9-2008

When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay

Uri Simonsohn
University of Pennsylvania

Dan Ariely

Recommended Citation
Simonsohn, U., & Ariely, D. (2008). When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay. *Management Science, 54* (9), 1624-1637. http://dx.doi.org/10.1287/mnsc.1080.0881

When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay

Abstract

People often observe others' decisions before deciding themselves. Using eBay data for DVD auctions we explore the consequences of neglecting nonsalient information when making such inferences. We show that bidders herd into auctions with more existing bids, even if these are a signal of no-longer-available lower starting prices rather than of higher quality. Bidders bidding a given dollar amount are less likely to win low starting price auctions, and pay more for them when they do win. Experienced bidders are less likely to bid on low starting price auctions. Remarkably, the seller side of the market is in equilibrium, because expected revenues are nearly identical for high and low starting prices.

Keywords

herding, auctions, biases, rationality, industrial organization

Disciplines

Business | Business Administration, Management, and Operations | Business Intelligence | Cognition and Perception | Cognitive Psychology | Community Psychology | E-Commerce | Marketing | Organizational Behavior and Theory | Sales and Merchandising | Social Psychology

When Rational Sellers Face Non-Rational Buyers: Evidence from Herding on eBay

Uri Simonsohn
The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania, 19104, uws@wharton.upenn.edu

Dan Ariely
Sloan School of Management, MIT, Cambridge, Massachusetts, 02142, ariely@mit.edu

We document that eBay bidders exhibit a biased preference for auctions with more bids, even if these are non-diagnostic of quality, creating an incentive for sellers to lower starting prices to attract early bids. We find that lowering starting prices succeeds in increasing the likelihood that an auction will receive additional bids, conditioning on its current price. We also find that, conditioning on dollar amount bid by bidders, those who engage in non-rational herding are less likely to win, and when they do win they pay higher prices. Supporting the premise that this is a mistake, experience reduces dramatically the tendency to engage in non-rational herding. Remarkably, the seller side of the market is in equilibrium: a high enough share of sellers chooses low starting prices for expected revenues to be identical for high and low starting prices. In sum, market forces in eBay eliminate the rents associated with exploiting the behavioral bias we identify, but not the bias itself.

Keywords: herding, auctions, biases, rationality, industrial organization.

---

1. Introduction

How do rational sellers respond to the non-rationality of the consumers they serve? A nascent literature, often referred to as behavioral industrial organization, attempts to address precisely this question. It contains a handful of empirical papers that provide explanations for otherwise puzzling firm behavior based on a particular deviation from rationality on the part of the consumers these firms serve (DellaVigna & Malmendier, 2006; Morgan & Hossain, 2006; Morton & Oster, 2003), and a couple of theoretical papers that demonstrate that competition among firms can lead to the elimination of rents associated with exploiting a bias without eliminating the bias itself (DellaVigna & Malmendier, 2004; Gabaix & Laibson, 2006).[1]

In this paper we contribute to this literature on both accounts. That is, we identify a specific bias in how consumers make decisions that incentivizes an otherwise suboptimal strategy on the part of sellers, and we demonstrate that enough sellers are exploiting the bias that in the margin they are indifferent between exploiting and not exploiting it.

More specifically, using data from eBay auctions for DVD movies we show that bidders have a tendency to choose auctions with more existing bids even when these do not provide useful information. This bias creates an incentive for sellers to obtain early bids, which they can do by lowering the starting price of their auctions. In our sample, for example, auctions starting at $1 accumulate 8.8 bids by the time they reach $10, compared to just 2.7 bids by those starting at $9.

Although standard auction models (e.g. Milgrom & Weber, 1982; Myerson, 1981) propose that sellers should not set the starting price of their auctions below the opportunity cost of the item they are offering, if bidders prefer auctions with more bids it may be optimal for (some) sellers to do so. Indeed, we find that additional bids obtained through lower starting prices are effective in obtaining additional bids. For auctions currently at $10, for example, we find that 83% of those starting at $1 receive an additional bid, compared to 60% of those starting at $10.

There is nothing surprising, of course, in bidders choosing to bid on auctions with low starting prices while they still have a lower price, but there is with them continuing to prefer them once their prices are no longer low. We believe that bidders' non-rational tendency to prefer auctions with more bids can explain the high prevalence of below-cost starting prices on eBay. In our sample of DVD movies, for example, 22.1% of auctions started at $1 or less, clearly below their opportunity cost considering that just 0.2% of auctions in the sample sold for less than $1.

[1] For a survey of this latest and also previous attempts in Industrial Organization to incorporate bounded rationality see (Ellison, Forthcoming).

Although lowering the staring-price has the advantage of attracting early bids, as more and more sellers do so, it becomes increasingly likely that the listed item will ultimately sell for a lower price. In the extreme, if an infinite number of items were started at $1, all sold items would sell for $1.

In equilibrium, the expected revenue associated with a low and high starting price should be the same (otherwise sellers would change the starting price of their auctions). We find evidence consistent with the seller side of the market being in equilibrium (i.e. with an *optimal* number of sellers exploiting this bias). The expected revenue associated with starting an auction at $1 is $9.260, virtually identical to the $9.265 expected for a starting price of $10.

Although we find that market forces have eliminated the rents associated with exploiting the identified bias, the bias itself survives. Indeed, the persistence of the bias explains why choosing a below cost starting price is not a dominated strategy *in equilibrium*. Furthermore, consumers not only continue engaging in non-rational herding after market forces have acted, they continue suffering the negative consequences from doing so as they are, conditioning on the dollar amount of their bid, less likely to win and when they do win they pay higher prices. For example, a bid for $10 on an auction that started at $1 has only a 16% chance of winning, while it has a 40% chance of winning an auction starting at $10. Similarly, winners of auctions that start at $1 pay around 3% more than winners of auctions starting at $10, again, conditioning on dollar amount bid.

The key assumption behind our interpretation of these findings as evidence of non-rational herding is that starting price is not correlated with (unobservable) quality differences across auctions and/or sellers. In section 5 we discuss in detail five arguments to support this assumption, among them: (i) excluding observable heterogeneity from our analyses barely influences the estimated impact of starting price, (ii) expected revenues for auctions with low and high starting price auctions are practically identical; if low starting price auctions are of superior quality or are offered by superior sellers they should collect more revenue, and (iii) experienced bidders are less likely to choose low starting price auctions, conditioning on current price, suggesting that doing so is a mistake experience teaches bidders to avoid.

In addition to unobserved heterogeneity, we also rule out as alternative explanations the possibility that our findings are driven by *attachment* (namely, early bidders increasing their willingness to pay for the item they have already bid on) or by *distracted snipers* (i.e. last-minute bidders choosing which auctions to bid on early during the auctioning process).

The paper contributes to various literatures. It is among the first to study herding utilizing individual level data from the field, and the first to propose a specific testable (and tested) alternative to rational information-based herding models that assume perfect Bayesian updating based on observed behaviors. It also contributes to the auctions literature by providing an explanation for sellers' marked tendency to start their auction well below the opportunity cost of the items they offer. Finally, as mentioned, it contributes to the developing field of behavioral industrial organization by both studying how rational sellers respond to biased consumers and by demonstrating the survivability of biases to market forces.

The remainder of the paper is organized in the following way: section 2 reviews the existing literature and puts forward four predictions, section 3 describes the data, section 4 presents the empirical results which we interpret as supporting the proposition that bidders engage in non-rational herding and that sellers are best-responding to such bias, section 5 discusses alternative explanations for our results and section 6 concludes.

2. Herding in auctions

People often observe the decisions of others before making a decision of their own. If these observed decisions reveal valuable information, it may be optimal for observers to imitate them, engaging in information-driven herding (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). A common example of this type of social learning consists of choosing busier restaurants, implicitly assuming that previous choosers had private information about them. [2]

[2] Of course people may engage in herding for non-information related reasons including network externalities (Katz & Shapiro, 1985), social sanctioning of deviants (Akerlof, 1980) and taste for conformity (Becker, 1991). None of these factors are likely to influence how people choose auctions and hence throughout this paper we will always refer to *information driven* herding.

In order for information-based herding to be rational, observers must make correct attributional inferences about the behaviors they observe. In particular, they must make unbiased estimates of the private information held by prior decision makers. Abundant research from psychology, however, suggests that people fall prey to systematic biases when making attributions about causality. Beginning with Heider (1958), psychologists have proposed that when people observe actions that can be attributed to multiple causes, they overattribute causality to focal ones (e.g. those they are assessing or that are perceptually salient), and underattribute it to non-focal ones.

A classical experiment by Jones & Harris (1967), for example, showed that people's inferences about the political views of a speaker were influenced by the topic of the speech (focal) but not by whether or not the topic had been assigned or chosen (non-focal). Another well known study is that of Schwarz & Clore (1983). They found that people reported higher overall life satisfaction on sunnier days, presumably because they failed to attribute to the weather their current mood. Taylor and Fiske (1975) had eight different subject observing *the same* conversation between two people from different angles. Subjects judged the person they were facing directly (the focal target) as having had a more central role in the conversation. For a review of the psychology literature on misattribution of causality behind observed behaviors see (Gilbert & Malone, 1995).

Returning to the issue of herding, if people overestimate the importance of focal causes, they will tend to make systematically erroneous inferences about the private information held by previous decision makers in a sequential choice setting. In particular, observers will tend to overestimate how good *their* focal attribute is for the most commonly chosen alternative, leading to non-rational herding, i.e. to herding driven by misinterpreted information.

For example, imagine two bars, only one of which offers a happy-hour promotion, attracting a larger number of costumers early in the evening. After the happy-hour is over, new costumers deciding between the two bars are likely to underestimate the importance the non-focal attribute (happy-hour prices) had on earlier decision makers. Doing so would lead observers to incorrectly believe that the crowd in the more popular bar is a signal of quality when in reality it is a signal of formerly lower prices.

Auctions are ideal for studying *non-rational* herding because an auction's starting price can, completely independently of the auctioned item's actual quality, influence the number of existing bids the auction will have by the time it reaches a certain price. A bidder choosing between auctions with the same current price faces a situation analogous to a customer choosing whether to enter a bar with a recently expired happy-hour: popularity is a signal of no longer available low prices rather than of enduring higher quality.

If bidders attribute causality the way subjects in psychology experiments do, they will underappreciate the role that starting price had on number of existing bids (since it is not focal) and be more likely to choose, from auctions with the same current price, the one with the lowest starting price. [3]

This leads us to our first prediction,

Prediction 1: Conditioning on current price, low starting price auctions are more likely to receive additional bids.

Although previous research has shown that low starting price auctions receive more bids that high starting price ones (see e.g. Bajari & Hortacsu, 2003; Haubl & Popkowski Leszczyc, 2003b; Morgan & Hossain, 2006), a distinction has not been made as to whether these additional bids are for amounts above or below the higher starting price. Setting a low starting price mechanically increases the number of bids placed below the high starting price because of the simple truncation effect of the starting price; bids for low dollar amounts cannot be placed on high starting price auctions. Prediction 1 states that setting a lower starting price will also increase the number of bids placed *above* the higher starting price, because late bidders herd behind the otherwise truncated away low value bids.

Another reason why auctions are ideal for studying non-rational herding is that bidders have an incentive *not* to herd, because the probability that they win the item they bid on, and the price they expect to pay for it, depend on the behavior of other bidders. Herding should, on average, hurt bidders who engage in it for at least two reasons. First, by choosing low starting price auctions bidders are choosing

[3] Information about an auction starting price is available to bidders, but, unlike current price and number of existing bids, it is not displayed unless bidders request it (with a single click).

auctions which are more likely to receive future bids. Secondly, choosing an auction with more existing bids increases the chances that a bid has already been placed for an amount above the current price. This leads us to two related predictions:

Prediction 2a: A bid of a given dollar amount is less likely to be a winning bid on a low starting price auction than on a high starting price one,

and

Prediction 2b: Winners of low starting price auctions will, conditioning on the dollar amount of their bid, pay higher prices than winners of high starting price auctions,

If sellers can increase their revenues by simply lowering the starting price of their auction, we would expect them to do so. Doing so increases the chances that they (and all other low starting price sellers) actually sell for a lower final price. In equilibrium there should be enough low starting price auctions that the marginal seller is indifferent between a high and a low starting price,

Prediction 3: Sellers' expected revenue from setting a low and a high starting price is the same.

After describing the dataset in the next section, we test these predictions in section 4.

3. Description of the Data

The dataset

The data was provided to us directly by eBay. It consists of auctions for DVD movies taking place during October 2002. We chose to study DVDs (a commodity) in order to reduce to a minimum unobserved heterogeneity across goods with different starting prices. The dataset consists of auctions for movie titles that were top-30 bestsellers in dvdmojo.com in September of 2002 or July of 2001. Six of these 60 titles had either too few observations or had titles that were easily confused with other movies and were hence dropped from the sample.[4]

[4] eBay does not use unique product identifiers so the identity of items being auctioned must be inferred from sellers' descriptions.

We excluded auctions with starting price above $10.49 primarily because some of our analyses control for starting price through dummies for each rounded amount (less than 4% of the sample had starting prices above that figure). We also excluded auctions with a reserve price and those offering the "buy-it-now" option (1% and 13% of the sample respectively). The "buy it now option" is a feature which essentially converts an auction into a fixed price item. The qualitative nature of our results remains unchanged if we do not impose these restrictions. After these exclusions the sample contains 54 movie titles for a total of 8,333 auctions, posted by 2,481 different sellers and receiving 37,535 bids,

Variables

For each auction we know the starting price, the final price, the seller's description of the item, the identity of the seller, their reputation (net number of positive evaluations they have received in previous transactions), whether they are an eBay store (if they have established a contractual relationship with eBay) and the total number of DVDs they have offered on eBay since January of 2002. Based on the description of the item by the seller we also created a dummy variable, *new*, which takes the value of 1 if the seller described the item as 'new', 'wrapped' or 'sealed', and 0 otherwise. Surprisingly, eBay collects shipping fees information only for items paid through their internal payment system and hence 28% of the data does not contain information on shipping charges. Controlling for shipping, therefore, reduces sample size.

For each bid we know the dollar amount of the bid, how many minutes were left when the bid was placed, the reputation of the bidder (analogous to the sellers') and the price the bidder faced when she placed her bid; we will refer to this price as *current price* throughout the paper. [5] Note that *current price* seldom corresponds to the highest bid placed on the auction so far, since these values are only revealed once outbid; current price equals either the second highest bid so far or the starting price if only one bid has been placed.

[5] Bidders submit bid amounts which correspond to the maximum they are willing to pay. eBay then automatically places bids for them, outbidding existing bids only by the minimally required increment. Our data consists of the actual maxima, not the proxy bids placed by eBay's automatic bidding system.

The dataset does not include bidders' identifiers; to determine whether a bid belongs to a new bidder or to a bidder who has already participated in that auction, we rely on the bidder's reputation. Bids coming into the same auction from different bidders who happen to have the exact same reputation will therefore be coded as if they were placed by the same bidder. Given the relative low number of bidders per auction and the large range of reputation, it is unlikely that we are incorrectly identifying a large number of bidders.

Descriptive Statistics

Figure 1a shows the distribution of (rounded) starting prices in our sample. It shows large dispersion in the starting prices chosen by sellers. Contrary to standard auction models, a large portion of sellers set a starting price that is clearly below the cost of the item being auctioned. For example, 22.3% of auctions start at $1 or less, clearly below the opportunity costs of popular DVD movies (only 0.2% of auctions sell for such low final prices).

Overall 78% of auctions resulted in a sale, figure 1b plots the probability of sale by (rounded) starting price; it shows that practically all movies with a starting price below $4 are sold, and that probability of sale decreases as starting prices increase above $4. Excluding non-sold items, the average auction received 5.5 bids. The average price of sold auctions was $10.29, and the average shipping charges were $3.53.

*** Figures 1a and 1b ***

Finally, Figure 2 shows the distribution of final prices for auctions starting at $1 and $10. The figure shows that auctions starting at $1 are more likely to obtain final prices below $10 than auctions starting at $10, of course, but they are also more likely to obtain final prices above $10, the expected losses and gains respectively. This highlights the aforementioned trade-offs involved in lowering a starting price: increase in the chance of a high price but *also* of a low price.

*** Figure 2 ***

4 Empirical Analyses

This section begins by documenting a correlation between the number of existing bids on an auction and the number of additional bids it receives. It then demonstrates that this tendency to follow existing bids persists even when it is entirely driven by lower starting prices. Then predictions 1, 2a and 2b are tested, followed by an assessment of the role of bidder experience. Finally, the expected revenues associated with low and high starting prices are examined, finding support for prediction 3: in the margin exploiting non-rational herding is as profitable as not exploiting it.

Existing bids predict future bids.

Although in this paper we are interested in variation in number of existing bids that results *only* from variation in starting price, before presenting the analyses of the impact of starting price it is useful to assess whether number of existing bids, caused by starting price or by any other factor, is a predictor of future bids. This introductory analysis suffers from the usual identification problems afflicting empirical work on peer-effects: the correlation between past and future choices could be caused by omitted variables (for example auctions that happen to end on a rainy afternoon may have more existing and forthcoming bids). Nevertheless, it would be hard to argue that starting price influences consumer choices by affecting the number of existing bids, if these were not a significant predictor by themselves.[6] Before assessing the impact of starting price, therefore, we begin by documenting that the number of existing bids is a significant predictor of the likelihood that an auction will receive additional bids.

To this end we estimated a regression where bids are the unit of observation, the dependent variable takes the value of 1 if at least one more bid is placed on the auction and 0 otherwise. The key predictor is how many bids have already been placed in the auction, controlling for current price, minutes left in the auction and various other controls.

The results from this regression are consistent with the notion that auctions with more existing bids are more likely to obtain more additional bids. The point estimate for log(existing bids) is β=1.52,

[6] One interpretation of our analyses that focus on starting price is that we are *instrumenting* for number of existing bids with an auction's starting price.

with a SE=.039. The full regression is presented in Column 1 of Table 1 (this table is discussed in detail a few paragraphs below).

Again, it is quite clear that this result does not provide unambiguous evidence of herding. The correlation we find could be the result of an omitted variable causing both the existing and the new bids. It does, nevertheless, lend plausibility to our explanation that starting prices influence an auction's outcome by influencing the number of existing bids bidders observe when they arrive at an auction.[7] We now move on to our main analyses which focus on starting prices.

Early bidding, a necessary condition for herding

For late bidders to herd behind early bidders there must be early bidders to follow; if in the extreme, all bids were placed in the last minute, herding would not be a plausible explanation for potential differences in the performance of low and high starting price auctions. Figure 3a plots both the average dollar amount of first bids and the number of hours left until the end of the auction when they were placed. The figure shows that low starting price auctions receive bids much earlier than auction with high starting prices: the average auction starting at $1 received the first bid around 5 days before the end of the auction, compared to 8 *hours* for auctions starting at $10. Figure 3a also illustrates that early bids are for lower dollar amounts, the first bid in auctions that start at $1 is, on average, for just $2.

*** Figures 3a & 3b ***

Since low starting price auctions receive low value bids early-on, by the time they catch-up with higher starting price ones they are likely to accumulate a much larger number of bids than auctions that started higher. Figure 3b plots the average number of bids received by the time auctions with different starting prices reached a price of $10. As expected, auctions with lower starting prices receive a much larger number of bids by the time they reach $10.

Since low starting price auctions receive bids early-on and accumulate a number of them by the time they catch up in price, the non-rational herding mechanism we propose is a plausible explanation for

[7] Dholakia and Soltysinski (2001) also propose that existing bids are correlated with new bids. They do not appear interested, however, in disentangling between a causal and a spurious correlation, or on how the market responds to such correlation.

potential differences in performance by low and high starting price auctions. Figures 3a and 3b are not evidence *of* herding, but of the necessary conditions *for* herding to occur.

Choosing Auctions – Testing Prediction 1

Prediction 1 states that, conditional on current price, lower starting price auctions are more likely to receive additional bids. We test prediction 1 with two closely related analyses. The first consists of pairwise comparisons of the probability of receiving an additional bid for auctions that started at $1 and achieved a price of $6, $7, $8, $9 and $10, and the analogous probability for auctions that started at those prices. We also estimated regressions that use the whole dataset and control for current price.

Pair-wise comparisons of auctions at the same current price

Figure 4 reports pairwise comparisons of the probability that an auction at a given current price, $x, will receive at least one additional bid, for auctions that started at $x and those that started at $1. Figure 4a shows the relative frequencies in the raw data (i.e. without any controls) while Figure 4b the predicted probabilities arising from logistic regressions, controlling for movie and seller observable heterogeneity.

The results presented in Figure 4 are consistent with prediction 1: conditioning on current price, low starting price auctions are more likely to receive additional bids. For example, Figure 4a shows that 91% of auctions starting at $1 and currently at $8 receive an additional bid, while only 76% of auction that start at $8 receive any bids. Figure 4b shows that once movie and seller characteristics are controlled for, the predicted probabilities are 90% and 77% respectively, almost identical.

***Figure 4 ***

Logistic regression including all auctions in the sample

To extend the previous analysis to all observations in the dataset, we estimated a logistic regression where every bid in the sample is an observation and the dependent variable takes the value of 1 if there was at least one more bid placed after it, and 0 otherwise (e.g. if an auction had three bids, the dependent variable is 1 for the first two bids, and 0 for the third). The results are presented on columns

2-6 of Table 1 (column 1 reports the previously discussed regression where number of existing bids is the key predictor).

*** Table 1 ***

It is obviously important to control for current price since only low starting price auctions were ever at a low current price, and auctions at current lower prices are more likely to receive additional bids. In order to avoid imposing an arbitrary functional form on this key control variable, we use 21 dummies (between $0 and $20) for the rounded dollar amount of the current price of the auction. This reduces the likelihood of starting price being a significant predictor of probability of receiving bids because current price is not adequately controlled for. Given than many auctions have multiple bids, standard errors are clustered by auction (with the exception of column 5 where there are too few observations per auction for the clustered standard errors to be computed).

Column 2 presents the baseline specification, column 3 adds controls for movie characteristics (movie title fixed effects and the "new" dummy) and column 4 adds seller controls (experience, reputation and the store dummy). As predicted, the coefficient of starting price is negative and significant across all specifications: auctions with lower starting prices are more likely to receive additional bids conditioning on current price. The parameter estimate for starting price is practically unaffected by the inclusion of observable heterogeneity, this suggests that unobserved heterogeneity is an unlikely alternative explanation. [8]

To further rule out the possibility that the significant influence of starting price reported in columns 2-4 is driven by the fact that only low starting price auctions were ever at low prices, column 5 reports the results from a regression run on the subset of observations when current price was at or above $10. Starting price remains negative and highly significant. The drop in the size of the parameter is not easily interpretable, for it refers to the average effect over a different range of current prices. Column 6 will be discussed in the alternative explanations section. In sum, both the pairwise comparisons and the regression analyses of all bids find evidence consistent with prediction 1.

[8] If current price is controlled for with a linear term, similar results are obtained (β=-0.171; *SE*=0.005).

Winning Auctions – Testing Prediction 2a

Prediction 2a indicates that bids for a given dollar amount are less likely to win auctions with lower starting prices. This means that a bidder willing to bid a certain amount of money for a given movie is more likely to win it if the bid is placed on a higher starting price auction. Two forces are behind this prediction: the first is that choosing low starting price auctions means choosing auctions which future bidders are likely to choose, and the second is that choosing an auction with existing bids increases the chances that a bid that has already been placed (but whose maximum dollar amount is hidden) is higher than the currently displayed price. As was the case with prediction 1, we begin with a simple test on a subset of the data and we then extend the analysis to the whole dataset.

Comparison of $10 bids across auctions

Figure 5 plots the probability that a $10 bid wins an auction as a function of the starting price of the auction where it is placed both controlling and not controlling for movie and seller variables. The probability estimates without controls correspond to the relative frequency in the raw data. For example, there were 1,277 $10 bids placed on auctions with a starting price of $1, of which 206 ended up winning the auction, hence the probability that an observed $10 bid wins an auction starting at $1 is 206/1,277=16.1%. [9]

The calculations with controls were obtained with a linear probability model where we included dummies for each starting price and controlled for both movie and seller characteristics; the reported probabilities correspond to the parameter estimates of each starting price dummy variable, plus a constant that facilitates comparisons.

The results presented on Figure 5 are consistent with prediction 2a. Bids of a given dollar amount ($10) are more likely to win higher rather than lower starting price auctions. For example, a $10 bid had a 16% chance of winning an auction that started at $1, but it had a 41% chance of winning an auction that

[9] Note that we are looking at the actual relative frequency of bids for a certain dollar amount winning auctions, rather than at whether a bid would have won had it been placed. The latter is a problematic counterfactual since it *assumes* that placing a bid on an auction does not influence the behavior of other bidders, which is precisely the question we address in this paper.

started at \$10. The similarity of both lines suggests heterogeneity across auctions with different starting prices is not what's behind the relationship between probability of winning an auction and starting price.

At face value these results mean that a bidder who is willing to pay up to \$10 for a specific DVD movie would increase her chances of winning it from 16% to 41% by placing her bid in an auction that started at \$10 rather than at \$1.

*** Figure 5 ***

Logistic regression including all bids in the sample

To conduct a more comprehensive test we run a regression where each bid is an observation, the dependent variable is whether the bid won the auction, and the key predictor is the starting price of the auction. As was the case for prediction 1, standard errors are clustered by auction.

It is of high importance to control for the dollar amount of the bid being placed, since only low starting price auctions can receive bids for low dollar amount, and such bids are less likely to win auctions. As we did with current price when testing prediction 1, we control for the dollar amount of the bid with dummy variables for each rounded dollar between \$0 and \$20, avoiding the need to impose an arbitrary functional form on our key control variable.

The results of these regressions are presented in Table 2. Column 1 controls for auction characteristics and for the number of minutes left when the bid was placed, column 2 adds movie controls and column 3 seller controls. The coefficient of starting price is positive and greatly significant across all specifications. Comparing the parameter estimates for starting price across columns 1-3 we see that, as was the case for prediction 1, including observable heterogeneity does not diminish the estimated influence of starting price, suggesting that unobserved heterogeneity is an unlikely alternative explanation. [10]

*** Table 3 ***

To further rule out the possibility that coefficient estimates for starting price from columns 1-3 are driven by the fact that only low starting price receive low value bids, Column 4 restricts the analysis

[10] Controlling for current price linearly leads to a similar point estimate for starting price (β=.0882, *SE*=.0049).

to bids for $10 or more. The coefficient for starting price is still positive and highly significant. The change in size of the coefficient is not easy to interpret because it refers to the average effect over a different range of bid amounts.

Price paid by winner, conditional on bid amount – Prediction 2b

Prediction 2b indicates that winners of low starting price auctions will pay higher prices for the auctions they win, conditional on the amount they bid. To test for prediction 2b we estimated a regression where each *winning* bid is an observation, the dependent variable is the price paid by the winner of the auction, the key predictor is the starting price of the auction and the key controls are the current price at the time the bid was place, and the dollar amount of the bid. The results are presented in Table 3.[11]

Table 3

Column 1 in Table 3 presents the regression estimates controlling only for dollar amount of bid, minute left in auction when bid was placed and current price when bid was placed. Column 2 adds movie controls, columns 3 seller controls, and column 4 shipping. Across all four columns the point estimate for starting price is, consistent with prediction 2b, negative and significant: conditioning on the amount of the bid, winners of lower starting price auctions pay higher prices. As was the case with predictions 1 and 2, introducing observable heterogeneity barely influences the point estimate of starting price.

The effect size is small, specially compared to those resulting from predictions 1 and 2a. According to the point estimates from column 4, winners of auctions starting at $10 pay 30 cents *less*, on average, than winners of auctions starting at $0, (again, conditional on bid amount), that's about 3% of the final price. It would be difficult to obtain larger effect sizes in this sample, however, considering that eBay's required minimum increment is just 50 cents (in this price range).

[11] The regression obtains such a high R^2 probably because it controls both for the dollar amount of the winning bid and the price at which the bid was placed.

The role of bidder experience

If the behavior of bidders that leads to the previous findings is a mistake, as we posit, then bidders may learn not to interpret bids that result from lower starting prices as informative and hence avoid low starting price auctions once they catch up in price with higher starting price ones.

We do not have data on bidder experience per-se, but we do know bidders' ratings, which consist of the net number of evaluations bidders have received from sellers they have purchased from. Sellers can evaluate buyers with a positive (+1), negative (-1) or neutral score (0); the variable we have consists of the sum of all of these scores. Although bidder rating is not perfectly correlated with experience it is probably a good proxy for it. There is ample variation in the ratings of bidders in the sample. For example, the average rating in the lowest decile is 1.27, compared to 651.3 for bidders in the highest decile.

To intuitively assess the role of experience, we compared the auctions bidders with different amounts of experience chose to bid on. In particular, we concentrated on bidders placing a bid on auctions currently at $10, and compared the share of these auctions that had a starting price of $1 and of $10 for bidders across different experience levels. The results are presented in Figure 6.

The figure shows, for example, that (of auctions currently at $10) bidders in the lowest decile of experience placed 32% of bids on auctions that started at $1, compared to 52% by bidders in the highest decile of experience. The slopes in the graph indicate that bidders with more experience are more likely to choose auctions with a starting price of $10, and less likely to choose auctions with a starting price of $1, conditioning on the current price.

Figure 6

We also estimated a regression where each bid is an observation, the dependent variable is the log of the rating of the bidder placing the bid, and the key predictor is the auction's starting price. We control for all observables, including dummy variables for the current price of the auction at the time the bid was placed. If bidders with more experience tend to choose auctions with higher starting prices the coefficient of starting price on the rating of bidders should be positive. As predicted, the point estimate of the relationship between starting price and buyer rating of the bidder placing the bid is positive and significant, β=.020, SE = .003.

It is worth noting that although both Figure 6 and this regression present evidence consistent with experienced bidders preferring higher starting price auction, given the cross-sectional nature of the data, we cannot distinguish between a learning explanation, where bidders learn not to bid on low starting price auction, and a selection one, where bidders who chose low starting price auctions are less likely to come back to eBay.

Are sellers best-responding to the herding behavior of bidders?- Prediction 3

Sellers seem to at least partially recognize bidders' non-rational herding, since a substantial proportion of auctions start at prices well below the cost of popular DVDs, contrary to standard auction model predictions. 22.3% of auctions start at $1 or less, well below the opportunity cost of popular DVD movies (only 0.2% of auctions *sell* for $1 or less). An interesting question is whether 22% is the *equilibrium* percentage of auctions starting at $1, i.e. whether a marginal seller could increase her expected revenue by lowering the starting price of her auctions.

There is a tradeoff involved in lowering an auction's starting price. Although it attracts low value bids which in turn may attract more bids, if no high dollar amount bid is placed, then rather than keeping the item, the seller has to sell it for a low price. In the extreme, if an infinite number of sellers listed DVD movies for $1 on eBay, all sold movies would go for just $1. In equilibrium the number of sellers setting low prices should be such that the expected revenue associated with starting at high and low prices was the same. This tradeoff between potential gains and losses was highlighted above in Figure 2, which shows the distribution of final prices for auctions starting at $1 and $10.

To test whether the seller side of the market is in equilibrium, i.e. if in the margin these two forces cancel each other out, one needs to compare the expected *revenues* associated with low and high starting prices. Revenues differ from prices because eBay charges listing fees which, as we shall see, will be (indirectly) affected by starting prices as well.

To compute expected revenues one needs to make assumptions about what sellers do with unsold items. Considering that if sellers had an alternative to listing on eBay that lead to higher expected revenues they would have not listed their item on eBay in the first place, we assume that unsold items are re-listed, for the same starting price, until they eventually sell.

Sellers pay a listing fee for each item they post on eBay, regardless of whether the item sells. If an item does not sell, however, sellers get one second listing for free; if on a second instance the item does not sell, the seller must pay for each listing after that. So if an item is listed either once or twice before selling, the seller pays the listing fee once ($.35), but if the item is listed three or more times before it sells, the sellers pays $.35 multiplied by the number of times the item was listed, minus one.

The average final prices for auctions starting at $1 and $10, the two most popular starting prices, controlling for all observables, are $9.61 and $9.71 respectively, i.e. auctions starting at $10 sell for around $.10 more than auctions starting at $1.[12] Auctions starting at $10, however, need to be listed more times, on average, before they are sold, because their probability of sale is so much lower (see figure 1b). Once we subtract the corresponding expected costs in listing fees, expected revenues for auctions starting at $1 and $10 are $9.260 and of $9.265 respectively. This suggests that, at least with respect to the starting price decision, the seller side of the market is in equilibrium; the gains a seller obtains in terms of increasing the chances of a higher final price are exactly cancelled out by the losses associated with the now possible lower final prices. [13]

This highlights an important point we make in this paper. Market forces have eliminated the *rents* associated with exploiting non-rational herding (i.e. with setting a low starting price) but they have

---

[12] These are the sum of the intercept plus the parameter estimates from starting price dummies in a regression where each sold auction is an observation, and both movie and seller observables are controls.

[13] Several papers have investigated the correlation between starting and final prices, obtaining mixed results. Some find a negative association (Kamins, Dreze, & Folkes, 2004; Ku, Galinsky, & Murnighan, in press.; Reiley, 2005), while others find a positive one (Brint, 2003; Haubl & Popkowski Leszczyc, 2003b; Lucking-Reiley, Bryan, Naghi, & Reeves, 2000; Park & Bradlow, 2004). These papers have many differences which are beyond the scope of this paper to discuss in detail. The most important differences between *our* paper and *most* previous ones are that (i) we concentrate on expected revenues rather than prices (taking into account fees and probability of sale) (ii) we compare the expected revenues for the two most commonly chosen starting prices, rather than arbitrarily "high" and "low" ones, and (iii) we used data from auctions for a commodity where unobserved heterogeneity (real or perceived) is trivial.

not eliminated non-rational herding per-se. Indeed setting a starting price of $1 is not dominated by a starting price of $10 *because* bidders continue to engage in non-rational herding.

5 Alternative Explanations

Our interpretation of the evidence presented above is that bidders engage in non-rational herding choosing auctions with lower starting prices because they have accumulated more bids by the time they catch up in price with higher starting price ones. In this section we entertain three alternative explanations. These are: (i) low starting price auctions are unobservably superior to high starting price ones, (ii) bidders become attached to auctions they have already placed bids on, and (iii) last-minute bidders choose auctions when current prices of low starting price auctions are still lower than that of high starting price ones.

Unobserved heterogeneity

The first alternative explanation we discuss is the possibility that bidders prefer low starting price auctions because they offer unobservably better products or are offered by unobservably better sellers. We present five arguments against this alternative explanation.

(i) *Lack of ex-ante candidates for correlates*: We intentionally selected DVD movies as the product for our study because we wanted to analyze goods that were highly standardized. Once the movie title, new vs. used, reputation of the seller, experience of the seller, shipping charges and whether the sellers is a store are controlled for, no obvious relevant attribute (likely to be correlated with starting price) seems to remain unobserved.

(ii) *Counterintuitive unobserved correlation*: in order for unobserved heterogeneity to explain our results, lower starting price auctions (or sellers of) would need to be unobservably superior to higher starting price ones. As we mentioned earlier, standard auction models predict that sellers set starting prices at or above the opportunity cost of the item they offer, however, and hence, according to existing rational models, failing to control for unobserved heterogeneity should bias our estimates towards finding a preference for *higher* starting price auctions.

(iii) *Observable heterogeneity does not alter estimates*: one way to assess the potential impact of unobserved heterogeneity on our parameter estimates for starting price is to examine the impact of excluding *observed* heterogeneity. If unobservable heterogeneity is behind our findings, the point estimates for starting price should be greatly influenced when observable heterogeneity is excluded. This, however, is not the case. None of the regressions presented in tables 1-3 show noticeable changes in the point estimate of the coefficient for starting price when observable heterogeneity is added to the regression, suggesting that unobservable heterogeneity is an unlikely explanation for our findings.

(iv) *Experienced bidders stay away from low starting price auctions*: as was reported above, experienced bidders are less likely to choose low starting price auctions, conditional on current price, that inexperienced bidders (see Figure 6). The fact that experience diminishes bidders' tendencies to choose low starting price auctions is consistent with such tendency being caused by a mistake (non-rational herding) but not with the alternative explanation based on unobservable higher quality. Why would experienced bidders shy away from bidding on superior items?

(v) *Equal expected revenues for auctions with low and high starting prices*: Finally, in a competitive market such as eBay, superior items and/or superior sellers of items should obtain higher revenues. The fact that revenues are nearly identical for auctions starting at $1 and $10 suggests that that the quality of items listed at $1 and $10 must also be virtually identical.

In sum, there is no evidence that points to low starting price auctions being of higher quality than high starting price auctions.

Attachment

The second alternative explanation we consider is that bidders who bid early-on on low starting price auctions (when the price is still low) become more determined to win the item than if they had not placed an early bid. This could be the result of selective attention to auctions one has already bid on, of the excitement or arousal generated by the bidding process itself (Ariely & Simonson, 2003; Haubl & Popkowski Leszczyc, 2003a; Ku, Malhotra, & Murnighan, 2005), or of a pseudo-endowment effect

(Dodonova & Khoroshilov, 2004; Heyman, Orhun, & Ariely, 2004). We refer to this general explanation as *attachment*.

To assess how much of the increased preference for low starting price auctions can be explained by attachment, we estimated the regression used for testing prediction 1 (i.e. bidder's tendency to prefer low starting price auctions, conditional on current price) excluding repeat bidders, i.e. not counting bids by bidders who had already placed a bid on the auction as a new bid. If the impact of starting price was solely due to attachment, the coefficient for starting price should no longer be significant once repeat bidders are excluded, while –on the other extreme- if attachment plays no role at all, the point estimate should remain unchanged. The relative drop in the coefficient of starting price, therefore, provides an estimate of the relative importance of attachment (in our data).

The results from this regression are presented in the column 6 in Table 1; the point estimate for starting price in this column, where repeat bidders are excluded, is virtually identical to the point estimate in column 4, where they are included ($\beta_{(\text{column } 4)}$=-1.54 and $\beta_{(\text{column } 6)}$=-1.56). Although this does not necessarily rule out attachment as a real phenomenon, it suggests it is not behind the reported tendency for preferring low starting price auctions.

Distracted Snipers

Various studies have shown that bidders tend to place their bids during the last few minutes of an auction (for a review see section 3 in Bajari and Hortacsu, 2004) . If last minute bidders (often referred to as snipers) choose early-on which auctions to snipe on, perhaps based on the current price at that time, and they do not update their decisions as prices increase, low starting price auctions may be preferred by bidders because their low starting prices act as bait for snipers. Under the *distracted sniper* explanation, winners of low starting price auctions are not being attracted by the high number of bids that the auction accumulates through time, but rather, they made up their minds even before these bids arrived. One might argue, however, that if snipers are strategic in their bidding behavior, it is unlikely that they will not be strategic also in their decisions of which auction to participate in. Furthermore, when placing a bid on eBay, a bidder is shown the current price, and hence it would be technically difficult to place a bid without being aware of the current price.

Nevertheless, it is worthwhile considering this explanation because of how prevalent sniping is in online bidding. A logical consequence of this account of the results is that low starting price auctions should receive more last minute bids. Figure 7 plots the proportion of last bids arriving within 5, 60 and 180 minutes of the end of the auction. Although there is plenty of last minute bidding in DVD movies, there is no evidence of a higher rate of last minute bidding in low starting price auctions.

***Figure 7 ***

6. Conclusions

In this paper we show that online bidders have a biased preference for auctions with more bids even if these bids are non-diagnostic of quality, that such bias creates an incentive for sellers to lower the starting price of their auctions, that enough sellers do so that their side of the market is in equilibrium but that despite such market forces bidders continue engaging in non-rational herding, being less likely to win auctions and having a higher expected final price if they do win. These findings contribute to various literatures, including herding, auctions and industrial organization in general.

In terms of the auctions literature, our findings provide an explanation for sellers' marked tendency to start their auction well below the opportunity cost of the items they offer, contrary to standard auction models. Also, this paper improves our understanding of how bidders choose where to place their bids when they have many parallel auctions offering similar or identical products, contributing to the recent interest in auctions where bidders endogenously decide whether to participate (see e.g. Bajari & Hortacsu, 2003; Reiley, 2005; Zeithammer, Forthcoming).

With regards to the herding literature, ours is among the first papers to study herding utilizing individual level data from the field. More importantly, it is the first to propose a specific testable (and tested) alternative to rational information-based herding models that assume perfect Bayesian updating based on observed behaviors. Standard herding models assume that observers make unbiased inferences from the actions they observe.

The fact that people misattribute causality behind the observed actions of others, however, is such a robust finding in social psychology that it has been termed the "*fundamental* attribution error." It seems likely that herding models which take such robust and systematic deviations into account would be able to make more accurate predictions of herding in the real world, as we do in this paper.

We believe that non-rational herding as a consequence of overattributing causality to focal causes is likely to occur in other domains where decisions are based, at least partially, upon inferences agents make from observed behavior. When hiring, for example, employers assessing the ability of an applicant may overattribute to the focal target of their evaluation (the applicant) the quality of the previous position held by her, and underweight the role played by non-focal causes, such as job market conditions when the previous job was obtained, leading workers who happen to obtain their first job under favorable job market conditions to continue receiving the benefits of such conditions, long after they cease to be present. Devereux (2002) and Oyer (2006) provide evidence consistent with this prediction

Another example consists of the inference problem firms face when attempting to understand the driver of price changes in the markets where they participate. Lucas (1973) seminal paper proposed that inflation can affect real output if producers confuse changes in the aggregate level of prices with changes in relative prices. One possible mechanism for this type of error is that producers over-attribute to focal targets (their own business) the increase in the prices of their product, rather than to the true yet non-salient cause (excessive printing of money).

Finally, in terms of industrial organization, our results highlight that market forces can eliminate rents associated with exploiting biases without eliminating the biases themselves. This means that (i) behavioral biases can be observed even after market forces have played their part, and that (ii) in order to understand the rational behavior of firms one must first understand the not necessarily rational behavior of consumers they are responding to.

Table 1. The Effect of Starting Price on Probability of Receiving Additional Bids (Logistic Regression with clustered standard errors)

Dependent Variable: 1 if at least one more bid was placed, 0 if last bid.

	(1) Number of existing bids as key predictor	(2) Controls for auction variables only	(3) adds movie controls	(4) adds seller controls	(5) Only bids placed once price>=$10	(6) Same as (4) excluding repeat bidders
Intercept	-4.027***	0.121	1.054	0.385	-2.293	-0.145
	(0.865)	*(0.671)*	*(1.036)*	*(0.997)*	*(6.712)*	*(1.477)*
Starting Price	--	-0.155***	-0.165***	-0.154***	-0.107***	-0.156***
	--	*(0.006)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.009)*
log(Minutes left on the auction)	0.392***	0.303***	0.278***	0.273***	0.240***	-0.160***
	(0.010)	*(0.008)*	*(0.009)*	*(0.009)*	*(0.010)*	*(0.031)*
Shipping Charges	-0.113***	0.044**	-0.076***	-0.085***	0.009	0.346***
	(0.027)	*(0.022)*	*(0.026)*	*(0.027)*	*(0.026)*	*(0.011)*
"New" Movie Dummy	0.235***	--	0.176***	0.138***	0.069	0.239***
	(0.051)	--	*(0.050)*	*(0.052)*	*(0.054)*	*(0.064)*
log(Seller Rating)	0.066***	--	--	0.138***	0.130***	0.193***
	(0.020)	--	--	*(0.021)*	*(0.024)*	*(0.025)*
log(Seller Experience)	0.007	--	--	-0.027**	-0.027*	-0.033**
	(0.013)	--	--	*(0.013)*	*(0.016)*	*(0.016)*
eBay Store Dummy	-0.158	--	--	-0.221**	-0.313***	-0.290**
	(0.101)	--	--	*(0.102)*	*(0.096)*	*(0.117)*
Log(Number of existing bids)	**1.515*** **	--	--	--	--	--
	(0.039)	--	--	--	--	--
Movie title fixed-effects (df=53)	YES	NO	YES	YES	YES	YES
Current price dummies (df=21)[a]	YES	YES	YES	YES	YES	YES
Pseudo R-Square		0.246	0.316	0.320	0.175	0.360
Number of observations	26,580	26,580	26,580	26,580	10,127	13,826

Notes: Standard errors, clustered by auction, reported in parenthesis below parameter estimates.

Column 5's standard errors are not clustered due to the reduced number of observations per auction

*,**,*** significant at 10%, 5% and 1% respectively

[a] Current price is controlled for with dummies for rounded dollar amounts (between $0 and $20), avoiding functional form assumptions.

Table 2. Effects of starting price on probability that bid of given $ amount wins the auction (logistic regression)
Dependent Variable: 1 if bid won the auction, 0 otherwise

	(1) No controls	(2) With Movie Controls	(3) With Seller Controls	(4) Only bids for $10 or more
Intercept	2.003*	2.510**	3.107**	3.464**
	(1.046)	*(0.892)*	*(0.891)*	*(1.277)*
Starting Price	0.083**	0.104**	0.097**	0.077**
	(0.006)	*(0.007)*	*(0.007)*	*(0.007)*
log(minutes left in auction when bid is placed)	-0.337**	-0.298**	-0.293**	-0.105*
	(0.008)	*(0.009)*	*(0.009)*	*(0.055)*
Shipping Charges	0.006	0.111**	0.105**	-0.243**
	(0.022)	(0.026)	(0.027)	(0.010)
"New" Movie Dummy	--	-0.236**	-0.197**	0.038
	--	*(0.051)*	*(0.052)*	*(0.027)*
log(Seller Rating)	--	--	-0.046**	-0.032
	--	--	*(0.020)*	*(0.024)*
log(Seller Experience)	--	--	-0.037**	-0.038**
	--	--	*(0.013)*	*(0.015)*
eBay Store Dummy	--	--	0.079	0.170*
	--	--	*(0.095)*	*(0.100)*
Dollar amount of bid dummies (df=21) [a]	YES	YES	YES	YES
Movie Title Fixed Effects (df=53)	NO	YES	YES	YES
Pseudo R-Square	0.257	0.304	0.306	0.157
Number of observations	25,368	25,368	25,368	9,883

Clustered (by auction) standard errors reported below parameter estimates.

Column 4's standard errors are not clustered due to the reduced number of observations per auction

*,** significant at the 5% and 1% respectively

[a] Bid Amount is controlled for with dummies for rounded dollar amounts (between $0 and $20), avoiding functional form assumptions. Results with linear controls are repoted in footnotes.

[b] Sample size is reduced when controlling for shipping because not all sellers report their shipping charges to eBay.

Table 3. Effects of starting price on price paid by winner (OLS)

Dependent variable: final price price paid (in $)

	(1) Only bid controls	(2) Adds movie controls	(3) Adds Seller controls	(4) Adds shipping charges[a]
Intercept	0.053	0.561**	0.490**	0.638**
	(0.049)	*(0.079)*	*(0.087)*	*(0.115)*
Starting Price	-0.025**	-0.029**	-0.028**	-0.029**
	(0.003)	*(0.003)*	*(0.003)*	*(0.004)*
Dollar amount of bid	0.519**	0.500**	0.498**	0.497**
	(0.006)	*(0.006)*	*(0.006)*	*(0.007)*
log (minutes left in auction when bid was placed)	0.096**	0.090**	0.089**	0.087**
	(0.005)	*(0.005)*	*(0.005)*	*(0.006)*
Current price when bid was placed	0.445**	0.417**	0.414**	0.412**
	(0.007)	*(0.007)*	*(0.007)*	*(0.008)*
"New" Movie Dummy	--	0.093**	0.092**	0.083**
	--	*(0.025)*	*(0.025)*	*(0.030)*
log(Seller Experience)	--	--	0.011	-0.001
	--	--	*(0.010)*	*(0.012)*
log(Seller Rating)	--	--	0.011	0.026**
	--	--	*(0.007)*	*(0.008)*
eBay Store Dummy	--	--	0.049**	0.054**
	--	--	*(0.051)*	*(0.056)*
Shipping Charges	--	--	--	-0.040**
	--	--	--	*(0.014)*
Movie Title Fixed Effects (df=53)	NO	YES	YES	YES
R-Square	0.899	0.903	0.903	0.903
Number of observations	6,333	6,333	6,333	4,572

Standard errors reported below parameter estimates.

*,** significant at 5% and 1% respectively

[a] Sample size is reduced when controlling for shipping because not all sellers report their shipping charges to eBay.

Figure 1a

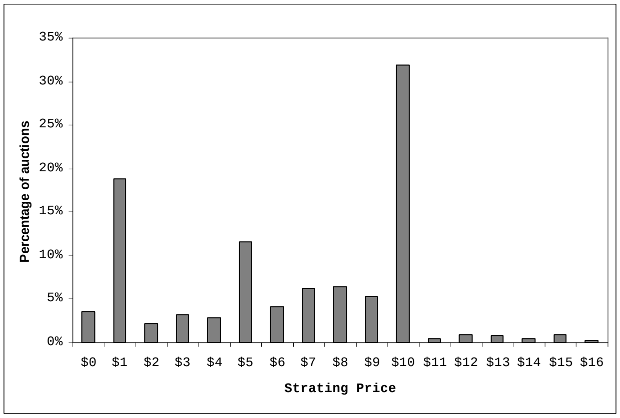
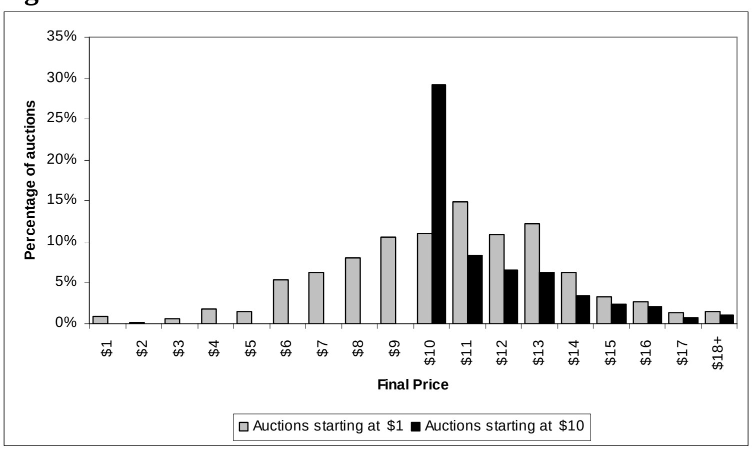


Figure 1b

Figure 1a. Distribution of starting prices.
Figure 1b. Probability of sale and starting price.

Figure 2.



Distribution of final prices for auctions starting at $1 and $10

Figure 3a

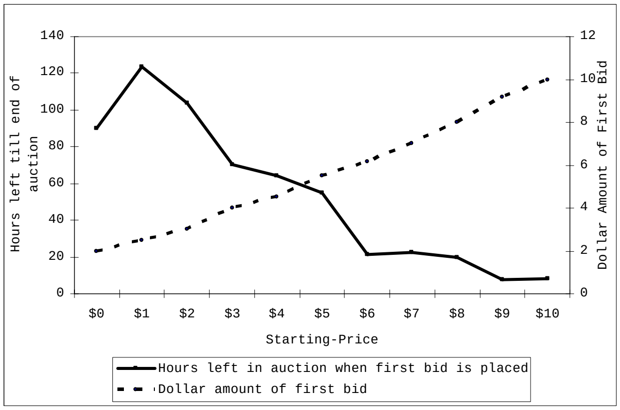


Figure 3b.

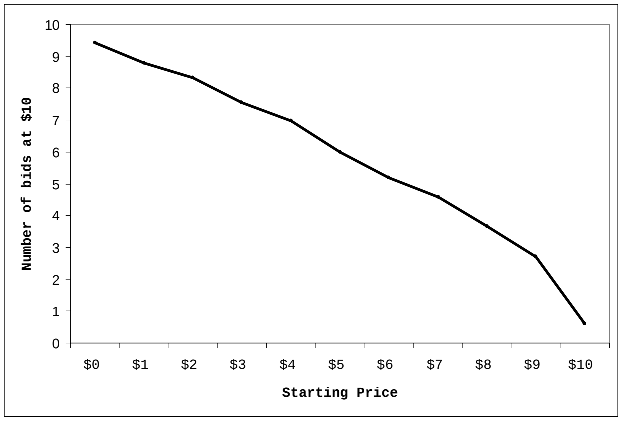
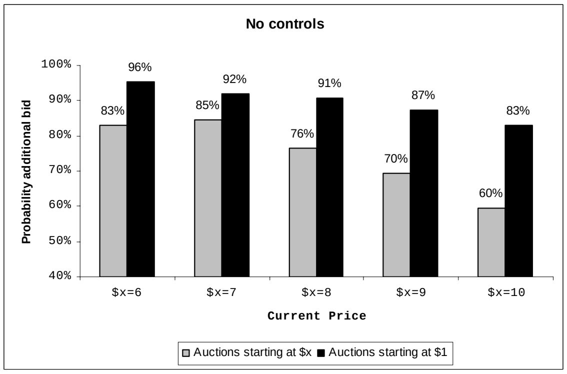
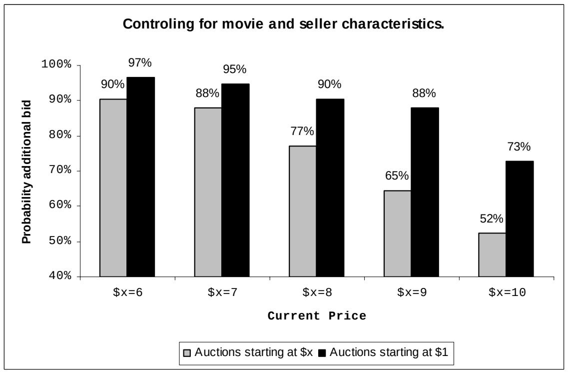


Figure 3b. Number of hours left and bid amount of first bid
Figure 3b. Number of existing bids when auction reaches $10

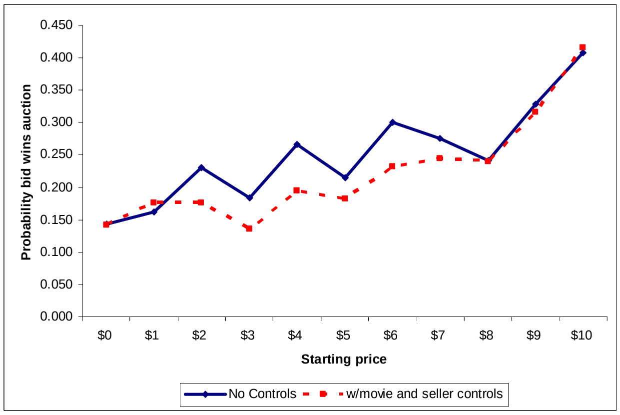
Figure 4.





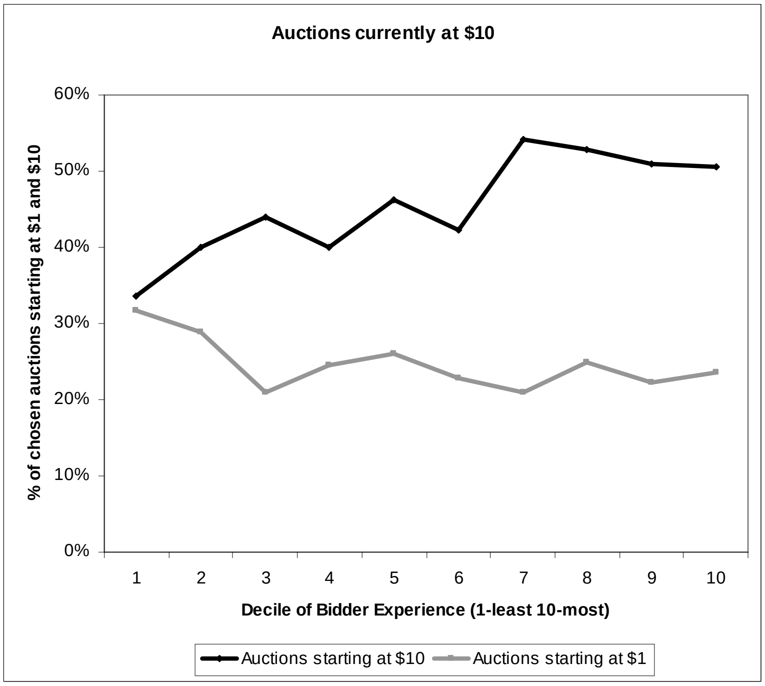
Probability of receiving at least one additional bid once auction achieves a certain price ($x), for auctions starting at $1 and starting at $x, with and without controls.

Figure 5.



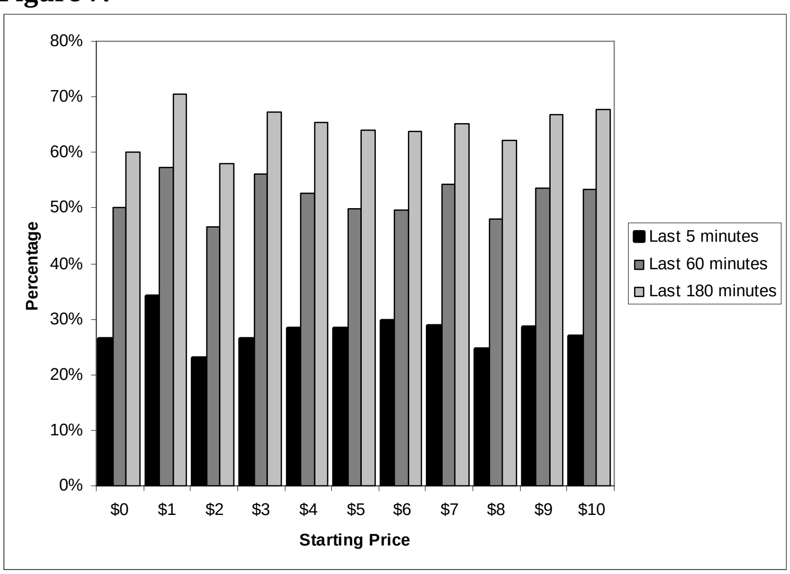
Probability a bid for $10 wins an auction, as a function of its starting price, with and without controls for movie and seller characteristics.

Figure 6.



Relationship between bidder experience and the starting price of auctions where bidders place bids, among auctions currently at $10.

Figure 7.



Percentage of auctions' last bid placed towards the end of the auctioning period

References

Akerlof, G. A. (1980). A Theory of Social Custom, of Which Unemployment May Be One Consequence. *Quarterly Journal of Economics, 94*(4), 749-775.

Ariely, D., & Simonson, I. (2003). Buying, bidding, playing, or competing? Value assessment and decision dynamics in online auctions. *Journal of Consumer Psychology, 13*(1-2), 113-123.

Bajari, P., & Hortacsu, A. (2003). The winner's curse, reserve prices, and endogenous entry: empirical insights from eBay auctions. *Rand Journal of Economics, 34*(2), 329-355.

Bajari, P., & Hortacsu, A. (2004). Economic insights from Internet auctions. *Journal of Economic Literature, 42*(2), 457-486.

Banerjee, A. V. (1992). A Simple-Model of Herd Behavior. *Quarterly Journal of Economics, 107*(3), 797-817.

Becker, G. S. (1991). A Note on Restaurant Pricing and Other Examples of Social Influences on Price. *Journal of Political Economy, 99*(5), 1109-1116.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural-Change as Informational Cascades. *Journal of Political Economy, 100*(5), 992-1026.

Brint, A. T. (2003). Investigating buyer and seller strategies in online auctions. *Journal of the Operational Research Society, 54*(11), 1177-1188.

DellaVigna, S., & Malmendier, U. (2004). Contract Design and Self-Control: Theory and Evidence. *Quarterly Journal of Economics, 119*(2), 353-402.

DellaVigna, S., & Malmendier, U. (2006). Paying not to go to the gym. *American Economic Review*, *96*(3), 694-719.

Devereux, P., J. (2002). *The Importance of Obtaining a High Paying Job*. UCLA working paper,

Dholakia, U. M., & Soltysinski, K. (2001). Coveted or overlooked? The psychology of bidding for comparable listings in digital auctions. *Marketing Letters*, *12*(3), 225-237.

Dodonova, A., & Khoroshilov, Y. (2004). *Optimal Auction Design when Bidders are Loss Averse*. Working Paper - University of Ottawa,

Ellison, G. (Forthcoming). Bounded Rationality in Industrial Organization. In *Advances in Economics and Econometrics: Theory and Applications. Ninth World Congress* (Vol. 2). New York, NY: Cambridge University Press.

Gabaix, X., & Laibson, D. (2006). Shrouded Attributes and Information Suppression in Competitive Markets. *Quarterly Journal of Economics*, *121*(2), 505-540.

Haubl, G., & Popkowski Leszczyc, P. T. L. (2003a). *Bidding Frenzy: How the Speed of Competitor Reaction Influences Product Valuation in Auctions*. Working Paper - University of Alberta,

Haubl, G., & Popkowski Leszczyc, P. T. L. (2003b). *Minimum Prices and Product Valuation in Auctions*. Unpublished Manuscript,

Heider, F. (1958). *The Psychology of Interpersonal Relations*. New York: Wiley & Sons, Inc.

Heyman, J., Orhun, Y., & Ariely, D. (2004). Auction Fever: The Effects of Opponents and Quasi-Endowment on Product Valuations. *Journal of Interactive Marketing, 18*(4), 7-15.

Jones, E. E., & Harris, V. A. (1967). Attribution of Attitudes. *Journal of Experimental Social Psychology, 3*(1), 1-24.

Kamins, M. A., Dreze, X., & Folkes, V. S. (2004). Effects of seller-supplied prices on buyers' product evaluations: Reference prices in an Internet auction context. *Journal of Consumer Research, 30*(4), 622-628.

Katz, M. L., & Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *American Economic Review, 75*(3), 424-440.

Ku, G., Galinsky, A. D., & Murnighan, K., J. (in press.). Starting Low But Ending High: A Reversal of the anchoring effect in auctions. *Journal of Personality and Social Psychology*.

Ku, G., Malhotra, D., & Murnighan, J. K. (2005). Towards a competitive arousal model of decision-making: A study of auction fever in live and Internet auctions. *Organizational Behavior and Human Decision Processes, 96*(2), 89-103.

Lucas, R. E. (1973). Some International Evidence on Output-Inflation Tradeoffs. *American Economic Review, 63*(3), 326-334.

Lucking-Reiley, D., Bryan, D., Naghi, P., & Reeves, D. (2000). *Pennies from eBay: the Determinant of Price in Online Auctions*. Unpublished Manuscript,

Milgrom, P. R., & Weber, R. J. (1982). A Theory of Auctions and Competitive Bidding. *Econometrica, 50*(5), 1089-1122.

Morgan, J., & Hossain, T. (2006). ...Plus Shipping and Handling: Revenue (Non)Equivalence in Field Experiment on eBay. *Advances in Economic Analysis & Policy, 6*(2), Article 3.

Morton, F. M. S., & Oster, S. M. (2003). Behavioral Biases Meet the Market: The Case of Magazine Subscription Prices. *Advances in Economic Analysis & Policy, 5*(1), Article 1.

Myerson, R. B. (1981). Optimal Auction Design. *Mathematics of Operations Research, 6*(1), 58-73.

Oyer, P. (2006). *The Macro-Foundations of Microeconomics: Initial labor market conditions and long-term outcomes for economists*. Working Paper - Stanford University,

Park, Y.-H., & Bradlow, E. (2004). *An Integrated Model for Whether, Who, When and How Much in Internet Auctions*.

Reiley, D. H. (2005). Experimental Evidence on the Endogenous Entry of Bidders in Internet Auctions. In A. Rapoport & R. Zwick (Eds.), *Experimental Business Research, Volume 2: Economic and Managerial Perspectives* (Vol. 2, pp. 103-121). Norwell, MA: Kluwer Academic Publishers.

Schwarz, N., & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality & Social Psychology, 45*(3), 513-523.

Taylor, S. E., & Fiske, S. T. (1975). Point of View and Perceptions of Causality. *Journal of Personality and Social Psychology, 32*(3), 439-445.

Zeithammer, R. (Forthcoming). Strategic Bid-Shading and Sequential Auctioning with Learning from Past Prices. *Management Science*.