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

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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.

Key words: herding; auctions; biases; rationality; industrial organization
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1. Introduction

Before making decisions, people can often observe what others before them have decided. Investors learn about the buying and selling decisions of fellow investors before themselves deciding what to buy or sell, out-of-towners can compare the number of people currently eating at different restaurants before determining which one to enter, and employers may inquire about previous employers of job applicants before deciding whether to hire them. It has long been recognized that in these kinds of sequential choice settings it may become optimal, ex ante, to imitate observed behaviors, in some cases even fully ignoring private information (Banerjee 1992, Bikhchandani et al. 1992).

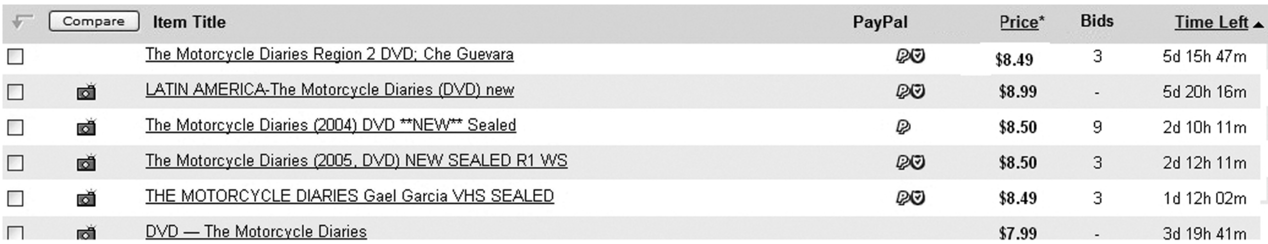
For herding to be rational, however, observers need to make unbiased inferences from the decisions they observe. In this paper, we empirically examine, analyzing herding behavior in eBay, the consequences of a likely bias in such inferential process: neglecting the role of nonsalient factors behind observed decisions.

It has long been hypothesized that people attend and respond much more to information that is salient (i.e., easily observable) than to information that is not (Heider 1958, Nisbett and Ross 1980). Taylor and Fiske (1975) showed that when subjects observed a group of individuals engaged in a discussion, they tended to pay more attention to the individuals sitting directly in front of them, and as a consequence to judge them as having had a larger influence on the group. In the context of decision making, Wilson and Schooler (1991) showed that directing the attention of participants toward experts' opinions makes them place less weight on their own preferences, and as a consequence make inferior choices. Mackenzie (1986) showed that having subjects attend more to specific attributes increases the importance placed on such attributes.

Recent field research has also found evidence of the importance of saliency in decision making. Researchers have found, for example, that consumers underrespond to nonsaliently displayed shipping costs (Hossain and Morgan 2006), that individual investors are net buyers of attention-grabbing stocks (Barber and Odean 2008), and that sufferers from natural disasters who have the additional misfortune of competing for attention with events like the Olympic games receive smaller donations (Eisensee and Strömberg 2007).

Returning to the sequential choice setting, if observers make inferences about the decisions they observe neglecting the impact of nonsalient factors on such decisions, then their inferences will be biased. This bias will be particularly damaging when the nonsalient factors were relevant for previous decision makers but are not for current ones, because observers may imitate ultimately irrelevant behavior.

Figure 1 **Results Page for Search on eBay.com; Current Price Is Displayed, But Starting Price Is Not**



Compare	Item Title	PayPal	Price*	Bids	Time Left ▲
	The Motorcycle Diaries Region 2 DVD; Che Guevara		$8.49	3	5d 15h 47m
	LATIN AMERICA-The Motorcycle Diaries (DVD) new		$8.99	-	5d 20h 16m
	The Motorcycle Diaries (2004) DVD **NEW** Sealed		$8.50	9	2d 10h 11m
	The Motorcycle Diaries (2005, DVD) NEW SEALED R1 WS		$8.50	3	2d 12h 11m
	THE MOTORCYCLE DIARIES Gael Garcia VHS SEALED		$8.49	3	1d 12h 02m
	DVD — The Motorcycle Diaries		$7.99	-	3d 19h 41m

Notes. Figure contains portion of print-screen of results page after querying "Motorcycle Diaries" on eBay. Price corresponds to current price.

For example, investors might erroneously herd behind investment decisions driven by idiosyncratic rebalancing needs of observed investors, out-of-towners might enter a crowded restaurant unaware of the "happy hour" promotion that just ended, and employers may choose to hire applicants currently employed at prestigious institutions, neglecting the role that prior job market conditions had on securing such positions. In all these examples, observers are in danger of making suboptimal decisions by neglecting the impact of nonsalient factors on the decisions they observe.

Nonrational herding of this nature can have two important consequences. The first is straightforward; biased inferences lead to suboptimal decisions. Continuing with the previous examples, investors would fail to optimize returns, consumers to maximize utility from their dining experience, and employers to hire the most able applicants. The second potential consequence of nonrational herding has to do with how rational agents may manipulate the environment of early decision makers, seeking to indirectly influence the decisions of observers. Restaurants, for example, could offer happy hour promotions precisely *because* they wish to generate a nondiagnostic signal that will be erroneously interpreted as diagnostic by latecomers.

In this paper, we study these two consequences of neglecting nonsalient factors in sequential choice settings: (i) suboptimal decisions by individuals, and (ii) reactions by their rational counterparts, analyzing eBay data for 8,333 DVD auctions from October of 2002. eBay auctions are ideal for this purpose because they involve sequential choices where current bidders observe the bidding decisions of previous ones.

Importantly, eBay displays some of the factors that were relevant for previous bidders' decisions saliently, and others not saliently. In particular, when bidders search for an item, the screen showing the resulting list of auctions saliently displays the amount of time left on each auction, and the items' *current* prices and number of existing bids, but it does not display the items' *starting* prices (see Figure 1).

Starting prices, of course, are essential for making unbiased inferences about previous bidders' decisions; auctions that start cheap will mechanically accumulate many more bids by the time their prices catch up with those starting more expensively. 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. It is worth noting that bidders can easily find out starting prices by clicking on an item (see Figure 2); starting price information is available, but it is not salient.[1]

A bidder choosing between auctions with identical current prices faces a situation analogous to a customer choosing which restaurant to enter after a recently expired happy hour special: popularity is a signal of the no-longer-available low prices rather than of enduring higher quality. Based on the notion that observers will (at least partially) neglect the role that nonsalient factors had on the actions of previous decision makers, we arrive at our first prediction:

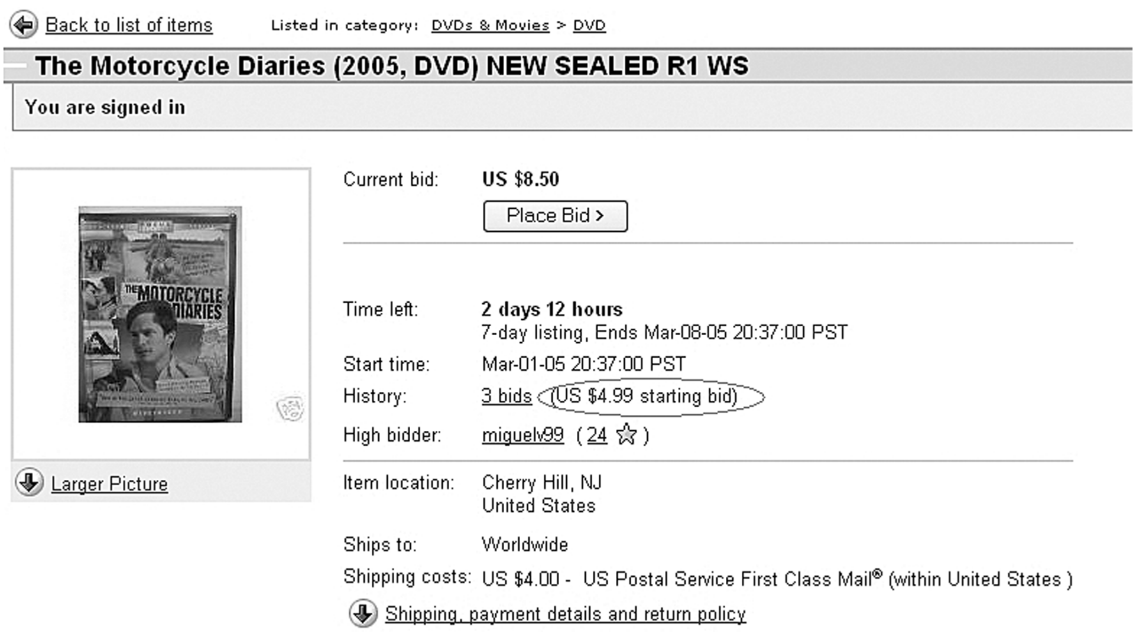
Prediction 1. *Conditioning on current price, low starting price auctions are more likely to receive additional bids.*

Consistent with this prediction we find, for example, that among auctions currently at $10, 83% of those starting at $1 receive an additional bid, compared to 60% of those starting at $10.

Previous research has shown that auctions with lower starting prices receive more bids (see, e.g., Bajari and Hortacsu 2003, Häubl and Popkowski Leszczyc 2003, Hossain and Morgan 2006). These studies, however, have not distinguished between bids for amounts above and below the higher starting prices. As was mentioned above, setting a low starting price mechanically increases the number of bids

[1] Several papers have investigated the correlation between starting and final prices, obtaining mixed results. Some find a negative association (Kamins et al. 2004, Ku et al. 2006, Reiley 2005), whereas others find a positive one (Brint 2003, Häubl and Popkowski Leszczyc 2003, Lucking-Reiley 2000, Park and Bradlow 2005). In contrast to the existing literature, here we focus on the importance of the fact that starting prices are not saliently displayed, and the impact of this fact on the optimality of herding.

Figure 2 Starting Price Is Easily Available by Following an Auction's Link (Oval Added by Authors)



Notes. This page is displayed if the hyperlinked title of the auction is clicked on. Detailed information about existing bids and starting price is hence "a click away" from any query.

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 increase the number of bids placed *above* the higher starting price, because late bidders will herd behind the otherwise truncated away low-value bids. Note, furthermore, that there is nothing wrong with bidders preferring a low starting price auction while it still enjoys a lower price, just like there is nothing wrong with choosing a restaurant because it currently has a price promotion. Prediction 1 refers to a preference for low starting price auctions after they no longer offer the opportunity to place a bid for a lower dollar amount.

Our recurrent restaurant analogy highlights another advantage of studying nonrational herding in an auctions setting: bidders, unlike restaurant patrons who may enjoy their meal more in the company of others, 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. Indeed, herding should, on average, hurt bidders who engage in it because the auctions they pick are more likely to both receive more bids in the future, and to already have a higher-value bid. 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 than on a high starting price auction.*

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.*

In other words, Predictions 2A and 2B postulate that falling prey to nonrational herding will hurt bidders. Consistent with these predictions we find, for example, that a bid for $10 on an auction that started at $1 has only a 16% chance of winning, whereas it has a 40% chance of winning an auction starting at $10, and that, conditioning on dollar amount bid, winners of auctions that start at $1 pay around 3% more than winners of auctions starting at $10.

Moving on to the second consequence of nonrational herding, i.e., to how rational agents may choose to modify their behavior if they realize others engage in nonrational herding. If bidders fail to take into account nonsalient factors when interpreting decisions they observe, then sellers have an incentive to lower the starting price of their auctions to attract early bidders whose choices may be misinterpreted by late bidders.

This is an interesting consequence of nonrational herding because it provides a mechanism by which it may be optimal for sellers to start their auctions with a price below cost, contrary to existing auction models (for a recent review see Ockenfels et al. 2008). Despite the theoretical consensus on the convenience of starting auctions at or above cost, an important share of auctions on eBay start well below cost. In our sample of DVD movies, for example, 22.1% started at $1 or less, whereas just 0.2% of them sold for $1 or less.[2]

It may seem at first that it would be optimal for *all* sellers to lower the starting price of their auctions. This is not so, however, because a lower starting price carries a downside: when no above-cost bid arrives, rather than keeping the item, low starting price sellers sell at a loss. As more and more sellers lower the starting price of their auctions, it becomes more and more likely that they will suffer such loss. In equilibrium, just enough auctions start low so that the expected revenue associated with a low and high starting price is the same, which is our third prediction:

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

We also find evidence consistent with this prediction. The expected revenue associated with starting an auction at $1 is $9.260, virtually identical to the $9.265 associated with starting at $10.

As we have briefly previewed following the presentation of each of our predictions, with simple pairwise comparisons of auctions starting at $1 and $10, we find evidence consistent with all of our predictions in our data. The key identifying assumption behind our interpretation of these findings as evidence of nonrational herding, of course, is that starting price is not correlated with (unobservable) quality differences across auctions and/or sellers. In §4 we discuss in detail multiple 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 prices are practically identical, and if low starting price auctions are of superior quality or are offered by superior sellers they should collect more revenue; and (iii) experience decreases bidders' tendency to bid on low starting price auctions, suggesting that doing so is a mistake that experience teaches bidders to avoid.

In addition to unobserved heterogeneity, we rule out as alternative explanations the possibility that our findings are driven by early bidders increasing their willingness to pay for an item they have already bid on, or by last-minute bidders who choose which auctions to bid on before low starting price auctions catch up with other auctions.

The remainder of this paper is organized as follows: §2 describes the data, §3 presents the empirical results that we interpret as supporting the proposition that bidders engage in nonrational herding and that sellers are best responding to such bias, §4 discusses alternative explanations for our results, and §5 concludes.

[2] Below-cost starting prices are common not only in the DVD category. Items starting at $0.01 (and with no reserve, i.e., secret minimum price) are found among such high-value items as car seats, billiard tables, and MP3 players.

2. Description of the Data

2.1. The Data Set

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 data set consists of auctions for movie titles that were bestsellers in dvdmojo.com in September 2002, December 2001, or July 2001. Sixteen of the initial list of 70 titles had too few observations or had titles that were easily confused with other movies, and were hence dropped from the sample.[3]

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). We also excluded auctions with a reserve price and those sold with the "buy-it-now" option (1% and 13% of the sample, respectively). The "buy-it-now option" is a feature that 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.

2.2. 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 one if the seller described the item as "new," "wrapped," or "sealed," and zero otherwise. Surprisingly, eBay collects shipping fees information only for items paid through their internal payment system, and hence 28% of the data do 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.

The data set does not include bidders' identifiers; to determine whether a bid belongs to a new bidder or

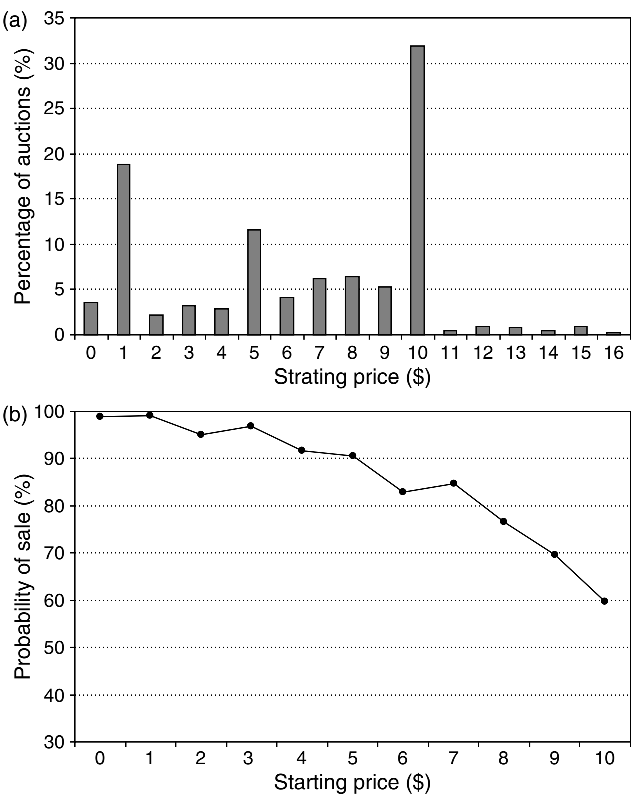
[3] eBay does not use unique product identifiers, so the identity of items being auctioned must be inferred from sellers' descriptions.

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 relatively 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.

2.3. Descriptive Statistics

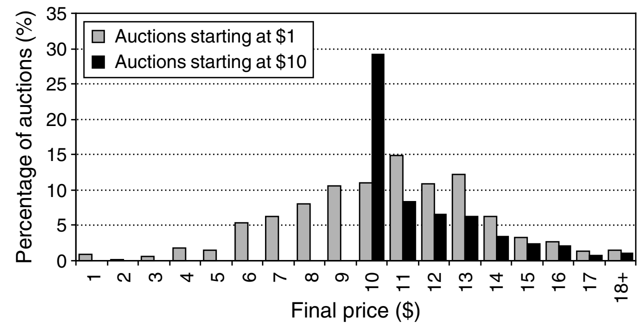
Figure 3(a) shows the distribution of (rounded) starting prices in our sample. It shows large dispersion in the starting prices chosen by sellers. Contrary to standard auction models, a large portion of sellers set a starting price that is clearly below the cost of the item being auctioned. For example, 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). The popularity of (rounded) \$1 and \$10 as starting prices may be due to the fact that eBay charges higher listing fees, the more expensive the starting price of an item, and both \$0.99 and \$9.99 are cutoff points for increment of such a listing fee.

Figure 3 **(a) Distribution of Starting Prices; (b) Probability of Sale and Starting Price**



Notes. Figures 3(a) and 3(b) round starting prices to closest integer to facilitate visual comparisons. Figure 3(a) includes all auctions in the sample and 3(b) includes only those with a starting price of \$10.49 or less.

Figure 4 **Distribution of Final Prices for Auctions Starting at \$1 and \$10**



Notes. Unsold items not included. The sample is restricted to auctions starting below \$10.49. Starting prices have been rounded to closest integer to facilitate visual comparisons.

Overall, 78% of auctions resulted in a sale. Figure 3(b) 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 nonsold 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.

Figure 4 shows the distribution of final prices for auctions starting at \$1 and \$10. It 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. This highlights the aforementioned tradeoffs involved in lowering a starting price.

Considering that many of our analyses contrast auctions starting at \$1 with those starting at \$10, Table 1 compares means and standard deviations for these two sets of auctions. Interestingly, although auctions differ across all observable variables in a statis-

Table 1 **Means and Standard Deviations for Auctions Starting at \$1 and \$10**

	Starting price (\$)	
	1	10
log(seller rating)	6.76 (1.76)	6.22 (1.38)
log(seller DVDs in 2002)	4.64 (2.75)	4.91 (2.25)
Auction duration (in days)	6.13 (2.00)	4.62 (0.71)
Shipping (\$)	3.68 (0.93)	3.17 (0.95)
Percentage of new items	43	71
Percentage of sellers who are eBay stores	10	6

Notes. Standard deviations in parentheses. All differences between auctions starting at \$1 and \$10 are significant at the 1% level (t-tests). *Seller rating*: Sum of all 1, 0, −1 evaluations in previous eBay transactions. log(*seller DVDs in* 2002) is the log of total number of DVDs posted by seller in 2002. *Shipping* charges are compared eliminating observations for which shipping is missing. *New items* are those that have the words "new," "wrapped," "sealed," or "never used" in the description. *eBay stores* are sellers that have a special contractual agreement with eBay. *Shipping amount* is set by seller and need not correspond to actual shipping costs.

tically significant manner (all ps from pairwise t-tests are <0.01), the differences are not systematic in terms of their expected impact on the performance of auctions. In particular, auctions starting at \$1 are listed by sellers with a higher rating, last more days, and are more likely to be listed by stores—all variables that we would expect to lead to better performance. At the same time, they are also listed by sellers with a lower total number of DVDs listed in 2002, they have higher shipping charges, and are less likely to contain a new item.

3. Empirical Analyses

This section begins by showing that low starting price auctions receive bids earlier than higher starting price auctions, and that these bids are for low dollar amounts. It then demonstrates that auctions that have more bids are more likely to receive additional bids. Predictions 1, 2A, and 2B are then tested, followed by an assessment of the role of bidder experience in the tendency to choose auctions with lower starting prices. Finally, Prediction 3 is explored by computing expected revenues for starting an auction with a high versus low starting price.

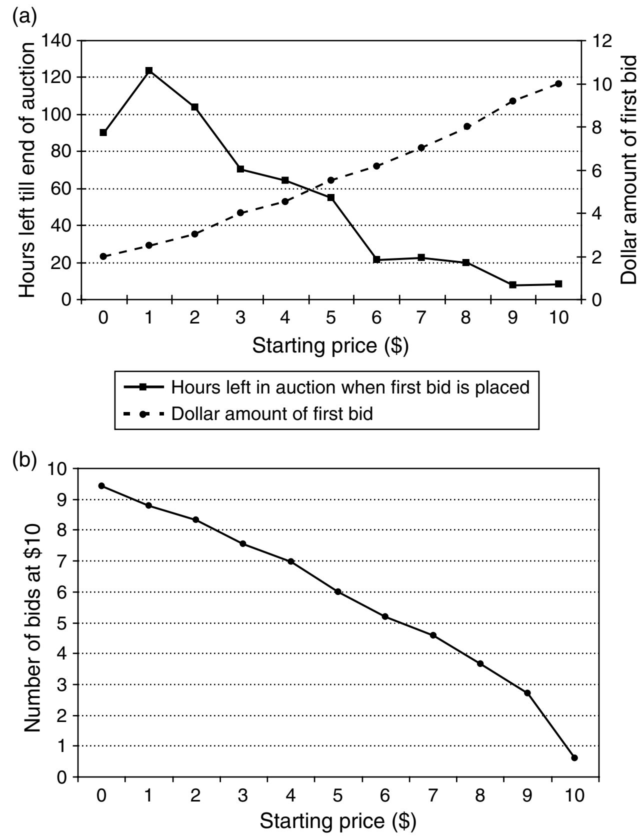
3.1. Early Bidding, A Necessary Condition for Herding

For late bidders to herd 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 5(a) 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 five days before the end of the auction, compared to eight *hours* for auctions starting at \$10. Figure 5(a) 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.

Because early bids in low starting price auctions are for low amounts, by the time these auctions catch up with higher starting price ones they are likely to accumulate a large number of bids. Figure 5(b) 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.

In sum, Figures 5(a) and 5(b) give plausibility to the nonrational herding mechanism we propose; although they are not evidence of herding, they are of the necessary conditions for herding to occur.

Figure 5 (a) Number of Hours Left and Bid Amount of First Bid; (b) Number of Existing Bids When Auction Reaches \$10



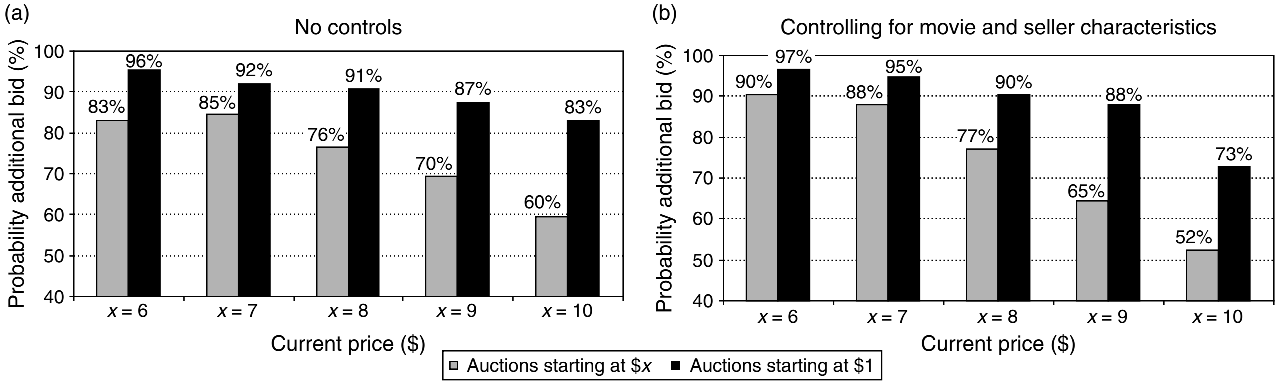
Notes. Prices have been rounded to closest integer to facilitate visual comparisons. Figure 5(a) includes only auctions receiving at least one bid, and Figure 5(b) includes only those achieving a price of at least \$10.

3.2. Existing Bids Predict Future Bids

Before presenting the analyses of the impact of starting price on auction outcomes, it is useful to assess whether the number of existing bids, caused by starting price or by any other factor, is a predictor of future bids. Such analysis suffers from the usual identification problems afflicting empirical work on herding: the correlation between past and future choices could be caused by omitted variables. 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.

We hence estimated a probit regression where bids are the unit of analysis, where the dependent variable takes the value of one if at least one more bid arrives to the auction and zero otherwise, and where the key predictor is how many bids the auction has already received. We control for current price (through 21 dummies for rounded dollar amounts to avoid functional form assumptions), minutes left in the auction, and various other controls. The marginal effect for number of existing bids is positive and significant

Figure 6 **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**



Notes. Starting prices have been rounded to the closest integer to facilitate visual comparisons. Figure 6(a) displays raw relative frequencies in the data (e.g., that 83% of auctions starting at $6, in the sample, received at least one bid). Probabilities from Figure 6(b) correspond to the point estimates in a linear probability model (plus a constant) predicting whether the auction received an additional bid after achieving a certain price, controlling for all item and seller observable.

($dF/dx = 0.144$, $p < 0.0001$),[4] indicating that the more bids an auction already has, the more likely it is to receive at least one more bid. The full set of results (marginal effects at sample means) is presented in column 1 of Table 2 (this table is discussed in detail a few paragraphs below).

3.3. 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 probabilities 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. The second consists of regressions employing the whole data set.

3.3.1. Pairwise Comparisons of Auctions at the Same Current Price. Figure 6 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 6(a) shows the relative frequencies in the raw data (i.e., without any controls), whereas Figure 6(b) shows the predicted probabilities arising from regressions that control for movie and seller heterogeneity.

The results presented in Figure 6 are consistent with Prediction 1: conditioning on current price, low starting price auctions are more likely to receive additional bids. For example, Figure 6(a) shows that 91% of auctions starting at $1 and currently at $8 receive an additional bid, whereas only 76% of auctions that start at $8 receive any bids. Figure 6(b) shows that once movie and seller characteristics are controlled for, the predicted probabilities are 90% and 77%, respectively.

3.3.2. Probit Regression Including All Auctions in the Sample. To extend the previous analysis to all observations in the data set, we estimated probit regressions where every bid in the sample is an observation and the dependent variable takes the value of one if there was at least one more bid placed after it, and zero otherwise (e.g., if an auction had three bids, the dependent variable is one for the first two bids, and zero for the third). The results are presented in columns 3–7 of Table 2 (column 1 reports the previously discussed regression where number of existing bids is the key predictor, and column 2 will be discussed later).

It is very important to control for current price because only low starting price auctions were ever at a low current price, and auctions currently cheaper are more likely to receive additional bids. 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 because current price is not adequately controlled for. Given that many auctions have multiple bids, standard errors are clustered by auction.

The entries in Table 2 report marginal effects estimated at sample means for all variables. In all specifications clustered standard errors, by auction, are reported in parentheses. Column 3 presents the baseline specification, column 4 adds controls for movie characteristics (movie title fixed effects and the

[4] dF/dx symbolizes the first derivative of the cumulative distribution function to the variable of interest; the marginal effect—estimated at sample mean—of a change in one unit of X on the probability of $Y = 1$.

Table 2 Probit Regression Assessing Impact of Existing Bids and Starting Price on Probability of Receiving Additional Bids (Marginal Effects)

	1	2	3	4	5	6	7
	Standard probit	Instrumenting existing bids with starting price	Controls only for auction variables	Adds movie controls	Only obs. Adds seller controls	Same as (4) with price at or above $10	excluding repeat bidders
	Dependent variable: 1 if at least one more bid was placed in auction, 0 if last bid						
log(number of existing bids)	**0.144*****	**0.107*****					
	(**0.004**)	(**0.004**)					
Starting price		Used as instrument	−**0.021*****	−**0.018*****	−**0.017*****	−**0.023*****	−**0.033*****
			(**0.001**)	(**0.001**)	(**0.001**)	(**0.002**)	(**0.002**)
log(minutes left on the auction +1)	0.038***	0.035***	0.040***	0.031***	0.030***	0.054***	0.074***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Shipping charges	−0.010***	−0.007***	0.004	−0.008***	−0.008***	0.002	−0.028***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
New item dummy	0.023***	0.018***		0.021***	0.016***	0.017	0.051***
	(0.005)	(0.004)		(0.005)	(0.005)	(0.013)	(0.013)
log(seller rating)	0.007***	0.010***			0.015***	0.029***	0.041***
	(0.002)	(0.002)			(0.002)	(0.006)	(0.005)
log(seller DVDs in 2002)	0.000	−0.000			−0.003**	−0.006*	−0.007**
	(0.001)	(0.001)			(0.001)	(0.004)	(0.003)
eBay store dummy	−0.018*	−0.018***			−0.025***	−0.069***	−0.059**
	(0.010)	(0.009)			(0.012)	(0.024)	(0.025)
Current price dummies (df = 21)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Movie title fixed effects (df = 53)	Yes	Yes	No	Yes	Yes	Yes	Yes
Number of observations	26,580	26,580	26,580	26,580	26,580	10,051	13,826
Pseudo R^2	0.369	0.321	0.249	0.318	0.321	0.167	0.357

Notes. Entries in table are marginal effects from probit regressions (dF/dx) with bids as the unit of observation. Standard errors, clustered by auction, are reported in parentheses below parameter estimates. Starting price is the minimum first bid set by the seller. *Shipping amount* is set by seller and need not correspond to actual shipping costs. Observations for which shipping is unknown are dropped. *New items* are those that have the words "new," "wrapped," "sealed," or "never used" in the description. *Seller rating*: Sum of all 1, 0, −1 evaluations in previous seller transactions. log(*seller DVDs in* 2002) is the log of the total number of DVD auctions posted by seller between January and September of 2002. The eBay store dummy takes the value of one for sellers that have a special contractual agreement with eBay and zero otherwise. Current price corresponds to 21 dummies for rounded dollar amounts for the auction's current price (that is, the price after the bid of which the observation consists); dummies are used to avoid functional form assumptions. Column 2 shows the results from an instrumental variable regression, where the first stage is an OLS regression, where ln(number of existing bids + 1) is the dependent variable and starting price (sp) is the key instrument ($B_{sp} = -0.12^{***}$). Key independent variables are shown in bold.

*, **, ***Significant at the 10%, 5%, and 1% level, respectively.

"new" dummy), and column 5 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 estimated marginal effect for starting price is only mildly affected by the inclusion of observable heterogeneity, suggesting it is an unlikely alternative explanation.[5]

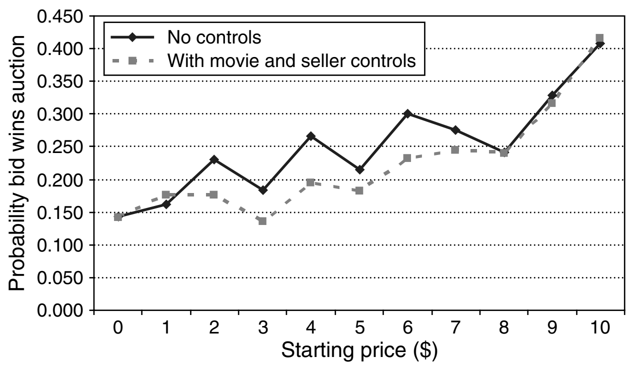
To further rule out the possibility that the significant influence of starting price reported in columns 3–5 is driven by the fact that only low starting price auctions were ever at low prices, column 6 reports the results from a regression run on bids placed on auctions that had already achieved a price of at least $10. Starting price remains negative and highly significant. Column 7 will be discussed in the alternative explanations section. In sum, both the pairwise comparisons and the regression analyses of all bids find evidence that is consistent with Prediction 1.

One way to think of the regressions just presented is that we are estimating a reduced-form instrumental variable (IV) regression, where starting price is instrumenting for number of existing bids. With this in mind, we report in column 2 of Table 2 the actual IV estimates, where starting price was employed in a first stage to obtain a predicted number of existing bids. The marginal effect for existing bids in the second stage ($dF/dx = 0.107$, $p < 0.0001$) is roughly 74% of the marginal effect from the standard probit regression reported in column 1, suggesting—although relying on a few functional form assumptions—that bidders respond about 74% as strongly to changes in number of existing bids that are driven by differences in starting prices as they do for those driven by any cause.[6]

[5] If current price is controlled for with a linear term, similar results are obtained ($dF/dX = -0.020$; $p < 0.0001$).

[6] If one estimates the regression with *both* starting price and number of existing bids as predictors, the point estimate for starting

Figure 7 **Probability a Bid for $10 Wins an Auction, as a Function of Its Starting Price, With and Without Controls for Movie and Seller Characteristics**



Notes. Starting prices have been rounded to the closest integer to facilitate visual comparisons. The line without controls corresponds to the actual relative frequencies in the data, whereas the line with controls corresponds to point estimates in a linear probability model that includes controls for all observables, plus a constant to facilitate visual comparison.

3.4. 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. 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 data set.

3.4.1. Comparison of $10 Bids Across Auctions. Figure 7 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 line without controls plots relative frequencies 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%.[7]

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 with the line without controls.

The results presented on Figure 7 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 started at $10. The similarity of both lines suggests that heterogeneity across auctions with different starting prices is not what is behind the relationship between probability of winning an auction and starting price.

3.4.2. Probit 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 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 3 (marginal effects). 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 estimated impact of starting price is positive and significant across all specifications. Comparing the results 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. 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 receive low-value bids, column 4 restricts the analysis to bids for $10 or more.

3.5. 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. The key controls are the current price at the time the bid was placed and the dollar amount of the bid. The results are presented in Table 4.

Column 1 in Table 4 presents the regression estimates controlling only for dollar amount of bid, minutes left in the auction when the bid was placed,

price becomes positive (and significant), consistent with the notion that the effect of starting price is mediated by number of bids. Controlling for starting price, the point estimate for number of bids remains positive and significant.

[7] 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 because 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.

Table 3 Probit Regression Assessing Impact of Starting Price on Probability of Winning Auction with Bid of a Given $ Amount (Marginal Effects)

	1	2	3	4
	No controls	With movie controls	With seller controls	Only bids for $10 or more
Dependent variable: one if bid won the auction, zero otherwise				
Starting price	**0.009*****	**0.009*****	**0.008*****	**0.016*****
	(**0.001**)	(**0.001**)	(**0.001**)	(**0.002**)
log(minutes left in auction when bid is placed +1)	−0.036***	−0.027***	−0.026***	−0.052***
	(0.001)	(0.001)	(0.001)	(0.002)
Shipping charges	0.001	0.009***	0.009***	0.008
	(0.002)	(0.002)	(0.002)	(0.006)
New item dummy		−0.022***	−0.018***	−0.024*
		(0.004)	(0.004)	(0.013)
log(seller rating)			−0.004**	−0.007
			(0.002)	(0.005)
log(seller DVDs in 2002)			−0.003***	−0.008**
			(0.001)	(0.003)
eBay store dummy			0.009	0.036
			(0.009)	(0.022)
Dollar amount of bid dummies (df = 21)	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

Notes. Entries in table are marginal effects from a probit regression (dF/dx) with bids as the unit of observation. Standard errors, clustered by auction, are reported in parentheses below parameter estimates. Starting price is the minimum first bid set by the seller. *Shipping amount* is set by seller and need not correspond to actual shipping costs. Observations for which shipping is unknown are dropped. *New items* are those that have the words "new," "wrapped," "sealed," or "never used" in the description. *Seller rating*: Sum of all 1, 0, −1 evaluations in previous eBay transactions. *Seller experience* is the total number of DVD auctions posted between January and September of 2002. The eBay store dummy takes the value of one for sellers that have a special contractual agreement with eBay and zero otherwise. Dollar amount of bid corresponds to 21 dummies for rounded dollar amounts for the amount that was bid (this is not the amount displayed to other bidders, but the proxy bid, i.e., the actual maximum amount the bidders has expressed a willingness to pay). Dummies are used to avoid functional form assumptions. Movie title fixed effects are 53 dummies, controlling for the 54 different movie titles in the sample. Column 4 drops observations corresponding to auctions at a rounded current price of $10 or less in light of the fact that only low starting price auctions are ever at a price below $10 (the highest starting price in the sample). Key independent variables are shown in bold.

*, **, ***Significant at the 10%, 5%, and 1% level, respectively.

and current price when bid was placed. Column 2 adds movie controls, column 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 the starting price.

The effect size is moderate, especially 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 is 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).

Table 4 OLS Regression Assessing Impact of Starting Price on Price Paid by Winner

	1	2	3	4
	Only bid controls	Adds movie controls	Adds seller controls	Adds shipping charges[a]
Dependent variable: Final price paid (in $)				
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 +1)	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 item dummy	—	0.093***	0.092***	0.083***
	—	(0.025)	(0.025)	(0.030)
log(seller DVDs in 2002)	—	—	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

Notes. Entries in table are point estimates of OLS regressions with auctions as the unit of observation. Standard errors are reported in parentheses below parameter estimates. Unsold auctions are dropped from the sample. The dependent variable is the amount paid by the highest bidder. *Dollar amount* of bid is the highest amount the bidder authorized eBay's automatic bidding process to bid in her behalf (the *proxy* bid). *Shipping amount* is set by seller; observations for which shipping is unknown are dropped when shipping is added to the regression. *New items* are those that have the words "new," "wrapped," "sealed," or "never used" in the description. *Seller rating*: Sum of all 1, 0, −1 evaluations in previous eBay transactions. *Seller experience* is the total number of DVD auctions posted between January and September of 2002. The eBay store dummy takes the value of one for sellers that have a special contractual agreement with eBay and zero otherwise. Movie title fixed effects are 53 dummies, controlling for the 54 different movie titles in the sample. Key independent variables are shown in bold.

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

*, **, ***Significant at the 10%, 5%, and 1% level, respectively.

3.6. The Role of Bidder Experience

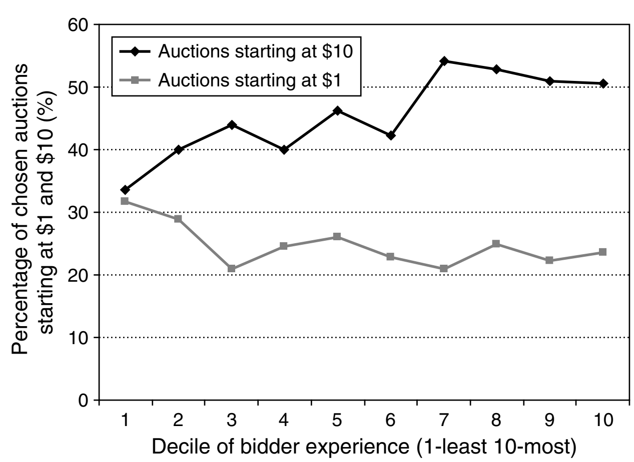
If the behavior of bidders that leads to the previous findings is a mistake, as we posit, then bidders may learn not to interpret bids that result from lower starting prices as informative, and hence avoid low starting price auctions once they catch up in price with higher starting price ones.

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 from whom they have purchased. 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 lowest decile has an average rating of 1.27, and the highest of 651.3.

To intuitively assess the role of experience, we compared the auctions on which bidders with different amounts of experience chose to bid. 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 8.

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 8 Relationship Between Bidder Experience and the Starting Price of Auctions Where Bidders Place Bids, Among Auctions Currently at $10



Notes. Calculations for this figure were conducted on the subset of bids placed on auctions with a current price of (rounded) $10. The figure depicts, for each decile of bidder experience (proxied by eBay's reputation score), the percentage of such bids placed on auctions that started at (rounded) $1 and at (rounded) $10.

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, $\beta = 0.020$, $p < 0.0001$.

It is worth noting that although both Figure 8 and this regression present evidence consistent with experienced bidders preferring higher starting price auctions, 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 auctions, and a selection one, where bidders who chose low starting price auctions are less likely to come back to eBay.

3.7. Are Sellers Best Responding to the Herding Behavior of Bidders?—Prediction 3

Sellers seem to at least partially recognize bidders' nonrational herding given the high share of below-cost starting prices in the data. Recall that lowering the starting price of an auction, however, has not only the potential benefit of increasing its final price, but also the potential downside of selling at a loss (Figure 4 nicely captures this trade-off). In equilibrium, these two forces should be of the same magnitude in the margin. To examine this empirically, one needs to compare expected *revenues* associated with low and high starting prices. Revenues differ from prices because eBay charges listing fees, which sellers must repay if their item must be listed more than once before it sells.

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 would lead to higher expected revenues they would not have 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 a second listing for free; if on a second instance the item does not sell, the seller must pay for each listing after that. Therefore if an item is listed either once or twice before selling, the seller pays the listing fee once, but if the item is listed three or more times before it sells, the sellers pays this fee 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 $0.10 more than auctions starting at $1. 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 3(b)). 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. Importantly, although these results are consistent with sellers optimally best responding to the nonrational behavior of buyers, we lack direct evidence of what is driving their choices of starting prices or the relative popularity of different starting prices.

Nevertheless, independent of the mechanism by which the seller side of the market has achieved equilibrium, the fact that it has highlights an important point we make in this paper. Market forces eliminate the *rents* associated with exploiting nonrational herding (i.e., with setting a low starting price), but they do not necessarily eliminate the nonrational behavior per se. Indeed, setting a starting price of $1 is not dominated by a starting price of $10 *because* bidders continue to engage in nonrational herding.

4. Alternative Explanations

Our interpretation of the evidence presented above is that bidders engage in nonrational 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: (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 those of high starting price ones.

4.1. 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 versus used, reputation of the seller, experience of the seller, shipping charges, and whether the seller 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*: 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 toward 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 2–4 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, than inexperienced bidders (see Figure 8). The fact that experience diminishes bidders' tendencies to choose low starting price auctions is consistent with such a tendency being caused by a mistake (nonrational 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.

4.2. Attachment

The second alternative explanation we consider is that bidders who bid early 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 and Simonson 2003, Ku et al. 2005), or of a pseudoendowment effect (Dodonova and Khoroshilov 2005, Heyman et al. 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, whereas—on the other extreme—if attachment plays no role at all, the point estimate should remain unchanged. The relative drop in the impact of starting price, therefore, provides an estimate of the relative importance of attachment (in our data).

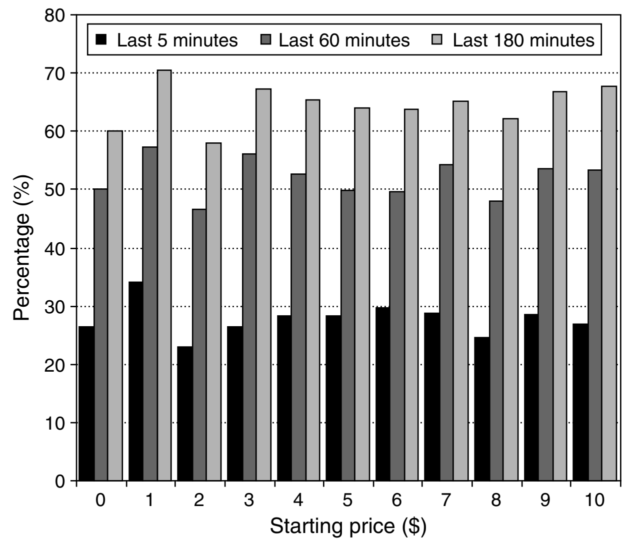
The results from this regression are presented in column 7 in Table 2; the point estimate for starting price in this column, where repeat bidders are excluded, is virtually identical to the point estimate in column 4, where they are included. Although this does not necessarily rule out attachment as a real phenomenon, it suggests it is not behind the reported tendency for preferring low starting price auctions.

4.3. 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 §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 snipers* 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 expect, 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 in which to participate. 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

Figure 9 **Percentage of Bids Placed Toward the End of the Auctioning Period**



of the results is that low starting price auctions should receive more last-minute bids. Figure 9 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.

5. Conclusions

Before making decisions, people often observe the decisions of other before them. Existing research on sequential decision making has assumed away any difficulty in making unbiased inferences from observed decisions. In this paper, we propose that the fact that people underattend to nonsalient factors can lead to biased inferences. Investors may imitate investing decisions made for idiosyncratic reasons; restaurant patrons may enter a busier restaurant expecting higher quality, when in reality the crowd is a signal of no-longer-available happy-hour prices; and a new employer may hire a job applicant leaving a prestigious institution, neglecting the role that prior job market conditions had on securing such position in the first place.

We have presented evidence consistent with herding behind nondiagnostic decisions in the context of eBay auctions, where starting prices—which are not saliently displayed—influence the number of bids an auction accumulates independently of the auctioned item's quality. We find that bidders not only herd behind nondiagnostic bids arising from lower starting prices, but also that they suffer negative consequences from doing so, because they pay higher prices and are less likely to win the auctions on which they bid.

Interestingly, enough sellers lower the starting price of their auctions for the seller side of the market to be in equilibrium.

In addition to providing an explanation for the otherwise puzzling prevalence of below-cost starting prices in online auctions, and to enriching our understanding of how bidders choose auctions, our findings might be generalized to domains other than online auctions. As the examples with investors, restaurant patrons, and employers demonstrate, settings in which decision makers observe previous decisions are ubiquitous. If observers neglect the role of (currently) nonsalient factors on previous decisions, then they will make erroneous inferences and make suboptimal decisions.

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 (i) that behavioral biases can be observed even after market forces have played their part, and (ii) that in order to understand the rational behavior of firms one must first understand the not necessarily rational behavior of consumers to whom they are responding.

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