Nonstandard Bidder Behavior in Real-World Auctions

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Empirical work on auctions has found that bidders deviate from standard behavior in important ways. We investigate a range of these behaviors, including nonrational herding, auction fever, quasi-endowment effect, and escalation of commitment. Our innovations are to more completely control for unobservables by using new data from a field experiment on eBay, and by accounting for censoring of bids below the starting price. Consistent with standard auction theory and in contrast to the predictions of the nonstandard behaviors, we find that auction starting price has no effect on bidder willingness to pay in a private-values setting. We conclude that there is little evidence that these nonstandard behaviors are important in the field.

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1. INTRODUCTION

Early laboratory studies of auctions by Kagel, Harstad, and Levin (1987) and Kagel and Levin (1993) found that bidders deviate from standard rational behavior in significant ways. In first-price auctions, overbidding by bidders quickly dissipated with experience. But in second-price auctions, overbidding was significant and persistent. Subsequent laboratory studies of second-price auctions by Harstad (2000), Cooper and Fang (2008), and Garratt, Walker, and Wooders (2011) found that bidders that gained certain types of auction experience subsequently performed closer to the standard model. These results suggest that bidders may sometimes exhibit bounded rationality and perhaps nonstandard preferences, but also that bidders may learn to avoid these behaviors with experience.

Key questions in this literature are if and how bidders deviate from standard behavior in real-world auctions.1 Because most real-world bidders may have significant experience (e.g., on eBay, bidders in the lowest quartile of experience have bid in dozens of auctions), one might expect less nonstandard behavior in the field than the laboratory.2 In this study, we provide new evidence from eBay on whether bidders in real-world auctions exhibit nonstandard behavior.3 Following previous work, we test for nonstandard behavior by estimating the effect of auction starting price on bidder willingness to pay, and so a second aim of the paper is to provide new evidence on the causal effect of starting price on bidder willingness to pay.

We examine the main nonstandard behaviors that researchers have used to explain overbidding in second-price auctions, including (1) “nonrational herding” (Simonsohn and Ariely 2008), whereby bidders prefer auctions with more previous bids despite these bids providing no valuable information; (2) “auction fever,” which is the excitement from competition that causes bidders to bid beyond their initial valuations; (3) “quasi-endowment effect” (Heyman, Orhun, and Ariely 2004), which is similar to the traditional endowment effect; and (4) “escalation of commitment” (e.g., Ku, Malhotra, and Murnighan 2005), where bidders

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1 We will use the term “standard behavior” to refer to what is predicted for a utility-maximizing bidder under traditional assumptions about rational preferences, and “nonstandard behavior” to refer to deviations from this.
2 There is evidence that individuals in real-world settings sometimes learn to avoid behavioral biases with experience (e.g., List 2003), and that bidder performance in real-world first-price auctions improves with experience (Pownall and Wolk 2013).
3 eBay uses a modified ascending second-price auction and is the largest consumer auction platform in the world. Bajari and Hortacsu (2004), Ockenfels, Reiley, and Sadrieh (2007), and Hasker and Sickles (2010) survey the literature on eBay and provide more detail about the platform.
may overbid in order to self-justify the sunk cost of the time and effort they have already committed. We will collectively refer to these behaviors as “bidder effects.”

Previous work has tested for bidder effects by estimating the effect of starting price on auction outcomes. The idea is that under bidder effects an auction with a low starting price (an “LSPA”), all else equal, will accumulate more bids as it is bid up to a high standing price compared to an auction with a high starting price (an “HSPA”); these extra bids will then trigger more activity at high standing prices. For example, because LSPAs have received more bids by the time they reach a given standing price compared to HSPAs, nonrational herding would cause new bidders to favor LSPAs. In contrast, in a standard private-values auction model, bidding activity at a given standing price is generally unrelated to starting price. We use this distinguishing prediction to test for bidder effects.

Previous estimates of starting-price effects in online second-price auctions have varied widely. Ariely and Simonson (2003) and Haubl and Popkowski Leszczyc (2003) found positive effects; Kamins, Dreze, and Folkes (2004), Ku, Galinsky, and Murnighan (2006), and Simonsohn and Ariely (2008) found negative effects; and Lucking-Reiley, Bryan, Prasad, and Reeves (2007) and Einav, Kuchler, Levin, and Sundaresan (2015) found mixed or no effects. We will comment on these results in Section 6, but for now we note the lack of consensus regarding the effects of starting price.

We approach the question of starting-price effects by analyzing data from a natural field experiment in which we sold 420 new movie-DVDs on eBay in matched pairs of simultaneous auctions. The matched auctions were identical except that one had a low starting price of $0.99 (the LSPA) and the other had a high starting price, which averaged $6.84 (the HSPA). By using new movie-DVDs, a standardized product for which buyers have private values, we avoid the possibility that buyers learn about product value from the seller’s choice of starting price or from competing bidders’ behavior. By employing variation in starting prices within matched auctions, we ensure that starting price is uncorrelated with unmeasured determinants of demand.\(^4\)

We estimate the causal effect of starting price on bidder willingness to pay by comparing the distributions over ending prices, including specific moments of the distributions, between the LSPAs and HSPAs. We find the two to be virtually identical, and hence we find no evidence of

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\(^4\) Note that we are not the first to use a matched-pair experiment on eBay. Others, with different objectives, include Katkar and Reiley (2006) and Hossain and Morgan (2006).
bidders. In other words, we find that starting price has no effect on bidder willingness to pay in a private-values auction setting.

An emerging empirical approach in economics is to use different types of experimental data together to infer the generalizability of a result (e.g., List 2006). In a similar spirit, we pair our experimental data with a new observational data set that we collected from eBay. The value of using experimental randomization to support a causal interpretation of an observation finding is well known. However, observational data can be used to test an experimental finding as well. In our case, the randomization of one factor, starting price, holding constant all other factors, isolates the causal effect of starting price. However, this key experimental feature – the controlled randomized variation – itself could introduce artificiality into the field setting. For example, bidders might view the presence of simultaneous auctions that are identical except for starting price as peculiar. With our observational data, we are able to closely reproduce our experimental findings, thereby providing support that our results are not an artifact of our experimental design. We believe our approach of combining experimental and observational data may be more widely useful.

We also note the closely related study of Schneider (forthcoming), which we view as a companion to the current article. That study examined another recent finding of nonstandard bidder behavior on eBay, providing evidence that the nonrational limited-attention result in Malmendier and Lee (2011), in which auction ending price often exceed fixed-price alternatives, can also readily be explained within the standard framework.

We view the current paper as making two contributions. First, it provides what we believe is particularly clean evidence that starting price does not affect bidder willingness to pay in a private-values setting. Second, it helps to reframe the existing literature on bidder behavior. The idle reader of the literature might be under the impression that the outcomes of real-world auctions are driven by a multitude of behavioral biases. We believe this impression would not be justified based on the currently available evidence. This is of course not the same as saying that bidders strictly conform to standard behavior, and we are not suggesting this is the case. Indeed, insights from psychology and related fields have been important for understanding consumer behavior in many settings (DellaVigna 2009), and auctions may ultimately be no different. Nevertheless, we see little evidence that nonstandard behavior is important in real-world auctions
based on our analysis of eBay DVD auctions and our review of previous work on overbidding in the field setting.

Finally, while we have examined one auction market (eBay) and one product (new movie-DVDs), we believe our results can be viewed together with Lucking-Reiley et al. (2007) and Einav et al. (2015) for a more complete picture about starting-price effects. Lucking-Reiley et al. (2007) found no starting-price effects in coin auctions where coin characteristics and quality were well defined, while Einav et al. (2015) found mixed but generally limited starting-price effects in aggregate across a wide range of products on eBay. While these studies used observational data, the general consistency suggests that our results may generalize beyond new movie-DVDs. We discuss broader inferences in Section 6.

2. STARTING-PRICE EFFECTS UNDER STANDARD AND NONSTANDARD BEHAVIOR

Our analysis aims to identify the causal effect of starting price (i.e., a visible reserve price) on bidder willingness to pay. This is a basic question of auction design and can shed light on whether bidders exhibit nonstandard behavior. We now describe the predicted effects of starting price under standard auction theory and under the nonstandard behaviors.

A) Predictions of standard auction theory

In ascending-price auctions with independent private values, standard auction theory tells us that starting price does not affect bidder willingness to pay.\(^5\) Of course, a higher starting price leads to a higher ending price conditional on sale. But starting price is not predicted to affect ending price conditional on LSPAs and HSPAs exceeding the high starting price, which is the censoring point. We discuss this further in Section 4.

The starting-price predictions are less clear in the common-values setting – where bidders have incomplete and heterogeneous information about product value, including when resale is a significant consideration. In the common-values setting, bidders must account for the winner’s curse in formulating their strategy. This concern is mitigated somewhat in an ascending-price auction because bidders in this setting gain information about product value from the behavior of other bidders (Milgrom and Weber 1981).\(^6\) This extra information limits potential loss due to the

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\(^5\) See Riley and Samuelson (1981) for this result concerning independent auctions and Peters and Severinov (2006) for competing (simultaneous) auctions.

\(^6\) There are differences between the stylized ascending-price auction modeled in Milgrom and Weber (1982) and the auction format employed by eBay, which further complicates the starting-price predictions under common-values.
winner’s curse, allowing bidders to bid more aggressively. Because LSPAs allow for more bidding activity and hence more information than HSPAs, LSPAs may have more active bidding at any standing price above the high starting price.

On the other hand, Milgrom and Weber (1982) showed that in a common-values setting, expected ending prices of HSPAs conditional on sale may be inflated relative to LSPAs because HSPAs have a higher “screening level.” A screening level is the lowest valuation such that a bidder with that valuation would bid at the starting price when no other bidders have bid. The screening level strictly exceeds the starting price because a rational bidder, upon winning the auction at the starting price and realizing that all other potential buyers had lower valuations, revises his own valuation downward. Therefore, conditional on the ending prices of LSPAs and HSPAs both exceeding the high starting price, the ending prices of HSPAs must exceed the screening level, while the ending prices of LSPAs need not.

Furthermore, when sellers have private information about product value and bidders have private signals of this common value, Cai, Riley, and Ye (2007) showed that sellers can signal higher value via a higher public reserve price. This would cause HSPAs to outperform LSPAs. The reason is that sellers with higher private-use values of the product have a lower cost of failing to sell the item, which permits them to set a higher reserve price. This signaling is less relevant when failed auctions can quickly and easily be relisted, as in the case of new movie-DVDs, because sellers would typically just relist the item rather than use it privately. But this signaling may apply to sellers with other selling channels (e.g., brick-and-mortar stores), as the “private use” of a higher value product may be selling the item for a higher price through this other channel.

In summary, under private values, starting price has no effect on bidder willingness to pay. In contrast, under common values, the information, screening, and signaling effects may all act in different directions, leading to an ambiguous overall prediction. For this reason, we will analyze private-values auctions (i.e., new movie-DVDs), for which standard auction theory gives the clear prediction that starting price does not affect bidder willingness to pay.

B) Nonstandard behaviors

We consider the four nonstandard behaviors (“bidder effects”) that have previously been examined using starting-price tests. Under “nonrational herding” (Simonsohn and Ariely 2008), bidders infer than an auction has higher unobserved quality if it has received more bids. The
herding is considered nonrational when the higher number of bids at a given standing price is due to a lower starting price, rather than higher quality. “Auction fever” is the excitement from competition that causes bidders to bid beyond their initial willingness to pay. As in the survey by Ockenfels, Reiley, and Sadrieh (2007), we use the term “auction fever” to encompass several similar behaviors from different studies, including “bidding frenzy” (Haubl and Popkowski Leszczyc 2004), “opponent effects” (Heyman et al. 2004), and “joy of winning” (e.g., Cooper and Fang 2008).

The “quasi-endowment effect” (Heyman et al. 2004) is related to the endowment effect (Thaler 1980), whereby buyers develop a sense of ownership and increase their valuation for the item while bidding, even without owning the item. Heyman et al. (2004) proposed that, “the greater amount of time that bidders are involved with an auction, the more their sense of ownership will increase. We also hypothesize that this effect will be exacerbated by the amount of time that a bidder is actually in the lead.” “Escalation of commitment” (Ku et al. 2005) is related to the “sunk-cost effect” (Thaler 1980) and arises when buyers overbid in order to win the auction so as to justify the sunk cost of their participation. Winning is a “self-justification that helps preserve a positive self-image.”

The bidder effects give a common prediction: Because LSPAs mechanically accumulate more bids and bidders by the time they reach the starting price in the HSPA, LSPAs will receive more future bids conditional on standing price than HSPAs. Specifically, under nonrational herding, because LSPAs have received more bids upon reaching a given standing price than HSPAs, subsequent bidders will favor the LSPA. The logic for auction fever is noted in Ockenfels et al. (2007): “Since auction fever supposedly derives from the thrill of competition, one might reasonably expect the effect to increase with the number of active bidders” and “may explain why some auctioneers prefer a low minimum bid,” which “would attract as many bidders as possible, in an attempt to promote auction fever.” Likewise, because LSPAs receive bids earlier in the auction period, bidders in LSPAs have participated in the auction for longer than

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7 Once an auction has begun, number of bids is saliently displayed in eBay search results, while starting price is not. Note that this prediction is only valid in a private-values setting for the reasons discussed in the previous subsection.
8 “Competitive arousal” (Ku et al. 2005) is related to auction fever, but the authors argued that the effect is stronger in offline auctions due to the live audience. Similarly, “spite” (Morgan, Steiglitz, and Reis 2003) causes buyers to receive disutility from other buyers’ surplus, which may cause overbidding. As modeled however spite is insensitive to the number of bidders beyond two for a setting like eBay. Thus our tests do not apply.
bidders in HSPAs. It follows that bidders in LSPAs are more likely to bid again when they are outbid under the quasi-endowment effect and escalation of commitment.⁹

In summary, in a private-values setting, standard auction theory predicts no effect of starting price on bidder willingness to pay, while the bidder effects predict a negative effect. In a common-values setting, however, the starting-price predictions are generally ambiguous and are less useful for identifying nonstandard behavior.

3. EXPERIMENTAL PROCEDURES AND DATA

We aim to estimate the effect of starting price on buyer willingness to pay. Because theoretical work predicts that a seller’s choice of starting price depends on expected demand (Riley and Samuelson 1981, Adams 2010, Virag 2010), identifying the causal effect of starting price hinges on controlling for this demand. While it will be easy to control for some determinants of demand (e.g., shipping method), it may not be for others (e.g., listing title wording). Table 1 shows a regression of starting price on auction and product characteristics using observational data of eBay auctions for movie-DVDs (the data are described below). It shows clearly that characteristics indicating higher quality are associated with higher starting price. It also shows that auctions with more competing auctions have lower starting prices. Therefore, naturally occurring starting prices that appear in observational data may be correlated with demand, and represents a significant identification risk.

To obtain exogenous variation in starting prices, we run a field experiment on eBay in which we conducted 420 auctions for new movie-DVDs from July 13 to August 22, 2007. We chose 21 movies titles from Billboard magazine’s bestseller list from June 2007. We auctioned new DVDs of each title in pairs of auctions, one with a $0.99 starting price (the LSPA) and one with a higher starting price (the HSPA). Twenty-one auction pairs, one for each movie title, began simultaneously as a cohort and ended 72 hours later. The experiment consisted of 10 such non-overlapping cohorts. All auctions had the same seller (us), the same layout and wording, a $3.00 shipping fee, and were for the regular editions of the DVD. We set the high starting price to be the mean ending price among new and used DVDs for that title from the previous week.

⁹ Kamins et al. (2004) proposed that higher starting prices might increase bidder willingness to pay by acting as a reference price. This would act in the opposite direction as the bidder effects. However, they find no evidence of this effect, and the product we examine (new movie-DVD) has a known quality and outside price.
(reported by eBay) plus a small increment.\footnote{The small increment is 10 and 25 percent in the first and second five cohorts, respectively, rounded to the nearest 25 cents. This change in markup had little effect on the probability of sale because the average price reported by eBay includes used DVDs, but we sold only new DVDs, and hence most of our auctions resulted in sale.} Table 2 reports the movie titles and starting and ending prices.

We chose new movie-DVDs because they are commodities and stated in the listing title that the DVD was new and sealed in original shrink-wrap in order to avoid any quality uncertainty and to ensure a private-values setting. It is also important that the matched auctions ran simultaneously because demand conditions can change significantly over time. For example, movie DVDs have the highest demand after initial release, and demand typically varies by day-of-week and time-of-day for more idiosyncratic reasons. Comparing simultaneous auctions controls for the composition of buyers that happen to be on eBay at a given time. In Section 5, we discuss the question of how buyers may react to seeing simultaneous identical auctions.

We complement our experimental analysis with observational data that we collected from eBay using a Java query tool that we created. We collected data on all eBay auctions that were active between September 5 and November 4, 2008 for DVDs of 17 movie titles from Billboard magazine’s bestseller list from August and September 2008.\footnote{During the sample period, eBay expanded the condition choices from “New” and “Used” to five choices from “Brand New” to “Acceptable.” We reclassify the five choices to “New” and “Used” for consistency.} As in previous work, we use buyer and seller feedback scores to measure experience. We identify the movie DVD versions (e.g., special edition) by visually inspecting all listing titles.\footnote{Following some previous work (e.g., Simonsohn and Ariely 2008), we exclude HD-DVD and Blu-ray DVDs because we will be reproducing some of this previous work in the Appendix. We also exclude the small number of auctions with a reserve price, a starting price or shipping fee above $10.49 (the cutoff in Simonsohn and Ariely 2008), multiple DVDs, bidders who set their identities to private, which conceals bidding activity, and a “Buy-It-Now” (BIN) option that was exercised (this format is distinct from a BIN listing that is not part of an auction).} Our observational data set contains 2,978 auctions, of which 1,922 resulted in sale. The mean starting price is $2.24 (58 percent have a starting price of 99 cents or less), and the mean ending price is $5.20 excluding shipping fees and $8.44 including shipping fees. Table 3 reports additional statistics.

\section*{4. EFFECT OF STARTING PRICE ON BIDDER WILLINGNESS TO PAY}

\subsection*{A) Censoring problem}

In a model of a single ascending or second-price auction under standard behavior, the ending price represents the second-highest valuation among potential buyers that are present at the auction (Vickrey 1961). For competing ascending second-price auctions, as on eBay, the
ending price may not reach the second-highest valuation because the competing auction or fixed-price alternative may place an upper bound on buyer willingness to pay (e.g., Peters and Severinov 2006, Backus, Podwol, and Schneider 2014). Therefore, we can think of ending price in our setting as the second-highest willingness to pay rather than the second-highest valuation among potential buyers. There is an exception when only one buyer has bid in the auction. In this case, the ending price is the starting price and exceeds the second-highest willingness to pay.

There is a censoring problem regarding willingness to pay. Let $S$ be starting price, $P^*$ be the second-highest willingness to pay, and $P$ be the observed ending price of an auction. Then $P^*$ is observed and equal to $P$ when at least two buyers have bid in the auction. Because the bidding rules on eBay require that the second bid (and further bids) exceed the standing price by at least a minimum bid increment, $b$, we know that $P^* \geq S + b$ when an auction has received bids from at least two buyers – i.e., whenever $P^*$ is not censored. But when only one buyer has bid in the auction, $P^*$ is left censored at $S + b$. We know this because the highest willingness to pay must have been at least $S$, and the second-highest willingness to pay must have been less than $S + b$. When the auction fails to sell, then the highest willingness to pay must have been less than $S$, causing $P^*$ to be left censored at $S$.

As discussed in Section 2, under private values, a defining prediction of the bidder effects is a negative relationship between $S$ and $P^*$. In contrast, the standard model predicts no relationship between $S$ and $P^*$. Therefore, we test for bidder effects by estimating the relationship between $S$ and $P^*$ in a private-values setting. When naively estimating the effect of $S$ on $P^*$ by OLS, the censoring mentioned above positively biases the starting-price estimate. This is because $P^*$ is only observed for HSPAs when latent demand is high enough to cause $P^* \geq S + b$. In contrast, $P^*$ is more often observed for LSPAs because $P^*$ more often exceeds the low starting price. We address this problem in several ways, discussed in the subsections below.

B) Nonparametric estimation

In the context of our experiment, let $\{S_L, S_H\}, \{P^*_L, P^*_H\}$, and $\{P_L, P_H\}$ be the starting prices, second-highest willingness to pay, and ending prices of the LSPAs and HSPAs, respectively. Consider the HSPA censoring point, $S_H + b$. Bidder effects predict that within a matched pair, $\Pr[P^*_L \geq S_H + b] > \Pr[P^*_H \geq S_H + b]$, while the standard model predicts that $\Pr[P^*_L \geq S_H + b] = \Pr[P^*_H \geq S_H + b]$. This test is appealing because we observe whether $P^* \geq S_H + b$ for all auctions. We find the two to be nearly identical: 84 of 210 (40.0 percent) of LSPAs reach the
HSPA censoring point, while 82 of 210 (39.0 percent) of HSPAs do so (the p-value of the difference is 0.84).

For a more complete picture of the distributions over \( P_L^* \) and \( P_H^* \), the top panel of Figure 1 shows survivor functions representing the fractions of LSPAs and HSPAs for which \( P \) is at least the indicated amount. Focusing on values meeting the HSPA censoring condition \( (P = P^* \geq S_H + b) \), the distributions over \( P_L^* \) and \( P_H^* \) are nearly identical. The bottom panel of Figure 1 contains the standard errors of the survivor functions, showing no statistical difference between the curves at any point of the uncensored region. Furthermore, a two-sided Kolmogorov-Smirnov test fails to reject the hypothesis that \( P_L^* \) and \( P_H^* \) are drawn from the same distribution \( (p=0.55) \). In summary, the observed values of \( P^* \) show no evidence that LSPAs outperform HSPAs.

We next estimate \( E(P_L^* - P_H^*) \) among the 51 matched pairs where \( P_L^* \) and \( P_H^* \) are observed (i.e., equal to \( P_L \) and \( P_H \)). Bidder effects predict that \( E(P_L^* - P_H^*) > 0 \) for this group, while the standard model predicts \( E(P_L^* - P_H^*) = 0 \). We find that the mean of \( P_L - P_H = -$0.40 (p=0.34) \), providing no evidence of bidder effects. We next examine the 90 matched pairs for which the HSPA had one bidder and an ending price of \( S_H \), and the 38 matched pairs for which the HSPA had zero bidders and failed to sell. As mentioned, in the first case, \( P_H^* \) is censored at \( S_H + b \), and in the second case, \( P_H^* \) is censored at \( S_H \). Therefore, we expect the mean of \( P_L^* \), which is not subject to censoring (all of the LSPAs have \( P_L^* \geq S_L + b \)), to be less than the HSPA censoring points. Indeed, for pairs where the HSPA had one bidder, the mean of \( P_L^* - (S_H + b) = -$0.73 (p<0.01) \). For pairs where the HSPA failed to sell, the mean of \( P_L^* - S_H = -$1.15 (p<0.01) \).

In summary, we find that (1) the masses of the distributions over \( P_L^* \) and \( P_H^* \) below the censoring point (the left tails) are approximately equal; (2) the distributions over \( P_L^* \) and \( P_H^* \) for values meeting the HSPA censoring condition (the right tails) are nearly identical; (3) the means of \( P_L^* \) and \( P_H^* \) among pairs that meet the censoring condition are not statistically different; and (4) the mean of \( P_L^* \) is significantly below the censoring points for pairs where the HSPA is censored.

C) Parametric estimation

A limitation of the nonparametric tests above is that they do not make full use of the available information – specifically, the survivor functions only use price thresholds and not actual prices, while the other tests do not use the censored cases. These are potentially interesting cases if we expect the bidder effects to be largest as the number of bidders increases from zero to one and one to two. For example, under nonrational herding, potential buyers may infer the
largest increase in quality upon the entry of the first or second bidder. By imposing parametric assumptions on the distribution over $P^*$, we can better use these censored observations.

We are interested in $E(P^*|S, X)$, where $X$ contains control variables. Columns 1 and 2 of Table 4 contain models estimated by OLS that do not account for censoring. As expected, the starting-price estimates are large and positive. Column 3 restricts the sample to auctions that meet the censoring condition, $P^* \geq S_H + b$, analogous to the comparison of mean ending prices in the previous subsection. The starting-price estimate is now close to zero, though still positive. Columns 4 and 5 account for censoring using a censored normal model, which is essentially a Tobit model that allows the censoring point to vary by observation. In these specifications, the starting-price effect disappears completely.\footnote{Note that the censored normal model assumes that selection and willingness to pay are determined by a common underlying process. In the Appendix, we show results from Heckman selection models that allow selection and willingness to pay to be determined by distinct processes. Results are similar. Also note that the censored normal model with matched-pair fixed effects in column 5 is subject to the incidental-parameters problem. However, the results in Greene (2004) suggest that this problem does not bias the estimates but just leads to understated standard errors. The results with movie-title fixed effects in column 4 are not subject to this concern.}

5. ANALYSIS OF ENDING PRICES USING OBSERVATIONAL DATA

Our experimental design involves the randomization of one factor, starting price, holding constant all other factors, in order to isolate the causal effect of starting price. But it is possible that this controlled randomization itself introduces artificiality into the field setting. One might wonder if the paired auctions are “too” similar in the sense that buyers would view them as interchangeable or peculiar in some way, and this might attenuate the bidder effects.

First, note that the auctions must be very similar in order to isolate the causal effect of starting price. It is also important for the auctions to be simultaneous because movie-DVD demand varies significantly over time, and fully controlling for this variation is very difficult. Regardless, we can provide direct support for our experimental design by reproducing our experimental findings with our observational data using auctions that are close but not identical, and hence are less subject to the concern that they are too similar.

We estimate the ending-price regression models from Section 4 using our observational data. We group together similar auctions and examine the effect of starting-price variation within these groups. We define groups according to movie-DVD version, new/used status, and auction end date. An example of a group is three new special-edition Batman Begins DVD auctions
ending on November 5, 2008. As discussed earlier, the starting-price variation in our observational data set is not due to experimental variation, and therefore could be correlated with uncaptured secondary factors that vary within groups, such as item description. Our purpose here is to provide support for our experimental design.

We reproduce the specifications in Table 4 using the observational data. Results are in Table 5. The first two columns do not address censoring and as expected the starting-price estimates are large and positive. In column 3, we limit the sample to auctions with ending prices that are at least the high starting price in the group plus the minimum bid (the censoring condition described in Section 4). The estimate is now approximately zero, showing no evidence of the bidder effects. In columns 4 and 5, we use the full data set, addressing censoring using a censored normal regression, and again the starting-price effect is approximately zero.

6. DISCUSSION OF PREVIOUS WORK

We now review previous work on the effects of starting price in ascending second-price auctions (primarily eBay). Our reading of this literature is that while much (though not all) of this work asserts the presence of nonstandard behavior, there is little actual support for this. Instead, the various empirical patterns can be explained by a combination of uncaptured unobservables, censoring, and a common-values component.

A) Estimated effect of starting price on ending price

Several previous studies examined the effect of starting price on ending price in online auctions. Using observational data, Ariely and Simonson (2003) found a large positive starting-price effect for football game ticket, while Ku, Galinsky, and Murnighan (2006) found a significant negative effect for Persian rugs and cameras. While these are interesting empirical patterns, they are difficult to interpret. For example, they did not account for censoring at the starting price or selection on the reserve price (see Bajari and Hortacsu 2003, p. 332-335, on this latter effect). The analyses also did not account for quality that was observable to buyers and sellers (e.g., football ticket seat location), which may positively bias the starting-price estimate due to the likely correlation between starting price and quality (e.g., as in Table 1).

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14 There is significant starting-price variation within groups: 82 percent of auctions are in groups with starting-price variation and the mean range of starting price in these groups is $4.98.

15 For example, Yin (2006) finds that eBay auctions with clearer descriptions have higher ending prices.
In online auction experiments, Haubl and Popkowski Leszczyc (2003) sold collectible stamps on eBay and found a positive starting-price effect, while Kamins et al. (2004) sold unsearched assortments of coins in manila envelopes on eBay and found that auctions with starting prices had lower ending prices compared to auctions without starting prices. Given the possible common-values component for stamps and unsorted coins, these results suggest a role for the signaling and information mechanisms discussed in Section 2.

Lucking-Reiley et al. (2007) examined eBay coin auctions using a large observational data set and found no starting-price effect after accounting for censoring. The characteristics of the coins in this study were clearly defined – specifically, Lucking-Reiley et al. (2007) examined auctions for single identified coins with published book values and clearly stated conditions, which suggests a private-values setting, as there is likely little informational in others’ bids once the book value is known. This may explain the difference in outcome from the unsearched-coins results in Kamins et al. (2004) above.

Finally, Einav et al. (2015) employed a creative new approach of using what they posited are eBay sellers’ own experiments with auction design to examine thousands of products. Specifically, they examined observational data where the same seller posted multiple listings with the same product category and listing titleSubtitle, with variation in only a few elements such as starting price. This approach is attractive because it permits a broad examination of products that generally would be infeasible with traditional experiments. The cost is to cede some control over the data generating process and identification. Einav et al. (2015) provides suggestive evidence about starting-price effects, showing mixed but generally little sign of a systematic starting-price effect (the most relevant result is Figure 4D). Figure 8 of that paper is also intriguing, providing starting-price effects by product category and showing widely disparate outcomes. Interestingly, products with more value uncertainty (e.g., memorabilia) have larger starting-price effects than products with more clearly defined values (e.g., DVDs and

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16 “Unsearched” means that the owner has not inspected the coins and removed the most valuable ones. One can imagine there being uncertainty over the types and the quality of unsearched coins as well as over the credibility of the seller’s claim that they have not been picked over.

17 For example, heterogeneity within seller experiments is apparent in Figure 1B of that paper, which shows that 12 of the golf clubs in the group are “regular” while 19 are “stiff.”
electronics). This suggests that the presence of common values is an important determinant of non-zero starting-price effects, as predicted theoretically (see Section 2A).\textsuperscript{18}

The biggest limitation of our own starting-price analysis is that we examine only one product category. But we believe there is value in viewing our paper together with these last two studies – specifically, the depth of our analysis provides a level of confidence in the zero starting-price effect in a private-values setting that is otherwise not available; while the limited effect that Einav et al. (2015) found across eBay overall suggests that this result may apply more broadly. Additionally, we view Lucking-Reiley et al. (2007) as the most careful previous study of starting-price effects in a (likely) private-values setting, which provides credible evidence for another product category. Our study builds on these findings by combining experimental and observational data in a setting that is clearly private values, allowing for a particularly clean test of nonstandard behavior. The general consistency across these studies suggests that our findings generalize beyond new movie-DVDs.

B) **Other tests**

Simonsohn and Ariely (2008) estimated the effect of starting price on the probability that an auction receives another bid using observational data on eBay auctions. Like our study, Simonsohn and Ariely (2008) focused on movie DVDs. They reported results from an additional-bid test where the unit of observation is the bid, and found a strong negative effect of starting price on the probability of another bid, inferring the presence of “nonrational herding.” We do not focus on the additional-bid test because it employs much of the same variation as our ending-price test and is subject to biases that have the potential to explain the negative starting-price effect reported in that paper. Using our data, we discuss and report results for this test in the Appendix, and show how unobservables can explain the negative estimate.

As noted earlier, Malmendier and Lee (2011) found that eBay auctions often exceed the fixed-price alternative that is available on the same website, and concluded that this outcome is “inconsistent with rational behavior.” We analyzed this finding in Schneider (forthcoming) and

\textsuperscript{18} For DVDs, Figure 8 of that paper shows that starting price has no effect on ending price conditional on sale, which implies a strong negative effect on willingness to pay. This is very different from our finding of no effect. However, the DVD category in Einav et al. (2015) includes both new and used DVDs, multi-unit lots, and other significant heterogeneity, and given the inherent quality uncertainty in this group, may contain a common-values component. Also, the auctions that were compared within a given seller experiment generally did not occur simultaneously, and temporal variation in supply and demand (likely correlated with starting price) is particularly acute for movie DVDs due to holiday shopping, movie release dates, and so on. Regardless, it highlights the complementary value of our controlled experiment.
found that this “overbidding” can readily be explained within a standard framework once we allow for the likely presence of traditional search costs. Similarly, Jones (2011) reported that 41 percent of eBay auctions for Amazon.com gift cards exceed the card’s face value and concluded that bidding fever best explains this result. While this is an intriguing result, there are additional patterns describing many or most winners of eBay gift-card auctions (not reported in that paper) that raise questions about this explanation: these buyers purchase almost exclusively gift cards, often do so dozens of times per month, and often pay above face value. Given this peculiar overall pattern, and the existing evidence that buyers quickly learn to avoid overbidding when the costs are apparent (e.g., Cooper and Fang 2008), bidding fever appears not to be a good fit. Internet forums suggest a number of rational explanations.

7. CONCLUDING REMARKS

We view the current results as providing the clearest evidence to date that starting price does not affect bidder willingness to pay in ascending-price auctions with private values in the field setting. We find no starting-price effect, and hence no evidence of nonstandard behavior associated with starting prices among eBay bidders. As mentioned, our conclusion is not that real-world auction participants strictly conform to standard behavior. We can only make inferences about the specific bidder effects that we examined, and there is some evidence that other nonstandard behaviors may be important. This includes competition neglect by sellers (Simonsohn 2011) and shipping-fee neglect by bidders (Hossain and Morgan 2006). We have also only reported results for one product category (new movie-DVDs) on one platform (eBay). eBay and eBay bidders may have also evolved over time, perhaps leading to less nonstandard behavior in recent years as a result of a clearer interface, better search functionality, or more experienced participants. Nevertheless, new movie-DVDs are homogeneous products for which buyers have private values, and therefore we believe this context is particularly well suited for investigating the causal effects of starting prices and testing for nonstandard behavior.

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APPENDIX

A) Additional parametric models of ending-price test

We now provide results from Heckman selection models as alternatives to the censored normal models from Section 4 of the main text. First, it is possible that $S_H + b$ and $S_H$ do not precisely represent the censoring points of zero and one-bidder auctions, respectively. For example, perhaps a buyer with a willingness to pay above $S_H + b$ is less likely to enter an auction if other buyers have already entered and she expects to be outbid. Therefore the censoring point may be a random variable that is unobserved but a function of $S_H + b$. We can address this by using a Heckman selection model, treating the censoring process as an incidental truncation problem.

In the selection equation, the dependent variable is equal to one if $P^*$ is observed and zero if $P^*$ is censored, and the explanatory variables are starting price and dummies for movie title and cohort. In the primary equation, the dependent variable is $P^*$, and the explanatory variables are starting price, and dummies for movie title and cohort. The selection and primary equations have the same explanatory variables, and so the selection effect is identified from the functional form of the inverse Mills ratio alone. This is less than ideal, but an instrument for the selection equation that is excluded from the primary equation is not readily available because of the close link between the processes that generate selection and willingness to pay (both are determined by underlying demand). The model however may be more viable than it first appears. Under the null hypothesis of no bidder effects, starting price by definition does not determine $P^*$ except through selection (i.e., the starting-price effect in the primary equation is zero), and so starting price is effectively excluded from the primary equation under the null. It is also clear that starting price is the primary determinant of selection (e.g., no LSPAs are censored while 61 percent of HSPAs are censored). Therefore, starting price is a valid excluded instrument under the null. This follows Livingston (2005) who uses (a function of) starting price as the excluded instrument in a Heckman selection model to estimate the effect of seller reputation on price in eBay auctions.

Under the alternative hypothesis that bidder effects are present, the starting-price estimate in the primary equation is negative (i.e., HSPAs underperform LSPAs). But accurately estimating this effect requires identifying the effect separately from that of the inverse Mills ratio, which is also a function of starting price. To our advantage, there is very significant variation in starting price and the effect is precisely estimated in the selection equation (z-
statistic of 5.75), and we expect the functional forms of the effects of starting price in the selection equation and primary equation to be distinct: selection into the sample requires only that two bidders have a willingness to pay above the selection criteria, and additional bidders do not affect selection; while ending price increases in expectation as the number of bidders with willingness to pay above the selection criteria increases beyond two. Hence the effects of the inverse Mills ratio and starting price in the primary equation may be reasonably well identified.\(^{19}\)

We estimate the model via the Heckman two-step procedure. The starting-price estimate in the primary equation is 0.156 (p=0.02), showing a positive rather than a negative effect of starting price, and hence no evidence of bidder effects. The estimated coefficient on the inverse Mills ratio is 0.810 (p=0.05), indicating the presence of selection. The starting-price estimate in the selection equation is -0.827 (standard error of 0.143, p<0.00). The correlation coefficient between the errors in the two equations is 0.523. We also estimate the model via maximum likelihood, which represents more efficient estimation but is more sensitive to model misspecification. The starting-price estimate is again positive and this time closer to zero.

We may be able to improve on the selection equation by distinguishing more clearly the censoring processes for auctions with zero versus one bidder. The approach above treats zero and one-bidder auctions the same except to set the censoring point at \(S_H\) versus \(S_H + b\). However, we expect zero-bidder auctions to be “more” censored (i.e., have lower latent demand) than one-bidder auctions because the two highest bidders, rather than just one of the highest bidders, have willingness to pay below the censoring point. By modeling the selection equation as an ordered probit, using zero, one, and at least two bidders as categories, we may obtain more efficient estimates than from a binary probit. We estimate an ordered probit selection model (using the “oheckman” command in Stata) again via the Heckman two-step procedure. The starting-price estimate is 0.175 (p=0.01), which is very close to the estimate above.

B) Effect of experience

We now investigate whether buyers initially exhibit bidder effects but subsequently learn to avoid them. Table A1 shows the experience levels of the highest and second-highest bidders, whose bids directly determine \(P^*\), in HSPAs that end above the matched LSPA, and in LSPAs that end above the matched HSPA. The sample examines the 46 matched pairs in which both auctions have \(P^* \geq S_H + b\), and one auction ends above the other. Learning would appear as

\(^{19}\) See Wooldridge (2010), p.806, for a helpful discussion of identification in the Heckman selection model.
inexperienced buyers explaining relatively more LSPAs ending above HSPAs compared to HSPAs ending above LSPAs. This pattern would then abate with experience. Buyer experience is represented by the buyer’s feedback score, split into ranges of 0-7, 8-22, 23-81, and 81+, corresponding to the percentiles 1-10, 11-25, 26-50, and 50-100.

Although the sample size is small, we do not observe meaningful evidence of learning. This null result could be due to most buyers on eBay having significant experience, as even buyers at the bottom quartile of experience have participated in dozens of auctions. It is possible that the lack of experience among subjects in most previous laboratory studies (highlighted in the Introduction), compared to the significant experience among nearly all eBay buyers, might explain why previous laboratory studies find nonstandard behavior while we do not.

C) Additional-bid test

We now conduct the additional-bid test that was proposed and conducted in Simonsohn and Ariely (2008) to reconcile our findings with theirs, as they also examine eBay auctions for movie DVDs. The unit of observation is the bid. The dependent variable, $y_{jk}$, is equal to one if auction $j$ receives another bid after bid $k$ and zero if not ($k$ begins at 1). $X_j$ are auction characteristics that are constant within an auction including starting price and movie title; and $Z_{jk}$ are bid characteristics that vary within an auction including standing price and time remaining after bid $k$ is placed. Standing price is rounded to the dollar and included as dummies to permit a flexible functional form. The model, $E(y_{jk} | \cdot ) = X_j \beta_X + Z_{jk} \beta_Z$, is estimated as a probit. We start by reproducing this test using our experimental data.\textsuperscript{20} The estimates are in column 1 of Table A2, reported as partial effects.\textsuperscript{21} Because the test uses multiple observations (bids) per auction, we cluster the standard errors by auction. We also find a strong negative starting-price effect.

But this starting-price estimate is subject to a negative bias. Figure A1 illustrates how the additional-bid test may generate a negative starting-price estimate even when the true starting-

\textsuperscript{20} Note that we include dummies for starting price rounded to the nearest $0.50 rather than $1.00 as in Simonsohn and Ariely (2008), and dummies for time remaining in deciles, because both of these variables are key determinants of an additional bid (i.e., a change in standing price, even by a small amount, affects the probability of an additional bid). Results are similar with starting-price dummies rounded to the dollar and without time-remaining dummies.

\textsuperscript{21} We calculate partial effects at a starting price of $5$, standing price of $7$, one hour remaining, mean seller score, and equal values for the 21 movie titles (0.048). Simonsohn and Ariely (2008) report partial average effects (partial effects calculated at sample means), which is limiting because it implies that some of their estimates across specifications in their Table 2, and between their estimates and ours, are not directly comparable because the samples and sample means vary across specifications.
price effect is zero. As discussed in Section 3, there is theoretical and empirical evidence that sellers set starting price as a function of expected demand. Setting starting price as a function of demand (the mean ending price for that movie title from the previous week) is also an important feature of our experimental design.

The top panel of Figure A1 illustrates the expected level of demand for each starting price in the experimental data under no bidder effects. Because all LSPAs are represented in the sample (none of the LSPAs are censored), and every matched pair includes an LSPA, LSPAs in the experimental sample as a whole have the mean level of demand. In contrast, underlying demand in HSPAs will be positively correlated with starting prices (because starting price is determined by the mean ending price from the previous week), increasing from the lowest high starting price, $S_H$, to the highest high starting price, $\overline{S}_H$.

The bottom panel of Figure A1 illustrates the problem this creates for the additional-bid test. Recall that the additional-bid regression conditions on current standing price. For standing prices in $[0, S_H)$, there is no variation in starting price, and hence these observations (i.e., bid-level observations with standing prices below $S_H$) alone do not identify the starting-price estimate. For standing prices in $[S_H, \overline{S}_H)$, the starting-price estimate is negative even when the true effect is zero. This is because all LSPAs may be represented at these standing prices (if they are bid up to the particular standing price), while only HSPAs with a starting price at or below the given standing price are represented in the sample. But because HSPAs with lower high starting prices have lower expected demand (from the top panel in Figure A1), the HSPAs that are represented in the sample at standing prices in $[S_L, S_H)$ have a lower probability of another bid than LSPAs on average. Finally, at standing prices of at least $\overline{S}_H$, there is no censoring based on starting price because LSPAs and HSPAs are equally likely to be represented in the sample under no bidder effects, and hence are equally likely to receive another bid. Note that 58 percent of auctions in our observational data set have $S < $1 and these auctions will have higher demand than auctions with a starting price that is above $1 but still relatively low. Thus, the observational data will exhibit a similar relationship between starting price and demand, and so this bias applies to the observational data as well.

One solution is to limit the sample to observations for which the standing price of the LSPA is at least $S_H$. To see this, note that because matched LSPA and HSPA are for the same
item, and have the same start and end times, they have the same set of potential buyers and hence the same latent demand. The auctions therefore are equally likely to receive another bid at a given standing price under no bidder effects. However, this requires the HSPA to not be left censored at that standing price. Otherwise, only the LSPA from the pair will appear at that standing price. Results from this restricted sample are in column 2 of Table A2. The estimate of the starting-price effect is now closer to zero and not statistically significant (p=0.29).

Another issue is that buyers may incur costs to switch between auctions. To see this problem, consider a matched pair where the auctions currently have the same standing price of $S_H$. In this case, we know the HSPA has zero or one bidder. In contrast, the LSPA necessarily has multiple bidders to reach $S_H$. Because eBay requires new bids to exceed the standing price by at least $b$, an auction will receive another bid if a second bidder with a valuation of at least $S_H + b$ is present in that auction. We know a second bidder with a valuation of at least $S_H - b$ is present in the LSPA because the LSPA was bid up to $S_H$. In the presence of even a small cost of finding or switching to the other auction, this second bidder may not be considering the HSPA, which has received bids from at most one bidder (because the standing price is $S_H$). Thus, the probability of another bid in the LSPA is the probability of a second bidder in the LSPA with a valuation of at least $S_H + b$ conditional on the presence of a second bidder with a valuation of at least $S_H - b$. In contrast, the probability of another bid in the HSPA is the unconditional probability of a second bidder in the HSPA with a valuation of at least $S_H + b$.

We address this in two ways. First, because observations where the auction so far only has one bidder may have lower demand than those with multiple bidders, excluding one-bidder observations avoids biasing the test in favor of LSPAs. Second, because a bidder’s first bid in an auction is not due to having previously bid in the auction, restricting the sample to these first bids also avoids biasing the test in favor of LSPAs.

Both corrections have drawbacks. If the marginal effect of nonrational herding weakens as the number of bids increases, then excluding one-bidder observations may understate the effect. Excluding repeat-bid observations instead would capture the entire nonrational herding effect, but is less helpful for testing for the other behaviors, which are predicated on sustained

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22 While this bias toward LSPAs may be somewhat offset if new bidders prefer HSPAs due to the presence of fewer competing bidders, the point is that different bid probabilities for LSPAs versus HSPAs when one-bidder observations are included is not inconsistent with standard behavior. Note that no bias occurs in a frictionless setting with simultaneous auctions because the second bidder in the LSPA equally considers the HSPA (Peters and Severinov 2006 theoretically analyze this setting).
participation in the auction by the bidders. Columns 3 and 4 report starting-price estimates for the samples that exclude repeat-bid and one-bidder observations, and the estimates are smaller and not statistically significant (p=0.64 and p=0.86, respectively). Columns 5 and 6 combine the different restrictions, and the estimate is now very close to zero. Note that the estimates in columns 2-6 are statistically different at the five percent level from the estimate from the Simonsohn and Ariely (2008) specification in column 1.\(^{23}\)

We now conduct the additional-bid test using our observational data set, which is very similar to that in Simonsohn and Ariely (2008). This is to confirm that our experimental results are not an artifact of our experimental design. Probit regression results are in Table A3. The models in columns 1 and 2 reproduce the models in columns 3 and 5 of Table 2 in Simonsohn and Ariely (2008), and show similarly large starting-price effects.\(^{24}\) Taking additional steps to control for unobserved demand in columns 3 and 4 reduces the starting-price effect significantly. As mentioned in the main text, it is unlikely that we are fully controlling for unobserved demand using the observational data. Additionally, the estimates in Table A3 are subject to the bias described in Figure A1. Hence, the modest starting-price effects in columns 3 and 4 are unsurprising.

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\(^{23}\) Simonsohn and Ariely (2008) presented additional evidence for nonrational herding. Predictions 2A and 2B are “a bid of a given dollar amount is less likely to be a winning bid on a low starting price than on a high starting price auction” and “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.” We cannot test these because our data do not contain the winning bid amount (only the second-highest). But these tests face similar concerns as the additional-bid test.

\(^{24}\) As mentioned in Footnote 21, a difference is that Simonsohn and Ariely (2008) report partial average effects, which has drawbacks. We report partial effects calculated at a starting price of $5, standing price of $7, shipping cost of $3, regular shipping method, one hour remaining, seven-day auction, one competing auction in the group, and the mean movie title.
Table 1: Predictors of starting price in observational data

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shipping fee</td>
<td>-0.304***</td>
<td>[0.038]</td>
</tr>
<tr>
<td>Priority shipping</td>
<td>0.023</td>
<td>[0.119]</td>
</tr>
<tr>
<td>Auction duration (days)</td>
<td>-0.037</td>
<td>[0.030]</td>
</tr>
<tr>
<td>Number of competing auctions</td>
<td>-0.054***</td>
<td>[0.020]</td>
</tr>
<tr>
<td>New DVD</td>
<td>0.783***</td>
<td>[0.125]</td>
</tr>
<tr>
<td>Special edition DVD</td>
<td>0.522**</td>
<td>[0.219]</td>
</tr>
<tr>
<td>Powerseller</td>
<td>-0.014</td>
<td>[0.145]</td>
</tr>
<tr>
<td>Log of seller score</td>
<td>-0.107***</td>
<td>[0.031]</td>
</tr>
<tr>
<td>Percent seller score positive</td>
<td>0.087***</td>
<td>[0.023]</td>
</tr>
<tr>
<td>eBay store</td>
<td>0.911***</td>
<td>[0.129]</td>
</tr>
</tbody>
</table>

Movie FE: Yes
Observations: 2,970
R-squared: 0.149

Notes: The unit of observation is an auction. The dependent variable is auction starting price. The model is estimated by OLS using the observational data. Standard errors are reported in brackets. “Number of competing auctions” is the number of competing auctions for that movie/version, new/used status, and end date, excluding the auction of observation. An intercept term is included but not reported. ** and *** indicate significance at the 5 and 1 percent levels.
<table>
<thead>
<tr>
<th>Movie title</th>
<th>HSPA starting price ($)</th>
<th>LSPA ending price ($)</th>
<th>HSPA ending price ($)</th>
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<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>N</td>
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<tr>
<td>Apocalypto</td>
<td>8.68</td>
<td>0.35</td>
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</tr>
<tr>
<td>Arthur and the Invisibles</td>
<td>7.60</td>
<td>0.84</td>
<td>10</td>
</tr>
<tr>
<td>Because I Said So</td>
<td>6.10</td>
<td>0.59</td>
<td>10</td>
</tr>
<tr>
<td>Blood Diamond</td>
<td>5.73</td>
<td>0.48</td>
<td>10</td>
</tr>
<tr>
<td>Casino Royale</td>
<td>8.70</td>
<td>0.37</td>
<td>10</td>
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<tr>
<td>Dreamgirls</td>
<td>4.60</td>
<td>0.41</td>
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<tr>
<td>Epic Movie</td>
<td>4.35</td>
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<td>10</td>
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<tr>
<td>The Fountain</td>
<td>5.85</td>
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<tr>
<td>Hannibal Rising</td>
<td>7.00</td>
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<tr>
<td>Letters from Iwo Jima</td>
<td>10.98</td>
<td>0.54</td>
<td>10</td>
</tr>
<tr>
<td>Music and Lyrics</td>
<td>7.45</td>
<td>0.37</td>
<td>10</td>
</tr>
<tr>
<td>Night at the Museum</td>
<td>8.70</td>
<td>0.91</td>
<td>10</td>
</tr>
<tr>
<td>Pan's Labyrinth</td>
<td>7.70</td>
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<td>10</td>
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<tr>
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<tr>
<td>Pirates of the Caribbean 2</td>
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<td>0.38</td>
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<td>The Queen</td>
<td>7.20</td>
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<td>10</td>
</tr>
<tr>
<td>Shrek 2</td>
<td>4.73</td>
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<td>10</td>
</tr>
<tr>
<td>Smokin' Aces</td>
<td>5.95</td>
<td>0.45</td>
<td>10</td>
</tr>
<tr>
<td>Stomp the Yard</td>
<td>6.98</td>
<td>0.56</td>
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</tr>
<tr>
<td>Déjà Vu</td>
<td>6.05</td>
<td>0.45</td>
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<table>
<thead>
<tr>
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<th>SD</th>
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<th>Mean</th>
<th>SD</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
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<tbody>
<tr>
<td>6.84</td>
<td>1.65</td>
<td>210</td>
<td>6.88</td>
<td>2.08</td>
<td>172</td>
<td>7.76</td>
<td>2.12</td>
</tr>
</tbody>
</table>

Notes: The table reports the movie titles and the starting and ending prices in the experimental data. There are 10 auctions per movie title/starting-price condition, though not all resulted in sale, and hence N is sometimes less than 10. The starting price of all LSPAs is $0.99.
Table 3: Summary statistics for auctions in observational data

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
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</thead>
<tbody>
<tr>
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<td>3.24</td>
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<td>9.99</td>
</tr>
<tr>
<td>Priority shipping</td>
<td>0.27</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Duration (days)</td>
<td>5.75</td>
<td>1.77</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Number of competing auctions</td>
<td>2.71</td>
<td>2.74</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>New DVD</td>
<td>0.29</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Special edition DVD</td>
<td>0.07</td>
<td>0.25</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Powerseller</td>
<td>0.57</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Log of seller score</td>
<td>7.07</td>
<td>2.44</td>
<td>0.00</td>
<td>13.55</td>
</tr>
<tr>
<td>Percent seller score positive</td>
<td>99.15</td>
<td>5.59</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>eBay store</td>
<td>0.36</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is an auction. The data set contains 2,978 auctions including auctions that did not result in sale. “Number of competing auctions” is the number of other auctions (excluding the auction of interest) for that movie/version and new/used status ending on the same day.

Table 4: Estimated models of willingness to pay using experimental data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>Censored normal</td>
<td>Censored normal</td>
</tr>
<tr>
<td>Starting price</td>
<td>0.268***</td>
<td>0.195***</td>
<td>0.081</td>
<td>-0.007</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>[0.036]</td>
<td>[0.048]</td>
<td>[0.058]</td>
<td>[0.031]</td>
<td>[0.019]</td>
</tr>
<tr>
<td>Movie FEs</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Cohort FEs</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matched-pair FEs</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>( P \geq S_H + b )</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>292</td>
<td>292</td>
<td>166</td>
<td>420</td>
<td>420</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is an auction. The dependent variable is ending price. The sample in columns 1 and 2 are auctions that have an uncensored ending price (at least two bidders). The sample in column 3 is auctions with an ending price of at least the censoring condition \( S_H + b \), described in the text. The samples in columns 4 and 5 are all auctions and use a censored normal model to account for censoring. All models include an intercept term. Note that seller score is constant within cohort and matched pairs. Heteroskedasticity-robust standard errors are reported in brackets. *** indicates significance at the 1 percent level.
Table 5: Estimated models of willingness to pay using observational data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>Censored</td>
<td>Censored</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>normal</td>
<td>normal</td>
</tr>
<tr>
<td>Starting price</td>
<td>0.450***</td>
<td>0.392***</td>
<td>-0.006</td>
<td>0.024</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>[0.077]</td>
<td>[0.141]</td>
<td>[0.082]</td>
<td>[0.028]</td>
<td>[0.021]</td>
</tr>
<tr>
<td>Shipping fee</td>
<td>-0.534***</td>
<td>-0.585***</td>
<td>-0.592***</td>
<td>-0.668***</td>
<td>-0.736***</td>
</tr>
<tr>
<td></td>
<td>[0.069]</td>
<td>[0.121]</td>
<td>[0.162]</td>
<td>[0.041]</td>
<td>[0.035]</td>
</tr>
<tr>
<td>Priority shipping</td>
<td>0.144</td>
<td>-0.023</td>
<td>-0.000</td>
<td>0.179</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>[0.164]</td>
<td>[0.215]</td>
<td>[0.356]</td>
<td>[0.121]</td>
<td>[0.103]</td>
</tr>
<tr>
<td>Auction duration (days)</td>
<td>0.143***</td>
<td>0.113</td>
<td>0.111</td>
<td>0.155***</td>
<td>0.110***</td>
</tr>
<tr>
<td></td>
<td>[0.039]</td>
<td>[0.072]</td>
<td>[0.118]</td>
<td>[0.027]</td>
<td>[0.030]</td>
</tr>
<tr>
<td>N competing auctions</td>
<td>-0.072**</td>
<td>-0.070***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.029]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New DVD</td>
<td>1.401***</td>
<td></td>
<td>1.388***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.182]</td>
<td></td>
<td>[0.137]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Special edition DVD</td>
<td>3.051***</td>
<td></td>
<td>2.533***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.402]</td>
<td></td>
<td>[0.370]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Powerseller</td>
<td>-0.326*</td>
<td>-0.248</td>
<td>0.249</td>
<td>0.009</td>
<td>-0.050</td>
</tr>
<tr>
<td></td>
<td>[0.185]</td>
<td>[0.250]</td>
<td>[0.429]</td>
<td>[0.143]</td>
<td>[0.127]</td>
</tr>
<tr>
<td>Log of seller score</td>
<td>0.179***</td>
<td>0.151***</td>
<td>0.050</td>
<td>0.101***</td>
<td>0.104***</td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td>[0.054]</td>
<td>[0.096]</td>
<td>[0.028]</td>
<td>[0.027]</td>
</tr>
<tr>
<td>% seller score positive</td>
<td>-0.022</td>
<td>0.025</td>
<td>0.064**</td>
<td>0.018</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>[0.027]</td>
<td>[0.035]</td>
<td>[0.030]</td>
<td>[0.024]</td>
<td>[0.018]</td>
</tr>
<tr>
<td>eBay store</td>
<td>0.215</td>
<td>0.173</td>
<td>-0.026</td>
<td>-0.084</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>[0.175]</td>
<td>[0.255]</td>
<td>[0.440]</td>
<td>[0.128]</td>
<td>[0.119]</td>
</tr>
<tr>
<td>Movie FEs</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Group FEs</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>$P \geq S_H + b$</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,435</td>
<td>1,435</td>
<td>735</td>
<td>2,970</td>
<td>2,970</td>
</tr>
</tbody>
</table>

Notes: The table reproduces the specifications in Table 4 using the observational data. The unit of observation is an auction. The dependent variable is ending price. Groups in columns 2, 3, and 5 are auctions with the same movie/DVD version, new/used status, and end date. “$P \geq S_H + b$” indicates that the sample is restricted to auctions with ending prices of at least the high starting price in the group plus the minimum bid increment for that high starting price. Heteroskedasticity-robust standard errors are reported in brackets (except for column 5, which reports non-adjusted standard errors due to computation challenges). “N competing auctions” is the number of other auctions (excluding the current auction) for that movie/version and new/used status that ended on the same day. All specifications include an intercept term. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.
Figure 1: Survivor functions and standard errors for ending prices of LSPAs and HSPAs

Notes: The top panel contains the survivor functions for the ending prices of the LSPAs and HSPAs. The survivor function is the fraction of auctions that resulted in sale with an ending price of at least the amount indicated on the x-axis, which is normalized to the high starting price, $S_H$. That is, the price on the x-axis is the difference between the ending price and the HSPA starting price. The vertical dashed line is the price at which the censoring condition occurs (approximately). The bottom panel contains the standard errors for the survivor functions.
Table A1: Bidder experience for auctions with higher ending price in pair in experimental data

<table>
<thead>
<tr>
<th>Score of highest bidder</th>
<th>LSPA ends above HSPA</th>
<th>HSPA ends above LSPA</th>
<th>Score of second-highest bidder</th>
<th>LSPA ends above HSPA</th>
<th>HSPA ends above LSPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>≤ 7</td>
<td>4</td>
<td>2</td>
<td>≤ 7</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>8 - 22</td>
<td>2</td>
<td>7</td>
<td>8 - 22</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>23 - 81</td>
<td>5</td>
<td>10</td>
<td>23 - 81</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>≥ 81</td>
<td>6</td>
<td>15</td>
<td>≥ 81</td>
<td>10</td>
<td>15</td>
</tr>
</tbody>
</table>

Notes: Buyer feedback scores of the highest bidder (left panel) and second-highest bidder (right panel) are reported for LSPAs that end above the matched HSPA and for HSPAs that end above the matched LSPA. The feedback scores are reported according to the 1-10, 11-25, 26-50, and 51-100 percentiles of feedback score. Only matched pairs where both auctions meet the censoring condition (\(P \geq S_H + b\)) are included. Note that five matched pairs met the censoring condition but the LSPA and HSPA had the same ending prices and hence are not included.

Table A2: Estimated probit models of probability of additional bid using experimental data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting price</td>
<td>-0.024***</td>
<td>-0.008</td>
<td>-0.003</td>
<td>-0.002</td>
<td>0.002</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>[0.008]</td>
<td>[0.007]</td>
<td>[0.007]</td>
<td>[0.010]</td>
<td>[0.006]</td>
<td>[0.006]</td>
</tr>
<tr>
<td>Stand price at least (S_H)</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repeat bids excluded</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First bid excluded</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>1,694</td>
<td>541</td>
<td>1,130</td>
<td>1,293</td>
<td>407</td>
<td>357</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a bid. The dependent variable is equal to one if the auction received another bid and zero if not. All specifications include dummies for movie title and cohort (note that seller score is constant within cohort). Estimates are reported as partial effects. The values at which the partial effects are evaluated are in the text. All specifications include an intercept term, dummies for current standing price rounded to the nearest half dollar, and dummies for deciles of time remaining in the auction. Standard errors are reported in brackets with heteroskedasticity-robust standard errors clustered by auction. “Repeat bids excluded” and “First bid excluded” are defined in the text. *** indicates significance at the 1 percent level.
Table A3: Estimated probit models of probability of additional bid using observational data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting price</td>
<td>-0.053***</td>
<td>-0.048***</td>
<td>-0.015***</td>
<td>-0.013**</td>
</tr>
<tr>
<td></td>
<td>[0.005]</td>
<td>[0.005]</td>
<td>[0.004]</td>
<td>[0.006]</td>
</tr>
<tr>
<td>Shipping fee</td>
<td>-0.029***</td>
<td>-0.056***</td>
<td>-0.053***</td>
<td>-0.030***</td>
</tr>
<tr>
<td></td>
<td>[0.007]</td>
<td>[0.008]</td>
<td>[0.008]</td>
<td>[0.009]</td>
</tr>
<tr>
<td>Priority shipping</td>
<td>-0.010</td>
<td>-0.005</td>
<td>-0.012</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>[0.017]</td>
<td>[0.018]</td>
<td>[0.014]</td>
<td>[0.020]</td>
</tr>
<tr>
<td>Log of minutes remaining</td>
<td>0.082***</td>
<td>0.073***</td>
<td>0.062***</td>
<td>0.078***</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.003]</td>
<td>[0.008]</td>
<td>[0.003]</td>
</tr>
<tr>
<td>Auction duration (days)</td>
<td>0.001</td>
<td>0.004</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>[0.005]</td>
<td>[0.005]</td>
<td>[0.004]</td>
<td>[0.006]</td>
</tr>
<tr>
<td>N competing auctions</td>
<td>-0.007**</td>
<td>0.000</td>
<td>-0.000</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.003]</td>
<td>[0.003]</td>
<td>[0.004]</td>
</tr>
<tr>
<td>New DVD</td>
<td>0.094***</td>
<td>0.088***</td>
<td>0.076***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.020]</td>
<td>[0.019]</td>
<td>[0.021]</td>
<td></td>
</tr>
<tr>
<td>Special edition DVD</td>
<td>0.190***</td>
<td>0.159***</td>
<td>0.191***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.034]</td>
<td>[0.031]</td>
<td>[0.036]</td>
<td></td>
</tr>
<tr>
<td>Powerseller</td>
<td>-0.016</td>
<td>-0.022</td>
<td>-0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.021]</td>
<td>[0.016]</td>
<td>[0.023]</td>
<td></td>
</tr>
<tr>
<td>Log of seller score</td>
<td>0.003</td>
<td>0.007**</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.003]</td>
<td>[0.005]</td>
<td></td>
</tr>
<tr>
<td>% seller score positive</td>
<td>0.008***</td>
<td>0.007***</td>
<td>0.004*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.002]</td>
<td>[0.002]</td>
<td></td>
</tr>
<tr>
<td>eBay store</td>
<td>-0.009</td>
<td>0.002</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.020]</td>
<td>[0.016]</td>
<td>[0.022]</td>
<td></td>
</tr>
<tr>
<td>Movie FEs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Repeat bids excluded</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First bid excluded</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,753</td>
<td>8,746</td>
<td>5,735</td>
<td>6,706</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a bid. The dependent variable is equal to one if the auction received another bid and zero if not. Estimates are reported as partial effects. The values at which the partial effects are evaluated are in the text. All specifications include an intercept term, dummies for current standing price rounded to the nearest dollar. Standard errors are reported in brackets with heteroskedasticity-robust standard errors clustered by auction. “Repeat bids excluded” and “First bid excluded” are defined in the text. *** indicates significance at the 1 percent level.
Figure A1: Bias of starting-price estimate due to relationship between starting price and demand

Expected level of demand in auctions of different *starting* prices under no bidder effects

Contribution to negative bias of starting-price estimate from bid-level observations at different *standing* prices under no bidder effects