# TESTING FOR NONSTANDARD BEHAVIOR IN AUCTIONS IN THE PRESENCE OF UNOBSERVED DEMAND[1]

Joseph Uri Podwol
Department of Economics
Cornell University

Henry S. Schneider
Johnson Graduate School of Management
Cornell University

September 2011

Abstract

Empirical work on auctions has found that bidders deviate from rational behavior under standard preferences in important ways. In the current paper, we investigate a range of these behaviors, including nonrational herding, auction fever, quasi-endowment effect, escalation of commitment, and irrational limited attention. Our innovations are to use new data from a field experiment on eBay and to examine the identifying assumptions of tests used in previous work. With these innovations, we now find that there is currently only limited evidence that bidders deviate from standard behavior in the field.

[1] We thank Emek Basker, Dan Benjamin, Ori Heffetz, Alice Isen, Justin Johnson, Ted O'Donoghue, Roni Michaely, Michael Waldman, and various seminar participants for comments, and Nate Woody for programming assistance.

# 1. INTRODUCTION

Early laboratory studies of auctions by Kagel, Harstad, and Levin (1987) and Kagel and Levin (1993) found that bidders deviate from rational behavior under standard preferences in significant ways. In first-price auctions, this behavior quickly dissipated with experience. In second-price auctions, however, there was significant and persistent overbidding. Subsequent laboratory studies of sealed-bid second-price auctions by Harstad (2000), Cooper and Fang (2008), and Garratt, Walker, and Wooders (2011) found less overbidding by bidders who had previously lost money by overbidding or who had experience with other auction formats (first-price, English, eBay). These results point to bounded rationality and perhaps nonstandard preferences, but also that bidders may learn to avoid these behaviors with sufficient experience.[2]

One of the ultimate questions of interest in this literature is if and how bidders deviate from standard rational behavior in real-world auctions.[3] Since most real-world bidders have significant experience (e.g., on eBay, even bidders in the lowest quartile of experience have participated in dozens of auctions), one might expect less nonstandard behavior in the field than in the laboratory. The objectives of the current study are to provide new evidence about the presence of nonstandard behavior in the field, and to highlight some of the methodological challenges that are involved in this endeavor. We study the setting of eBay, which uses modified ascending second-price auctions and is the largest consumer auction platform in the world.[4]

[2] In a non-auction setting, List (2003) finds that endowment effects (which we test for) abate with experience.
[3] We use "standard rational 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.
[4] eBay allows bidders to submit a maximum bid, where proxy bids are placed for the bidder when she is the high bidder but then is outbid, for an amount equal to this new bid plus an increment, up to her maximum bid. This format represents a hybrid of an ascending-price auction and a sealed-bid auction in the sense that bidders can submit one maximum bid and have eBay bid automatically for them, or can alternatively submit each bid manually. Bajari and Hortacsu (2004) survey the literature on eBay and provide an example of proxy bidding (p. 461). Hasker and Sickles (2010) also provide details about eBay, including the auction and BIN mechanisms.

While we provide more detail in Section 2, the nonstandard behaviors we test for are: (1) "nonrational herding" (Simonsohn and Ariely 2008), whereby bidders herd into auctions with more previous bids despite these previous bids providing no valuable information; (2) "auction fever," which is the excitement from the thrill of competition that causes bidders to bid beyond their initial valuations (surveyed in Ockenfels, Reiley, and Sadrieh 2007); (3) "quasi-endowment effect" (Heyman, Orhun, and Ariely 2004; Wolf, Arkes, and Muhanna 2005, 2006), which is similar to the traditional endowment effect (Thaler 1980); (4) "escalation of commitment," where bidders may overbid in order to self-justify the sunk cost of the time and effort they have committed (e.g., Ku, Malhotra, and Murnighan 2005); and (5) "irrational limited attention" (Lee and Malmendier 2011), whereby bidders ignore fixed-price auction alternatives for the same item and consequently pay more than necessary.

While researchers can test for nonstandard behavior in the laboratory by assigning valuations to subjects and then tracking bidding behavior (e.g., Kagel and Levin 1993), identification in the field involves additional challenges. To illustrate these challenges, consider Figure 1, which shows the ending prices of all auctions on eBay for the "Casino Royale" movie DVD in October 2008. The figure also shows the lowest-price fixed-price options on eBay, called Buy-It-Now (BINs), for the DVD.[5,6] Significant price variation is apparent. Auction 12 ends \$16 above auction 13, but is for the collector's edition while auction 13 is for the regular edition. Auction 3 ends \$3 above auction 1, but the auctions are temporally separated, and the price difference may simple reflect random differences in the number of bidders who happened to be online. Auction 15 ends \$3 above auction 14, but is for the 2006 movie while auction 14 is for a 1967 movie with the same title.

[5] The figure shows only new, regular-format DVDs, and hence excludes many of additional listings bidders must distinguish between (used DVDs, Blu-ray and HD-DVD-format DVDs, and BIN listings at higher prices).
[6] BINs have become central to eBay and now represent 42 percent of transaction value (Hasker and Sickles 2010).

Most auctions end below the BINs, which is perhaps not surprising given that the BINs represent a reservation option. However, auctions 23 and 26 end above BINs B7, B10, and B13. Yet, the auctions are for different editions than B7 and B10. Further, the phrase "collector's edition" in the title of B13 is abbreviated. eBay's default search algorithm requires all words in a bidder's search string to appear fully in the listing title for the auction to appear in search results. Hence, any bidder who searched with "collector's edition" would have found the auctions but not B13. This could generate higher demand in the auctions. Together, these patterns indicate the presence of many idiosyncratic determinants of price that are not inconsistent with standard behavior. Ruling them out so that we can identify nonstandard behavior is the challenge.

Previous work has tested for nonrational herding, auction fever, quasi-endowment effect, and escalation of commitment, which we collectively call "bidder effects," by examining the effects of starting price on auction outcomes. The idea is that auctions with a low *starting* price mechanically accumulate more bids while being bid up to a high *standing* price, and these bids themselves trigger more activity at high standing prices.[7] For example, since low starting price auctions have received more bids at a given standing price versus high starting price auctions, nonrational herding causes future bidders to favor the low starting price auction.[8] In contrast, bidding activity at a given standing price is unrelated to starting price in a standard private-value auction model.[9] This distinguishing prediction is the basis of our tests of 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) find positive

[7] Starting price on eBay acts as a visible reserve price; all bids must be at least the starting price. Standing price is the current price level of the auction during the auction period.
[8] This approach uses starting price to proxy for the interim level of bidding activity in an auction, which is the driver of future bidding activity under the bidder effects. Directly estimating the relationship between current and future bidding activity (e.g., current number of bids on future bids) risks severe endogeneity problems since unobserved demand determines both current and future bidding activity (Simonsohn and Ariely 2008 discuss this point).
[9] This is conditional on the standing price exceeding the starting price, a point we discuss later.

effects; Kamins, Dreze, and Folkes (2004), Ku, Galinsky, and Murnighan (2006), and Simonsohn and Ariely (2008) find negative effects; and Lucking-Reiley, Bryan, Prasad, and Reeves (2007) find no effect.[10] This disparity in findings highlights the challenges of isolating the causal effect of starting price on auction outcomes: Since starting price is effectively the seller's reserve price, it may be correlated with factors that determine demand. Some of these factors are straightforward to control for, such as a seller's reputation score, but some are harder to quantify, such as the number of competing auctions for similar (though distinct) items.[11]

An innovation of the current study, and the way we address this challenge, is to analyze data from a field experiment that we conducted on eBay that involved selling 420 movie DVDs in matched pairs of simultaneous auctions. The matched auctions were identical except that one had a low starting price ($0.99) and the other had a high starting price (average of $6.85). By relying exclusively on variation in starting price within a matched pair, we can ensure that starting price is uncorrelated with auction, item, and seller characteristics, and any time-varying determinants of demand in a particular auction such as the presence of a similar auction.

Using this starting-price variation, we reproduce the test in Simonsohn and Ariely (2008) of the effect of starting price on the probability that an auction receives an additional bid at a given standing price (low starting price auctions should have a higher probability under bidder effects). While Simonsohn and Ariely (2008) find a very significant effect, we find no effect. Then, following a range of previous studies, we estimate the effect of starting price on ending price directly by comparing the average ending prices of the low starting price auctions (LSPAs)

[10] Reiley (2006) also finds starting-price results that are consistent with standard behavior in first-price auctions.
[11] Bajari and Hortacsu (2004), p. 471, make a similar regarding estimating the effect of seller reputation in auctions.

and the high starting price auctions (HSPAs).[12] The average ending prices for the two are approximately equal. Both sets of results are inconsistent with bidder effects.

To better understand the discrepancies between our results and the previous findings, and to ensure that our results are not an artifact of our experimental procedures, we reproduce several of the previous analyses using a new observational data set that we collected from eBay. We are able to replicate the starting-price effects of the previous studies but show that the effects also disappear in the observational data set when we better control for demand.

A second approach that has been used to test for nonstandard behavior in auctions is to measure directly whether bidders bid above what should be their maximum willingness to pay under standard behavior. We follow Lee and Malmendier (2011) in using the lowest contemporaneous BIN price as the maximum willingness to pay in eBay auctions. Since BINs are available immediately and are typically displayed in eBay search results alongside auctions, bidding above BINs may be a costly mistake that indicates irrational limited attention.

While Lee and Malmendier (2011) find a high rate of overbidding in auctions relative to BINs and that auction ending prices are significantly *above* the lowest BIN prices on average, we find only a moderate rate of overbidding relative to BINs and that auction ending prices are significantly *below* BIN prices on average. Further, in the cases of overbidding we do observe, there are usually significant differences in the wordings of the listing titles such that the BIN and auction were unlikely to have appeared in the same search results for some bidders. We confirm this conjecture with a formal test, concluding that traditional search and monitoring frictions may generate much of the observed overbidding. Using the data set of Lee and Malmendier (2011), we then reconcile our results with theirs. We find that most of the cases of significant

[12] We condition on both auctions exceeding the high starting price to avoid a left-censoring problem that HSPAs cannot end below the high starting price.

overbidding in their study are due to data-coding errors, and that traditional frictions can explain much of the remaining overbidding in their data set as well. We conclude that there is little evidence that irrational limited attention is important in the eBay setting.[13]

Our collective takeaway from this wide range of generally null results is that there is currently only limited evidence that a standard rational model of bidder behavior can be rejected in the field. Of course, this is not the same as showing that bidders 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 behavior in many economic settings (see DellaVigna 2009 for a survey) and it would be surprising if auctions were the exception. Nevertheless, bidder behavior in the field appears to be less nonstandard than a significant number of empirical studies have suggested and indicates that much more work is needed before we understand consumer behavior in this dynamic marketplace.[14]

The paper proceeds as follows. Section 2 describes the nonstandard behaviors we examine. Section 3 describes our empirical strategy. Section 4 describes the experiment and observational data sets. Sections 5, 6, and 7 contain the results for the additional-bid test, the ending-price test, and the fixed-price-alternatives tests, respectively. Section 8 concludes.

## 2. DESCRIPTION OF NONSTANDARD BEHAVIORS

We now summarize the five nonstandard behaviors that we investigate.[15] Under "nonrational herding" (Simonsohn and Ariely 2008), bidders form beliefs about unobserved item

[13] We also comment on Jones (2011), which is a second paper on overbidding relative to fixed-price alternatives.
[14] Einav, Kuchler, Levin, and Sundaresan (2011) introduce the very promising new approach of using sellers' own experimenting with auction designs to investigate consumer behavior in Internet markets. They provide some results that are consistent with our findings, notably the limited rate of overbidding in auctions relative to BINs
[15] With the exception of irrational limited attention and a variation of auction fever (joy of winning) in Cooper and Fang (2008), the behaviors were not formally modeled in the original studies. We use our best interpretations of how they were originally described.

or seller quality based on the number of existing bids the auction has received thus far. Number of bids is displayed saliently in eBay search results next to the listing title. The herding behavior is characterized as nonrational because bidders appear to be making biased inferences about unobserved quality: the larger number of bids may be due to the auction having a lower starting price, which mechanically generates more bids in order for the auction to have reached a given standing price, and not to higher unobserved quality.[16]

"Auction fever" is the excitement that develops during auction competition that causes bidders to bid beyond their initial willingness to pay. The term auction fever is used in the survey of Ockenfels, Reiley, and Sadrieh (2007) to encompass several similar behaviors from different papers. We similarly use auction fever to encompass "bidding frenzy" (Haubl and Popkowski Leszczyc 2004), "opponent effects" (Heyman, Orhun, and Ariely 2004), and "joy (or utility) of winning" (e.g., Cooper and Fang 2008).[17]

The "quasi-endowment effect" (Heyman, Orhun, and Ariely 2004) relates to the endowment effect (Thaler 1980, Kahneman, Knetsch, and Thaler 1990) and proposes that a bidder develops a sense of ownership over the item while bidding, even without owning the item. This causes her valuation of the item to increase during the bidding process. Heyman, Orhun, and Ariely (2004) propose 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" (p. 11).

---

[16] In contrast, Banerjee (1992), and Bikhchandani, Hirshleifer, and Welch (1992) show how herding can be a rational response to incomplete information. Also note that Ely and Hossain (2009) report that early bidding ("squatting") may deter future bidders from that auction, which is somewhat at odds with herding in auctions.

[17] "Competitive arousal" (Ku, Malhotra, and Murnighan 2005) is related. However, the authors argue that the effect is stronger in offline auctions due to the presence of a live audience, and is not increasing in the number of bidders beyond two. Similarly, "spite" (Morgan, Steiglitz, and Reis 2003) is the effect of a bidder receiving disutility from a competing bidder's surplus, which may lead to overbidding. As modeled, however, spite is insensitive to the number of bidders beyond two for a setting like eBay. Hence, our tests are not relevant for these two behaviors.

"Escalation of commitment" (Ku, Malhotra, and Murnighan 2005) is related to the "sunk cost effect" (e.g., Thaler 1980) and arises when bidders who are outbid feel the need to justify the sunk cost their participation up to that point. Winning the auction is a "self-justification that helps preserve a positive self-image," and leads bidders to bid beyond their initial valuation.

"Irrational limited attention" is described in Lee and Malmendier (2011) as occurring when "inattentive bidders overlook the fixed price, even though it is available on the same webpage" (p. 756). They use BIN prices, which are typically listed on eBay alongside auctions, as the benchmark above which standard rational bidders should not bid. They find significant overbidding relative to BINs, which they attribute to irrational limited attention.

## 3. EMPIRICAL STRATEGY

### A) Bidder effects

Our approach to testing for nonrational herding, auction fever, quasi-endowment, and escalation of commitment (bidder effects) is based on the observation that they offer a common prediction: since LSPAs mechanically accumulate more bidders and bids, and bidders will have participated in the auction for longer, by the time the auction has reached the high starting price, LSPAs will have more future bidding activity at a given standing price than HSPAs.[18]

Specifically, under nonrational herding, since LSPAs have received more bids upon reaching a given standing price than HSPAs, subsequent bidders are more likely to bid in the LSPAs. The logic for auction fever is similar and is noted in the survey by Ockenfels, Reiley, and Sadrieh (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

[18] At a given standing price, the data (described later) show clearly that LSPAs accumulate more bidders and bids, and winning bidders spend more time in the auction and as the high bidder, compared to HSPAs. For example, LSPAs had 4.8 bidders and 7.6 bids on average by the time their standing price reached the high starting price.

explain why some auctioneers prefer a low minimum bid," which "would attract as many bidders as possible, in an attempt to promote auction fever" (p. 23).[19] Likewise, since LSPAs typically receive bids earlier in the auction period, bidders in a LSPA have participated in the auction, and have been the high bidder, for longer on average than bidders in a HSPA. It follows that bidders in LSPAs are more likely to increase their bids in response to being outbid under the quasi-endowment effect and escalation of commitment. This heightened bidding activity of LPSAs compared to HSPAs gives rise to two predictions.[20]

Prediction 1: Under bidder effects, LSPAs have a higher probability of an additional bid than HSPAs, conditional on (a) standing price and (b) at least two bidders having bid in each auction.

Prediction 1 is from Simonsohn and Ariely (2008), who propose (p. 1625) and test the prediction, except that we add condition (b). We require condition (b) to avoid biasing the test in favor of the bidder effects.[21] To see this, consider a setting with two simultaneous auctions that are identical except for their starting prices. The HSPA has a starting price of $S_H$, and suppose that the LSPA and HSPA currently have standing prices of $P_L = S_H$ and $P_H = S_H$ respectively. Since the standing price of the HSPA is equal to its starting price, we know the HSPA has received bids from only one bidder (due to eBay's second-price format). In contrast, the LSPA has necessarily received bids from multiple bidders to reach $S_H$. Now suppose that bidders incur even small costs from searching for or monitoring a second auction or from switching between

[19] Since auction fever has not been defined precisely, it is possible (though to us less plausible) to imagine an interpretation in which auction fever is not increasing in the number of bidders beyond two. However, auction fever should still increase in the participation time of the bidders, and hence the test would still be informative.
[20] As noted in Footnote 8, directly estimating the relationship between current and future bidding activity risks potentially severe bias. Variation in starting price is a less imperfect source of variation in bidding activity.
[21] Condition (a) addresses that LSPAs trivially more bids because bidders favor auctions with a lower standing price.

bidding in the auctions. Then the LSPA is more likely to receive an additional bid than the HSPA simply due to its additional previous bidders.[22] Since one-bidder auctions have lower expected demand conditional on standing price, one-bidder auctions should be excluded to avoid biasing the test in favor of the LSPAs and hence the bidder effects.[23]

<u>Prediction 2</u>: Under bidder effects, LSPAs have a higher expected ending price than HSPAs, conditional on the auctions exceeding $S_H$.

We require the ending prices to exceed $S_H$ to avoid biasing the test *against* the bidder effects.[24] To see this, note that LSPAs appear in the data with ending prices of at least $S_L$, while HSPAs only appear in the data with ending prices of at least $S_H > S_L$. Thus, the ending prices of LSPAs and HSPAs are both left-censored, but in a more restrictive way for HSPAs. This inflates the mean observed ending price of HSPAs compared to LSPAs. Further, HSPAs with an ending price of exactly $S_H$ are truncated from below at $S_H$. This is because the starting price acts as a competing bidder when only one bidder is present (again due to eBay's second-price format). Lucking-Reiley, Bryan, Prasad, and Reeves (2007) further discuss this issue (p. 231-232).

[22] To be precise, since eBay requires new bids to exceed the standing price by at least $e$, an auction will receive another bid if a second bidder with a valuation of at least $S_H + e$ is present in that auction. We know a second bidder with a valuation of at least $S_H - e$ is present in the LSPA because the LSPA was bid up to $P_L = S_H$. Under any frictions, this second bidder may not be considering the HSPA, which has necessarily only received bids from one bidder. 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 $S_H + e$ *conditional* on the presence of a second bidder with a valuation of at least $S_H - e$. 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 $S_H + e$. While this bias toward the LSPA may be somewhat offset if new bidders prefer the HSPA due the presence of fewer competing bidders, the point is that different bid probabilities for LSPAs versus HSPAs when one-bidder auctions are included is *not* inconsistent with standard behavior. Note that no bias occurs in a frictionless setting with simultaneous auctions since the second bidder in the LSPA equally considers the HSPA (Peters and Severinov 2006 theoretically analyze this setting). However, the bias occurs in a frictionless setting when the auctions are temporally separated since the second bidder in the LSPA does not consider the HSPA.

[23] We find no starting-price effect in the experimental data even without excluding one-bidder auctions. However, the results are stronger when one-bidder auctions are excluded, and hence meaningful frictions appear to be present.

[24] We also report results from a regression model of starting price on ending price that treats ending price as a censored dependent variable. The findings are the same.

The alternative hypotheses are that bidder effects are absent, and that otherwise identical LSPAs and HSPAs have the same bidding activity conditional on standing price. That is, LSPAs and HSPAs have the same probability of an additional bid conditional on standing price and at least two bidders, and the same average ending price conditional on exceeding $S_H$.[25]

B) <u>Irrational limited attention</u>

Our first test of irrational limited attention is from Lee and Malmendier (2011). They show theoretically that some overbidding relative to contemporaneous BINs is consistent with standard behavior when bidders incur transaction costs from switching between auctions and BINs, or face uncertainty about the future availability of BINs.[26] However, auctions should end below the lowest BIN price in expectation. A test of nonstandard behavior, then, is whether auctions end above the lowest BIN price on average.

<u>Prediction 3</u>: Under irrational limited attention, auction ending prices may exceed the lowest contemporaneous BIN prices in expectation.

This is the primary test of irrational limited attention in Lee and Malmendier (2011). A key identifying assumption of this test is that any information acquisition costs that bidders incur to identify and monitor auctions and BINs are inconsequential. That is, the test assumes bidders are costlessly aware of all listings.[27] Our second and we believe more important test of irrational

[25] Kamins, Dreze, and Folkes (2004) propose that starting price might act as a reference price, whereby a higher starting price increases a bidder's willingness to pay. This would act in the opposite direction as the bidder effects. However, they find a negative (or no) starting-price effect, and to our knowledge no studies claim to find otherwise.
[26] As in Lee and Malmendier (2011), we sometimes use the term "overbidding" when a bidder wins an auction for a price that exceeds that of another available listing. Even though we do not know bidders' valuations, the term still captures the idea that the bidder did not pay the lowest available price.
[27] The condition is described in Lee and Malmendier (2011) as "the fixed prices, so-called buy-it-now prices, are shown together with the auction listings in the results for any Cashflow 101 search on eBay" (p. 750) and "our

limited attention is a test of the validity of this assumption. A failure of this assumption implies that overbidding may be due to traditional frictions and, regardless of the observed rate of overbidding, may not be inconsistent with standard behavior.

eBay's search results are quite sensitive to which search terms are used. This sensitivity is due to the operation of eBay's default search, which is "all words any order." It generally requires every word in the search string to appear in the listing title for the listing to appear in search results.[28] For example, on September 27, 2010, a search for Batman Begins DVDs using the string "Batman Begins DVD" returned 699 listings, "Batman Begins 2005 DVD" returned 265 listings, and "Batman Begins on DVD" returned 5 listings. This disparity is due to many titles omitting the year and most titles not including the word "on."

Given this search algorithm, bidders have several approaches for how to use the search function. One is to use a limited number of search terms. This returns most of the relevant listings, but also many irrelevant listings. For popular items, this can return many hundreds of listings.[29] Another approach is to narrow the search with modifier words. This excludes many irrelevant listings, but also some relevant listings. For example, including "new" excludes many used-DVD listings, but fails to return many new-DVD listings without "new" in the title. Further, these searches must be repeated, perhaps many times, to identify any changes in which listings are available and their standing prices. In short, information acquisition costs could be significant.

---

identification strategy requires that homogeneous items are simultaneously auctioned and sold at a fixed price on the same webpage … any bidder who searches for the item at any time finds the same fixed price" (p. 758-759).

[28] During the second half of 2008 into 2009, eBay improved the navigation options through which bidders can refine search results, and somewhat updated its search algorithm (though did not opt-in most bidders to this algorithm until after the sample periods in Lee and Malmendier 2011 and our study). The updated algorithm examines some types of wording similarities, product category, seller-specified product attributes, spelling errors, and abbreviations. These changes did not alter the basic point that search results are very sensitive to which search terms are used.

[29] For example, the string "Casino Royale" returns the regular edition, special edition, and full and widescreen versions of *new* DVDs for the 2006 movie Casino Royale, and also *used* DVDs of these versions, DVDs for 1954 and 1967 movies that also have the title Casino Royale, movie posters, t-shirts, poker chips, and playing cards.

Our fourth prediction is based on the idea that these wording differences may generate disparate search results and hence disparate demand across listings for the same items. To further illustrate the idea, consider that 23 percent of new-DVD auctions in our observational data set (described below) had titles that *did not* contain the word "new" while the corresponding BIN *did* contain "new." In these cases, bidders including "new" in their search string would find the auction but not the BIN. If this friction is important, then the overbidding rate should be highest when the auction title contains words not in the BIN title, lower when the auction and BIN titles contain the same words, and lowest when the BIN title contains words not in the auction title. More formally, let $W_k^A = 1$ if an auction title contains word $k$ and $W_k^A = 0$ otherwise, and $W_k^B = 1$ if the BIN title contains word $k$ and $W_k^B = 0$ otherwise. Then,

$$W_k^A - W_k^B = \begin{cases} 1 \text{ if the auction contains word } k \text{ and the BIN does not} \\ 0 \text{ if the auction and BIN both contain word } k \text{ or both do not} \\ \text{-1 if the auction does not contain word } k \text{ and the BIN does} \end{cases}$$

Further, when the auction title contains multiple words not in the BIN title, the overbidding rate should be even higher. We can represent the number of word differences for an auction-BIN pair as $\sum_k (W_k^A - W_k^B)$ and state the prediction as follows.[30]

<u>Prediction 4</u>: If information acquisition costs from wording differences cause overbidding, then the overbidding rate is increasing in $\sum_k (W_k^A - W_k^B)$.

[30] Listing-wording differences could generate rational overbidding in two other ways. First, given the large number of listings that appear in search results, bidders may favor listings with titles that directly indicate the desired item even if listings with and without the words both appear in the search results. Second, some words may reflect higher quality in a way that is observed (or inferred) by the bidder but not observed by the researcher (e.g., bidders with more descriptive titles may be more reliable). We believe disparate search results is the most plausible channel, but the alternatives are consistent with standard behavior and hence we are indifferent between the three explanations.

## 4. THE DATA

### A) Motivation for field experiment

While Section 3 describes the tests of bidder effects, these tests involve comparing auctions that are identical except for starting price. In a field setting, such sets of auctions are not typically available, even among simultaneous auctions for the same movie. This is a concern because theoretical work predicts that sellers set starting price as a function of factors that are correlated with demand, including the seller's valuation for the item (Riley and Samuelson 1981), the level of demand for the item (Virag 2010), and the number of competing auctions for similar items (Adams 2010). In other words, the underlying determinants of demand predict both starting price and outcomes, and identification hinges on whether we have adequately controlled for these factors. While it is straightforward to control for some factors (e.g., shipping method), other aspects are harder to quantify (e.g., the number of bidders the seller expects that day).

Table 1 reports results from a simple linear projection of starting price on auction characteristics using auction-level observational data from eBay (these data are described below). Relationships between starting price and many of these attributes are apparent. Generally, characteristics indicating a higher quality appear to predict a higher starting price.

To address this challenge, we conducted a field experiment on eBay for the purpose of obtaining exogenous variation in starting price. The experiment involved selling movie DVDs in matched pairs of auctions that were identical except that one auction had a low starting price and the other auction had a high starting price. By relying only on this variation in starting price within matched pairs, we avoid any biases from the correlations that are evident in Table 1.

B) Experimental design and data

The experimental data consist of the starting prices, ending prices, and bid histories of 420 auctions for new-movie DVDs conducted on eBay from July 13 to August 22, 2007. Twenty-one movies titles were chosen from Billboard magazine's bestseller list from June 2007. We auctioned new DVDs of each title in pairs, one with a 99-cent starting price (the LSPA), and the other with a higher starting price (the HSPA).[31] Auctions for 21 pairs (one for each movie title) began simultaneously as a cohort and ended exactly three days later. The experiment consisted of 10 such non-overlapping cohorts, such that 420 auctions were conducted in total.

All of the auctions had the same seller (us), the same layout and wording, a $3.00 shipping charge, and were for the regular edition of the DVD.[32] To avoid any perception of heterogeneous quality that might potentially lead bidders to interpret starting price as a signal of quality, the listing title stated clearly that the DVD was new and sealed in original shrink wrap.[33]

Since we expected the ending prices to differ widely across titles in a cohort and within titles over time, we chose starting price distinctly for each auction to maximize variation in starting price while still ensuring that most auctions resulted in sale. For starting price, we used the average ending price among new and used DVDs for that title from the previous week, which is reported by eBay, plus a small increment. The increment was 10 percent in the first five

[31] A 99 cent starting price is very common on eBay. In our observational data set, 99 cents was the mode starting price, accounting for 45 percent of auctions. The next most common starting prices were 1 cent, with 11 percent of auctions, and $1.99, $2.99, $3.99, and $4.99, with approximately 4 percent of auctions each.

[32] "Letters From Iwo Jima" and "Pirates of the Caribbean: The Curse of the Black Pearl" were marketed as special editions, but these were the most basic versions offered.

[33] Also recall that the sample for our starting-price tests consists of auctions with at least two bidders (conditions of Predictions 1 and 2) and starting price is not reported in eBay search results once the auction has received at least one bid. Further, a key finding of the experimental results will be the large *change* in the starting-price effect due to more completely controlling for demand, which is not directly related to a signaling mechanism. One might also wonder if the strong similarity of auctions in a matched pair (same start and end time, listing wording, and seller) could attenuate the behavioral effects. This does not appear to be an issue given the large variation in outcomes within matched pairs that is evident (e.g., the standard deviation of the difference in ending prices in pairs where both auctions exceed $S_H$ is $1.86). Further, excluding one-bidder auctions appears to be at least as important in obtaining unbiased results as using within-matched-pair starting-price variation. We also corroborate our findings using observational data (described below), which contain auctions without the same degree of similarity.

cohorts, and 25 percent in the second five cohorts.[34] The mean and standard deviation of the high starting price are \$6.83 and \$1.58. Table 2 lists the movie DVDs and their starting prices.

C) Observational data

We additionally collected observational data from eBay in order to: (1) provide corroboration that are results are not an artifact of our experimental procedures; (2) reconcile some conflicting results from previous studies that use observational data; and (3) test for irrational limited attention by comparing auction and BIN outcomes. Using a Java query tool that we created, we collected data on all auctions that were active between September 5 and November 4, 2008 for DVDs of 16 movies from Billboard magazine's bestseller list in August and September 2008. We identified relevant listings by searching the text of the listing title and body for the movie name (e.g., "Batman Begins") using this Java query tool.[35]

For each auction, our data include item characteristics such as title, new/used condition, DVD format (regular, HD-DVD, Blu-ray) and shipping fee and type (e.g., priority); seller characteristics such as feedback score, percentage of feedback that is positive, and whether the seller is an eBay store; bid characteristics such as the amount and time of each bid, whether the bid is a proxy bid or actual bid; and bidder characteristics, notably bidder feedback score.[36] After each transaction, the buyer can evaluate the seller, and vice versa, with a positive (+1), negative (-1), or neutral feedback (0); the feedback score is the sum of these feedbacks. In line we previous work, we use these feedback scores as measures of buyer and seller experience.

---

[34] This change in markup had little effect on the probability of sale. Because the reported average price by eBay includes used DVDs, but we sold only new DVDs, most of the experimental auctions resulted in sale. In cohorts 1-5 versus 6-10, 87 of 105 versus 85 of 105 HSPAs resulted in sale.

[35] By using the minimum number of search terms (i.e., only the movie title without modifier words like "movie"), our search is designed to capture all listings that at least some eBay users may identify in their searches. We discuss the eBay search algorithm and our search procedures in the Appendix.

[36] During the sample period, eBay expanded the condition choices from "New" and "Used" to five choices from "Brand New" to "Acceptable." We reclassify the updated choices to "New" and "Used" for consistency, and drop the 0.05 percent of listings that do not report condition. Also, note that actual bid amounts are available only for non-winning bids since only the second-highest bids are reported.

We identify the version of a particular movie DVD (e.g., special edition) by visually inspecting all listing titles. Since a primary use of the observational data is to reproduce previous work, we exclude HD-DVD and Blu-ray format DVDs as in some previous studies (e.g., Simonsohn and Ariely 2008).[37] From the bid data, we reconstruct the standing price after each actual bid (as opposed to proxy bid), and create an indicator variable for whether an additional bid is placed at that standing price.[38] Our working observational data set contains 8,788 bids (excluding proxy bids) from 1,920 auctions and 1,141 unique sellers. Table 3 lists the movies and their starting and ending prices. Table 4 provides additional statistics for these data.

## 5. EFFECT OF STARTING PRICE ON PROBABILITY OF ADDITIONAL BID

For Prediction 1, we estimate the effect of starting price on the probability that an auction receives an additional bid at a given standing price. A negative effect is taken as evidence that at least one of the bidder effects is present. No (or a positive) effect is taken as evidence against all of the bidder effects.

### A) Experimental results

The unit of observation is the individual bid. There are $j = 1, \ldots, J$ auctions and $k = 1, \ldots, K_j$ bids in auction $j$. The dependent variable, $y_{jk}$, is equal to one if the auction receives an additional bid after bid $k$ and zero if not. $X_j$ are auction characteristics that are constant across bids in a given auction, including movie title, seller feedback score, and starting price. $Z_{jk}$ are bid characteristics that vary within an auction, including time remaining in the auction and

[37] We also exclude a small number of auctions with: a hidden 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 prevents us from tracking bidding activity, and a BIN option that was exercised (sellers can include a BIN option in the auction that disappears after the first bid; this format is distinct from a BIN listing that is not part of an auction).

[38] Standing price changes only in response to actual bids, so there is no loss in restricting attention to actual bids. We describe our procedures for determining standing price in the Appendix.

standing price after bid $k$ is placed. Following Simonsohn and Ariely (2008), standing prices are rounded to the nearest dollar and included as dummy variables to permit a flexible functional form. We additionally include dummy variables, $\gamma_g$, for each matched pair, $g = 1, \ldots, J/2$, to control for unobserved demand for that movie title at that time. We estimate the following fixed-effects logit model on the experimental data,

[1] $$\Pr(y_{jk} = 1 | X_j, Z_{jk}, \gamma_g) = \Lambda(X_j\beta_1 + Z_{jk}\beta_2 + \gamma_g)$$

where $\Lambda$ is the evaluation of the standard logistic distribution.

The maximum likelihood estimator of $\beta$ (the vector of $\beta_1$ and $\beta_2$) that is obtained from maximizing the log likelihood function over $\beta$ and $\gamma$ (the vector of $\gamma_g$, $\forall g$) is inconsistent. However, a consistent and $\sqrt{N}$-asymptotically normal estimate of $\beta$ can be obtained via a conditional maximum likelihood estimator. This maximum likelihood function conditions on the sum of the dependent variable over the observations in the matched pair, which is the number of bids that were placed in the matched pair of auctions (after the first bid, i.e., $k = 1$), $n_g = \sum_{j\in g}\sum_{k=1}^{K_j} y_{jk} = \sum_{j\in g}(K_j - 2)$.[39]

We estimate several versions of the model and report results in Table 5 as odds ratios.[40] We start by providing estimates from specifications that incompletely control for unobserved demand. The specification in column (1) excludes the matched-pair fixed effects ($\gamma$) and does not exclude observations from one-bidder auctions (i.e., ignoring condition (b) of Prediction 1).

[39] The bias of the unconditional maximum likelihood estimator is large when there are few observations per group, approaching $\hat{\beta} = 2\beta$ (Abrevaya 1997). However, Katz (2001) reports that the bias is modest when there are 9 to 15 observations per group, and virtually zero for over 15 observations. The mean number of observations per group in the our experimental data is 9.03, and hence we use conditional maximum likelihood. Results from unconditional maximum likelihood are similar with a slight bias in the predicted direction. Wooldridge (2002), Section 15.8, is a reference on conditional maximum likelihood estimation (we use the log likelihood function in equation 15.73).

[40] Recall that an odds-ratio less than/greater than one indicates a negative/positive partial effect of the explanatory variable, while an odds-ratio of one indicates no effect. Also, since conditional maximum-likelihood estimation of the fixed-effects logit model does not provide estimates of the group fixed effects ($\gamma$), it is generally not possible to compute partial effects from this model. However, our primary interest is the direction of the starting-price effect, and specifically whether the estimate is negative (support for bidder effects) or not (evidence against bidder effects).

A strong negative relationship between starting price and the probability of an additional bid is evident. The specification in column (2) includes the matched-pair fixed effects but still does not exclude one-bidder auctions. The starting-price effect is now smaller in magnitude (closer to one) and no longer statistically different from zero. The specification in column (3) does not include the fixed effects, but excludes one-bidder auctions. The starting-price effect is again smaller in magnitude than in column (1). Column (4) is the primary specification of interest and includes the fixed effects and excludes one-bidder auctions. The negative starting-price effect disappears completely, and the estimates of the starting-price effect in columns (1) and (4) are different at the one-percent significance level.[41]

B) Reconciling results with previous findings

Simonsohn and Ariely (2008) estimate this additional-bid test using observational data on eBay DVD auctions. In contrast to the current results, Simonsohn and Ariely (2008) find a very significant negative relationship. To better understand this discrepancy, and to ensure that our results are not an artifact of our experimental design, we estimate the model in equation [1] using our observational data set, which is very similar to the data set in Simonsohn and Ariely (2008).

Results are reported in Table 6. The models in columns (1), (2), and (3) control for increasing amounts of demand, and reproduce the models in columns (3), (4), and (5) of Table 2 in Simonsohn and Ariely (2008).[42] Following Simonsohn and Ariely (2008), these models do not include matched-pair fixed effects (since they are not available in the observational data), and do not exclude one-bidder auctions. We find the same large starting-price effects.

[41] Previous researchers have identified the common practice of sniping, which is bidding close to the end of the auction period. Twelve and 22 percent of bids in our experimental data occurred in the last 10 and 60 minutes of the auction period, respectively. We do not believe the presence or absence of sniping is particularly relevant to our null results, except to note that widespread sniping would be further evidence against several of the nonstandard behaviors (e.g., escalation of commitment stipulates active bidder participation for a period of time).

[42] Simonsohn and Ariely (2008) use a probit model while we use a logit model. The fixed-effects probit model gives biased estimates, so the logit allows us to estimate the fixed-effects specifications in columns (4) and (6). The logit and probit results are very similar when the unbiased probit model is available (columns 1, 2, 3, and 5).

While matched pairs of auctions are not available in the observational data set, we can still group together similar auctions and examine the effect of starting-price variation across auctions within these groups. We define groups according to movie/DVD version, new/used status, and auction end day.[43] This approach is far from perfect since starting-price variation within groups is not from a natural experiment, and hence is unlikely to be purely random. That is, it could be correlated with secondary factors that are hard to control for, but that vary within groups such as the detail of the item description.[44] Column (4) includes these group fixed effects. The starting-price effect is modestly smaller in magnitude.[45] Column (6) includes these group fixed effects and excludes one-bidder auctions, and is the preferred specification. As with our experimental results, the negative starting-price effect disappears completely. In summary, we are able to reproduce the additional-bid results in Simonsohn and Ariely (2008), but find that the effect disappears completely after more completely controlling for demand.[46]

Note that unobserved demand may also generate attenuated estimates of the effect of *standing* price. This is because an auction only appears in the data at a high standing price if it received bids, and hence had a sufficiently high realization of demand, at all previous standing prices. But this simultaneously increases the probability of another bid at that standing price. We can examine the standing-price effect for additional intuition about how well we are controlling

---

[43] An example group has three new special-edition Batman Begins DVD auctions that end on November 5, 2008. Sixty-nine percent of auctions are in groups with starting-price variation. The mean range in these groups is $3.56.
[44] Yin (2006) finds that eBay auctions with clearer descriptions have higher ending prices.
[45] As expected, when we define groups more narrowly (e.g., similar listing title wording), the starting-price effect is smaller in magnitude but also less precise due to the decrease in within-group variation in starting price.
[46] Simonsohn and Ariely (2008) present two other results in support of nonrational herding as well. Predictions 2A and 2B are that "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 that "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 predictions directly because they require knowing the winning bid amount, which is not in our data. However, these tests are susceptible to the same biases as the additional-bid test. Prediction 3 in Simonsohn and Ariely (2008) is that sellers' expected revenue does not depend on starting price. We note that this result is not inconsistent with standard behavior.

for demand: we know the probability of an additional bid should be strictly decreasing in price in a correctly-specified model, but may be flatter (or even increasing) under this bias.

Figure 2 shows standing-price effects from the models in columns (1), (3), (5), and (6) (recall that standing price is rounded to the dollar and included as dummies), which control for increasing amounts of demand. Intuitively, the curves can be thought of as demand curves, keeping mind that the effects are reported as odds ratios. The top three curve omit some controls and give the counterintuitive result that demand is insensitive to starting price about $5, $9, and $9, respectively. The bottom curve is from the desired specification and is decreasing over the entire range. It is apparent that including group fixed effects and excluding one-bidder auctions are necessary for controlling for demand.

## 6. EFFECT OF STARTING PRICE ON ENDING PRICE

We now test Prediction 2, which is that LSPAs have a higher ending price on average than HSPAs conditional on both auctions exceeding $S_H$. This result would be taken as evidence that at least one of the bidder effects is present. The alternative is that the LSPAs do not have higher ending price than the HSPAs. This is evidence against all of the bidder effects.

### A) Experimental results

We start by reporting the differences in ending prices between LSPAs and HSPAs. The last set of columns in Table 2 show that for the 114 auctions from pairs meeting the ending-price condition of Prediction 2, LSPAs ended 49 cents *below* the matched HSPAs.[47] Thus, the result is inconsistent with bidder effects.[48]

---

[47] Excluding "The Queen," which is an outlier, gives an average difference of 29 cents rather than 49 cents.

[48] We also test whether the LSPAs ends above $S_H$ of the matched auctions when the HSPA fails to sell or ends at $S_H$. This would be evidence in favor of the bidder effects. This test is weaker than the first since a finding that the ending price of LSPAs is below $S_H$ is consistent with standard behavior but does not rule out bidder effects. Nevertheless,

As a robustness check, we follow Lucking-Reiley, Bryan, Prasad, and Reeves (2007) and estimate a model on the sample of all auctions, treating the ending price of auctions that failed to sell as left censored. This is essentially a Tobit model with a censoring point (the starting price) that varies by observation. There are several reasons we prefer the ending-price test from Prediction 2 to this regression model. First, the test is simpler, and its primary drawback of inefficiency (due to excluding some auctions) is not a concern given the high precision of the estimates. Second, the fixed-effects Tobit model produces biased estimates, and matched-pair fixed effects are central to ensuring that we are controlling for demand. Third, when the HSPA results in sale but ends at $S_H$, the ending price is still left-censored (since the ending price is the starting price and not the second-highest bid), but less severely compared to auctions that failed to sell. We are not aware of a way to precisely model both forms of censoring in the same model.

Nevertheless, we estimate the main variations of this regression model: (1) with and without matched-pair fixed effects. (2) Treating HSPAs that end at $S_H$ as left-censored in the same way as HSPAs that fail to sell. (3) Treating HSPAs that end at $S_H$ as left-censored but over the restricted interval, $[S_H - R, S_H]$, with different values of $R$ across specifications. This allows auctions that end at $S_H$ to be "less" censored than auctions that fail to sell. In all cases, starting price does *not* have a statistically significant negative effect on ending price (the effect is positive in most specifications). This is true even in models with fixed effects, where the estimates are biased away from zero and hence a null effect is more likely to be rejected.

B) Effect of experience

We now investigate whether bidders initially exhibit bidder effects but subsequently learn to avoid them. Table 7 reports the experience of bidders who cause one of the auctions in an

we find that the average ending price of the 38 LSPAs where the corresponding HSPA failed to sell is $1.15 below the average $S_H$ of the matched HSPA, and the average ending price of the 90 LSPAs where the matched HSPA ended at $S_H$ is 25 cents below the average $S_H$ of the matched HSPA.

experimental matched pair to end above the other. It shows the experience of the highest and second-highest bidders (whose bids directly determine ending price) in HSPAs that end above the LSPA, and in LSPAs that end above the HSPA. The sample includes the 51 pairs that met the ending-price condition of Prediction 2 (5 pairs with the same ending price are excluded.)

Learning would appear as inexperienced bidders being relatively more likely to overbid in LSPAs than HSPAs, and hence explaining relatively more LSPAs ending above HSPAs compared to HSPAs ending above LSPAs. This pattern should then abate with experience. Bidder experience is represented by the bidder's feedback score, split into ranges of 0-7, 8-22, 23-81, and above 81, corresponding to the 0-10, 11-25, 26-50, and above the 50$^{th}$ percentile.

Although the sample size is small, we observe limited or no evidence of learning. Only bidders in the bottom 10$^{th}$ percentile of experience show any indication of favoring the LSPA. This null result could be due to the significant experience of most bidders on eBay (even bidders at the bottom 25$^{th}$ percentile of experience have participated in dozens of auctions). We also speculate that lack of experience among subjects in most previous laboratory studies (highlighted in the Introduction), compared to the significant experience among nearly all eBay participants, might explain why previous laboratory studies find nonstandard behavior while we do not.

C) Reconciling results with previous findings

Several previous studies examine the effect of starting price on ending price in online-auctions. Ariely and Simonson (2003) find a positive relationship between starting price and ending price for football game tickets, while Ku, Galinsky, and Murnighan (2006) find a negative relationship for Persian rugs of various conditions and sizes, new or refurbished Nikon cameras, and Hawaiian-themed shirts that vary in perceived quality.

These analyses may not identify the causal effect of starting price for several reasons. First, they do not control for quality (e.g., ticket seat location). This can introduce a positive bias since starting price and quality may be positively correlated, as indicated in Table 1. Second, they do not control for reserve price. In auctions for higher-value items (e.g., football tickets), reserve price and starting price tend to be substitutes from a seller's perspective, since starting price is a visible reserve price (see Bajari and Hortacsu 2003, p. 332-335, for more on this issue). This can introduce a negative bias since auctions with a low starting price tend to have a high reserve price, and will only result in sale when they have a high ending price.[49]

Haubl and Popkowski Leszczyc (2003) sell collectible postage stamps and jackets in experiments in online auctions, and vary whether there is a starting price. The auctions with a starting price end 6 to 11 percent *above* auctions without a starting price. Kamins, Dreze, and Folkes (2004) sell one-pound assortments of wheat pennies and foreign coins in a manila envelope in an experiment on eBay, and also vary whether there is a starting price. The auctions with a starting price end 21 percent *below* auctions without a starting price. Ariely and Simonson (2003) also sell movie DVDs and computer peripherals in an experiment on eBay, and vary the starting price. When the auctions occur simultaneously, as in our analysis, they find no starting-price effect. Our experiment is closest to Ariely and Simonson (2003) in the sense that uncertainty about product quality is minimal (i.e., new, homogeneous products), and a high starting price is compared with a low starting price as opposed to no starting price. In contrast, there is an inherent uncertainty about product quality in the other two studies that may cause bidders to infer quality from starting price. It is also unclear how buyers perceive the absence of a starting price (i.e., does it indicate a low starting price or provide no direct information).[50]

---

[49] Only five auctions in our observational data set had a reserve price and we excluded them.
[50] Also note that the sample sizes of our data sets are two to thirty times larger that those of the previous studies.

Finally, Lucking-Reiley, Bryan, Prasad, and Reeves (2007) examine observational data on eBay auctions for collectible coins. Although they cannot ensure that quality is fully controlled for (which they discuss on p. 8-9), they are careful to address left-censoring of the ending price. They find no starting-price effect (except for one-bidder auctions), as we find.[51]

To better understand the role of unobserved demand in the ending-price that use observational data, we estimate the effect of starting price on ending price with our observational data set. The desired specification includes the group fixed effects defined earlier for the observational data set and includes only auctions that ended above the high starting price in the group (the ending-price condition of Prediction 2). The unit of observation is auction. The model is $E(\overline{P}_j|X_j) = X_j\delta + \eta_g$, where $\overline{P}_j$ is the ending price of auction $j$, $X_j$ are auction and seller characteristics, and $\eta_g$ are the group fixed effects. We estimate the model by OLS.

Results are reported in Table 8. For all specifications without group fixed effects and with auctions that end at or below the highest starting price, we find a large positive effect of starting price on ending price. However, in the desired specification in column (4), which includes group fixed effects and excludes auctions ending at or below the high starting price, the effect is absent completely.[52] The results again demonstrate the risks from unobserved demand for this test and corroborate the findings in Lucking-Reiley, Bryan, Prasad, and Reeves (2007).

## 7. OVERBIDDING IN AUCTIONS RELATIVE TO FIXED-PRICE ALTERNATIVES

[51] Though not the focus of their analyses, we note that the eBay field experiments in Hoppe and Sadrieh (2009) and Brown, Hossain, and Morgan (2010) also contain starting-price variation, and no effect on ending price is apparent.
[52] Also note that the effect of shipping fee is less than one, which is consistent with the "shrouded attributes" aspect of shipping fee (Hossain and Morgan 2006; Brown, Hossain, and Morgan 2010).

A) <u>Overbidding in auctions relative to BINs</u>

Using our observational data set, we now look for evidence of irrational limited attention by testing Prediction 3, which is that auction ending prices exceed the lowest contemporaneous BIN price on average. Following Lee and Malmendier (2011), we restrict attention to new regular-format DVDs and exclude auctions where the DVD was bundled with other items or failed to sell.[53,54] We add the shipping fee to the ending prices since this amount reflects how much bidders actually pay (Lee and Malmendier 2011 report the results both ways).[55] We use the lowest-price BIN at the time the winning bid in the auction was placed.[56] To ensure that the compared auctions and BINs are for the same items, we visually inspected all listings titles.[57]

The last set of columns in Table 3 are for the new movies/versions in our observational data set, and provide the fraction of auctions that are overbid and the average different between the auction and the lowest BIN price. We find that 23 percent of DVD auctions end above the lowest BIN price, and that auction ending prices are 18 percent *lower* than the lowest BIN price on average ($p<.01$). The auction ending price is also below the lowest BIN price for 23 of the 25 movie versions. Einav, Kuchler, Levin, and Sundaresan (2011) find similarly modest rates of

---

[53] Limiting the sample to new DVDs reduces the risk of unobserved differences in DVD quality between auctions and BINs. We use sellers' self-reported item condition (e.g., new, good) that is input by sellers into eBay fields.

[54] Including auctions that failed to sell is a reasonable alternative. Since 45 percent of auctions in our sample failed to sell, and these auctions would count as non-overbid cases, including these cases would reduce the overbidding rate significantly. Lee and Malmendier (2011) footnote 14 discusses this point.

[55] Adding shipping fee also avoids biasing the results towards overstating the overbidding rate. To see this, suppose all BINs for a particular item have approximately the same total price (item price plus shipping fee), but BIN sellers randomize the fraction of the total price that is the item price versus the shipping fee. By comparing the auction *item* price with the lowest BIN *item* price, we systematically choose BINs with low *item* price but high *shipping* fees.

[56] This is a small procedural improvement over Lee and Malmendier (2011), who use the lowest-price BIN within an hour of the auction close. This timing might matter because buyers often place winning bids hours or days before the auction closes, and BINs may have been initiated or removed after the winning bid was placed. Results however are not affected by this change. Results are also similar when we use the lowest-price BIN at the time the winning bidder's first-bid is placed, which might be meaningful if the winning bidder did not monitor competing auctions after entering the auction, and when we use the lowest-price BINs one hour after the auction closes.

[57] Some movies are offered in both widescreen and full-screen versions, and many bidders may prefer one (e.g., a bidder with a widescreen television may only seek a widescreen DVD version). Our data are not sufficiently comprehensive to identify this attribute for all listings, and hence some apparent overbidding may simple be due to this format difference. This only implies that our results are conservative.

overbidding in auctions relative to BINs. The tests of overbidding, and, in particular, the finding that auction ending prices exceed BIN prices on average, are the primary evidence in Lee and Malmendier (2011) of irrational limited attention.[58]

B) Evidence of frictions from auction-BIN wording differences

Despite the lower average price of auctions relative to BINs, 23 percent of auctions still ended above the BIN. We now provide evidence that the assumption of inconsequential information acquisition costs may fail such that frictions may explain many of these cases. We test Prediction 4, which is that the overbidding rate is highest when the auction title contains words not in the BIN title, lower when they both contain or both do not contain the words, and lowest when only the BIN contains the words.

Words that appear frequently in new-DVD listing titles are "new," "dvd," "special," and "disc." In 24 percent, 11 percent, 3 percent, and 3 percent of cases, the auction contained the word and the BIN did not, and in 27 percent, 3 percent, 3 percent, and 2 percent of cases, the BIN contained the word and the auction did not, respectively. Figure 3 shows overbidding rates for each of these words and for all words together. Large differences in overbidding rates across these word differences are apparent. For example, 35 percent of auctions are overbid when only the auction contains "new," 21 percent are overbid when both or neither contain "new," and 16 percent are overbid when only the BIN contains "new."

Particular movies contain idiosyncratic word differences as well. For example, "Camp Rock" (the movie appearing most frequently in our data, with 97 auctions) has wording differences for "Jonas" (i.e., Jonas Brothers) and "Disney." For "Jonas," 56 percent, 25 percent,

[58] Further, we find that overbidding does not decrease with experience. Overbidding rates are .23, .22, .22, .27, .19, and .25 for bidders with feedback scores of 0-9, 10-29, 30-129, 130-499, 500-999, and at least 1000. The lack of any learning to avoid this behavior if it were indeed a costly mistake strikes us as somewhat inconsistent with the learning to avoid nonstandard behavior found in the laboratory studies (discussed in the Introduction).

and 19 percent of auctions are overbid when only the auction, when the auction and BIN both or neither, and when only the BIN contain the word, respectively. For "Disney," these rates are 38 percent, 24 percent, and 0 percent. While 27 percent of "Camp Rock" auctions are overbid overall, only 12 percent of auctions with none of these word differences are overbid, and only 4 percent of auctions with none of these wording differences are overbid by over $1. These results are consistent with search and monitoring frictions explaining much of the overbidding.

C) Reconciling results with previous findings

In contrast to our results, Lee and Malmendier (2011) find very significant overbidding in eBay auctions relative to BINs. They analyze 166 auctions for the Cashflow 101 board game and 1886 auctions in 12 product categories such as books and consumer electronics. Seventy-three percent of Cashflow 101 auctions are overbid and auction ending prices are $2.69 *above* BIN prices on average; and 43 percent of auctions in the 12 other product categories are overbid and auction ending prices are 4.7 percent *above* BIN prices on average.[59]

To reconcile these results, we test whether wording differences contribute to overbidding in their data set as well.[60] We start by replicating their analysis for the 12 product categories. We are able to reproduce these results. However, upon visually inspecting the listing titles, we discovered a significant number of data errors. In 99 auctions (6.4 percent of the sample), and nearly all of the grossly overbid auctions, the auction was compared to a BIN for a different item. For example, the auction "Norelco Cordless Cord Electric Razor Shaver 8140XL New" (total price of $79.50) was compared with the BIN "Norelco Shaver Retainer Plate Smart Touch

[59] Ariely and Simonson (2003) provide a related result that most eBay prices for common items exceed the lowest non-eBay price found within a 10-minute search. As Lee and Malmendier (2011) note, however, this could be due to higher information and transaction costs and lower trustworthiness associated with non-eBay vendors.
[60] We obtained the data from the American Economic Review website via the journal's data availability policy.

& Speed XL" (total price of $17.75), a replacement part for the shaver.[61] After excluding mismatches, auction ending prices exceed BIN prices by 0.7 percent instead of 4.7 percent.

We then test Prediction 4 on the sample without mismatches. We consider the word "new," which is the most frequently cause of listing-title differences in our data set and applies to all 12 product categories in the Lee and Malmendier (2011) data set (as opposed to product-specific words like "disc" and "dvd"). Results are in Table 9. When only the auction contains "new," 60 percent of auctions are overbid and auction ending prices *exceed* BIN prices by 11.9 percent. However, when the auction and BIN both contain or both do not contain "new," 38 percent of auctions are overbid and auction ending prices are 1.2 percent *below* BIN prices. Thus, accounting for the data errors and this one wording difference reverses the primary evidence for irrational limited attention.

Finally, we split out the results by product instead of product category (e.g., "Audacity of Hope" by Barack Obama instead of "Books") and discovered that one outlier product (out of the 37 products) explains the results. The book "The Secret" is the most common item in the data set (12.1 percent of the sample). Ninety-two percent of auctions for "The Secret" are overbid and auction ending prices are 35 percent above BIN prices. After removing "The Secret," auction ending prices are 3.8 percent *below* BIN prices (versus 0.7 percent *above*). Figure 4 shows the average difference between auction and BIN prices for the 35 products with at least 10 auctions. For nearly all products, the auctions end below or only slightly above the BINs.

Lee and Malmendier (2011) also investigate eBay outcomes for the Cashflow 101 board game. We cannot examine the effect of wording differences for the game directly since the auction titles are not in their data set (and, regardless, the absence of an effect for the other 12

[61] It was also apparent to us that comparing auctions and BINs without shipping fees generated a significant number of grossly overbid auctions that were not overbid when shipping fees are included. Including shipping fees appears to be a more reliable approach for estimating overbidding. We discuss the potential bias in footnote 55.

product categories indicates that the results do not generalize). Nevertheless, Lee and Malmendier (2011) identify two BINs as the lowest-price BINs for all auctions in their sample period. Their titles are "CASHFLOW 101 Robert Kiyosaki Plus Bonuses!" and "NEW CASHFLOW 101 KIYOSAKI Buy Now FREE OFFER." Neither title contains "game" and both contain "cashflow" and not "cash flow." The importance of these wordings is evident in the following: On September 13, 2010, the search strings, "cashflow 101," "cashflow game," "cash flow game," "cashflow 101 game," and "cash flow 101," returned 135, 150, 30, 150, 21 listings, respectively ("cashflow game" and "cashflow 101 game" returned a different 150 listings).[62] Many bidders, then, may have found the auctions but not the BINs. Hence wording differences may explain the overbidding, which would not be inconsistent with standard behavior.

D) Comment on Jones (2011)

Jones (2011) also tests for overbidding in auctions relative to fixed-price alternatives. He examines eBay auctions for Amazon.com gift cards, using the card's face value as the fixed-price alternative. He finds that auctions end above the face value of the gift card in 41 percent of auctions. Jones attributes this outcome to bidding fever. While this is a very intriguing pattern, any explanation needs to also account for additional stylized facts about most winners of eBay gift-card auctions (not reported in Jones 2011): they purchase almost exclusively gift cards, do so frequently (often dozens per month), and pay above face value with some regularity. Figure 4 shows a typical bid history of a bidder who overbids on gift cards. Given the previous laboratory

[62] According to Alexa.com, these are the top search strings used in Google searches to find the website Cashflowboardgame.com, a website where the game can be purchased that was the first result in a Google search of "cashflow 101 game" on September 13, 2010.

evidence (discussed in the Introduction) that bidders quickly learn to avoid overbidding when the costs are apparent, as they would be here, we wonder if bidding fever is indeed important.[63]

## 8. CONCLUDING REMARKS

This paper tests for the presence of a range of nonstandard behaviors that have been attributed to bidders in auctions. Building on previous work, we use estimates of the effects of starting price on auction outcomes to test for nonrational herding, auction fever, quasi-endowment, and escalation of commitment. We find no starting-price effect regardless of the outcome variable (additional bid or ending price) or data source (experimental or observational). Hence, we find no indication that these effects are important in the field.

We also follow previous work to test for irrational limited attention. We examine the frequency of overbidding in auctions relative to fixed-price alternatives using a new data set, and provide a test of the identifying assumptions used in previous work. We find little support for this behavior as well. Given these results, and in contrast to a relatively large literature on consumer behavior in auctions, we conclude that there is currently only limited evidence that bidders in real-world auctions deviate from standard behavior. We again emphasize that this is not the same as showing that bidders conform to standard behavior. However, it does indicate that more work is needed before we can conclude otherwise.

[63] Internet forums suggest several rational explanations. These include arbitrage opportunities, such as credit-card cash-back, which award a percentage of the transaction price, and various Paypal and eBay coupons and discounts, which can represent 10 percent or more of transaction price. Bidders can also build a feedback score by buying what is essentially cash (i.e., Amazon gift cards) with cash, which would be consistent with the finding in Jones (2011) of more overbidding among lower-rating bidders. Given the ease of purchasing gift cards, its cash-like property, and that only the gift-card identification number is necessary to redeem the card's value, money laundering has also been suggested. Finally, purchasing Amazon gift cards via eBay using a PayPal account allows buyers without credit cards to purchase from Amazon, which does not accept PayPal. Eighty-five percent of gift-card purchases in Jones (2011) are for less than $1 over face value, and so even small benefits can explain most of purchases.

## REFERENCES


Abrevaya, Jason (1997) “The equivalence of two estimators for the fixed effects logit model,” Economics Letters, 55, 41-43.

Adams, Christopher (2010) “Identification and Estimation with Competing Auctions,” unpublished manuscript.

Ariely, Dan, and Itamar Simonson (2003) “Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions,” Journal of Consumer Psychology, 13(1&2), 113-123.

Bajari, Patrick, and Ali Hortacsu (2003) “The Winner’s Curse, Reserve Price, and Endogenous Entry: Empirical Insights from eBay Auctions,” Rand Journal of Economics, 34(2), 329-355.

Bajari, Patrick, and Ali Hortacsu (2004) “Economic Insights from Internet Auctions,” Journal of Economic Literature, 42, 457-486.

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

Bikhchandani, Sushil, Hirshleifer, David, and Welch, Ivo (1992) “A Theory of Fads, Fashion, Custom, and Cultural Change in Informational Cascades,” Journal of Political Economy, 100(5), 992-1026.

Brown, Jennifer, Tanjim Hossain, and John Morgan (2010) “Shrouded Attributes and Information Suppression: Evidence from the Field,” Quarterly Journal of Economics, 125(2), 859-876.

Cooper, David, and Fang, Hanming (2008) "Understanding Overbidding in Second-Price Auctions: An Experimental Study," Economic Journal, 118(532), 1572-1595.

DellaVigna, Stefano (2009) “Psychology and Economics: Evidence From the Field,” Journal of Economic Literature, 472(2), 315-372.

Einav, Liran, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan (2011) “Learning from Seller Experiments in Online Markets,” unpublished manuscript.

Ely, Jeffrey C., and Tanjim Hossain (2009) “Sniping and Squatting in Auction Markets,” American Economic Journal: Microeconomics, 1:2, 68-94.

Garratt, Rodney J., Mark Walker, and John Wooders (2011) “Behavior in Second-Price Auctions by Highly Experienced eBay Buyers and Sellers,” Experimental Economics.

Harstad, Ronald (2000) “Dominant Strategy Adoption and Bidders’ Experience with Pricing Rules,” Experimental Economics, 3, 261-280.

Hasker, Robin, and Kevin Sickles (2010) “eBay in the Economic Literature: Analysis of an Auction Marketplace,” Review of Industrial Organization, 37, 3-42.

Haubl, Gerald, and Peter T.L. Popkowski Leszczyc (2004) “Bidding Frenzy: Intensity of Competitive Interaction Among Bidders and Product Valuation in Auctions,” Advances in Consumer Research, 31, 90-93.

Heyman, James, Yesim Orhun, and Dan Ariely (2004) “Auction Fever: The Effect of Opponents and Quasi-Endowment on Product Valuations,” Journal of Interactive Marketing, 18(4), 7-21.

Hoppe, Tim and Abdolkarim Sadrieh (2009) “An Experimental Assessment of Confederate Reserve Price Bids in Online Auctions,” unpublished manuscript.

Hossain, Tanjim, and John Morgan (2006) “…Plus Shipping and Handling: Revenue (Non) Equivalence in Field Experiments on eBay,” Advances in Economic Analysis & Policy, 6(2), article 3.

Jones, Matthew T. (2011) “Bidding Fever in eBay Auctions of Amazon.com Gift Certificates,” Economics Letters, 113, 5-7.

Kagel, John, Ronald Harstad, and Dan Levin (1987), “Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study,” Econometrica, 55(6), 1275-1304.

Kagel, John, and Dan Levin (1993) “Independent Private Value Auctions: Bidder Behavior in First-, Second- and Third Price Auctions with Varying Numbers of Bidders,” Economic Journal 103(419), 868-879.

Kamins, Michael, Xavier Dreze, and Valerie Folkes (2004) “Effects of Seller-Supplied Prices on Buyers’ Product Evaluations: Reference Prices in an Internet Auction Context,” Journal of Consumer Research, 30, 622-629.

Katz, Ethan (2001) “Bias in Conditional and Unconditional Fixed Effects Logit Estimation,” Political Analysis, 9:4.

Kahneman, Daniel, Jack Knetsch, and Richard Thaler (1990) “Experimental Tests of the Endowment Effect and the Coase Theorem,” Journal of Political Economy, 98(6), 1325-1348.

Ku, Gillian, Adam D. Galinsky, and J. Keith Murnighan (2006) “Starting Low But Ending High: A Reversal of Anchoring in Auctions,” Journal of Personality and Social Psychology, 90(6), 975-986.

Ku, Gillian, Deepak Malhotra, and J. Keith Murnighan (2005) “Towards a Competitive Arousal Model of Decision-Making: A Study of Auction Fever in Live and Internet Auction,” Organizational Behavior and Human Decision Processes, 96(2), 89-103.

Lee, Young Han, and Ulrike Malmendier (2011) “The Bidder’s Curse,” American Economic Review, 101(2), 749-787.

List, John (2003) “Does Market Experience Eliminate Market Anomalies,” Quarterly Journal of Economics, 118(1), 41-71.

Lucking-Reiley, David, Doug Bryan, Naghi Prasad, and Daniel Reeves (2007) “The Determinants of Price in Online Auctions,” Journal of Industrial Economics, 55(2), 223-233.

Morgan, John, Ken Steiglitz, and George Reis (2003) “The Spite Motive and Equilibrium Behavior in Auctions,” Contributions to Economic Analysis & Policy, 2(1), article 5.

Ockenfels, Axel, David H. Reiley, and Abdolkarim Sadrieh (2007) “Online Auctions,” in Handbook of Information Systems and Economics, ed. Terrence Hendershott. Elsevier Science, 571-628.

Peters, Michael, and Sergei Severinov (2006) “Internet Auctions with Many Traders,” Journal of Economic Theory, 130, 220-245.

Reiley, David H. (2006) “Field Experiments on the Effects of Reserve Prices in Auctions: More Magic on the Internet,” Rand Journal of Economics, 37(1), 195-211.

Riley, John G., and William F. Samuelson (1981) “Optimal Auctions,” American Economic Review, 71(3), 381-392.

Simonsohn, Uri, and Dan Ariely (2008) "When Rational Sellers Face Non-Rational Buyers: Evidence from Herding on eBay," Management Science, 54(9), 1624-1637.

Thaler, Richard (1980) “Towards a Positive Theory of Consumer Choice,” Journal of Economic Behavior and Organization, 1(1), 39-60.

Virag, Gabor (2010) “Competing Auctions: Finite Markets and Convergence,” Theoretical Economics, 5(2), 241-274.

Wolf, James, R., Hal R. Arkes, and Waleed A. Muhanna (2005) “Is Overbidding in Online Auctions the Result of a Pseudo-Endowment Effect?” unpublished manuscript.

Wolf, James, R., Hal R. Arkes, and Waleed A. Muhanna (2006) “Do Auction Bidders ‘Really’ Want to Win the Item, or Do They Simply Want to Win?” unpublished manuscript.

Wooldridge, Jeffrey M. (2002) Econometric Analysis of Cross Section and Panel Data, The MIT Press, Cambridge, MA.

Yin, Pai-Ling (2006) “Information Dispersion and Auction Prices,” HBS Working Paper 06-011.

Table 1: Predictors of starting price in observational data

| | |
|---|---|
| Shipping fee | -0.407*** |
| | [0.039] |
| Priority shipping | 0.685*** |
| | [0.179] |
| Auction duration (days) | -0.103*** |
| | [0.030] |
| N competing auctions | -0.110*** |
| | [0.036] |
| Log of seller score | -0.012 |
| | [0.030] |
| % seller score positive | 0.071*** |
| | [0.019] |
| eBay store | -0.208 |
| | [0.130] |
| Powerseller | 0.109 |
| | [0.138] |
| New DVD | 0.439*** |
| | [0.119] |
| Special-edition DVD | 0.929*** |
| | [0.193] |
| Constant | -2.848 |
| | [1.899] |
| Movie fixed effects | Yes |
| Observations | 1920 |
| R-squared | 0.139 |

Notes: The unit of observation is auction. The dependent variable is auction starting price. The model is estimated by OLS. Standard errors are reported in brackets. "N competing auctions" is the number of auctions for that movie/version and new/used status that ended on the same day. *** indicates significance at the 1 percent level.

Table 2: Movies, starting prices, and ending prices in experimental data

| | HSPA starting price ($) | | Unconditional (LSPA - HSPA) ($) | | | Conditional (LSPA - HSPA) ($) | | |
|---|---|---|---|---|---|---|---|---|
| Movie title | Mean | SD | N | Mean | SE | N | Mean | SE |
| Apocalypto | 8.67 | 0.38 | 18 | -0.92 | 0.65 | 12 | -1.35 | 0.86 |
| Arthur and the Invisibles | 7.83 | 0.47 | 12 | -0.86 | 0.45 | 0 | . | . |
| Because I Said So | 6.10 | 0.59 | 20 | -0.48 | 0.45 | 14 | -1.04 | 0.48 |
| Blood Diamond | 5.73 | 0.48 | 20 | -0.08 | 0.54 | 12 | -0.45 | 0.61 |
| Casino Royale | 8.63 | 0.38 | 16 | -1.77 | 0.56 | 0 | . | . |
| Dreamgirls | 4.56 | 0.44 | 16 | 0.64 | 0.63 | 8 | 1.31 | 1.15 |
| Epic Movie | 4.25 | 0.46 | 16 | 0.11 | 0.90 | 2 | -0.49 | . |
| The Fountain | 5.81 | 0.43 | 18 | -0.71 | 0.65 | 14 | -0.34 | 0.79 |
| Hannibal Rising | 6.97 | 0.91 | 18 | -0.17 | 0.57 | 0 | . | . |
| Happy Feet | 7.58 | 0.17 | 20 | -0.61 | 0.59 | 2 | 2.25 | . |
| Letters from Iwo Jima | 10.75 | 0.59 | 12 | -0.88 | 0.47 | 2 | -0.13 | . |
| Music and Lyrics | 7.45 | 0.37 | 20 | 0.16 | 0.40 | 6 | -0.19 | 0.75 |
| Night at the Museum | 8.70 | 0.91 | 20 | -0.19 | 0.36 | 10 | -0.19 | 0.37 |
| Pan's Labyrinth | 7.70 | 0.31 | 20 | -1.97 | 0.85 | 6 | -0.33 | 0.60 |
| Pirates of the Caribbean: The Curse of the Black Pearl | 5.40 | 0.65 | 10 | 0.43 | 0.43 | 2 | 1.00 | . |
| Pirates of the Caribbean: Dead Man's Chest | 6.31 | 0.13 | 8 | -0.33 | 0.86 | 4 | 0.88 | 1.13 |
| The Queen | 7.06 | 0.55 | 16 | -1.64 | 1.23 | 4 | -4.75 | 3.25 |
| Shrek 2 | 4.68 | 0.31 | 14 | -1.00 | 0.49 | 6 | -1.00 | 1.04 |
| Smokin' Aces | 5.88 | 0.48 | 16 | -0.40 | 0.32 | 4 | 0.25 | 0.25 |
| Stomp the Yard | 6.97 | 0.57 | 16 | -1.03 | 0.25 | 2 | -0.51 | . |
| Déjà Vu | 6.03 | 0.48 | 18 | -1.37 | 0.48 | 4 | 0.25 | 0.25 |
| | 6.83 | 1.58 | 344 | -0.64 | 0.14 | 114 | -0.49 | 0.25 |

Notes: The table reports the movie titles in the experimental data, the starting prices of the HSPAs (“HSPA starting price ($)”), the difference between the mean ending prices of the LSPAs and HSPAs for pairs where both auctions resulted in sale (“Unconditional difference in ending prices”), and the difference between the mean ending price of LSPAs and HSPAs conditional on both auctions in a pair exceeding the high starting price (“Conditional difference in ending prices”). All DVDs are the regular version. There were 20 auctions per movie title, though not all resulted in sale or met the ending-price condition, and hence N is sometimes less than 20. The starting price of all LSPAs is 99 cents.

Table 3: Movies, starting prices, and ending prices in observational data

| | | New and used DVDs | | | | | New DVDs | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Start Price ($) | | End Price ($) | | | Fraction | Auction - BIN price ($) | |
| Movie Title | Version | N | Mean | SD | Mean | SD | N | overbid | Mean | SE |
| Batman Begins | Regular edition (1 disc) | 173 | 1.68 | 1.73 | 3.28 | 2.01 | 35 | 0.34 | -0.56 | 0.29 |
| | Special edition (2 disc) | 23 | 1.69 | 2.01 | 5.59 | 2.48 | 1 | 0.00 | -4.91 | . |
| Camp Rock | Regular edition (1 disc) | 124 | 2.48 | 2.61 | 9.57 | 3.08 | 97 | 0.27 | -1.30 | 0.27 |
| Casino Royale | Regular edition (2 disc) | 151 | 2.47 | 2.31 | 4.57 | 2.44 | 18 | 0.17 | -1.55 | 0.51 |
| | Special edition (3 disc) | 8 | 6.74 | 3.81 | 13.93 | 5.87 | 3 | 0.00 | -8.10 | 2.84 |
| College Road Trip | Regular edition (1 disc) | 68 | 2.15 | 1.92 | 4.89 | 3.02 | 30 | 0.03 | -3.98 | 0.40 |
| Harold and Kumar Escape From Guantanamo Bay | Regular edition unrated (1 disc) | 56 | 2.95 | 2.37 | 5.38 | 2.90 | 10 | 0.00 | -9.63 | 1.43 |
| Knocked Up | Regular edition unrated (1 disc) | 134 | 1.83 | 1.89 | 3.33 | 2.15 | 34 | 0.18 | -2.34 | 0.38 |
| | Special edition unrated (2 disc) | 9 | 2.44 | 3.24 | 7.75 | 3.77 | 1 | 0.00 | -14.92 | . |
| Live Free or Die Hard | Regular edition unrated (1 disc) | 103 | 1.72 | 1.61 | 3.72 | 2.63 | 9 | 0.44 | 1.39 | 2.21 |
| | Special edition unrated (2 disc) | 3 | 5.66 | 3.52 | 6.50 | 2.29 | 1 | 1.00 | 0.02 | . |
| Miss Pettigrew Lives For a Day | Regular edition (1 disc) | 37 | 3.02 | 2.57 | 6.64 | 2.72 | 16 | 0.00 | -6.39 | 0.64 |
| Pirates of the Caribbean 3 | Regular edition (1 disc) | 158 | 2.01 | 1.75 | 4.52 | 2.36 | 62 | 0.39 | -0.36 | 0.28 |
| | Special edition (2 disc) | 4 | 3.12 | 2.78 | 7.76 | 3.36 | 1 | 0.00 | -3.40 | . |
| Riddick Trilogy | Regular edition (2 disc) | 46 | 1.59 | 1.68 | 3.65 | 2.89 | 4 | 0.25 | -3.42 | 3.79 |
| Shark Tale | Regular edition (2 disc) | 68 | 1.40 | 1.32 | 2.78 | 1.70 | 6 | 0.67 | -0.20 | 1.62 |
| Street Kings | Regular edition (1 disc) | 113 | 3.28 | 2.45 | 5.26 | 2.17 | 39 | 0.21 | -1.89 | 0.33 |
| | Special edition (2 disc) | 8 | 3.87 | 4.16 | 7.66 | 3.14 | 7 | 0.43 | -1.30 | 1.21 |
| The Bank Job | Regular edition (1 disc) | 90 | 2.28 | 2.25 | 3.92 | 2.00 | 27 | 0.48 | -0.78 | 0.59 |
| | Special edition (2 disc) | 5 | 6.39 | 3.78 | 7.29 | 2.49 | 2 | 0.50 | -9.53 | 10.01 |
| The Notebook | Regular edition (1 disc) | 138 | 1.90 | 2.24 | 6.74 | 2.34 | 30 | 0.07 | -2.25 | 0.28 |
| The Scorpion King 2 | Regular edition (1 disc) | 79 | 2.54 | 2.13 | 4.26 | 1.95 | 50 | 0.14 | -2.40 | 0.28 |
| Transformers | Regular edition (1 disc) | 199 | 2.24 | 2.02 | 5.69 | 2.37 | 37 | 0.05 | -4.56 | 0.57 |
| | Special edition (2 disc) | 68 | 2.96 | 3.20 | 8.14 | 4.31 | 31 | 0.26 | -1.73 | 0.88 |
| Additional DVDs with only used versions | | 55 | 1.96 | 2.28 | 5.67 | 3.09 | 0 | . | . | . |
| | | 1920 | 2.24 | 2.24 | 5.15 | 3.18 | 551 | 0.23 | -2.13 | 0.15 |

Notes: The table reports the number of auctions (N), and the mean and standard deviation of starting and ending prices (excluding shipping fee), for each movie title and version that resulted in sale in the observational data set. “Fraction overbid” is the fraction of auctions with an ending price that exceeds the corresponding lowest-price BIN. “Auction - BIN price ($)” is the mean difference between the auction and the matching low-price BIN, where shipping fees are included.

Table 4: Summary statistics for auctions in observational data

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Shipping fee ($) | 3.17 | 1.29 | 0.00 | 9.99 |
| Log of seller score | 6.97 | 2.40 | 0.00 | 13.55 |
| % seller score positive | 99.19 | 5.22 | 0.00 | 100.00 |
| Duration (days) | 5.86 | 1.68 | 1 | 10 |
| N competing auctions | 2.24 | 1.42 | 1 | 9 |
| eBay store | 0.29 | 0.45 | 0 | 1 |
| Powerseller | 0.55 | 0.50 | 0 | 1 |
| New DVD | 0.29 | 0.45 | 0 | 1 |
| Special-edition DVD | 0.08 | 0.27 | 0 | 1 |
| Priority shipping | 0.09 | 0.28 | 0 | 1 |

Notes: The unit of observation is auction. N=1920 auctions. "N competing auctions" is the number of auctions for that movie/version and new/used status that ended on the same day.

Table 5: Estimated models of probability of additional bid using experimental data

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Starting price | 0.886*** | 0.959 | 0.929* | 1.091 |
| | [0.029] | [0.034] | [0.038] | [0.060] |
| Log of minutes remaining | 1.372*** | 1.421*** | 1.509*** | 1.867*** |
| | [0.048] | [0.078] | [0.062] | [0.178] |
| Log of seller score | 0.845* | | 0.861 | |
| | [0.081] | | [0.085] | |
| Movie fixed effects | Yes | No | Yes | No |
| Group fixed effects | No | Yes | No | Yes |
| One-bidder auctions excluded | No | No | Yes | Yes |
| Standing-price dummies | Yes | Yes | Yes | Yes |
| Observations | 1894 | 1894 | 1493 | 1491 |
| Pseudo R-squared | 0.389 | 0.653 | 0.342 | 0.706 |

Notes: The unit of observation is bid. The dependent variable is equal to one if the auction received another bid and zero if not. Columns (1) and (3) are logit models estimated by maximum likelihood. Columns (2) and (4) are fixed-effects logit models estimated by conditional maximum likelihood, where the groups are the matched pairs. Estimates are reported as odds ratios. Standard errors are reported in brackets with heteroskedasticity-robust standard errors clustered by auction for the regular logit models in columns (1) and (3). Dummy variables for standing price rounded to the nearest dollar are included. An intercept term is also included but not reported. * and *** indicate significance at the 10 and 1 percent levels.

Table 6: Estimated models of probability of additional bid using observational data

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Starting price | 0.795*** | 0.812*** | 0.805*** | 0.824*** | 0.936** | 1.060 |
| | [0.016] | [0.018] | [0.018] | [0.024] | [0.024] | [0.043] |
| Shipping fee | 0.884*** | 0.781*** | 0.774*** | 0.634*** | 0.875*** | 0.765*** |
| | [0.027] | [0.028] | [0.029] | [0.030] | [0.034] | [0.044] |
| Priority shipping | 0.914 | 0.883 | 0.917 | 0.744* | 0.857 | 0.714 |
| | [0.123] | [0.114] | [0.124] | [0.134] | [0.130] | [0.157] |
| Log of minutes remaining | 1.424*** | 1.374*** | 1.378*** | 1.492*** | 1.406*** | 1.546*** |
| | [0.017] | [0.017] | [0.017] | [0.025] | [0.018] | [0.031] |
| Auction duration (days) | 1.012 | 1.029 | 1.017 | 1.011 | 1.012 | 1.002 |
| | [0.021] | [0.022] | [0.023] | [0.034] | [0.025] | [0.042] |
| N competing auctions | 1.036 | 0.984 | 0.985 | | 0.970 | |
| | [0.024] | [0.025] | [0.025] | | [0.027] | |
| New DVD | | 1.443*** | 1.478*** | | 1.360*** | |
| | | [0.122] | [0.126] | | [0.126] | |
| Special edition DVD | | 2.353*** | 2.376*** | | 2.299*** | |
| | | [0.366] | [0.370] | | [0.360] | |
| eBay store | | | 0.946 | 0.939 | 0.931 | 1.073 |
| | | | [0.088] | [0.127] | [0.092] | [0.181] |
| Powerseller | | | 0.935 | 0.965 | 0.910 | 1.033 |
| | | | [0.089] | [0.130] | [0.094] | [0.168] |
| Log of seller score | | | 1.009 | 1.023 | 1.029 | 1.026 |
| | | | [0.020] | [0.029] | [0.023] | [0.035] |
| % seller score positive | | | 1.037*** | 1.062*** | 1.019* | 1.048** |
| | | | [0.012] | [0.019] | [0.011] | [0.022] |
| Movie fixed effects | No | Yes | Yes | No | Yes | No |
| Group fixed effects | No | No | No | Yes | No | Yes |
| One-bidder auctions excluded | No | No | No | No | Yes | Yes |
| Standing-price dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8788 | 8788 | 8781 | 8621 | 6740 | 6624 |
| Pseudo R-squared | 0.214 | 0.257 | 0.258 | 0.386 | 0.246 | 0.398 |

Notes: The unit of observation is bid. The dependent variable is equal to one if the auction received another bid and zero if not. The models in columns (1), (2), (3) and (5) are logit models estimated by maximum likelihood. The models in columns (4) and (6) are fixed-effects logit models estimated by conditional maximum likelihood, where the groups are auctions with the same movie/DVD version, new/used status, and end date. Estimates are reported as odds ratios. Standard errors are reported in brackets with heteroskedasticity-robust standard errors clustered by auction for the regular logit models in columns (1), (2), (3), and (5). Dummy variables for standing price rounded to the nearest dollar are included. "N competing auctions" is the number of auctions for that movie/version and new/used status that ended on the same day (i.e., in the same group). An intercept term is also included but not reported. *, **, and *** indicates significance at the 10, 5, and 1 percent levels, respectively.

Table 7: Bidder experience for auctions with higher ending price in pair using experimental data

| Score of *highest* bidder | LSPA ends above HSPA | HSPA ends above LSPA | Score of *second-highest* bidder | LSPA ends above HSPA | HSPA ends above LSPA |
|---|---|---|---|---|---|
| ≤ 7 | 4 | 2 | ≤ 7 | 2 | 5 |
| 8 - 22 | 2 | 7 | 8 - 22 | 1 | 3 |
| 23 - 81 | 5 | 10 | 23 - 81 | 4 | 11 |
| ≥ 81 | 6 | 15 | ≥ 81 | 10 | 15 |

Notes: Feedback scores of the highest bidder (left panel) and second-highest bidder (right panel) are tabulated 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 bottom $10^{th}$, $11^{th}$ to $25^{th}$, $26^{th}$ to $50^{th}$, and above the $50^{th}$ percentiles of feedback score. Only matched pairs where both auctions exceed the high starting price are included (the ending price condition of Prediction 2). Five matched pairs that had the same ending price are not included.

Table 8: Estimated models of ending price using observational data

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Starting price | 0.325*** | 0.306*** | 0.346*** | -0.007 |
| | [0.025] | [0.031] | [0.043] | [0.063] |
| Shipping fee | -0.615*** | -0.638*** | -0.498*** | -0.524*** |
| | [0.043] | [0.053] | [0.062] | [0.086] |
| Priority shipping | 0.269 | -0.006 | 0.212 | -0.184 |
| | [0.191] | [0.229] | [0.287] | [0.333] |
| Auction duration (days) | 0.140*** | 0.089** | 0.155*** | 0.135** |
| | [0.032] | [0.041] | [0.048] | [0.062] |
| N competing auctions | -0.157*** | | -0.096 | |
| | [0.039] | | [0.059] | |
| New DVD | 1.385*** | | 1.094*** | |
| | [0.128] | | [0.179] | |
| Special edition DVD | 2.641*** | | 3.141*** | |
| | [0.209] | | [0.273] | |
| eBay store | 0.175 | 0.161 | 0.358* | 0.161 |
| | [0.138] | [0.165] | [0.206] | [0.267] |
| Powerseller | -0.174 | -0.194 | -0.259 | -0.112 |
| | [0.147] | [0.171] | [0.213] | [0.246] |
| Log of seller score | 0.152*** | 0.148*** | 0.126*** | 0.081 |
| | [0.032] | [0.037] | [0.046] | [0.051] |
| % seller score positive | 0.007 | 0.024 | -0.023 | 0.064* |
| | [0.021] | [0.024] | [0.031] | [0.038] |
| Intercept | 2.245 | 2.653 | 5.511* | 0.117 |
| | [2.036] | [2.391] | [3.047] | [3.741] |
| Movie fixed effects | Yes | No | Yes | No |
| Group fixed effects | No | Yes | No | Yes |
| Only auctions that exceed high starting price in group | No | No | Yes | Yes |
| Observations | 1916 | 1916 | 1099 | 1099 |
| Pseudo R-squared | 0.513 | 0.792 | 0.473 | 0.873 |

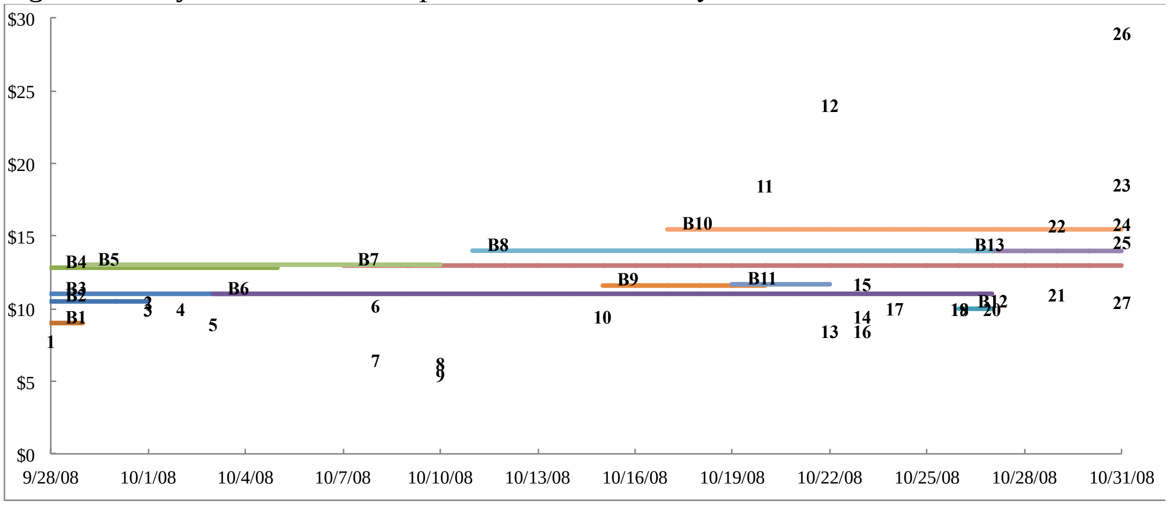
Notes: The unit of observation is auction. The dependent variable is the auction's ending price. The models are estimated by OLS. Groups in columns (3) and (4) are auctions with the same movie/DVD version, new/used status, and end date. Standard errors are reported in brackets. "N competing auctions" is the number of auctions for that movie/version and new/used status that ended on the same day (i.e., in the same group). *, **, and *** indicates significance at the 10, 5, and 1 percent levels, respectively.

Table 9: Listing wording differences and overbidding in Lee and Malmendier (2011) data

| | N | Fraction auctions overbid | Fraction auctions overbid by over 5% | Auction price - BIN price (%) |
|---|---|---|---|---|
| Auction has "new," BIN does not | 259 | 0.60 | 0.52 | 11.9 |
| Auction and BIN both have or do not have "new" | 884 | 0.38 | 0.26 | -1.2 |
| Auction does not have "new," BIN does | 308 | 0.36 | 0.24 | -3.4 |
| All auctions | 1451 | 0.41 | 0.30 | 0.7 |

Notes: "Fraction auctions overbid" is the fraction of auctions that end above the corresponding lowest-price BIN. "Auction price - BIN price (%)" is the mean difference of auction ending price and the lowest BIN price expressed as a percentage of the auction price.

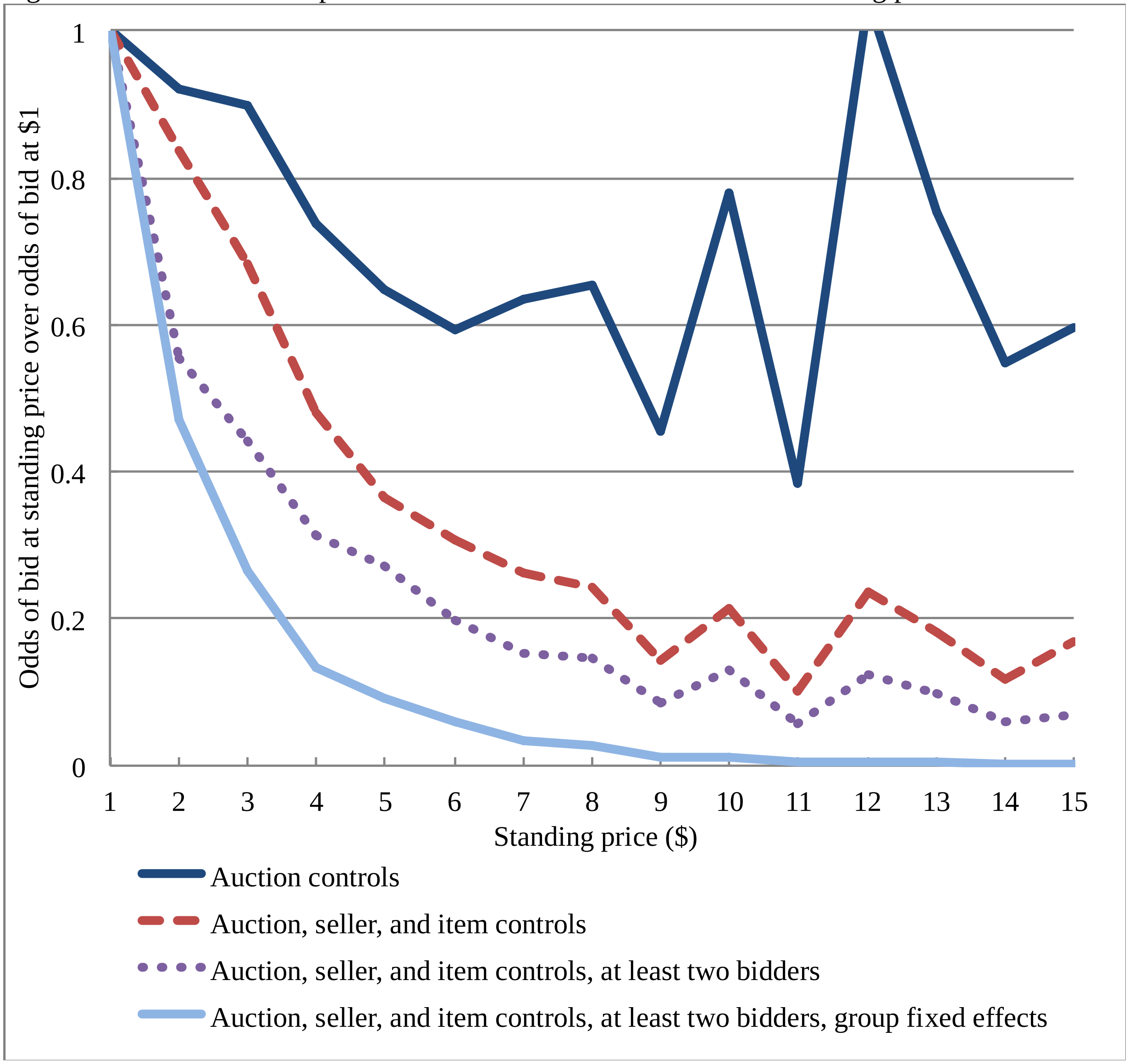
Figure 1: eBay auction and BIN prices for "Casino Royale" movie in October 2008




| | Listing title | Version | Edition | Widescreen | Seller percent of feedback positive | Seller score |
|---|---|---|---|---|---|---|
| 1 | Casino Royale (2007, DVD) Wide Screen NEW!! | 2006 | Regular | 1 | 100 | 3987 |
| 2 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 100 | 211 |
| 3 | Casino Royale (2 DVD) bond 007 widescreen sealed | 2006 | Regular | 1 | 99.8 | 22962 |
| 4 | Casino Royale-James Bond-007- (2007, DVD) *NEW*SEALED* | 2006 | Regular | 0 | 100 | 57 |
| 5 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 99.7 | 7187 |
| 6 | Casino Royale (2 DVD) bond 007 widescreen sealed | 2006 | Regular | 1 | 99.8 | 22962 |
| 7 | Casino Royale (2007, DVD) 99 CENTS - NO RESERVE | 2006 | Regular | 0 | 100 | 256 |
| 8 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 99.7 | 7185 |
| 9 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 99.7 | 7185 |
| 10 | Casino Royale (2 DVD) bond 007 widescreen sealed | 2006 | Regular | 1 | 99.8 | 22962 |
| 11 | Casino Royale BRAND NEW COLLECTOR'S DVD w/ movie cash | 2006 | Collector's | 1 | 99.7 | 2671 |
| 12 | CASINO ROYALE COLLECTOR'S EDITION DANIEL CRAIG DVD | 2006 | Collector's | 1 | 99.9 | 7991 |
| 13 | Casino Royale (2007, DVD)factory sealed | 2006 | Regular | 0 | 97 | 124 |
| 14 | Casino Royale *COLLECTOR'S EDITION* (2008, DVD) | 1967 | Collector's | 1 | 100 | 311 |
| 15 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 100 | 821 |
| 16 | Casino Royale Collector's Edition (2008, DVD) NEW | 1967 | Collector's | 1 | 100 | 4305 |
| 17 | Casino Royale (2002, DVD) | 1967 | Regular | 1 | 99.7 | 7187 |
| 18 | Casino Royale (2008, DVD) | 1967 | Collector's | 1 | 99.1 | 1878 |
| 19 | Casino Royale Deluxe 40th Anniversary Edition new DVD | 1967 | Collector's | 1 | 100 | 1102 |
| 20 | Casino Royale BRAND NEW Collector's Ed 40th Anniversary | 1967 | Collector's | 1 | 99.7 | 2670 |
| 21 | Casino Royale (2007, DVD) New | 2006 | Regular | 0 | 100 | 598 |
| 22 | Casino Royale (2007, DVD) NEW & SEALED | 2006 | Regular | 0 | 99.8 | 5448 |
| 23 | Casino Royale 3 Disc collectors Edition. Still Sealed | 2006 | Collector's | 1 | 100 | 7 |
| 24 | Casino Royale (2008, DVD) (Collector's Edition) | 2006 | Collector's | 1 | 100 | 5796 |
| 25 | Casino Royale (2007, DVD) BRAND NEW SEALED | 2006 | Regular | 0 | 100 | 959 |
| 26 | Casino Royale-Collector's Edition (2008, DVD) | 2006 | Collector's | 1 | 100 | 5796 |
| 27 | Casino Royale (2007) DVD 007 James Bond 2d WS, NEW NEW! | 2006 | Regular | 1 | 99.2 | 8216 |
| B1 | *NEW* Casino Royale (2007, DVD) | 2006 | Regular | 0 | 99.6 | 1174 |
| B2 | Casino Royale - W/S ***Brand NEW!!*** | ? | ? | 1 | 99.9 | 3142 |
| B3 | DVD - Casino Royale, BRAND NEW | ? | ? | 0 | 99.6 | 1261 |
| B4 | Casino Royale 2Disc WS Edition Brand New Factory Sealed | 2006 | Regular | 1 | 100 | 1013 |
| B5 | Casino Royale (2007, DVD) | 2006 | Regular | 0 | 100 | 405 |
| B6 | Casino Royale (2007, DVD) NEW! | 2006 | Regular | 0 | 100 | 277 |
| B7 | DVD Casino Royale 2Disc WideScreen Factory Sealed 2006 | 2006 | Regular | 1 | 100 | 1013 |
| B8 | CASINO ROYALE (2006) Daniel Craig New DVD | 2006 | Regular | 0 | 99.8 | 978 |
| B9 | Casino Royale DVD 2-Disc Widescreen Daniel Craig NEW | 2006 | Regular | 1 | 100 | 6260 |
| B10 | Casino Royale (2007, DVD) ~ NIP | 2006 | Regular | 0 | 100 | 268 |
| B11 | Casino Royale (2007, 2-Disc FS) - Brand New | 2006 | Regular | 0 | 100 | 2972 |
| B12 | Casino Royale (2007, DVD) SEALED 2 DISC FULL JAMES BOND | 2006 | Regular | 0 | 99.1 | 32618 |
| B13 | James Bond Casino Royale (DVD) New 007 Collector's Ed. | 2006 | Collector's | 1 | 100 | 18949 |

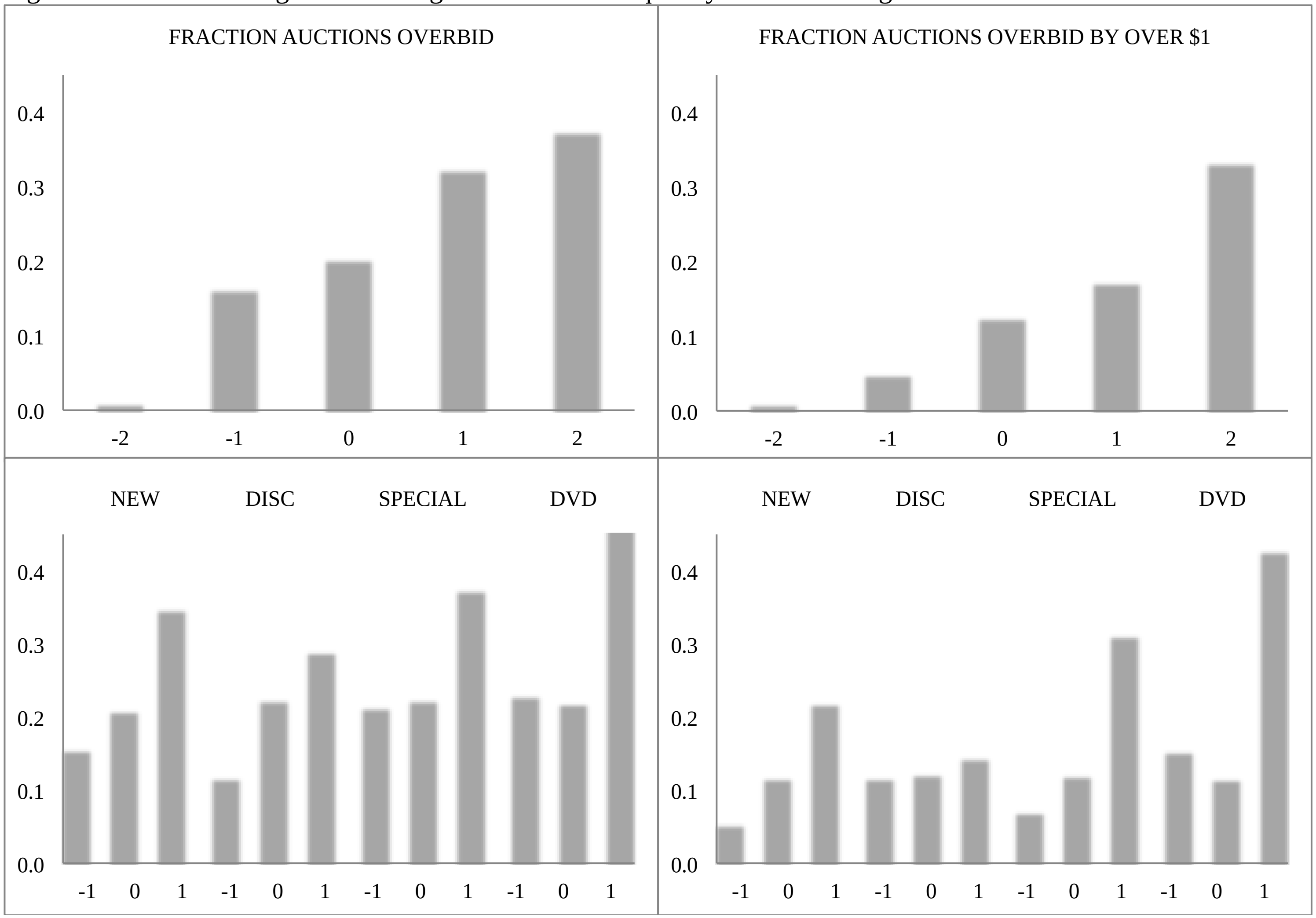
Notes: Numbers in the top panel are auction identifiers placed at the price and date of the auction close. Horizontal lines in the top panel are BINs, and are placed at the BIN price, with the length corresponding to its start and end times. The markers at the beginning of the BIN lines (beginning with "B") are BIN identifiers. The bottom panel reports the listing title, DVD version, edition, format, and seller characteristics. Only new, regular-format DVDs are included.

Figure 2: Effect of model specification on estimated odds ratios of standing price effect



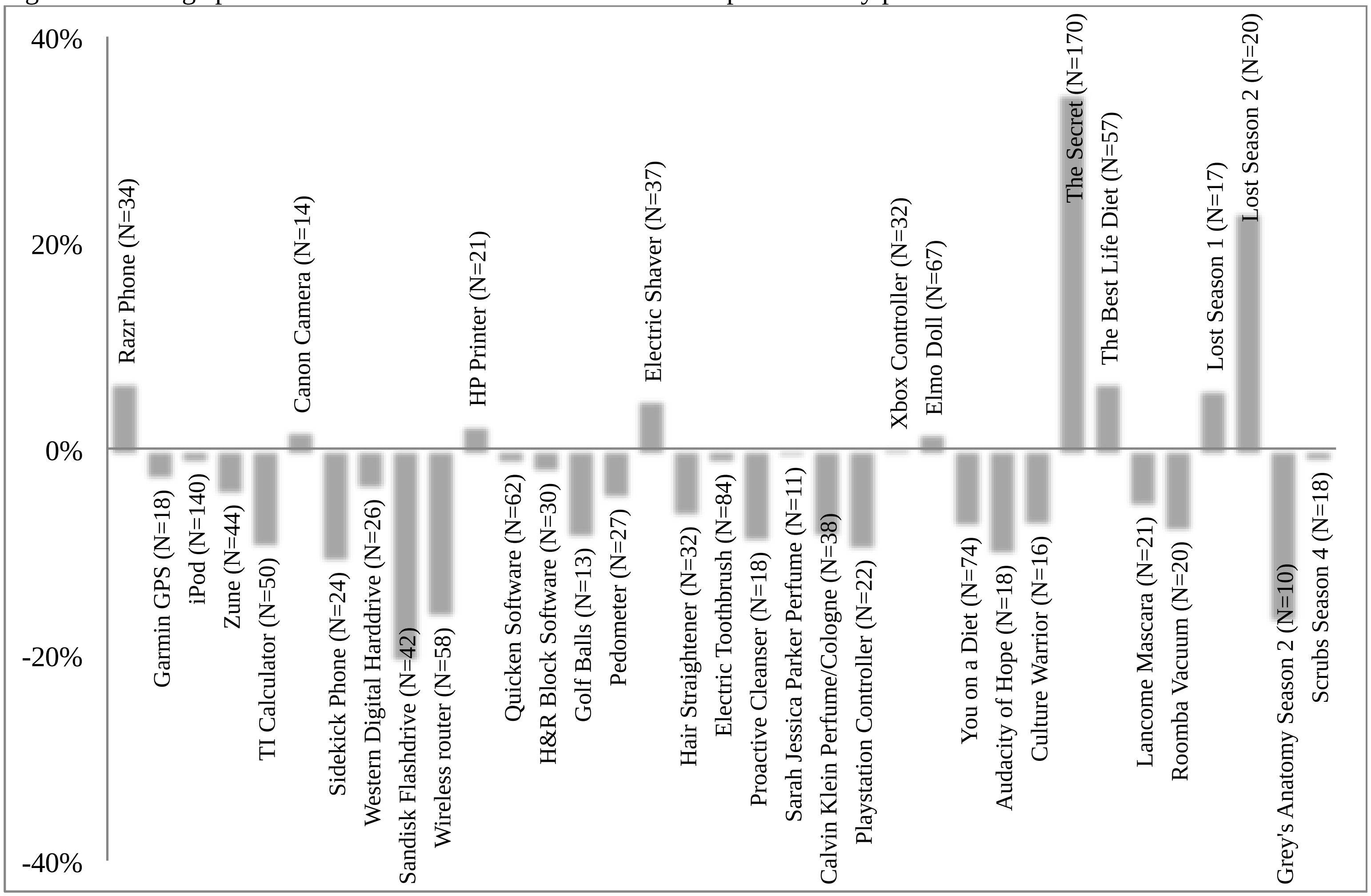

Notes: The curves show estimated odds ratios of standing price dummies rounded to the nearest dollar from a bid-level regression model where the dependent variable is the probability the auction receives another bid. The curves, from top to bottom, control for increasing amounts of unobserved demand (specifications 1, 3, 5, and 6 of Table 7).

Figure 3: Effect of listing-title wording difference on frequency of overbidding in observational data




Notes: Bar heights indicate the fraction of auctions with an ending price exceeding the lowest contemporaneous BIN price in the left panels, and exceeding the lowest contemporaneous BIN price by over $1 in the right panels. The top panels show these fractions according to the sum of word differences as in Prediction 4. The bottom panels show these fractions for individual words.

Figure 4: Average price difference between auction and lowest-price BIN by product




Notes: Bar heights represent the average percentage difference between the auction ending price and the lowest contemporaneous BIN price for that product.

Figure 5: Screen shot of typical 30-day eBay history of bidder who pays more than face value of gift card

## Bid History: Details

### Bidding Details

**Bidder Information**

| | |
|---|---|
| Bidder: | 2***7 ( 1718 ★ ) |
| Feedback: | 100% Positive |
| Item description: | $20.00 Amazon.com Gift Certificate |
| Bids on this item: | 1 |

**30-Day Summary**

| | |
|---|---|
| Total bids: | 49 |
| Items bid on: | 44 |
| Bid activity (%) with this seller: | 2% |
| Bid retractions: | 0 |
| Bid retractions (6 months): | 0 |

### 30-Day Bid History

| Category | No. of Bids | Seller | Last Bid |
|---|---|---|---|
| Gift Cards & Coupons > Gift Cards | 1 | Seller 1 | 1d 21h |
| Coins & Paper Money > Dollars | 3 | Seller 2 | <1h |
| Gift Cards & Coupons > Gift Certificates | 1 | Seller 3 | 1d 19h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 4 | 13h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 5 | 13h |
| Gift Cards & Coupons > Gift Certificates | 1 | Seller 6 | 1h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 6 | 1h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 7 | 1d 12h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 8 | 2d 8h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 9 | 13h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 10 | 2d 9h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 11 | 12h |
| Gift Cards & Coupons > Coupons | 2 | Seller 12 | 1h |
| Gift Cards & Coupons > Gift Certificates | 1 | Seller 6 | 2h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 13 | 4d 4h |
| Gift Cards & Coupons > Gift Certificates | 1 | Seller 14 | 3d 12h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 15 | 3d 7h |
| Gift Cards & Coupons > Coupons | 1 | Seller 16 | 2d 15h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 17 | 2d 15h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 18 | 2d 13h |
| Gift Cards & Coupons > Gift Cards | 2 | Seller 19 | 2d 12h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 20 | 2d 3h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 19 | 2d 12h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 19 | 2d 12h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 21 | 2d 11h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 22 | 1d 19h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 23 | 1d 11h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 24 | 1d 7h |
| Gift Cards & Coupons > Gift Cards | 1 | Seller 25 | 7h |
| Gift Cards & Coupons > Gift Certificates | 1 | Seller 6 | 4h |

## APPENDIX

A) <u>Details of data procedures</u>

We provide additional details about our data procedures here. To identify movie-DVD listings for our observational data set, our Java query tool was designed to be inclusive in the sense of capturing as many listings as could be reasonably expected to appear in a bidder's search. We searched in the "DVD, HD-DVD, and Blu-ray" category for U.S. based listings, and searched the title and body description of listings for our search terms (eBay's default search algorithm only searches the listing title) with a minimum of modifier terms (that is, our search string included the movie title only without additional terms to narrow the search). For example, we searched for DVDs for the 2005 movie "Batman Begins" using the string "Batman Begins" instead of "Batman Begins (2005)," "Batman Begins movie," or other search terms. As discussed in Section 3, the wording is important because of the "all words any order" aspect of eBay's search algorithm, which generally requires all terms in the search string to be present and exactly as spelled in the listing title for the listing to appear in search results. This rule can generate large differences in search results based on subtle differences in search strings.

The "all words any order" rule has caveats. The algorithm is not case sensitive, nor is it sensitive to the singular versus plural versions of search terms. For example, a search for the 2008 movie "Street Kings" returns listings for the 2002 movie "The Street King" and the 2003 movie "King of the Streets." Also, starting in late summer 2008, some bidders were opted in to an updated search algorithm, which additionally returns listings that do not contain the word "DVD" but are in a corresponding eBay listing category (DVD, HD-DVD, and Blu-ray). For example, a search of "Batman Begins DVD" returns all listings that contain the words "Batman

Begins DVD" and also listings in eBay's "DVDs & Movies" listing category that contain the words "Batman Begins" without the word "DVD."

The standing price after each bid is not directly in the eBay data. We reconstruct the standing price after each bid as follows: (1) Standing price is the starting price when only one bidder is in the auction (regardless of how many bids she has placed). (2) Standing price is the previous high bid amount plus the minimum bid increment, $e$, if the current bid amount is the high bid and the high bid exceeds the previous high bid by at least $e$. (3) Standing price is the current bid amount if the current bid is the high bid but is less than the previous high bid amount plus $e$. (4) Standing price is the current bid amount plus $e$ if the current bid amount is less than or equal to the high bid amount but greater than the current standing price. (5) Standing price is the high bid amount if the current bid amount is less than the high bid amount but greater than the high bid amount minus $e$. (6) Standing price is the previous standing price if the previous bidder increases her bid sequentially and her previous bid was the high bid amount.