EBAY'S HAPPY HOUR: NON-RATIONAL HERDING IN ONLINE AUCTIONS

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Abstract:
We hypothesized that on-line auction bidders would herd behind other bidders even when observed choices did not reveal private information. A model that inserts bidders engaging in this type of non-rational herding into a competitive market shows that, in equilibrium, (some) sellers set low starting-price in order to attract low valuation bidders who in turn bring high valuation ones. The model leads to three predictions, all of which found support in a sample of 8,300 eBay auctions for DVD movies: (1) conditioning on current price, low starting-price auctions are more likely to receive additional bids, (2) a bid of a certain dollar amount is less likely to win a low starting-price auction, and (3) low starting-price auctions are more likely to attain high selling prices. We rule out alternative explanations based on unobserved heterogeneity across items with different starting-prices, on the possibility that bidders may become attached to items they place early bids on, and that snipers decide what auctions to bid on while prices are still low.

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I. Introduction

People often observe the decisions of others before making a decision of their own. Informational-cascade models propose that if the behavior of others reveals valuable information, it may become optimal for observers to herd behind those that have already decided. A common example of this type of social learning is choosing busier restaurants, implicitly assuming that others hold private information about them. [1]

While herding behavior might be rational, a long history of literature in Psychology suggests that some of the herding behaviors we observe might not be. Beginning with Heider (1958), psychologists have shown that when people observe outcomes that can be attributed to multiple causes, they overattribute causality to focal ones (those they are directly 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 judgments 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 experiment is that of Taylor and Fiske (1975), where people observing *the same* conversation between two people, but from different angles, judged the person they were facing directly (the focal target) as having had a more central role in the conversation.

If people over-attribute causality to salient causes, they will make erroneous inferences from the actions of others if the motive of their actions is not salient. This type of erroneous inference may in turn trigger herding behind actions that are interpreted as informative when in actuality they are not.

In order to examine this type of non-rational herding empirically, an environment where herding could be observed and yet choices of others do *not* convey information is required. One environment that fits these criteria is a market for online auctions such as eBay. Online auctions are an ideal setting for studying herding because bidders choose sequentially what auction to bid on, and before doing so they can observe the choices of those before them.

Auctions are ideal for studying *non-rational* herding in particular, because identical products have different starting-prices; eBay sellers are free to choose the starting-price of their

[1] Of course people may engage in herding for non-information related reasons including such as 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 herding that's motivated by information.

auctions, and there is indeed substantial variation in the prices they choose. In our sample of DVD movies, for example, the most popular starting-prices are $1, $5, and $10 (see figure 1a). Because auctions differ in their starting-prices, they accumulate different numbers of bids by the time they achieve a certain price, yet this variation in number of bids is diagnostic of starting-price, not of quality.

For example, auctions in our sample that started at $1 accumulated 8.13 bids by the time they got to $10, compared to just 2.7 bids by auctions starting at $9. A bidder choosing between two auctions at a price of $10, then, faces a situation analogous to a customer choosing whether to enter a bar with a recently expired happy-hour: its popularity is driven by no longer existent low prices, rather than by enduring quality differences.

If bidders attribute causality the way subjects in psychology experiments do, they will underappreciate the role of starting-prices (since they are not saliently displayed) and be more likely to choose, from two auctions currently at $10, the one that started at $1 rather than at $9. [2]

Finally, online auctions are a particularly appropriate environment for studying non-rational herding because there are incentives for bidders *not* to respond to non-diagnostic information; non-rational herding in online auctions is *detrimental* to the bidder, because the more bidders an auction receives, the less likely any given bidder is to win the item, and the higher the price the winner is expected to pay. If non-rational herding is present in a setting where there are incentives for individuals to avoid it, then it is likely to be a general phenomenon.

The paper begins with a model that explores the market consequences of bidders engaging in non-rational herding. The model generates three testable predictions, all of which are supported by the data: (1) after the price of a low starting-price auction catches up with higher starting-price ones, low starting-price auctions are more likely to receive additional bids than higher starting-price auctions, (2) conditioning on the dollar amount of the bid, a bid placed on a low starting-price auction is less likely to become a winning bid, and (3) low starting-price auctions are more likely to obtain a higher selling price.

[2] Starting-prices for auctions are available but are not salient; the information is not displayed by default but it is just 'a click away.'

In addition to these specific predictions, the model provides two important insights. First, the model shows that, in equilibrium, market forces eliminate the *rents* associated with exploiting non-rational herding behavior (i.e. with setting a low starting-price) but they do not eliminate the behavior itself, nor do they eliminate its negative welfare consequences (to bidders). Although this contradicts the usually held intuition that market forces eliminate individual biases, it is consistent with recent work examining the market outcomes of non-rational agents in competitive environments (for example Della Vigna & Malmendier (2003) in Gyms, Morton & Oster (2003) in the magazine industry, Shui & Ausubel (2004) with credit-cards, and Gabaix & Laibson (2004) with add-on features to durable goods).

The second insight from this model is that rational agents can engage in behavior that at first hand appears irrational, but which is actually optimal once one considers what it is best-responding to. In particular, standard auction models (e.g. Milgrom & Weber (1982) and Myerson (1981)) show that it is a *dominated* strategy to set a starting-price below the opportunity cost of the item being auctioned, yet almost 25% of the auctions in the sample started at \$0 or \$1 (clearly below the costs of a DVD movie). What at first appears to be an irrational choice on the part of sellers, however, is actually rational once we take into account that bidders tend to choose auctions with more existing bids.

After introducing the model, the paper presents the analysis of bidding data from over 8,300 eBay auctions for DVD movies; the analyses support all three model predictions. After presenting the results we discuss three possible alternative explanations, the most important being the possibility an auction's starting-price may be (negatively) correlated with its (unobservable) quality. Based primarily on the fact that we are analyzing a commodity with limited unobserved heterogeneity, and that excluding *observed* heterogeneity *weakens* our estimates, we conclude that this is an unlikely explanation.

In addition, we consider two alternative *behavioral* explanations for bidders preferring low starting-price auctions: *attachment* and *sniper-bait*. Attachment could explain a preference for low starting-price auctions (even after they catch up in price) if early bidders became attached to the items they have bid on and increased their willingness-to-pay for them (Ariely & Simonson, 2003; Dodonova, 2004; Heyman, Orhun, & Ariely, forthcoming). Sniper-bait could explain a premium for low starting-price auctions if bidders who place bids on the very last minute of an auction (snipers) decided what auction to place such bids early on, and hence ended up disproportionately choosing auctions that were originally at a lower price (bait).[3] Our analyses suggest that neither of these explanations can account for the results.

II. Analytical Framework

In this section we develop a model that allows us to assess the consequences of non-rational herding in a competitive environment. We begin by laying out the general features of the model, then we present a simple example with 3 sellers and 2 buyers in order to convey the intuition of the model, and then we extend the model to free entry on the supply side and uncertainty over demand.

II.A. Setup

We analyze an auction market with multiple parallel auctions offering identical units of a commodity. In this market there are sellers, consumers and arbitragers. All auctions last the same amount of time and end simultaneously. Each auction is won by its highest bidder, paying a price equal to the bid of the second highest bidder (or the starting-price if there is only one bidder). As is the case on eBay, a bidders' bid amount is not public until the auction ends, but bidders do observe how many bids have been placed and the current-price of all auctions.

In addition to the auction market, there is a wholesale market where sellers and arbitragers can sell units of the auctioned commodity for a fixed price equal to H. Units that are listed in the auction market and fail to sell can later be sold in the wholesale market, without any transaction costs.

Bidders

Bidders arrive to the auction market sequentially in an exogenously determined order. They observe the current-price and number of existing bids of all auctions and then decide what auction to place a bid on. There are two types of bidders: *arbitragers* and *consumers*.

Consumers participate in the auction market seeking to own a unit of the commodity. All consumers have a reservation price of V, with $V>H$. Consumers choose to place their bid on the auction with the lowest current-price and they break price-ties by choosing the auction with the highest number of existing bids. In other words, consumers choose lexicographically among

[3] We thank Gerard Cachón for bringing this alternative explanation to our attention.

auctions, first based on price, then on number of bids. Consumers do not have access to the wholesale market.

Arbitragers, on the other hand, participate in auctions solely to profit from potential price differentials between the auction and wholesale markets. They will only bid, therefore, if the expected price, conditional on winning, is less than H (the price in the wholesale market). Arbitragers do not know how many consumers will participate in the auction market and hence always bid on low starting-price auctions hoping to win the item for a low price. To simplify the model we assume that arbitragers place bids on low starting-price auctions as soon as they begin (by the time a consumer arrives, all low starting-price auctions already have a bid).

We assume that all bidders (both consumers and arbitragers) get only one opportunity to bid and hence always bid their true valuation: arbitragers bid H and consumers bid V.

Sellers

Sellers have access to both markets, and choose one of two starting-prices for their auctions: a low price (L) or a high price (H). Sellers choose starting-prices seeking to maximize expected revenue (i.e. they are risk neutral).

II.B. A simple example with three sellers and two consumers.

In order to convey the intuition of how consumers choose auctions, and how their behavior influences sellers and arbitragers, we begin by analyzing an example with three sellers, two consumers, and a large number of arbitragers. We examine the consequences of all possible combination of starting-prices among the three sellers.

(i) All sellers choose a high starting-price.

If all three sellers choose H as a starting-price, no arbitrager places a bid (no hope of winning with price below H). The first consumer encounters three auctions at a price of H with 0 bids, and hence chooses randomly. The second consumer encounters three auctions at a price of H, one with 1 bid and the other two with 0. Consistent with the notion non-rational herding, this second consumer places a bid on the *same* auction as the first consumer (even though doing so is a dominated strategy).

The one seller who, by chance, got the first consumer, would obtain a price of *V,* while the other two sellers would not sell and therefore get *H* in the wholesale market. The expected revenue for all sellers is $\frac{V+2H}{3}>H$, so the market is not in equilibrium.

Both consumers obtain suboptimal outcomes. The first consumer pays a price of *V* when she could have paid just *H*, while the second consumers fails to buy a good that was valued above the closing price of non-sold auctions ($V>H$).

(ii) Only one seller chooses L, the other two H.

When all sellers are choosing *H*, there is an incentive for one of them to choose *L* in order to guarantee herself the first bidder. If only one seller chooses a low starting-price, her auction immediately receives a bid by an arbitrager (hoping that no consumer will show up). The first consumer encounters an auction at *L* with 1 bid, and two auctions at *H* with 0 bids, so she bids on the auction with the low starting-price. The second consumer encounters three auctions at *H,* one of them with 2 bids and the other two with 0, so she (being a non-rational herder) also chooses the low starting-price auction.

The low starting-price seller guarantees herself *V* while the high starting-price sellers obtain *H* in the wholesale market, so the market is not in equilibrium. The first consumer still over-pays and the second still does not purchase an item though her valuation is above the price of non-sold items.

(iii) Two sellers choose L, one chooses H

Clearly if sellers can increase their revenue from $\frac{V+2H}{3}$ to *V* by simply setting a lower starting-price they will do so. If two sellers were to set a low price, however, they would no longer be obtaining above normal profits.

When two sellers set a low starting-price, they each immediately receive a bid from arbitragers. The first consumer encounters two auctions at *L,* both with 1 bid, and one auction at *H* with 0 bids, so she chooses randomly between the two *L* auctions.

The second consumer encounters one auction at L with 1 bid, and two auctions at H, one with 0 and one with 2 bids. Since consumers choose first on price and only break ties with number of bids, the second bidder would place a bid on the *other* auction with a low starting-price, raising its final price to H as well. The two low starting-price sellers sell for H in the auction market, and the high starting-price seller also obtains H but in the wholesale market. The expected revenue is H for high and low starting-prices so the market is in equilibrium. Note that the equilibrium is achieved with a non-zero proportion of sellers setting their starting-price below the cost of the units they are listing.

(iv) All three sellers choose L

All three auctions immediately receive a bid by an arbitrager. The first consumer, therefore, encounters three auctions at L, all with 1 bid, and so chooses randomly among them. The second consumer encounters two auctions at L with 1 bid, and one at H with 2 bids, so she chooses randomly from the two auctions currently at L.

All sellers sell in the auction market. One of them gets L for the sold item, while the other two get H. The expected final price is $\frac{L+2H}{3} < H$ so sellers are not in equilibrium.

Both consumers get a unit of the commodity and pay equilibrium prices and hence incur no losses for being non-rational herders. An arbitrager profits H-L by buying in the auction market and selling in the wholesale market.

II.C. A more general framework

While the previous example with three sellers and two consumers transmits the intuition of how consumers choose between auctions, and how rational sellers respond to such behavior, it is useful to examine the consequences of non-rational herding under more general conditions. To this end we extend the previous example to a situation where there is free entry in the supply side of the market, and where sellers exhibit uncertainty with respect to aggregate demand. [4]

[4] If the number of consumers is known with certainty, in equilibrium there are just as many low starting-price auctions as consumers, and all low starting-price auctions sell for H, as was the case in the previous example where in equilibrium two sellers set a low starting-price.

We represent the number of sellers who choose a low starting-price by S_L and the number of those choosing a high starting-price by S_H (there are a total of S_L+S_H auctions).

Sellers are uncertain, when they choose their starting-prices, as to how many total consumers (C) will arrive at the auction market. In particular, they hold the (correct) belief that there is a probability p that $C=\overline{C}$, and probability 1-p that $C=\underline{C}$, with $\overline{C} > \underline{C}$.

Recall that a low starting-price seller obtains a price of L if only an arbitrager bids (and they always do), of H if exactly one consumer bids (in addition to the arbitrager) and of V if two consumers bid (also in addition to the arbitrager). The expected final price for a low starting-price seller, therefore, is a function of how many consumers arrive at *their* auction (i.e. of *residual* demand), and hence of C and S_L.

By following the logic of sequential bidding described in the three seller example, we calculated the probabilities associated with a low starting-price seller receiving 0,1 and 2 consumer bids as a function of C and S_L. The results are presented in table 1. Column 1 in that table, for example, shows the outcomes when $C<S_L$. Since there are more low starting-price sellers than buyers only some sellers ($\frac{C}{S_L}$)will receive a consumer bid and sell for H, while (1-$\frac{C}{S_L}$) of them will not receive a consumer bid and will hence sell to an arbitrager for L.

*** Table 1 ***

Equilibrium

In equilibrium a low starting-price seller must have an expected price of H. Low starting-price sellers can obtain a price of V,H or L for their items, depending on whether they receive two, one, or no consumer bids respectively. Using the probabilities from table 1 we see that for low starting-price sellers:

(1) $$\text{Expected Price} = (1-p)(1-\frac{\underline{C}}{S_L})L + (1-p)(\frac{\underline{C}}{S_L})H + p(1-\frac{\overline{C}-S_L}{S_L})H + p(\frac{\overline{C}-S_L}{S_L})V$$

Solving for S_L in equation (1) with Expected Price=H one obtains:

(2) $$S_L{}^* = \frac{\overline{C}p(V-H)+\underline{C}(1-p)(H-L)}{p(V-H)+(1-p)(H-L)}$$

where S_L* is the equilibrium number of low starting-price sellers.

Equation (2) shows that the optimal number of low starting-price sellers is a weighted average of $\underline{C}$ and $\overline{C}$, where the weights correspond to the respective probabilities and relative prices obtained under both outcomes. Sellers deciding whether to enter with a low starting-price, trade-off the potential gains of succeeding at attracting additional bidders and obtaining *V>H* with the possibility of failing to attract any consumers and selling to an arbitrager for *L<H.* [5] Equation 2 shows that, contrary to standard auction models, when bidders engage in non-rational herding it is optimal for a non-zero proportion of sellers to choose a starting-price below the cost of the item they are offering.

II.D Predictions

Although market forces eliminate the rents associated with setting low prices (the expected price is *H* for both low and high starting-price auctions), they do not eliminate non-rational herding. Indeed, $S^*_L>0$ *because* bidders continue to prefer auctions with more bids among auctions with the same current-price. This leads us to our first prediction, which states that even in equilibrium non-rational herding leads low starting-price auctions to be more likely to be chosen once they catch up in price with higher starting-price ones.

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 (e.g. Bajari & Hortacsu (2003b) and Haubl & Popkowski Leszczyc (2003)), a distinction has not been made as to whether these additional bids are for amounts

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[5] The formula presented in equation (1) assumes that the parameters L,H,V,p, $\underline{C}$ and $\overline{C}$ are such that, in equilibrium, $2S_L^*<\overline{C}$. If this was not the case, the expected final price for low starting-price sellers is $\text{EP} = (1-p)(1-\frac{\underline{C}}{S_L})L + (1-p)(\frac{\underline{C}}{S_L})H + pV$, and $S_L^* = \frac{\underline{C}(H-PH-L+PL)}{H-PV-L+PL}$. The differences between these two equilibria are not important for the present discussion.

above or below the higher starting-price. Setting a low starting-price naturally increases the number of bids placed *below* the high starting-price because of simple truncation, prediction 1 states that it can also increase the number of bidders placed *above* it.

We are interested in the welfare implications for buyers who engage in non-rational herding. The predictions from the model are easier to discuss if the consequences of non-rational herding are looked at separately for the two possible values of C.

When C=$\overline{C}$ there are more consumers than low starting-price auctions (since S_L* is a weighted average of $\overline{C}$ and $\underline{C}$) and hence some (or all) low starting-price auctions receive two consumer bids. For every auction that receives two consumer bids, there is a consumer who does not win an item although she is willing to pay a price that's higher than the closing price of unsold items (*H*), and one consumer that pays *V* for an item she could have bought for *H* if she had placed a bid in a high starting-price auction.

When C=$\underline{C}$, on the other hand, there are more low starting-price auctions than consumers and hence all consumers buy a low starting-price auction, and all of them pay *H*. Consumers, then, are just as well off bidding in low starting-price auctions as in high starting-price ones.

Choosing auctions based on the number of existing bids, then, leaves bidders worse off when C=$\overline{C}$ and just as well off when C=$\underline{C}$. Ex-ante, therefore, since bidders do not know whether S_L*<C or S_L*>C, non-rational herding is a weakly *dominated* strategy. This leads us to predictions 2 and 3,

Prediction 2: 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 3: Lower starting-price auctions are more likely to obtain a *high* final price than a low starting-price auction.

Note that one consequence of prediction 3 is that winners of low starting-price auctions will pay more for the items they win than what they could have paid had they bid on a higher starting-price auction.

It is worth highlighting that prediction 3 is compatible with the assumption that the average final-price of low and high starting-price auctions is the same. Low starting-price auctions have greater variance in their final prices; they are more likely to obtain higher prices, but also more likely to obtain lower prices.

III. Empirical Analyses

This section is divided into six (short) subsections. Section III.A describes the database of auctions and bids that is used for the analysis, III.B demonstrates that low starting-price auctions get started earlier and accumulate a considerable number of bids by the time they catch up in price with higher starting-price auctions, III.C assesses the influences of starting-price on the final price of sold auction, primarily to provide a comparison between our results and recent empirical research on auctions. Subsections D,E, and F test each of the three predictions.

III.A The Database

The data was kindly provided to us directly by eBay, it consists of a subset of DVD movie auctions 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; once the seller's reputation, the title of the DVD and whether the DVD is new or used is known, there is little else that DVDs can differ on.

eBay does not utilize a unique product identifier for their postings, so both bidders and researchers must rely on the item description written by sellers to identify what is being auctioned. To ensure that we could correctly identify the titles of the DVDs being analyzed, we restricted the sample to a subset of DVD titles that were manually checked.

In order to obtain a high number of observations per title, we restricted our sample to popular DVD titles. In particular we constructed a sample with movies that were (at some point) in a bestseller lists. Since a high percentage of bestsellers from one month are also bestsellers on nearby months, we chose lists that were temporally distant. In particular we used two bestseller lists, one from the month prior to the sample, September of 2002, and one from slightly over a year prior to the sample, July 2001, guaranteeing no overlap between the two.

We also excluded auctions with starting price above $10.49 primarily because some of our analyses control for starting-price through dummies for each rounded amount and less than

4% of the sample had starting-prices higher than that. We also excluded auctions for multiple items, those with a reserve price and those offering the "buy-it-now" option. The "buy it now option" is a feature whereby bidders can choose to purchase the item for a fixed price – as long as no bids have been placed in the auction. We should note that the qualitative nature of the 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 and 37,535 bids. [6]

Variables

For each auction we know the starting-price, the final price, the shipping costs, the seller's description of the item, the identity of the seller, their reputation (net number of positive feedbacks they have received), 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.

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 and the price the bidder faced when she placed her bid; we will refer to this price as *current-price* throughout the paper. Note that *current-price* doesn't necessarily correspond to the highest bid placed on the item 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.

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. [7]

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[6] Six movie titles were dropped because they proved too difficult to uniquely identify (i.e. we couldn't with a high degree of confidence be sure what exact movie was being auctioned because other movies had titles that were too similar).

[7] As we shall see in the alternative explanations section, our results are robust to excluding all repeat bidders from the sample.

Around 30% of the sample does not contain information on shipping charges. We present results where we control for shipping charges separately, in order to avoid loosing a large share of our data.

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. As mentioned earlier, standard auction models propose that starting-price should not be placed below the cost of the item and yet figure 1a shows that almost one fourth of all auctions have a starting price of $1.49 or less, clearly below the cost of popular DVD movies.

Overall 78% of auctions resulted in a sale, figure 1b plots the probability of sale by (rounded) starting-price; practically all movies with a starting-price below $4 are sold, and the probability of sale decreases after that. Excluding non-sold items, the average auction received 5.5 bids.

*** Figure 1 ***

III.B Early bidding, a necessary condition for herding

For late bidders to herd behind early bidders there must be early bidders to follow; if on the extreme, all bids were placed on the last minute, herding would not be a plausible explanation for potential differences in the performance of low and high starting-price auctions. Figure 2 plots both the average amount of the first bids and the time left until the end of the auction when the first bid was placed as a function of rounded starting-prices between $0 and $10. Low starting-price auctions do indeed receive bids much earlier than auction with high starting-prices: an auction starting at $1 received the first bid around 5 *days* before the end of the auction, while auctions starting at $10 don not get bid-on until there are just 8 *hours* left. Figure 2 also illustrates that early bids are of low monetary value, the first bid in auctions that start at $1 is, on average, for just $2. [8]

[8] Note that since we got the data from eBay we know the actual bid amount and not just the price posted by eBay's proxy bidding system. The values we report throughout the paper are the bids – the maximum WTP prices that individuals are posting.

*** Figure 2 ***

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 with higher prices. Figure 3 plots the average number of bids received by the time auctions with different starting prices reached a price of $10**.** Indeed auctions with lower starting-price receive a much larger number of bids prior to reaching a price of $10. [9]

Since low starting-price auctions receive bids early-on and accumulate a number of them by the time they catch up in price, our happy-hour mechanism is a plausible explanation for potential differences in performance by low and high starting-price auctions. Note, however, that this is not evidence *of* herding but only of the necessary conditions *for* herding to occur.

*** Figure 3 ***

III.C Relationship between starting-price and final-price.

We begin by looking at the relationship between starting and final-price, even though it doesn't directly address any of the three predictions from our model, because final-price has been the dependent variable of choice by most researchers studying auctions.

Figure 4 shows the distribution of final prices for sold items. Overall, the average final price was $10.23 with a standard deviation of $2.97. It is worth noting that the variation depicted in figure 4 is not driven solely by variation across movie titles; the average variation coefficient of final price by movie title is 23.4%, only 6 percentage points below the overall variation coefficient of 29.0% ($2.97/$10.23).

Figure 5 plots the average final-price on the y-axis and rounded starting-price on the x-axis. It depicts a U-Shaped relationship between the two: low starting-price auctions achieve higher prices than medium starting-prices, which in turn sell for less than high starting-price ones.

[9] The number of bids for auctions starting at $10 is not exactly zero because, as mentioned earlier, the x-axis corresponds to *rounded* starting-prices; some of the auctions in the $10 bin had a starting-price between $9.50 and $9.99 and hence they required at least two bids to achieve a price of $10.

***Figure 4 ***

Existing research studying the relationship between starting and final-price shows mixed results; some find a negative association (Kamins, Dreze, & Folkes, 2004; Ku, Galinsky, & Murnighan, 2004; Lucking-Reiley, 1999), while others find a positive one (Brint, 2003; Haubl & Popkowski Leszczyc, 2003b; Lucking-Reiley, Bryan, Naghi, & Reeves, 2000; Park & Bradlow, 2004). These studies have estimated the influence of starting-price on final-price by either conducting pairwise comparisons between arbitrarily chosen low and high starting-prices, or by estimating linear regressions. One possible explanation for the mixed results in the literature is that different researchers have obtained their estimates on different ranges of prices, in other words, that their estimates have not allowed the data to depict the 'true' u-shaped relationship it has. This hypothesis is of course only speculative, since all studies have used different data for their estimates.

Figure 5 does not control for any observable differences among auctions with different starting-prices. To do so we estimated regressions where the dependent variable is the final-price of sold items, and the key predictor is the auction's starting-price. In line with the non-linear relationship depicted in figure 5 we incorporate both a linear and a quadratic term for starting-price. The results are presented in table 2.

Column (1) is the baseline specification, column (2) adds controls for movie heterogeneity, column (3) for seller heterogeneity and column (4) controls for shipping charges in the subset of observations for which shipping costs are known.

Across all columns the coefficients for starting-price and starting-price squared are highly significant. The net effect of starting-price on final-price depends on the relative influence of the linear and quadratic terms, since they go in opposite directions. Through straightforward calculations it is easy to see that across all columns the net effect is negative for prices below around $4.70, and positive for those above it, indicating that the U-Shaped relationship between starting-price and final-price is maintained once observable heterogeneity is controlled for. [10]

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[10] The marginal net effect of starting-price (SP) on final-price (FP) is easy to compute. For example if $FP = -\beta_1 SP + \beta_2 SP^2 + \varepsilon$, where $\beta_1, \beta_2 > 0$, the point at which the net effect of SP on FP switches signs is when the

It is worth noting that the size of both the linear and the quadratic coefficients is clearly attenuated when observable heterogeneity is controlled for; the linear coefficient drops from -.80 to -0.15 and the quadratic one from 0.087 to 0.016. Importantly, this is the only regression where we shall find that observable heterogeneity has a dramatic impact on the size of the coefficients.

*** Table 2 ***

The model assumes that expected final price of low and high starting-price auctions is the same (*H*). The heavy attenuation in the coefficients for starting-prices is, hence, encouraging. In addition, once we consider listing fees charged by eBay (which depend on starting-price), and the number of periods an item must be listed before it gets sold on average (which also depends on starting-price since it corresponds to one over probability of sale), the expected *revenue* for auctions with a starting-price of $1 and $10 are virtually identical: $9.18 and $9.09 respectively. [11]

III.D Choosing Auctions – Testing Prediction 1

The first prediction in the model is that auctions with lower starting-prices are more likely to receive bids once they catch up in price with higher starting-price ones. In this subsection we present evidence consistent with this prediction.

It is obviously important to adequately control for the price bidders were facing when they chose to place a bid on an auction, since only low starting-price auction were at some point at a low current-price, and auctions with lower current-prices are more likely to receive additional bids.

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derivative with respect to SP equals zero, or when $\beta_1=2\beta_2x^*$. x^* is 4.60, 4.84, 4.68 and 4.81 in columns 1-4 respectively.

[11] Since not all auctions are sold, the expected revenue associated with a starting-price must take into account what happens with non-sold items. We assumed that non-sold items were listed again with the same starting-price until they were eventually sold. Expected revenue for a given starting-price, then, corresponds to the average final price for that starting-price minus the *listing* fees charged by eBay, multiplied by the average number of periods an item is listed before being sold.

We test prediction 1 with two closely related analyses. We begin by conducting pairwise comparison of the probability of receiving an additional bid for auctions that started at $1 and were at some point at $6, $7, $8, $9 and $10, and the analogous probability for auctions that *started* at those prices. If lower starting-price auctions are more likely to be chosen, an auction that started at $x should have a lower likelihood of receiving an additional bid than an auction that started at $1 but is now at $x. This simple approach provides straightforward and intuitive results, but it is restricted to a subset of the data. We hence extend this approach to the whole dataset via regressions that *control* for current-price.

Pair-wise comparisons with auctions starting at $1

Table 3 reports pairwise comparisons for the probability that an auction currently at price $x will receive an additional bid, for auctions that *started* at $x and those that started at $1. Panel A correspond to the relative frequencies in the raw data (i.e. without any controls) while panel B presents the predicted probabilities from a logistic regression (including only the subset of auctions starting at $1 and $x) which controls for movie and seller observable heterogeneity.

The results from table 3 are consistent with prediction 1: conditioning on current-price, low starting-price auctions are more likely to receive additional bids. For example, Panel A 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. Panel B shows that once movie and seller characteristics are controlled for, the predicted probabilities are 90% and 77% respectively, almost identical. Rows 3 in both panels will be discussed in the alternative explanations section.

***Table 3 ***

Logistic regression including all auctions in the sample

Table 3 presents the results for pairwise comparisons for a subset of bids placed on a subset of auctions in the data. We extend this analysis to incorporate all observations in the dataset by estimating a logistic regression where every bid in the sample is an observation, and the dependent variable equals 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).

In order to avoid imposing an arbitrary functional form on the key control variable, current-price, we introduce 21 dummies (between \$0 and \$20) for the rounded dollar amount of the current-price of the auction. This reduces the probability that starting-price can be a significant predictor of probability of receiving bids because current-price is not adequately controlled for. [12]

Column 1 presents the baseline specification, column 2 controls for movie characteristics (title and "new") and column 3 ads seller controls (experience, reputation and a store dummy). As predicted, the coefficient of starting-price is negative and greatly significant across all specifications.

The parameter estimates for starting-price across columns 1-3 show that including observable heterogeneity barely influences the estimated impact of starting-price. This suggests that unobserved heterogeneity is an unlikely alternative explanation.

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 auctions were ever at low prices, column 4 reports the results from a regression run on the subset of observations when current-price was of above \$10. Starting-price remains negative and highly significant. Note that 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. [13]

In column 5 the regression controls for shipping charges. As was mentioned earlier, the data only includes shipping information for around 70% of the sample, so sample size is reduced. The point estimate remains negative and highly significant. Column 6 will be discussed in the alternative explanations section.

*** Table 4 ***

[12] The data does include a few observations (45) where prices above \$21 were obtained. These outcomes were so uncommon, however, that the routine for Logistic regression in SAS did not converge when they were all included. Running a linear probability model without excluding these observations leads to qualitatively identical results.

[13] If current-price is controlled for with a linear term, similar results are obtained (β=-1.40; *SE*=0.006).

In sum, both the pairwise comparisons and the regression analyses of all bids find evidence consistent with prediction 1: once a low starting-price auction catches up in price with a higher starting-price one, it is significantly more likely to receive an additional bid.

III.E Winning Auctions – Testing Prediction 2

Prediction 2 in the model indicates that, because bidders herd towards lower starting-price auctions, bids of 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 an item, is more likely to win it if the bid is placed in a higher starting-price auction.

As was the case with prediction 1, we begin with a simple test on a subset of the data and then we extend the analysis to the whole dataset.

Comparison of $10 bids across auctions

Table 5 reports the number of $10 bids placed on auctions with different starting-prices and the probability that a $10 bid wins an auction of a certain starting-price, controlling and not controlling for observables. The probability estimates without controls consist of the percentage of all $10 bids that ended up winning the auction where they were placed. For example, of the 1,277 $10 bids placed on auctions with a starting-price of $1, only 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%. [14]

The calculation *with* controls, presented in the second column, 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 dummy variable plus a constant that facilitates comparisons across columns.

The results from table 5 are consistent with prediction 2. For example, a $10 bid had a 14% chance of winning an auction that started at $0 but it had a 41% chance of winning an auction that started at $10. The estimates hardly differ between the two columns. At face value these results mean that a bidder who is willing to pay up to $10 for a specific DVD movie would

[14] 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 an auction had it been placed in time.

increase her chances of winning the DVD from 14% to 41% by placing her bid in an auction that started at $10 rather than at $0.

*** Table 5 ***

Logistic regression including all bids in the sample

Although the results presented in table 5 are consistent with prediction 2, they were obtained from a subset of all bids. 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.

It is of high importance to control for the dollar amount of the bid being placed, since only low starting-price auctions can receive low value bids, and low value bids are less likely to win auctions. We control for the dollar amount of the bid with dummy variables for each rounded dollar between $1 and $21, avoiding the need to impose an arbitrary functional form on our key control variable.

The results of these regressions are presented in table 6. Column 1 shows the baseline specification, column 2 adds movie controls, column 3 adds 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 with prediction 1, including observable heterogeneity does not diminish the estimated influence of starting-price, suggesting that unobserved heterogeneity is an unlikely alternative explanation. [15]

*** Table 6 ***

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 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.

[15] Controlling for current-price linearly leads to a slightly stronger effect of starting-price (β=.0937, *SE*=.0047).

Column 5 shows that controlling for shipping charges the coefficient of starting-price is still positive and significant. Column 6 will be discussed in the alternative explanations section.

III.F Likelihood of higher final price – Prediction 3

Prediction 3 in the model indicates that because early bidders attract late bidders, low starting-price auctions should be more likely to obtain high final prices; if late bidders ignored early bidders, on the other hand, all auctions should be equally likely to receive high final prices (i.e. prices above the highest starting-price in the sample). The intuition behind the null hypothesis is the following: by lowering the starting-price a seller should be able to attract bidders who are willing to pay less, but not more than the higher starting-price; the distribution of final-prices for prices above the highest starting-price, in the absence of non-rational herding, therefore, should be the same for all starting-prices.

Figure 6 shows the cumulative distribution of final prices for auctions with starting-prices of \$1 and \$10. The line for auctions with a starting-price of \$10 starts at 40% because that's the proportion of auction that did not sell. The graph shows that for all prices above \$10 the cumulative distribution for auctions starting at \$1 is below that of auctions starting at \$10, consistent with prediction 3; no matter what threshold is used to define what a *high price* is, an auction with a starting-price of \$1 is more likely to beat that high price than an auction starting at \$10.

*** Figure 6 ***

Figure 6 emphasizes the tradeoffs, identified earlier in the model section, that a seller choosing between a low and a high starting-price faces; setting a low starting-price increases the probability that an auction will sell for a low price (from 0 to positive), but it also increases the probability that it will sell for a higher price. In equilibrium these two forces cancel out and sellers are indifferent between low and high starting-prices.

To test prediction 3 controlling for observables and utilizing the whole dataset we constructed a dependent variable that takes the value of 1 if an auction obtains a final-price above a certain threshold, and 0 otherwise. We chose this threshold to be above the highest starting-price in the sample (\$10.49) in order to completely get rid of the effects of truncation.

The key predictor in the regression is starting-price, which in line with prediction 3 we expected to have a negative coefficient. The results are presented in table 7.

Table 7

Column 1 in table 7 presents the regression estimates without any controls, and columns 2-4 introduce progressively movie, seller and shipping controls. Across all four columns the point estimate for starting-price is negative and significant, in line with prediction 3. The point estimate increases in size as controls are incorporated suggesting unobserved heterogeneity is an unlikely explanation for the effect. Column 5 replicates with a threshold of $11.50 and the point estimate remains negative and significant. Column 6 excludes repeat winners and will be discussed in the next section.

V Alternative Explanations

In section IV we found support for all three of our predictions: (i) low starting-price auctions are more likely to receive bids even after they catch up in price with auctions with higher starting-prices, (ii) bids of certain dollar amount are less likely to win a low starting-price auction, and (iii) auctions with low starting-prices are more likely to achieve a high final price. We interpret these results in line with non-rational herding, where bidders use the amount of previous bids as a (positive) factor in their decisions, even when these bids result (only) from lower starting-prices.

In this section we entertain three alternative explanations for our findings. The first is that that our results are spurious: low starting-price auctions differ in performance because we have failed to properly control for heterogeneity across auctioned items, *and* –for some reason- *higher* quality items are systematically listed with *lower* starting-prices. This explanation essentially questions the validity of our identifying assumption and we shall refer to it as *unobserved heterogeneity*

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 they 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 et al., 2004), or of a pseudo-endowment effect (Dodonova, 2004; Heyman et al., forthcoming). We refer to this general explanation of low value bidders increasing their interest and then continuing to bid as *attachment*.

The third explanation we consider is that snipers (bidders who place their bids as an auction is about to end) choose their auctions early on, before the price of low starting-price auctions have caught up with high starting-price ones, and that they do not change their selections of what auctions to bid on when they come back to bid in the last few minutes of the auction. Low starting-price auctions do better, then, because they are attractive targets when snipers are choosing among auctions. We refer to this explanation as *sniping-bait*.

IV.A. Unobserved heterogeneity

The first alternative explanation we discuss is the possibility that low starting-price auctions receive more attention because they offer unobservably better products or are offered by unobservably better sellers.

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, not many relevant attributes (likely to be correlated with starting-price) seem to remain unobserved. In addition, it seems counterintuitive that sellers of *better* items would set *lower* starting-prices for their auctions. Standard auction models predict that sellers set their starting-price at or above the opportunity cost of the item (Milgrom & Weber, 1982; Myerson, 1981), we hence should expect that items with higher starting-prices are of actually higher rather than lower quality. Ex-ante, it seems, unobserved heterogeneity makes our estimates conservative.

One way to assess the potential impact of *unobserved* heterogeneity on our results is to look at the impact of *observed* heterogeneity on them. If the estimated impact of starting-price is greatly influenced when we control versus when we don't control for observable heterogeneity, there is reason to believe that unobserved heterogeneity may be a problem. The regressions we estimated for all three predictions (tables 3,5 and 7) show very similar estimates when absolutely no control for heterogeneity is included, and when all observable heterogeneity is included. To facilitate the comparison we show the key parameter estimates again in table 8.

For each prediction the table shows the number of the original table and the dependent variable. Column 1 doesn't incorporate any controls, column 2 all observable controls and column 3 excludes repeat bidders, we will refer to column 3 in the discussion of the next alternative explanation. The estimates obtained with covariates are slightly lower for prediction 1, slightly *higher* for prediction 2, and much *higher* for prediction 3. In order for unobserved heterogeneity to explain our results, therefore, it would need to influence our predictions in the opposite direction that observed heterogeneity does.

In sum unobserved heterogeneity is ex-ante unlikely to play an important role in our estimates. If it did, it is likely to make our estimates conservative both because of theoretical reasons in terms of how sellers should set starting-prices, and because of empirical reasons, in terms of how observed heterogeneity influences our point estimates

***Table 8 ***

IV.B. Attachment

The second alternative explanation we consider is that early bidders do not attract later bidders, but rather, that early bidders become attached to items they have bid on and hence continue choosing them over items they have not placed bids on. A necessary condition for attachment to be able to explain our results is low starting-prices auctions having a larger number of bidders placing more than one bid per auction (repeat bidders).

Figure 7 shows the percentage of all bidders, and of winners in particular, who placed more than one bid in the same auction. For example it shows that around 17% of winners in auctions that start at $0 placed more than one bid. Consistent with an attachment explanation, Figure 7 shows a downward trend: high starting-price auctions have a lower percentage of winners placing multiple bids.

***Figure 7 ***

Because this trend is consistent with an attachment explanation, it is possible that attachment can account for at least a portion of the influence of starting-price. To assess how much of the increased preference for low starting-price auctions can be explained by attachment, we run all of the analyses testing prediction 1,2 and 3 excluding repeat bidders.

If repeat bidders are the drivers of the effect, once they are excluded from the sample the effects should disappear. The results from regressions that exclude repeat bidders are presented on the last column of each of regression tables 4,6 and 7, and then again, to simplify comparison, in column 3 of table 8.

For all three predictions, the impact of starting-price is, if anything, magnified when repeat bidders are excluded from the analysis. Although this doesn't rule out that attachment as a real phenomenon, it suggests that our results cannot be accounted by it.

IV.C Sniping-bait

Various studies have shown that bidders tend to place their bids during the last few minutes of an auction (Bajari & Hortacsu, 2003; Roth & Ockenfels, 2002 ; Wilcox, 2000), a practice commonly referred to as sniping. Whether sniping can account for the effects of starting prices noted here depends on the timing of snipers' decisions of which auctions they want to participate in. If snipers choose early-on based on an auction's current-price and they do not update their decisions as prices increase, low starting-price auctions may outperform others because their low starting-price acts as bait for snipers.

Under the sniper-bait 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 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. Never-the-less it is worthwhile checking 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 8 plots the proportion of winning bids arriving within 5, 60 and 300 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. In light of Figure 8 we do not believe sniping-bait is a plausible explanation for our findings.

***Figure 8 ***

V. Conclusions

Based on the notion that people underweight the causal influence of non-salient factors, it was hypothesized the bidders in on-line auctions would use the number of existing bids as if they were an informative signal, even when they were not, engaging in what we referred to as non-rational herding. A simple model where bidders who engage in this type of behavior participate in an auction market with rational sellers and arbitragers lead to three predictions, all of which were supported by the data: (i) low starting-price auctions are more likely to receive bids even after they catch up in price with auctions with higher starting-prices, (ii) bids of certain dollar amount are less likely to win a low starting-price auction, and (iii) low starting-price auctions are more likely to achieve high final prices. Additional analyses ruled out the possibility that low starting-price auctions are preferred because of unobserved heterogeneity, attachment or sniper-bait.

We believe that our results apply beyond the specifics of on-line bidding, and that non-rational herding arising from misattribution of causality is likely to be present in many other domains where economic decisions are based, at least partially, upon inferences agents make from observed behavior. Employers assessing unobserved ability of job applicants, for example, may overattribute to the focal target of their evaluation (the applicant) the quality of the previous position held, and underweight the role played by non-focal causes, such as job market conditions when the previous job was obtained. [16]

Erroneously attributing causation can lead to problems other than non-rational herding. For example, 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 may over-attribute to focal targets

[16] See (Devereux, 2002) for evidence consistent with this prediction.

(their own business) the increase in the prices of their product, rather than to the true yet non-salient cause (excessive production of new money).

This paper also contributes to the recent literature highlighting that in order to understand the rational behavior of firms, one must often first understand the non-rational behavior of consumers. As was mentioned earlier, standard auction models propose that rational sellers should not set starting-prices below the cost of the product they are offering. This prediction is clearly violated by the large share of eBay sellers settings their auctions for valuable items at $1 and even $0.01. This paper demonstrates that once we consider how consumers deviate from optimal behavior, we can better understand the decision of rational sellers. Incorrectly assuming that all consumers behave rationally not only hurts the predictive power of our models about consumer behavior, but also of those of firm behavior.

Our results also contradict the often held intuition that market forces eliminate individual biases by showing that, at least sometimes, market forces simply eliminate the rents that arise from *exploiting* them. If market forces do not necessarily work towards eliminating deviations from rationality, and if even in order to understand the behavior of rational agents we need to first understand that of non-rational ones, it becomes increasingly obvious that economics needs to consider psychologically valid assumptions when attempting to explain and predict human behavior.

Table 1. Expected final-price and probabilities associated with receiving 0,1 and 2 consumer bids (in addition to the guaranteed arbitrager's bid) by *low* starting-price sellers.

Bids by Consumers	Final-Price	Ex-ante probability as a function of C and S_L		
		(1)	(2)	(3)
		$C \leq S_L$	$S_L < C \leq 2S_L$	$2S_L < C$
0	L	$1-\frac{C}{S_L}$	0	0
1	H	$\frac{C}{S_L}$	$1-\frac{C-S_L}{S_L}$	0
2	V	0	$\frac{C-S_L}{S_L}$	1

Notes:
C = Total number of consumers participating in the auction market
S_L = Total number of seller choosing a low starting-price for their auction

Table 2. The Effect of Starting Price on Final Price of Sold Units (OLS Regression)

Dependent Variable: Final Price of Sold Units

	(1)	(2)	(3)	(4)
	No controls	With Movie Controls	With Seller Controls	Controlling for Shipping Costs[b]
Intercept	10.87**	10.82**	9.108**	9.603**
	(0.086)	*(0.150)*	*(0.242)*	*(0.259)*
Starting Price	-0.801**	-0.407**	-0.300**	-0.154**
	(0.043)	*(0.037)*	*(0.038)*	*(0.046)*
Starting Price Squared	0.087**	0.042**	0.032**	0.016**
	(0.003)	*(0.003)*	*(0.003)*	*(0.004)*
"New" Movie Dummy	--	0.765**	0.728**	0.682**
	--	*(0.067)*	*(0.067)*	*(0.079)*
Movie Title Fixed Effects (df=53)[a]	--	yes	yes	yes
	--	*(47.32)*	*(49.94)*	*(37.29)*
log(Seller Rating)	--	--	0.195**	0.153**
	--	--	*(0.026)*	*(0.031)*
log(Seller Experience)	--	--	0.054**	0.118**
	--	--	*(0.017)*	*(0.021)*
eBay Store Dummy	--	--	-0.113	-0.087
	--	--	*(0.134)*	*(0.149)*
Shiping Charges	--	--	--	-0.163**
	--	--	--	(0.036)
R-Square	0.094	0.384	0.405	0.403
Number of observations	6,254	6,254	6,254	4,492

Standard errors reported below parameter estimates

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

[a] F-Value for joint test of all 53 movie dummies being equal to zero reported in parenthesis below "yes"

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

Table 3. Probability that a new bid will be placed on an auction after its price is $x

Panel A. No Controls

	$x=6	$x=7	$x=8	$x=9	$x=10
Starting at $x	83%	85%	76%	70%	60%
Starting at $1	96%	92%	91%	87%	83%
Auctions starting at $1 excluding repeat bidders	95%	91%	89%	85%	80%

Panel B. With Controls[a]

	$x=6	$x=7	$x=8	$x=9	$x=10
Auctions starting at $x	90%	88%	77%	65%	52%
Auctions starting at $1	97%	95%	90%	88%	73%
Auctions starting at $1 excluding repeat bidders	97%	94%	88%	85%	66%

[a]Predicted values from logistic regressions including only auctions that start at $1 and at $x and controlling for movie title, seller experience, seller reputation 'new' and 'store'.

Table 4. The Effect of Starting Price on Probability of Receiving Additional Bids (Logistic Regression)

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

	(1) No controls	(2) With Movie Controls	(3) With Seller Controls	(4) Only bids placed once price>=$10	(5) Controlling for Shipping Costs[c]	(6) Subset of bidders' first bid
Intercept	1.343	1.801*	0.872	0.062	1.412	0.860
	(0.702)	*(0.809)*	*(0.809)*	*(0.736)*	*(0.947)*	*(1.155)*
Starting Price	-0.125**	-0.127**	-0.120**	-0.085**	-0.132**	-0.120**
	(0.004)	*(0.005)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.006)*
Current Price Dummies [a,b]	yes	yes	yes	yes	yes	yes
	(1755.9)	(5402.5)	(3103.9)	(461.4)	(3103.9)	(2183.8)
"New" Movie Dummy	--	0.271**	0.252**	0.193**	0.212**	0.315**
	--	*(0.033)*	*(0.034)*	*(0.041)*	(0.041)	(0.051)
Movie Title Fixed Effects[b]	no	yes	yes	yes	yes	yes
	--	(2633.2)	(2655.8)	(1174.6)	(1968.7)	(1679.9)
log(Seller Rating)	--	--	0.135**	0.121**	0.140**	0.180**
	--	--	(0.013)	(0.018)	(0.017)	(0.020)
log(Seller Experience)	--	--	-0.016	-0.041**	-0.003	-0.005
	--	--	(0.009)	(0.011)	(0.011)	*(0.013)*
eBay Store Dummy	--	--	-0.201**	-0.277**	-0.204*	-0.250*
	--	--	(0.069)	(0.082)	(0.079)	*(0.097)*
Shiping Charges	--	--	--	--	-0.096**	-0.155**
	--	--	--	--	(0.019)	*(0.023)*
Pseudo R-Square	0.164	0.251	0.256	0.117	0.274	0.294
Number of observations	36,477	36,477	36,477	14,678	26,580	13,826

Standard errors reported below parameter estimates.

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

[a] Current price is controlled for with dummies for rounded dollar amounts (between $0 and $21), avoiding functional form assumptions. Results with linear controls are repoted in footnotes.

[b] Chi-square values from Wald test of all dummies being equal to zero reported in parenthesis below 'yes'

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

Table 5. Percentage of $10 bids winning auctions

Starting-price	No Controls	With Controls[a]
$0	0.143	0.142
$1	0.161	0.176
$2	0.230	0.176
$3	0.183	0.135
$4	0.266	0.194
$5	0.214	0.182
$6	0.301	0.231
$7	0.275	0.244
$8	0.242	0.240
$9	0.329	0.317
$10	0.408	0.416

[a]Probability estimate with controls obtained from linear probability model that controls for seller and movie characteristics.

Table 6. Effects of starting price on probability that a bid wins an auction (logistic regression)

Dependent Variable: 1 if auction was won with bid,0 otherwise

	(1) No controls	(2) With Movie Controls	(3) With Seller Controls	(4) Only bids for $10 or more	(5) Controlling for Shipping Costs[c]	(6) Subset of bidders' first bid
Intercept	0.340	0.809**	1.462**	1.791**	0.943**	-0.320
	(0.217)	*(0.245)*	*(0.255)*	*(0.26)*	*(0.314)*	*(1.306)*
Starting Price	0.075**	0.088**	0.082**	0.059**	0.102**	0.165**
	(0.004)	*(0.004)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.007)*
Bid Dollar Amount Dummies [a,b]	yes	yes	yes	yes	yes	yes
	(2315.1)	(3353.2)	(3413.6)	(917.3)	(2571.2)	(1016.8)
"New" Movie Dummy	--	-0.321**	-0.297**	-0.216**	-0.251**	-0.208**
	--	(0.035)	(0.036)	(0.042)	(0.043)	(0.056)
Movie Title Fixed Effects[b]	no	yes	yes	yes	yes	yes
	--	(1930.26)	(1975.3)	(1042.5)	(1471.4)	(1016.8)
log(Seller Rating)	--	--	-0.081**	-0.068**	-0.065**	-0.106**
	--	--	(0.014)	(0.018)	(0.018)	*(0.022)*
log(Seller Experience)	--	--	-0.022*	-0.002	-0.045**	-0.020
	--	--	(0.009)	(0.011)	(0.011)	(0.015)
eBay Store Dummy	--	--	0.132*	0.220**	0.126	0.051
	--	--	(0.073)	(0.085)	(0.083)	(0.112)
Shiping Charges	--	--	--		0.115**	0.133**
	--	--	--		(0.020)	(0.027)
Pseudo R-Square	0.160	0.232	0.236	0.095	0.243	0.215
Number of observations	34,859	34,859	34,859	10,770	25,372	11,212

Standard errors reported below parameter estimates.

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

[a] Bid Amount is controlled for with dummies for rounded dollar amounts (between $0 and $21), avoiding functional form assumptions. Results with linear controls are repoted in footnotes.

[b] Chi-square value from Wald test of all dummies being equal to zero reported in parenthesis below 'yes'.

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

Table 7. Effects of starting price on probability that auction obtains price above threshold (logistic regression)

Dependent Variable: 1 if final-price above threshold, 0 otherwise

	(1)	(2)	(3)	(4)	(5)	(6)
Threshold	\$10.50	\$10.50	\$10.50	\$10.50	\$11.50	\$10.50
	No controls	With Movie Controls	With Seller Controls	Controlling for Shipping Costs[b]	Same as (4)	Excludes repeat winners
Intercept	-0.004	0.817**	-0.657**	-0.307	-1.624**	-0.393
	(0.044)	*(0.122)*	*(0.176)*	*(0.251)*	*(0.264)*	*(0.344)*
Starting Price	-0.094**	-0.153**	-0.146**	-0.167**	-0.113**	-0.219**
	(0.006)	*(0.008)*	*(0.008)*	*(0.010)*	*(0.010)*	*(0.014)*
"New" Movie Dummy	--	0.570**	0.529**	0.386**	0.492**	0.370**
	--	(0.064)	(0.065)	(0.080)	(0.085)	(0.112)
Movie Title Fixed Effects[a]	no	yes	yes	yes	yes	yes
	--	(1428.9)	(1436.5)	(1017.9)	(822.9)	(597.6)
log(Seller Rating)	--	--	0.238**	0.211**	0.172**	0.285**
	--	--	(0.027)	(0.033)	(0.035)	(0.046)
log(Seller Experience)	--	--	0.001	0.037	0.048*	0.004
	--	--	(0.017)	(0.021)	(0.023)	(0.029)
eBay Store Dummy	--	--	-0.208	-0.109	-0.118	0.088
	--	--	(0.139)	(0.159)	(0.160)	(0.220)
Shiping Charges	--	--	--	-0.041	-0.049	-0.054
	--	--	--	(0.037)	(0.039)	(0.052)
Pseudo R-Square	0.021	0.290	0.307	0.304	0.271	0.346
Number of observations	7,838	7,838	7,838	5,676	5,676	3,548

Standard errors reported below parameter estimates.

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

[a] Chi-square value from Wald test of all dummies being equal to zero reported in parenthesis below 'yes'.

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

Table 8. Summary of parameter estimates for starting-price with and without controls, and without repeat bidders

Prediction	Dependent Variable	Original Table	(1)	(2)	(3)
			Estimates of Starting-Price Coefficient		
			No controls	Seller and Movie Controls	Excludes Repeat Bidders
Prediction 1	Probabitliy of additional bid	Table 3	-0.125**	-0.120**	-0.120**
			(0.004)	*(0.004)*	*(0.006)*
Prediction 2	Probability of winning auction	Table 5	0.075**	0.082**	0.165**
			(0.004)	*(0.004)*	*(0.007)*
Prediction 3	Probability of high price	Table 7	-0.094**	-0.146**	-0.219**
			(0.006)	*(0.008)*	*(0.014)*

Standard error reported in parenthesis below parameter estimates

Figure 1A

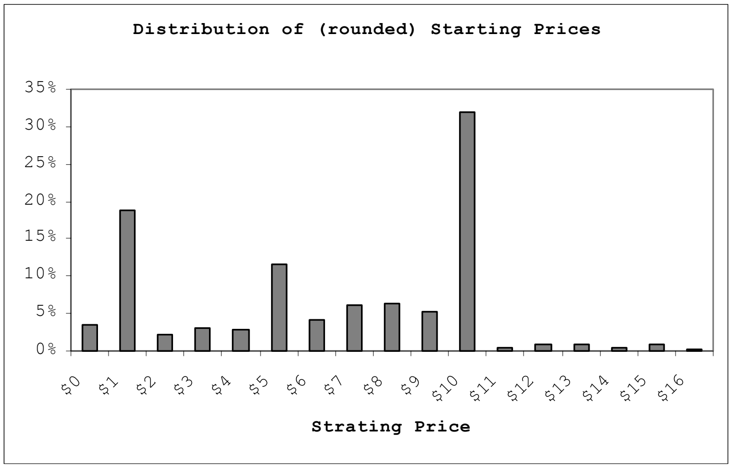


Figure 1B

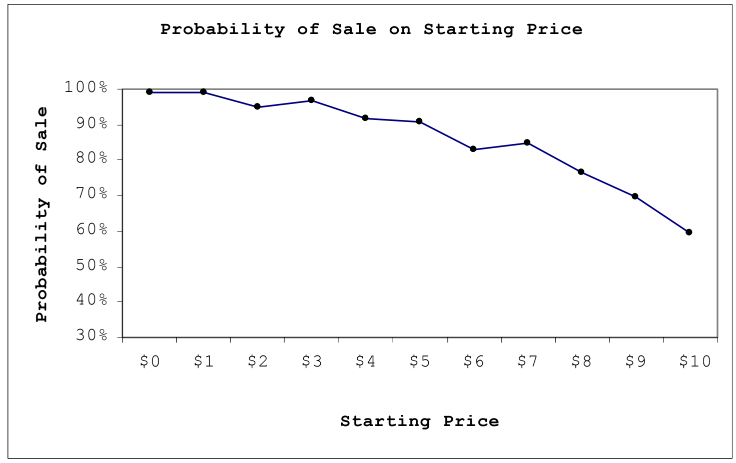


Figure 2

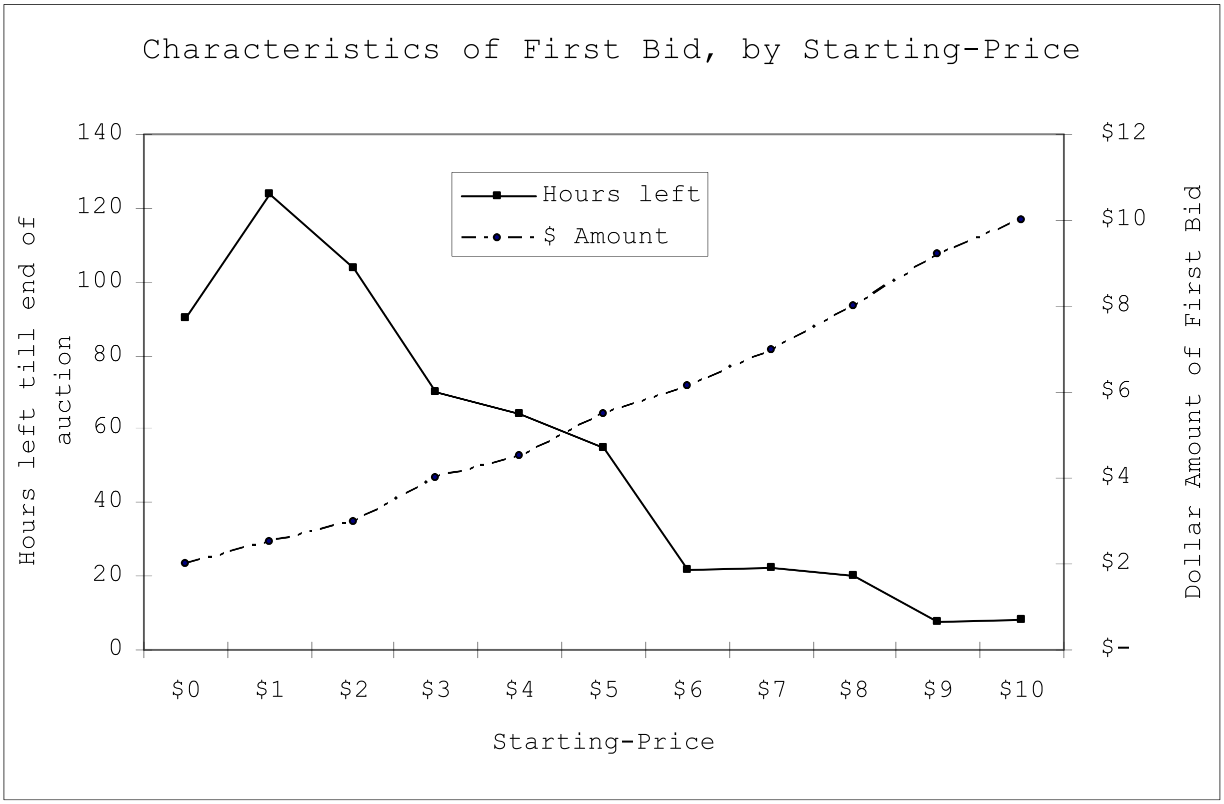

Characteristics of First Bid, by Starting-Price
Hours left
$ Amount
Hours left till end of auction
Dollar Amount of First Bid
Starting-Price
140
120
100
80
60
40
20
0
$12
$10
$8
$6
$4
$2
$-
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10

Figure 3

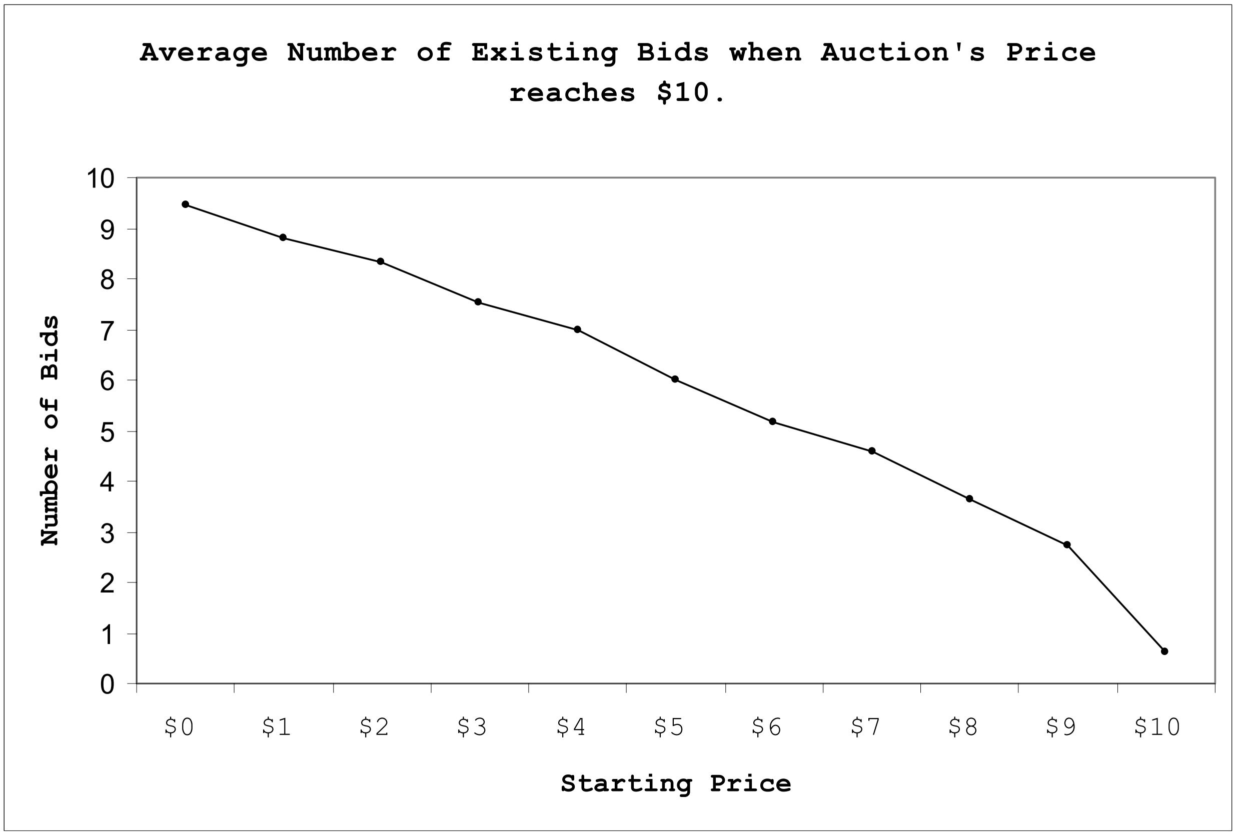

Average Number of Existing Bids when Auction's Price reaches $10.
Number of Bids
0
1
2
3
4
5
6
7
8
9
10
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10
Starting Price

Figure 4

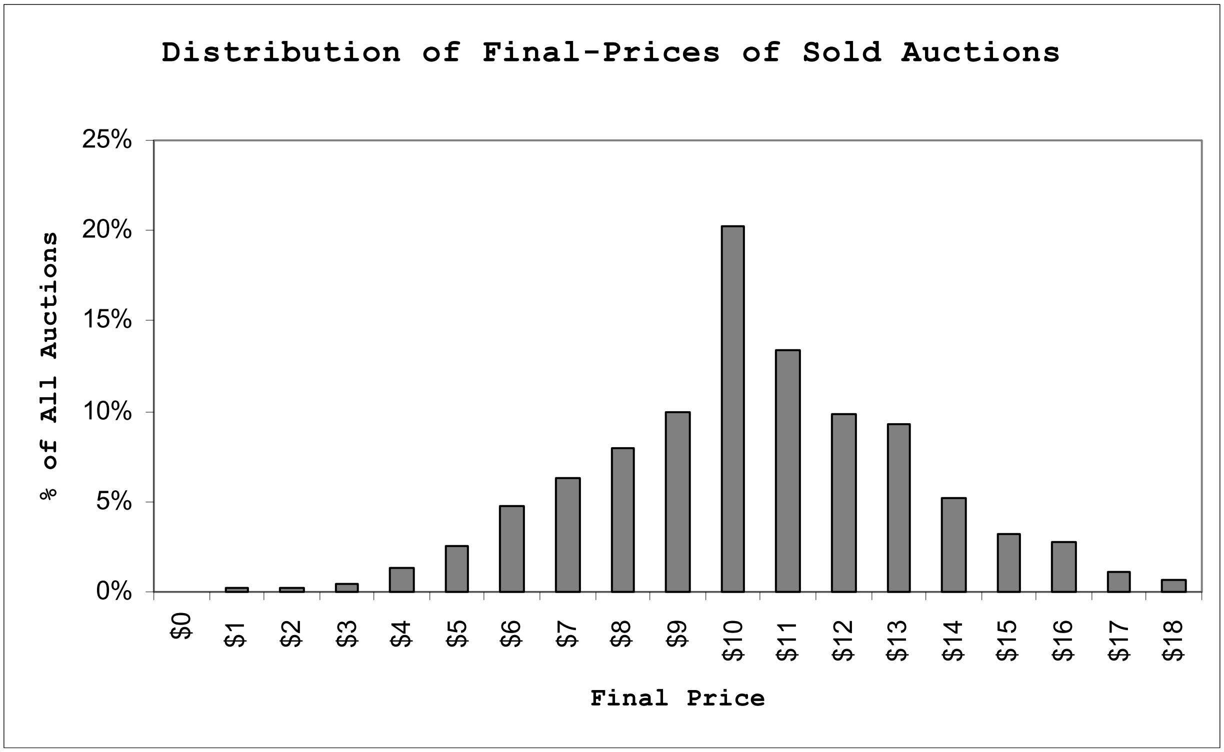
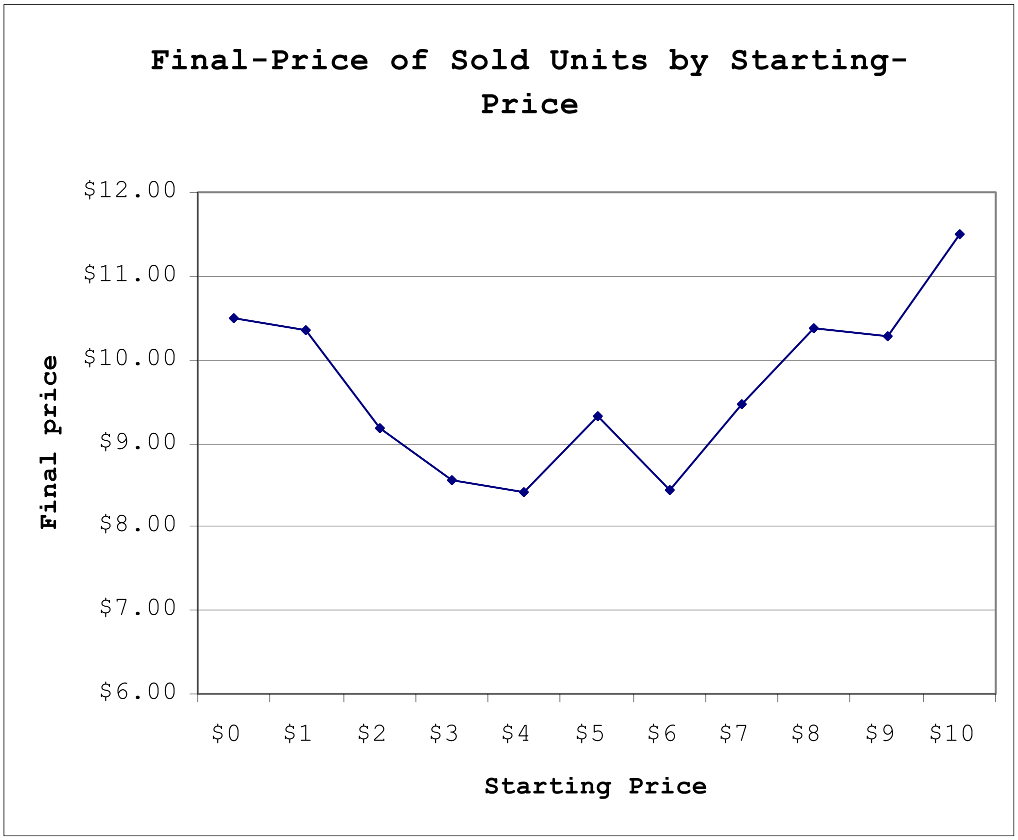

Distribution of Final-Prices of Sold Auctions
% of All Auctions
25%
20%
15%
10%
5%
0%
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10
$11
$12
$13
$14
$15
$16
$17
$18
Final Price

Figure 5



Final-Price of Sold Units by Starting-Price
$12.00
$11.00
$10.00
$9.00
$8.00
$7.00
$6.00
Final price
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10
Starting Price

Figure 6

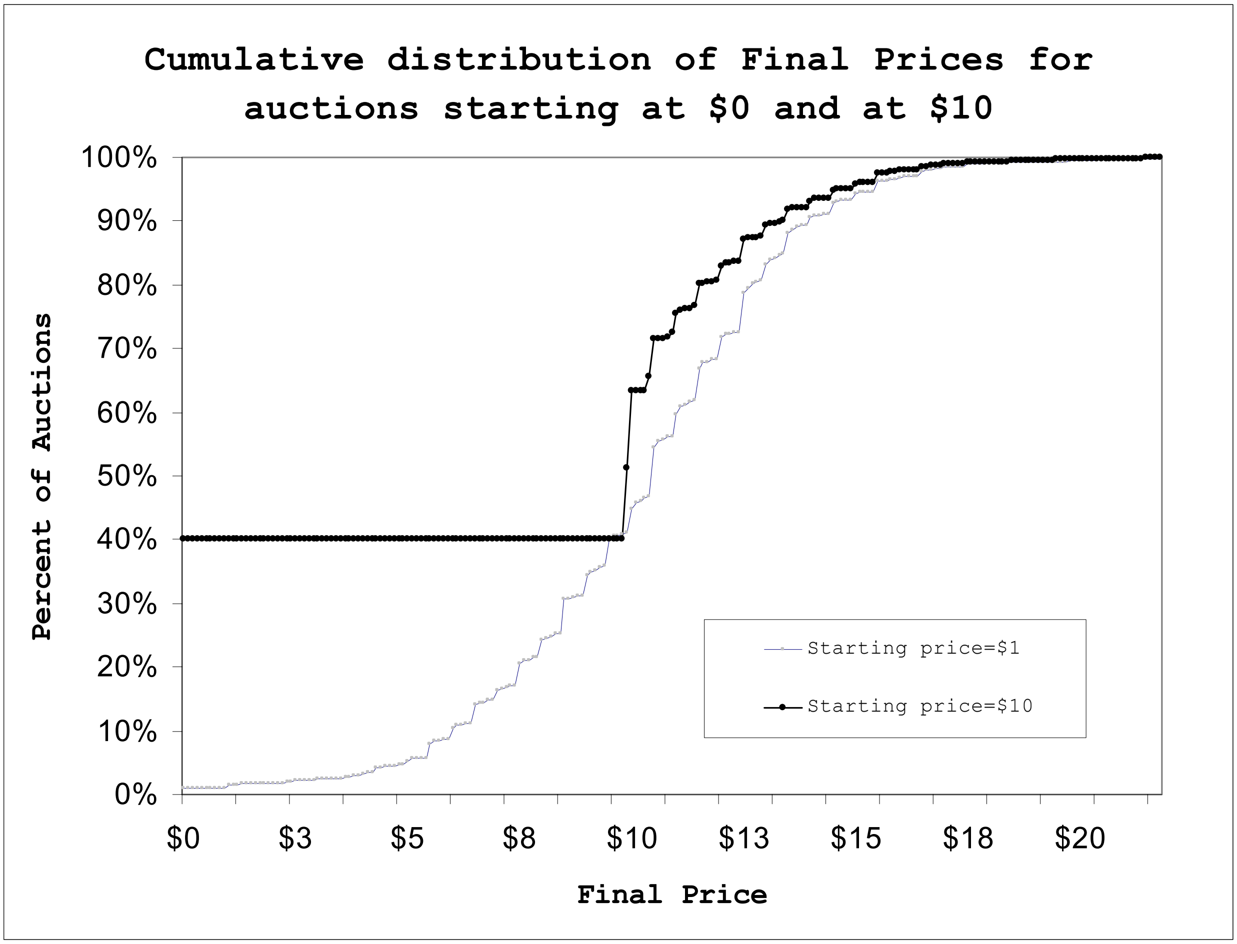

Cumulative distribution of Final Prices for auctions starting at $0 and at $10
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Percent of Auctions
$0
$3
$5
$8
$10
$13
$15
$18
$20
Final Price
Starting price=$1
Starting price=$10

Figure 7

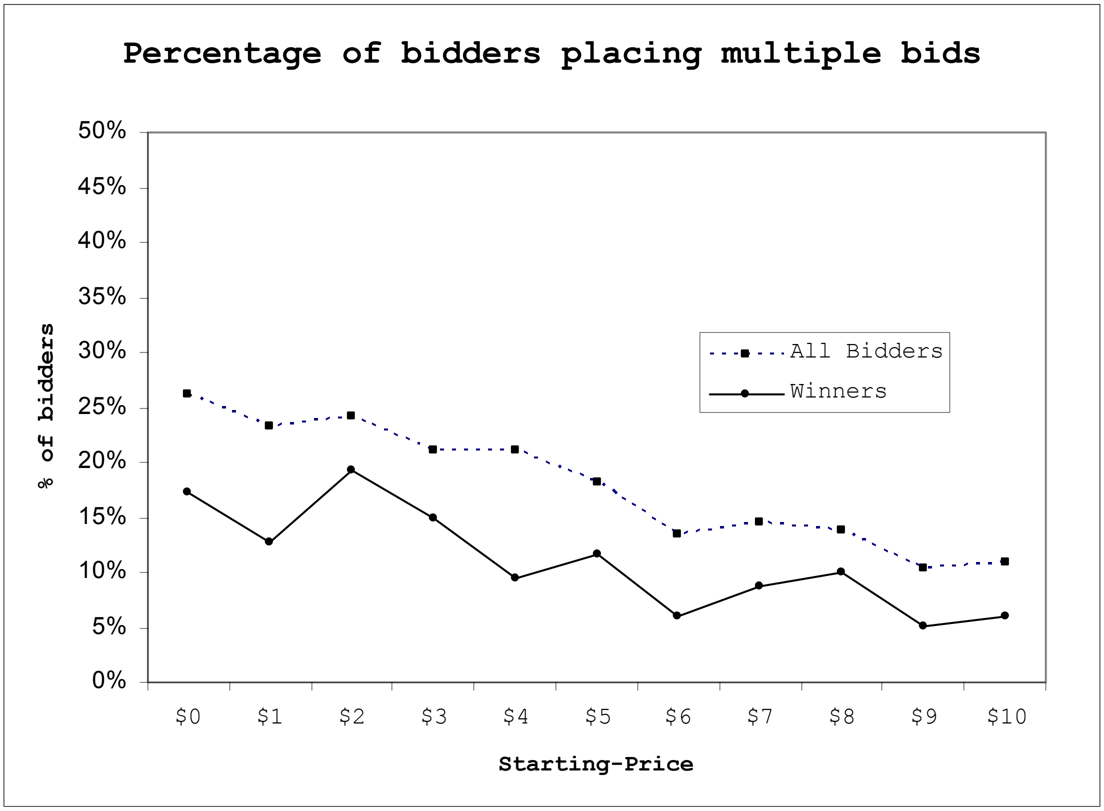
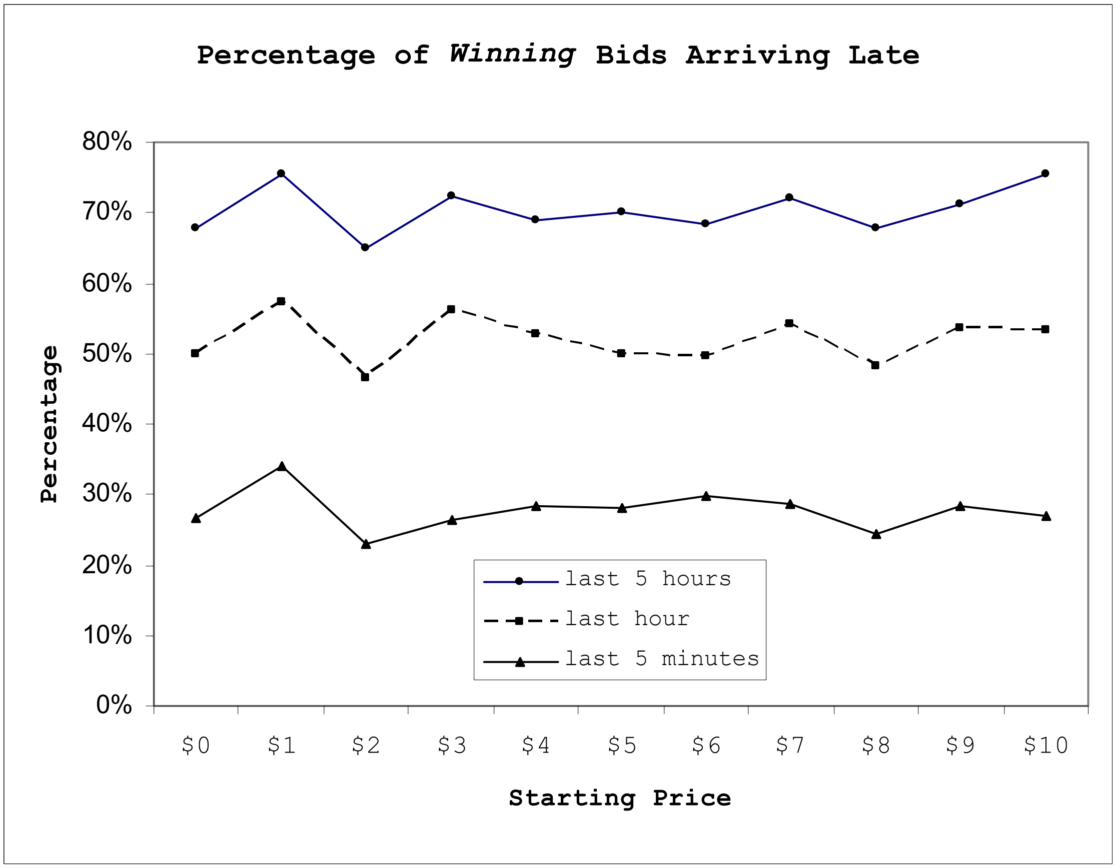

Percentage of bidders placing multiple bids
50%
45%
40%
35%
30%
25%
20%
15%
10%
5%
0%
% of bidders
All Bidders
Winners
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10
Starting-Price

Figure 8


Percentage of *Winning* Bids Arriving Late
80%
70%
60%
50%
40%
30%
20%
10%
0%
Percentage
$0
$1
$2
$3
$4
$5
$6
$7
$8
$9
$10
Starting Price
last 5 hours
last hour
last 5 minutes

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