby eliminating the observed dispersion. These explanations include the unseen non-monetary transaction and arbitrage costs, the level of sophistication necessary to capitalize on opportunities, and the persisting immaturity of the consumer-to-consumer on-line auction market.
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1. Introduction

As you know, auctions for many goods and services (energy, telecom capacity, transportation, auto parts, retail goods) are cropping up on the Internet, as convenient, low-cost and direct mechanisms for connecting buyers and sellers. While there has been much research on traditional auction theory (e.g. bidding strategies for the four major auction types, and the revenue equivalence theorem), the nature and functioning of the new and wildly popular on-line auctions is largely unexplored. The unique structure of Internet auctions offers unprecedented insights into consumer demand, and the quasi-logical behavior of consumers when they interact with one another in a competitive market.

eBay is the oldest and most widely used auction website devoted to the consumer to consumer market. From an economic standpoint, the most interesting aggregate feature of eBay’s auctions is the high level of price dispersion for auctions of the same good. Winning bids vary widely even in the most “liquid” markets with a large number of bids per item. For example, in a three-week period in July, the winning bids for the 94 auctions of new Polaroid PDC-3000 digital cameras ranged from $450 to $750. My thesis examines this price dispersion, and explores several possible explanations.

2. eBay History and Mechanism

2.1 History
eBay wasn’t the first consumer to consumer auction, nor was it the first consumer to consumer auction on the Internet (as early as 1993, there was a secondary market on the Internet for cards from the role-playing game, “Magic: The Gathering”). However, it cannot be disputed that eBay brought on-line auctions from obscurity to a well-known and well-used retail marketplace. In the process, eBay became a household name, and a touchstone for consumer activity on the Internet.
eBay was launched in September of 1995 and rapidly grew into the “world's largest personal online trading community”. eBay currently has upwards of 1,600 categories, including collectibles, antiques, sports memorabilia, computers, toys, Beanie Babies, dolls, figures, coins, stamps, books, magazines, music, pottery, glass, photography, electronics, jewelry and gemstones. These 1600+ categories house over 2.7 million items, which account for 1.5 billion page views per month which routinely makes eBay’s website the top five visited each month. In late 1999, eBay is also one of the top five most searched words on Internet search engines, along with MP3 and sex.

How did this happen? Is this all of our yard sales moving on-line or part of something bigger? eBay is a new delivery channel for the yard sale, but it is also part of the greater move to find more efficient ways of connecting buyers with sellers, enabled by communications technology. On-line auctions are the ultimate in streamlined commerce. In the 1970’s mall-based department and specialty stores on superhighways replaced the small stores on main street. Now the Internet allows customers to research product choices at manufacturer’s websites, and buy via on-line super-retailers, cutting out the brick and mortar retail shops. eBay takes this even further by acting as forum or a simple bulletin board with rules without holding inventory, maintaining a warehouse, or even settling and clearing sales. Although eBay is not a primary market, and tends to deal in uncommon and often unique items unavailable in retail channels, it is a force to be reckoned with and has brought auctions into many primary markets.

2.2 Sample Listing

The following page shows a typical item listing taken from the eBay website:
New Polaroid PDC-3000 Digital Camera w/30mb

Item #220066139

Computers:Digital Cameras
Bidding is closed for this item.

Currently $550.00 (reserve met)  First bid $100.00
Quantity 1  # of bids 11 (bid history) (with emails)
Time left Auction has ended.  Location Rocky MTNS
Started 12/13/99, 20:37:07 PST (mail this auction to a friend)
Ends 12/20/99, 20:37:07 PST (request a gift alert)

Seller (Rating) bl!80s99 (158) (view comments in seller's Feedback Profile) (view seller's other auctions)
(ask seller a question)

High bid alexmaddox (4)
Payment Money Order/Cashiers Checks, Personal Checks. See item description for payment methods accepted
Shipping Buyer: pays fixed shipping charges, Seller ships to home country only. See item description for details. See item description for shipping charges
Relist item Seller: Didn't sell your item the first time? eBay will refund your relisting fee if it sells the second time around. Relist this item.

Seller assumes all responsibility for listing this item. You should contact the seller to resolve any questions before bidding. Currency is U.S. dollar ($) unless otherwise noted.

Description

Polaroid PDC-3000 Digital Camera Kit *New! *

BRAND NEW IN THE BOX!!! For Pc and Mac--1.92 Million pixels In addition to the digicamera the PDC-3000 kit gives you all the necessary accessories to get you shooting immediately, including software, a 30MB Compact Flash card, AC adapter, cables, and documentation. Other features of the Polaroid-3000 include 1600x1200 max. resolution, 1/25 to 1/500 second shutter speed, automatic and manual controls, and much, much more!!.....This camera is awesome!!If you need specific specs email me and I will give them to You.... WARRANTY.....ONE FULL YEAR ...I accept Money orders or cashier checks(camera shipped same business day I receive the money) or Personal check(7-10 days to clear and then shipped). Winning bidder to pay shipping of $13(Continental US). Thanks for BidDING!

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2.3 Listing and Selling an Item

The auction process is, on the whole, quite simple. eBay users who want to sell an item must register their name, address email and telephone number on eBay’s website. eBay’s registration process then verifies the user’s email address and issues the user a user id. Sellers then fill out a form describing their item, choosing a category for its listing, defining opening price, bid increments and an optional reserve price, as well as define shipping terms and payment forms accepted. Sellers can include a picture of their item. Sellers incur an “insertion fee” for listing their items with eBay ranging from $0.25 to $50 according to a rate schedule that depends on the amount of the opening bid or reserve price. A reserve price is a hidden floor that the seller specifies the winning bid must clear in order for the auction to be honored. After the auction, the seller is charged a “final value fee” that is a regressively graduated percentage of the winning bid, starting at 5% and leveling off at 1.25%. Sellers can use check, money order or credit card to pay eBay for listing and selling fees.

2.4 Notable Variables in a Item Listing

Even if the items being sold are identical, their listings will invariably be different: either slightly or greatly. Other than the unique textual description (complete with varying amounts of capitalization, underlining, symbols, misspellings and the like) submitted by each seller, there are a number of quantifiable variables that may have significance to the buyer. These include: seller’s feedback rating, quoted shipping cost, amount of opening bid, accepted payment types, presence of a picture in listing, and the use of reserve prices.

2.5 Feedback Rating

eBay has developed a mechanism to provide its members some measure of protection from fraud. This mechanism places a value on the reputation or “feedback rating” of each of its members, and is billed as an important indicator of the trustworthiness of the seller.

eBay’s feedback rating is essentially a single number that is totaled by adding one point for all submissions of positive feedback from transaction partners and subtracting one
point for all submissions of negative feedback. The value of this feedback number translates to a colored star that accompanies the user ID of the eBay member for all bids and offer activity. There are types of colored stars, each corresponding to a certain feedback profile:

eBay awards Stars to our members when they achieve a certain number of positive Feedback messages from other users.

- A "Yellow Star" (🌟) represents a Feedback Profile of 10 to 99.
- A "Turquoise Star" (💎) represents a Feedback Profile of 100 to 499.
- A "Purple Star" (⭐️) represents a Feedback Profile of 500 to 999.
- A "Red Star" (⭐️⭐️) represents a Feedback Profile of 1,000 to 9,999.
- A "Shooting Star" (🌟🌟🌟) represents a Feedback Profile of 10,000 or higher.

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Clearly, there are anecdotal reports of people preferring to buy from sellers with a high feedback rating, as well as reports of people contracting through sellers with high feedback ratings to sell their goods. In fact, the going fee for consignment sales, or selling an item through another eBay user, is a steep 50%. There are also anecdotes of experienced sellers developing a personal reputation for doing good business. These experienced sellers have developed their user ID into a brand that is trusted and recognized by a cadre of repeat customers that are loyal to the individual (not the feedback rating) and willing to pay more for an item sold by that person. These anecdotes as well as common sense would suggest that buyers would be willing to pay a premium for goods sold by experienced sellers with high feedback ratings. However, there is no published research that empirically and links feedback ratings with price of goods sold on online auction sites such as eBay.

The only literature reference is a brief mention in a paper by Peter Kollock: “The Production of Trust in Online Markets”. This paper references a 1998 working paper by Kollock, “The Value of Reputation” that has apparently not yet been published and makes the following assertion about feedback ratings and pricing:
“Conceptually, we should expect reputations to affect not just rates of cooperation, but also the price of goods in these markets. If these reputation systems do in fact provide useful information and an incentive to behave in a trustworthy manner, buyers should be willing to pay more for a good if it comes from a highly rated seller, at least when the transaction involves significant risk. Preliminary evidence from a quantitative study of reputations on eBay suggests this is in fact the case (Kollock 1998c). At least for some high value goods, the seller’s reputation had a positive and statistically significant effect on the price buyers paid for identical goods of equivalent quality. This effect of reputation seems to diminish or disappear for low value goods.”

My initial hypothesis was that the variance in pricing for the same good in subsequent auctions was due to the different feedback ratings of sellers. That is, buyers were willing to pay a measurable premium for goods sold by a trustworthy or reputable seller.

2.6 Bidding on and Buying an item

Bidding on an item is even easier than listing one. Like sellers, all bidders must have registered their name, address email and telephone number with eBay, had their email address verified, and received a user id. Then, bidders browse the categories on eBay’s website or use its search engine to find the item they are looking for. All active auctions are listed most of which last for 1 week. Users simply submit a bid on an item of their choosing, along with their user id.

eBay uses a proxy mechanism for all submitted bids. Bidders are asked to submit the maximum amount they are willing to pay. eBay then enters the minimum bid on the bidder’s behalf, and looks to see if the current high bidder has reached his maximum bid. If not, eBay conducts a bidding war in the minimum allowable bid increments until one of the warring bidders reaches her maximum bid and cannot top the other’s last bid. This becomes the new high bid. The high bidder and the seller are notified at the close of the auction by email and are told to contact each other via the provided email addresses to exchange payment and the good within three days.
2.7 Clearing and Settlement

The only real sticky part of the eBay trading process is the exchange of payment and the good between the buyer and seller. As the process is structured the winning bidders are required to send payment first, while sellers send the good only on the receipt of payment. Accordingly, the buyers bear the fraud risk of the settlement process. Despite the possibilities for fraud, as of July 1999, eBay’s CEO Meg Whitman stated that only 27/1,000,000 transactions are a “problem”. To date only two cases of fraud through eBay have come to trial.

eBay relies on three factors to safeguard the successful completion of its transactions:

- **Escrow.** eBay has partnered with I-Escrow to provide a third-party escrow service. For a fee of 5% of the final item value ($5 minimum, maximum of $250) the buyer sends payment to i-Escrow, and releases payment to go to the seller after goods have been satisfactorily received. This form of buyer insurance requires seller cooperation, which may not be consistently available. If this service has been priced correctly, it would seem that a 5% premium is the most buyers would be willing to pay for trust or assurance that the deal will be honored.

- **Insurance.** Lloyds of London provides insurance that covers qualified items bought on eBay listed on or after March 1, 1999. Purchases are covered for up to $200, less a $25 deductible. This insurance is provided at no cost to the buyer.

- **Feedback Ratings.** One of the areas explored by this research is whether or not buyers use feedback ratings when making bidding decisions. That is, does the accumulation of positive transaction experiences translate into trust, which is has value to buyers and can be observed via a measurable premium.
3. Theoretical Background: Auction Theory

From a theoretical standpoint, eBay’s auctions combine elements of both the English and Vickrey classical auction models.

The traditional English auction is the most popular real world auction method. It is generally facilitated by an auctioneer in a public forum, such as the art auctions run by Sotheby’s and the seized property auctions run by the Government. The English auction follows an open outcry format, where the bidding starts at a low price and participants publicly submit progressively higher bids until the bid reaches a price when no one will bid higher. In this bidding process, each bidder remains in the auction until the going price reaches their reservation price. Assuming that the bid increments are small, the bidding will stop at just over the reservation price of the second highest bidder. In other words, the winning bidder will not pay their own reservation price, the reservation price of the second highest bidder will be sufficient to win the auction.

The traditional Vickrey or second price sealed bid auction functions quite differently, but with the same final result. In this auction method, all bidders submit private, sealed bids. The highest bidder wins the auction, but only pays the price submitted by the second highest bidder. Each bidder will want to maximize his chance of gaining economic rent (however small), and therefore his strategy will be to bid as high as possible, without the risk of overpaying. If the bidder bids more than his reservation price, he runs the risk of having the highest bid, with the second highest bid at a price just slightly below his bid, and above his reservation price. Therefore armed with this logic and no knowledge of what other bidders are bidding, all bidders will submit their reservation price in the hope that their bid is significantly higher than that of the second highest bidder. Should the bidder win, the bidder will get the item and the non-negative economic rent that is the difference between the reservation price of the bidder and price actually paid.
The eBay auction has elements of both the English and the Vickrey auctions. That is, it elicits the strategy or bidding behavior of the English auction in some of the participants and the strategy of the Vickrey auction in others.

Due to the availability of the proxy mechanism, one would expect all bidders to behave as if they were in a Vickrey auction, where each bidder privately submits their reservation price for the maximum bid amount and then simply waits for the auction to end. If they win the auction, they will have achieved a non-negative economic rent. There is no logical incentive for bidders to enter a maximum bid amount that is less than their actual reservation price, because they cannot improve their economic rent by doing so, nor can they gain any useful information on what the maximum bid amount of competing bidders are. Furthermore, even if you knew all the reservation prices of the competing bidders, you would have not incentive to submit a final bid of anything other than your reservation price.

However, the behavior that we can observe would indicate that participants are submitting very bids early on in the bidding process, as well as several bids. This would suggest that some participants are following the English model, which may be encouraged by the framing characteristic of a stated “opening bid” by the seller in the traditional English format, which is often trivially low ($1). Furthermore, the auction runs over a period of up to 7 days and the current high bid is always listed with the item, which is similar to the public going price of the English auction. The most likely explanation for English auction bidding behavior is that people derive pleasure and excitement from English-style bidding, despite the additional effort required, which is meaningless to the outcome of the auction. Another likely explanation is that some bidders either do not understand, do not trust or simply choose not to use convenience of the proxy bidding mechanism.

It is interesting to mention that the two other classical auction models are the first price sealed bid auction (same as the second price, except that the winner actually pays what he or she bid) and the Dutch Auction. eBay in fact offers a “Dutch Auction” option,
however eBay’s “Dutch auctions” are misnamed. The accepted definition of a Dutch Auction is an auction with a steadily descending price where the item goes to the first open outcry. eBay’s version of the Dutch Auction is actually much more similar to the Federal Reserve’s auction process for US treasury securities, where the n top bidders win the n items for auction at the lowest winning bidder’s price.

Finally, Vickrey’s revenue equivalence theory states that it does not matter what auction method is chosen, under ideal conditions, the selling price or revenue generated from the auction will be the same.

4. Experimental Approach

I initially planned to run my own set of auctions by contracting through sellers of various feedback levels. This approach was rejected for the following reasons. After engaging in several auctions, I found that that gathering data by running one’s own auctions to be impractical, and moreover, inferior to a thorough gathering of actual auction results. My thoughts were as follows:

Own auctions are slow with limited volume. The time it takes to list, sell and settle an item is 2-3 weeks if there are no delays or problems. Add to this the time it takes to obtain an item (items that are liquid on eBay are illiquid everywhere else) which can take another 2-3 weeks (find, bid, settle). This means 4-6 weeks per item, and since you don’t want to move the market by buying or selling a significant proportion of the total volume, for an item with good liquidity like Polaroid PDC-3000 digital cameras, it would be unwise to transact more than every other day. This would provide data on 60 transactions by the end of the year.

Own auctions are costly, especially with no budget. Buying and selling the same items will require significant transaction costs: eBay’s listing and sales commission, shipping and insurance, deflation, and most importantly a going rate of consignment (selling an item through another seller) premium of 50% of selling price.
Obtaining data on actual auctions is cheap (no cost), and the data can be amassed in high volume. Unfortunately, the easiest method of data collection (access to eBay’s database) was unavailable. At the time I requested this access eBay had just experienced service outages that dropped its market capitalization by billions of dollars, so they were understandably unwilling to donate their database engineers’ time to my research.

Fortunately, eBay maintains three weeks of data on completed auctions on its publicly available website, and I adopted the time-consuming and painstaking approach of manually recording this data. By periodically recording data during the last six months of 1999, I was able to amass data on transactions for 300 Polaroid PDC-3000 digital cameras, 200 Disney Lion King Videos and 150 3Com Palm Pilot Vs.

Although a spider or bot could have been designed and used to gather and organize this data automatically, context issues would have been a major stumbling block and source of inaccuracies. For example, if I am collecting data on auctions of only new items, I could require the word “new” to be in the listing. However, I would have to avoid accepting listings describing the item as “almost new”, “like new”. Furthermore, I would miss items described as “unopened”, “sealed in the original shrink wrap” but not described as “new”.

In summary, I gathered historical auction data on the high, mid and low value goods chosen for their high levels of homogeneity and market liquidity. Data gathering began in July and continued through December of 1999, yielding sufficient data for statistically significant observations for each of the following types of goods:

- New high value goods ($550 Polaroid digital cameras)
- New medium-high value goods ($350 Palm Pilot 5s)
- New low value goods ($30 lion king videos)
- Used low value goods ($20 lion king videos)
Finally, although data was gathered on the same items spanning a period of six months, the entire data set was not used. Due to price deflation of the technology goods (Palm Pilots and Digital Cameras), data was only used in three week periods. While it would certainly be possible to attempt to normalize for deflation over time and for slight changes the good (e.g. gradual replacement of the 20 MB memory card with 30 MB memory card in digital cameras), it was not deemed necessary for the purposes of this research.

5. Regression Results and Analysis:

5.1 Feedback Rating

I have looked for this “reputation premium” in actual historical records of eBay auctions for items with high liquidity. I ran regressions of price against feedback rating for high value goods ($550 Polaroid digital cameras) (Exhibit 1), medium-high value goods ($350 Palm Pilot 5s) (Exhibit 2) and low value goods ($30 lion king videos) (Exhibit 3). In addition, I ran similar regressions for both new and used goods (new and used lion king videos) (Exhibits 3,4).

Exhibit 1
Although contrary to common sense, public opinion, and Peter Kollok’s stated observation, I found no significant correlation of winning bid price with feedback rating. This was consistent when looking at auctions by sellers spanning the full range of feedback ratings (0-1500+), as well as limiting the sample to feedback ratings of as small as 0-25 (Exhibits 1,5,6). This is true for low, medium-high and high value goods and for both new and used goods. This observation holds for all ranges of feedback ratings.

Exhibit 5

53 New Polaroid digital cameras auctioned 6/27 - 7/17 (no f.r.>100)

Exhibit 6

34 New Polaroid digital cameras auctioned 6/27 - 7/17 (no f.r.>25)
5.2 Other variables in listing

I have also looked at a number of other variables to explain the price dispersion in on-line auctions. These include shipping costs, amount of opening bid, number of bids, accepted payment types, picture in listing, and the use of reserve prices (a hidden price set by the seller that if the winning bid does not exceed, the seller need not sell the item). For the variables of shipping costs, amount of opening bid, number of bids, accepted payment types, I did not find significant correlation with the winning bid price. (Exhibits 7,8,9,10). However, items with a picture in the listing, and items with no reserve price did exhibit positive and significant correlation with winning bid price (Exhibits 11,12).

Exhibit 7

![Graph showing scatter plot with regression output](image)

Exhibit 8

![Graph showing scatter plot with regression output](image)
Exhibit 9

Exhibit 10

Exhibit 11
5.3 Experience earns no bargains
The below regression plots address the question of whether or not experienced eBay participants are more likely to win auctions with lower bid amounts than their inexperienced peers.

The data are 124 auctions of Polaroid pdc-3000 digital cameras auctioned in a three-week period in July and August. Exhibit 13 shows all 124 auctions with price regressed against the feedback rating (a measure of eBay auction experience). There is a negligible effect. Exhibit 14 shows only the 36 auctions where the winner had a feedback rating of 5 or higher. Again the results were negligible.
5.4 Serial correlation of Auction Winning bid amounts

It may be postulated that winning bid amounts are serially correlated. That is, the winning bid price for an auction is influenced by the auction immediately preceding it. If this is the case, a use of the Durbin Watson statistical test should point this out:

The Durbin-Watson test statistic is calculated from the residuals $\hat{e}_t$ as taken from a linear regression equation as: $d = \text{sum of }_{t=2}^{N} (\hat{e}_t - \hat{e}_{t-1})^2 / \text{sum of }_{t=1}^{N} \hat{e}_t^2$. The $d$-statistic has values in the range $[0,4]$. Low values of $d$ are in the region for positive autocorrelation. Values of $d$ that tend towards 4 are in the region for negative autocorrelation.

In fact, the experimental data did show weakly positive autocorrelation: A calculation of the Durbin Watson $d$-statistic consistently yielded values around 1.6 for the range of goods evaluated. As might be expected, the autocorrelation was stronger for higher value goods, where it is presumed the bidders perform a more careful research the current going price of the good.
6. Hypothesis to Explain Price Dispersion

6.1 Hypothesis
My hypothesis to explain the price dispersion stems from the assertion that on-line auctions have the unique ability to obtain the reservation prices of buyers in the market, through their use of maximum bid amounts and proxy bidding. My research indicates that these reservation prices can be assumed to be normally distributed, and when these are artificially grouped into “auctions” of an average size of 10 participants they will yield results that mirror those of the auctions actually recorded on eBay.

In theory, the best way to construct a demand curve for a good within a certain population, would be to gather a sufficiently sized subset of this population, and ask them to write on slip of paper the largest amount that they would be willing to pay for that good. Then a simple plot of the reservation prices ranked from most to least would give an excellent approximation of the demand curve. This has undoubtedly been done in numerous previous studies. The main drawback of this method is that the reservation prices elicited are not true reservation prices. Such prices can only be reliably obtained in a real world setting, where the buyer’s own money is at stake, and the participants are not conscious of the study.

A graph can be constructed by ordering the winning bid prices from highest to lowest for all auctions of that good over a period of time (see Exhibits 15a). The shape of this auction winning bid curve is strikingly similar for different goods (see Exhibits 15b and 15c).

One explanation for the downwardly sloping and isoelastic shape of the curve is a function of the range of premiums buyers are willing to pay (on top of a base value of the good) in order to increase their chances of winning the auction, and getting the item sooner.
There are several assumptions useful to make when exploring this hypothesis. First, bidders do not know the full range of historical winning bids. They do, however, have a general idea of the average winning bid by looking at the current and completed auctions. Second, all bidders want to get the good for as low a price as possible, but they also intrinsically know that the higher their bid, the more likely they are to win (get) the item. Finally, we can even assume that all bidders place the same value on a good. We don’t need to consider income and substitution effects on the value each consumer places on a good. We only need to assume that bidders vary how soon they want the good.

Looking at the graph above: lets assume that everyone values the Polaroid digital camera at $490. That would be the price all buyers would be willing to pay if they were indifferent as to when they would actually get it. In other words, bidders who are unwilling to pay a premium to increase their chances of winning sooner, and only care if they eventually win a camera will bid this amount. If a bidder is willing to pay $530, or a premium of $40 they will have a 50% chance of winning a camera. If a bidder is willing to pay $570 or a premium of $80, his chances will increase to 75%. A bid of $610 (a premium of $120) will increase the chances of winning to 87.5%. A bid of $650 (a premium of $160) will increase the chances to 94%.
As the laws of probability indicate, large gains in chances of winning can be achieved with initial premiums but subsequent premiums produce ever smaller increases in the probability of winning. This accounts for the isoelastic shape of the auction winning bid amount curve. This also indicates that the value (to each bidder) of increasing the chances of winning an auction to be $40 for this good. In other words, by paying an extra $40, the bidder can shorten the equivalent number of auctions by one, that he would have to plan to enter to have the same chance of winning.

Again, the explanation for the distribution in the reservation prices assumed the members of the population only differed in their eagerness for the good. In fact, this distribution could simply be explained by actual differences in income and price elasticity across the population. A wealthy person might be willing to pay more for a palm pilot than a poor person. Similarly, a prolific seller on on-line auctions might be willing to pay more for a digital camera (to post pictures with her listings) than someone who would occasionally use a digital camera for personal enjoyment. Although we cannot get into the minds of the members of the population to extract the true explanation for their reservation prices, the macro explanation for the general shape of the auction is probably a combination of timing preferences, income elasticity and substitutability.

6.2 A more precise explanation of the Auction Winning Price curve
The previous section details why we see a downwardly sloping, isoelastic auction winning bid amount curve that describes bidders behavior in auctions. To further explain and predict the exact shape of the auction winning price curve we must look into the statistical effects of how auctions are actually conducted and the grouping of bids. Exhibits 16a through 18b are six examples of organizing systematically generated random numbers into groups of varying sizes, and then picking the second highest number will generate different curves.
The three curves on the left (the “a” Exhibits) use the same set of 2,000 values between 450 and 750 as randomly generated from a uniform distribution. The three curves on the right (the “b” Exhibits) use a different set of 2,000 values that were randomly generated from a normal distribution with an average of $550 and a standard deviation of $60.

As you can see the normal distribution “b” Exhibit curves come closer to the actual auction winning bid curve shape than the uniform distribution. This observation can be confirmed by plotting the frequency of bid amounts from actual auctions. Exhibit 19 shows such a frequency plot for 49 auctions of new Palm Pilot Vs. Note the “English” bid activity that creates a left-skewed frequency plot of bids.

Exhibit 19

![Frequency of all Bid Amounts for 49 Auctions of Palm Pilot Vs](image)

Exhibits 16 through 18 also show that the number of bidders in an auction have a large impact on the auction winning bid curves. Exhibit 16 is the arrangement that results from using 100 groups of 20. Exhibit 17 is the arrangement that results from using 200 groups of 10. Exhibit 18 is the arrangement that results from using 400 groups of 5. As the group size gets smaller, the curves Exhibit progressively stronger “S” curves. The winning bid amounts trail off sharply dip as the curve get to the lower end of the Y-
variable range. Exhibit 20 shows the actual breakdown of the bidding for 49 auctions of new Palm Pilot Vs. The average number of independent bidders in each auction is 12.

Exhibit 20

Bidding Breakdown of 49 auctions of new Palm Pilot Vs
7. Arbitrage Opportunity or Efficient Market?

One interesting question, is whether or not this consistent disparity in pricing of like goods can be arbitraged. The degree to which the consumer to consumer online auction market can accommodate profitable arbitrage can be used to indicate the degree of efficiency of the market.

The basic principle of arbitrage is to buy low and sell high. The challenge is to find the strategy that generates the maximum profit per daily auction. Maximum bid limits could be used to only buy at prices that are lower than the average winning bid. Reserve prices or high initial bids could be used to only sell at prices that are higher than the average winning bid. Of course, the transaction costs need to be subtracted from the calculated profits.

The lower you buy and the higher you sell, your arbitrage profit per successful auction wins goes up. At the same time, your chance of successfully winning auctions goes down. At some combination of bid limit and starting ask price there is a maximum expected arbitrage profit per occurring auction. Finally, the success rates in purchases and sales need to be matched to keep the running inventory from growing or shrinking uncontrollably.

It should be noted that this arbitrage analysis ignores the price effect demonstrated in the previous regression analyses that indicate that you would adversely affect selling price with the use of reserve prices. Although my findings indicated that there was no adverse effect of high initial asking prices (that would resulting in lower winning bid amounts), it is still a possibility that this may be negative factor.

7.1 Theoretical approach to finding the optimal arbitrage strategy
As was demonstrated by the observed auction winning bid curves in exhibits 15a, 15b and 15c, the curves are concave and have an irregular curve shape. Therefore, due to the nature of the curve, and its slight differences from time period to time period and from
item to item makes constructing formulas to calculate the optimal arbitrage strategy difficult. Instead I worked directly from the plots of the actual auction winning bid curve: I used an iterative trial and error method that is described below and illustrated in Exhibit 21.

Exhibit 21

First I set about to find the selling price. I set the minimum asking price. This limited the data set of possible winning bid amounts to all those above the minimum set asking price, from which an average winning selling price could be calculated. The minimum set asking price also yielded the probability of selling the item directly from the auction winning bid curve. Expected revenues from sales could be calculated by taking the product of the average winning selling price and the probability of actually selling the item at that average winning selling price.

Second I followed a similar process to find the purchase price. I set the maximum bid limit at a level that yielded the same probability of successfully buying the item from the
auction winning bid curve as was observed in the selling price procedure above. The maximum bid limit restricted the possible winning bid amounts to all those below maximum bid limit, from which an average winning buying price could be calculated. Expected costs from purchases could be calculated by taking the product of the average winning buying price and the probability of actually buying the item at that average winning buying price.

Then the applicable transaction costs of listing, selling and shipping items based on the probability of winning auctions could be calculated. Finally, the expected profit per occurring auction could be calculated by computing the expected revenue from sales, less the computed expected costs from purchases, and less the expected transaction costs.

It is important to emphasize that the probability of successfully selling and buying items were matched in the process outlined above. For example, if the strategy was more successful at buying than selling, then continued arbitrage would build an ever-increasing inventory of items.

7.2 Estimating the maximum expected profit from selling high and buying low
This section applies the method described above to the actual auction winning bid curve of 94 auctions of Polaroid digital cameras as shown in Exhibit 15a. Below are some of the examples of the values “plugged into” the curve to generate expected profit per auction via at various strategy point. Specifically, the formula used was the probability of winning the auction multiplied by (resulting average sell price from setting reserve prices or having a high initial bid amount - resulting average buy price from setting low bids – transaction costs). Note that transaction costs include of the costs of buying: shipping and handling ($12), and the costs of selling: ($0.25 per each listing and $14.25 average sales commission) for an approximate total of $27.

Hence, for a 75% probability of successfully winning an auction as both a high-ask seller and low-bid buyer, the profit/auction = 75% * ($560-525-26.75) = $6.18/auction
For 60% win probability, profit = 60% * ($571-515-26.75) = $17.55/auction
For 50% win probability, profit = 50% * ($580-509-26.75) = $22.12/auction

For 33% win probability, profit = 33% * ($597-500-27) = $23.33/auction

For 25% win probability, profit = 25% * ($609-494-27.25) = $21.94/auction

For 20% win probability, profit = 20% * ($620-489-27.50) = $20.70/auction

For 10% win probability, profit = 10% * ($651-457-28.75) = $16.52/auction

As is indicated in bold above, the optimal arbitrage strategy would be to set minimum ask prices and maximum buy limits at prices such that the arbitrageur would win 1 out of every 3 of auctions entered, both those as a buyer and those as a seller. The resulting expected profit per auction of $23.33, is about 4% of the average winning bid amount of $547. Given that there are about 4.5 of the Polaroid digital cameras listed above auctioned per day, theoretically an arbitrageur could make about $23.33/auction or $105/day from the Polaroid digital camera eBay market alone.

The question remains: Is this an indication of market inefficiency, and a genuine money making arbitrage opportunity, or are there factors that haven’t been considered in this simplified analysis that effectively reduce the theoretical maximum arbitrage opportunity, and explain the continued existence of price dispersion?

7.3 Additional factors that affect ability to arbitrage

There are several factors that, in practice, would negatively impact the actual expected profitability of the arbitrage strategy outlined above.

The auction winning bid curve as recorded in this thesis includes a small percentage of auctions (about 5-10%) where the winning bid was not higher than the reserve price, and therefore these transactions were not consummated. As a result the curve is an accurate gauge of what bidders are willing to pay (consumer demand) but not of what sellers are willing to sell for (consumer supply). Taking into account this factor would likely reduce the number opportunities to buy low, thereby reducing potential arbitrage profits.
Certainly, the cost of labor is significant and has not been factored in. It takes time to collect data and to construct an auction winning bid curve, as well as to list, bid on, monitor and complete transactions on eBay. One solution to the labor costs would be to use a bot or spider to collect data on current auction markets on eBay. The bot would be programmed to look for high value items and would record the recent historical auction winning bid curve for that market. An algorithm could also be constructed to calculate the profit-maximizing price to bid on auctions as figured via the brute force method above. However, human intervention would still be needed for the e-mail correspondence, item handling and payment settlement.

Another factor is that by the time the winning bid curve can be historically characterized and acted upon, it has shifted enough to lose a significant portion of the arbitrage margin. Exhibit 22 is the auction winning bid curve of 47 Polaroid digital cameras where the data collection period was only nine weeks later than the data for the 94 cameras depicted in Exhibit 15a. The average winning bid has declined from $547 to $454. That is a drop of $93 or 17% of the observed average winning bid from the earlier period. This is especially significant when compared with the maximum theoretical arbitrage opportunity of $23.33/auction or 4% of the average winning bid amount.

Due to random variation in the auction winning bid results, the working inventory will fluctuate substantially around zero, especially because both ends of the auction winning bid curve are so steep. One solution to this would be to run an arbitrage operation using large volumes of transactions to “smooth” out inventory swings. However, the volume of transactions is strictly limited due to the low number of auctions per day, which precludes operating in bulk. As a result, a significant inventory would have to be maintained, as one half of the time, the arbitrage strategy would result in an unacceptably negative balance of goods. Furthermore, the serial correlation of winning bids as demonstrated earlier by the Durbin Watson test would result in a larger variance, which would require a larger inventory. Maintaining an inventory would require a capital investment and would result in depreciation losses as most of the arbitrage item candidates are technology products with deflating prices.
Also, eBay does not have very many liquid commodity-like markets. The items that this thesis examines were carefully sought out for their liquidity, while most items are unique collectibles. Of the 1600+ item categories on eBay, there might be 10 that are liquid enough for arbitrage. In addition, most of the commodity-like markets that do exist are for lower priced goods than the Polaroid digital camera (e.g. Palm Pilots, Disney Videos, Beanie Babies). These lower priced goods should have proportionally lower dollar-value arbitrage opportunities as transaction costs will be a higher percentage of the winning bid prices. Assuming an average selling price of $250, a ratio of arbitrage profit/average selling price that was observed in the Polaroid digital camera example (4%), and 5 auctions per category per day, then the total ideal arbitrage opportunity would be $500/day. While this is a significant haul for one person, it is not an opportunity for starting an industry around it.

Another factor is that the level of analysis and sophistication required to efficiently arbitrage a thin and changing market would have a high opportunity cost. Someone with the wherewithal and resources to effectively perform such an arbitrage could probably make more doing something else, like day trading, or working for an investment bank.
On deeper reflection, persistent price dispersion in on-line consumer to consumer auctions makes sense because even the commodity-like items that this thesis focuses on can be observed to be illiquid. It is not uncommon to see auctions with less than five bidders. A lack of liquidity can help to account for items where the winning bid is substantially less than the average. By looking at the feedback ratings, one may observe that many bidders are new to the eBay bidding process (and the Internet) and this renewable “collective inexperience” may account for the small number of winning bids that are substantially above average. Arbitrageurs cannot make a market more efficient when there is a persistent minority that does not have a sense of the going price and regularly overbids, driving a small percentage of auctions well over the average winning bid price.

All things considered, while there clearly are some arbitrage opportunities and examples of market inefficiencies, the online consumer to consumer auction market does appear to be at least weakly efficient. As with older formats of consumer to consumer transactions such as garage sales, classified ads and private sales, there will always be the opportunity for the savvy businessperson to find bargain buys and to sell items for a premium. eBay is no exception. As the eBay market becomes more liquid and more users fully understand how to use the bidding mechanism and the available historical data, the opportunity for arbitrage should diminish (but not disappear) and the market will become more efficient.
References


