

The Bidder's Curse*

Hanh Lee
Stanford University
yolee@stanford.edu

Ulrike Malmendier
UC Berkeley
ulrike@econ.berkeley.edu

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Abstract

Do biases matter in markets where consumers interact frequently and have opportunities to learn and sort? We study auction markets and argue that auctions exacerbate the effect of individual biases to overbid. Auctions systematically pick those consumers as winners whose willingness to bid is most upward biased.

Using a novel data set on eBay auctions, we find that, in the majority of auctions, the final price is higher than a fixed price at which the same good is available for immediate purchase on the same webpage. Such overbidding is most likely in auction with long listing periods, high bidder participation, high position on the website, and if the item description explicitly mentions the (higher) manufacturer price. Few biased bidders (12%) suffice to generate overbidding on average since they win the majority of auctions. Moreover, the most experienced market participants are most likely to bid suboptimally. Thus, experience does not eliminate overbidding. The latter result also indicates that overbidding reflects individual biases rather than search cost or other standard explanations for suboptimal purchase decisions.

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1 Introduction

Auctions have been a wide-spread and popular market mechanism for centuries (Cassidy, 1967). Already in ancient Rome, auctions were vastly popular, ranging from the sale of war spoils – documented in Rome’s earliest documents – over household objects to the allocation of tax collection rights by the Roman government.¹ A burgeoning auction literature in economics analyzes revenue maximization and efficiency of auctions under incomplete information as core reasons for this popularity.²

We consider another reason for the popularity of auctions: the potential for overbidding. In the heat of an oral auction or in the last minutes of an internet auction, some bidders may bid beyond their valuation. Or, their valuation increases over the course of the auction due to utility from gambling or competitiveness. In both cases, the auction increases expected revenues: it identifies the buyers with an inclination to overbid, induces them to overbid, and leads to a price above their valuation outside the auction.

Auctions, then, are a powerful case for the importance of non-standard preferences in economics. Overbidding biases do not negligible in real-world markets. Rather, they provide a (partial) explanation for one of the most important market mechanisms, the auction.

Concerns about overbidding are as old as auctions. In ancient Rome, legal scholars debated whether auctions are void if the winner was infected by “bidder’s heat” (*calor licitantis*).³ Experimental economics revived the debate about overbidding in economics when documenting the persistent failure of the revenue equivalence theorem in experimental auctions (Kagel, 1995). The role of overbidding is, however, is very hard to test empirically since we do not have objective measure of value for buyers.

¹Malmendier, 2002, p. 94 ff.; Girard and Senn, 1929, p. 305 f.

Livy (2,16,8 ff.) and Plutarch (Vitae parallelae, Poplikos 19,10) mention the sale of prisoners of war, the *venditio sub corona*, for the 6th century B.C. In the 2nd century B.C., Cato (De agr. 2,7) recommends auctions in the agricultural business – both the harvest and for tools not longer needed – and, in *Orationum reliquae* 53,303 (Tusculum) [42nd ed. JORDAN], for any household goods.

²See Milgrom (1987) for an analysis of auction formats and informational environments.

³The classical legal scholar Paulus argues in the *Corpus Iuris Civilis* (D. 39,4,9 pr. [PS 5,1a,1]): “A tax lease that has been inflated beyond the usual sum due to bidding fever shall only be admitted if the winner of the auction is able to provide reliable bondsmen and securities.” (*Locatio vectigalium, quae calor licitantis ultra modum solitae conductionis inflavit, ita demum admittenda est, si fideiussores idoneos et cautionem is qui licitatione vicerit offerre paratus sit.*) Thus, auctions won “under bidding fever” are not generally valid. See Malmendier (2002).

We use a novel design that detects overbidding in eBay auctions. I compare the prices paid in auctions to fixed prices at which the same good is available for immediate purchase on the same webpage. Despite equal or higher quality and better seller reputation in the fixed-price sale, we find that 72% of the auctions end at a price above the fixed price. While part of the overbidding is due to the neglect of shipping cost (Hossain and Morgan, 2006), 43% of auctions end at prices above the fixed price even without accounting for the differences in shipping costs.

We also analyze the causes of such overbidding. We find that overbidding is most likely in auctions that have long listing periods, high bidder participation, a top position on the eBay webpage, and if the item description explicitly mentions the (higher) manufacturer price of the good. Most importantly, 89.9% of overbids are follow-up bids to earlier bids below the fixed price by the same bidder in the same auction (only 77% if accounting for shipping cost). This suggests that bidders may initially account for the lower-price outside option but fail to account for it when eBay's outbid notice comes in – whether due to limited attention or due to competitiveness and bidding fever.

Third, we show that, while overbidding is common across auctions, it is not a common bidding strategy. Only 12% of bidders systematically overbid ever and only 11% of bids are above the concurrent fixed price. Thus, a small number of biased consumers suffices to generate overbidding in most auctions. We label this phenomenon the bidder's curse: auctions pick those bidders as winners who are most likely to overbid. Finally, we also show that suboptimal bidding is most prevalent among the most experienced bidders. Those who have concluded the highest number of eBay transactions display, for example, the strongest reaction to a description that mentions the higher manufacturer price. Thus, experience does not eliminate overbidding.

The last two findings lead us to the key message of the paper: the role of biases in markets. Experimental evidence from economics and psychology provides convincing evidence of non-standard preferences and non-standard belief formation among consumers. As economists, we are however interested in the question whether such biases affect market outcomes. Do consumers display non-standard behavior also in market settings where they may interact with other, unbiased agents (“arbitrageurs”); where they can seek advice; and where they have opportunities to learn and sort? The answer to this question varies. List (2003) provides evidence that experience reduces biases in a market for sports cards. Levitt and List (2005) argue that experiments can exacerbate biases due to sorting. On the other hand,

a growing literature on the “Behavioral Economics of Industrial Organization”, surveyed in Ellison (*forthcoming*), points out how biases may matter for contract and product design and that firms may, in fact, exacerbate their impact.⁴

In this paper, we provide evidence that not only market outcomes (winning prices in auctions) are affected by non-standard behavior; what is more, also the popularity of an important market institution – auctions – appears to reflect the impact of consumer biases. Moreover, this market institution functions as an amplifier of biases: it selects those consumers as participants in a transaction who display the strongest biases.

For our analysis, we hand-collected a novel data set on eBay auctions of a popular boardgame, Cashflow 101 from February to September 2004. A key feature of eBay’s Cashflow 101 listings is the continuous presence of a stable fixed-price offer on the same website. The standard eBay auction is a form of second-price auction. Bidders submit the maximum willingness to pay, and an automated proxy bidding system increases their bids up to that amount as competing bids are submitted. Under the fixed price, or “buy-it-now” format, the item goes to the person that bids the buy-it-now price first. The buy-it-now option is widely used on eBay and, in particular, by professional online retailers for whom eBay serves as an additional outlet.⁵ If identical items are simultaneously sold via regular auctions and the buy-it-now option, the fixed buy-it-now price provides an upper limit to bidders’ willingness to pay.

While our identification and finding of significant overbidding is specific to the auction object, the implications are likely to apply to other segments of today’s vast online auction market, involving more than 130m users and 1.4bn listings on eBay alone. The inducement to overpay and its prevalence among high-frequency participants are likely to be important components of the enormous growth of this market over the last decade.

We also conducted a survey of 306 Stanford students about their eBay experience. The results corroborate that overbidding occurs and also alleviate concerns about alternative explanations.

⁴See DellaVigna and Malmendier (2004) and (2006); Oster and Scott-Morton (2005); Gabaix and Laibson (2006); Heidhues and Koszegi, (2005).

⁵About one third of the transactions on eBay occur at a fixed price, the majority listings of small- or medium-sized firms. See *The Independent*, 07/08/2006, “eBay launches ‘virtual high street’ for small businesses” by Nic Fildes. New eBay products, such as “Express” reflect the large and increasing importance of fixed-price transactions; see *Wall Street Journal*, 05/25/2006, “eBay launches set-price site in challenge to online retailers.”

Finally, we complemented our data with an experiment, asking subjects to choose which items they would like to purchase, based on their description. The experiment addresses concerns that unobserved wording differences may explain our results.

Our paper relates to a growing literature in Economic Theory and Industrial Organization, analyzing the functioning of online auction markets, surveyed in Bajari and Hortascu (2003) and (2004). Our paper relates to the literature on unstable or unknown preferences. For example, Ariely, Loewenstein, and Prelec (2003) show that subjects' valuations of products and hedonic experiences are affected by arbitrary "anchors" such as a person's social security number. Our paper also relates to previous literature on online auctions. Ariely and Simonson (2003) find that almost all eBay buyers (98.9%) bid more than the lowest price available from other websites within a 10 minute web search. On average, eBay consumers pay 15.3% more than the lowest regular online retail prices they found. Our results add to these previous findings by eliminating alternative explanations, in particular transaction costs. Using different website can be time-consuming. The user does not only need to find the website but also needs to set up separate IDs with new passwords, credit card information etc. Moreover, bidders may be paying for the trustworthiness of eBay, such as the feedback system or the payment protection plan via PayPal. Our analysis eliminates those explanations since the data contains only alternative purchasing options *within* eBay. We also add to the previous literature by documenting the simultaneous neglect of relevant lower prices and over-adjustment for irrelevant higher prices.

Section 2 presents some institutional background about eBay and explains the auction design. Section 3 describes the auction object, the boardgame Cashflow 101, and provides details about our data set. In Sections 4 and 5, we present the empirical results and discuss potential explanations. Section 6 concludes.

2 Background Facts on Online Auctions

Since their inception in 1995 (Onsale and eBay), online auctions have undergone an explosion in volume and revenues. The largest market participant, eBay, earns profit from listing fees and sales commissions, without carrying any inventory. For 2004, the year of our sample period, eBay reported \$3.27bn revenues, and \$4.55bn for 2005. 135.5m registered users bid for,

bought, listed or sold an item in 2004, placing 1.4bn eBay auction listings, and the gross merchandise volume amounted to \$34.2bn.⁶

The success of online auctions has been traced to the reduction of transaction cost, both relative to traditional auctions and relative to classified listings (Lucking-Reiley, 2000b). The internet lowers transaction costs for sellers since they can use standardized online tools to set up the auction and do not need to organize announcements or other advertising. Buyers benefit from the low-cost online bidding technology and search engines, which reduce search cost within an auction site and between different sites. During an auctions, bidders receive automatic updates at almost no cost (via update email). Participants on both sides benefit since they do not need to physically meet and commit time for the full auction length. All of these benefits suggest that online auctions should increase consumers' price sensitivity and thus reinforce the law of one price.

To trade on eBay, users must generate an ID using a valid email address and a credit card number. Members can both sell items and bid for listed items. Sellers choose categories for the items to be listed, listing periods, and starting prices. In addition, sellers can specify a reserve price. Differently from the starting price, the reserve price is not visible to the seller. If the highest bid does not meet the secret reserve price, the seller does not have to sell the item. Sellers can choose 1, 3, 5, or 7 listing days for free; or they can choose 10 days for an extra listing fee of \$0.20 (as of our sample period). Sellers also incur the following three types of fees. First, they have to pay an insertion fee for the listing, regardless of whether an item is ultimately sold. If an item is sold, eBay charges a sales fee, which is proportional to the final sale price to the seller.⁷ Also, if the winner makes a payment through PayPal⁸, another fee, in proportion to the transaction amount, is applied to the sellers' account. Buyers do not pay any fee to eBay or PayPal.

To bid for items, users have to log in using their IDs. eBay follows a modified sealed bid second price auction with a proxy bidding system. The bidder who submitted the highest bid wins the item but only pays the second-highest price plus a small increment. An overview of the increments is in Table I.⁹ Alternatively, items can be bought at a fixed price via the "Buy-it-now" option. Whoever bids the price first gets the item. Note that

⁶ Annual reports 2004 and 2005.

⁷ Detailed information in on <http://pages.ebay.com/help/sell/fees.html>.

⁸ Founded in 1998, PayPal, enables any individual or business with an email address to send and receive payments online. PayPal was acquired by eBay in 2002.

⁹ For details see <http://pages.ebay.com/help/buy/proxy-bidding.html> and <http://pages.ebay.com/help/welcome/questions/buy-item.html>.

items are often available multiple times in one listing. It is common that online retailers list their items using eBay. In this case, they typically offer a “buy-it-now” purchase only. eBay also offers a hybrid “auction with buy-it-now.” In that case, bidders can choose immediate purchase at the buy-it-now price. However, after the first bidder decided not to click on the buy-it-now option but to place a (lower) bid, the buy-it-now option disappears.

The reliability of buyers and sellers on eBay is measured with so-called “Feedback Scores.” The score is always shown in parentheses next to the user ID. It is calculated as the number of members who left a positive feedback minus the number of members who left a negative feedback. One member can only contribute to the score by +1, 0 or -1. For example, if the number of positive reactions minus number of negative reactions of a given member is positive, the score is affected by +1. An additional feedback measure is the “Positive Feedback Percentage.” It is the percentage of positive feedback out of the total feedback. It is naturally volatile for bidders with a short history, and is not recorded for bidders without previous history.

3 The Data

We test for evidence of overbidding using a novel data set of online auctions downloaded from eBay.

3.1 The Auction Object

The auction object, Cashflow 101, is a boardgame that aims at entertaining while teaching financial and accounting knowledge.¹⁰ The manufacturer sells the game on his website (<http://www.richdad.com>) at the retail price of \$195 plus shipping cost of around \$10.¹¹ Cashflow 101 can be purchased at lower prices on eBay and from other on-line retailers. During the early period of our sample period, the boardgame was available at \$123 plus \$9.95 shipping cost from an online retailer outside eBay. The lowest outside price varies somewhat over the sample period. For example, on August 11, 2004, the lowest price we could identify was \$127.77 plus shipping cost of \$7.54.

We chose the auction market with three requirements in mind. First, our analysis requires a deep enough market for a homogenous item to provide

¹⁰Richard Kiyosaki invented the game in 1996 “to help people better understand their finances.” See ‘The Rising Value of Play Money’, *New York Times*, 02/01/2004.

¹¹See <http://www.richdad.com>. The details of the shipping cost are (as of 11/10/2004): UPS ground \$8.47, UPS 2nd-day air \$11.64, UPS next-day air \$24.81.

sufficient statistical power. Second, we were aiming for an item with a non-negligible price. Third, and most importantly, we aimed for a market with a stable and continuously present fixed price offered for the same good on the same webpage. In this case, any bidder who searches for the item at any time would find the fixed price offering on the screen that displays the current listings. Such a setting would allow us to use the fixed price as an upper limit for rational bidding behavior.

The auction market for Cashflow 101 satisfies all criteria. As the summary statistics in Table II reveal, its market was very active in 2004. Prices typically ranged from \$100 to \$200. Most importantly, it is a key feature of our auction data that, simultaneously, two professional retailers offered the same item on the same webpage at fixed prices, so-called “buy-it-now” prices. Both retailers posted the same fixed price of \$129.95 until end of July 2004. From August 1 on, both raised the fixed price to \$139.95.¹² Throughout the sample period, the sellers charged shipping costs of \$10.95 and \$9.95, respectively. Thus, eBay’s “buy-it-now” price is slightly more expensive than the cheapest possible price from outside eBay.

We exploit the stability of the buy-it-now prices and argue that they provide bidders with an upper limit of their willingness to pay for Cashflow 101. Since these prices were available to any bidder at any point in time during the auctions in our sample, bidders should not have bid beyond those prices. The prices are a conservative upper limit since other individual sellers sometimes also posted fixed prices, which were lower, and because of the lower prices on other online sites.

3.2 The Auction Data

We collected the data of all eBay listings of *Cashflow 101* between 2/11/2004 and 9/6/2004. Data is missing on the days 7/16/2004 to 7/24/2004 since eBay changed the data format requiring an adjustment of our downloading format. Our initial search for all listings in U.S. currency and excluded bundled offers (e.g. with Cashflow 202 or including additional books) yielded a sample of 287 auctions and 401 fixed-price listings by the two professional sellers. We eliminate auctions that ended early or were not sold, as identified by (i) lack of an auction winner, (ii) eBay indicating that the “seller ended” the auction, or (iii) lack of a final price. This is the case in exactly 100 auctions. Out of the remaining 187 auction listings, 20 were combined with a buy-it-now option, which was exercised in 19 cases. In the one remaining

¹²The manufacturer’s price at <http://www.richdad.com> remained unchanged.

case of listing with fixed-price options, the first bidder chose to bid below the buy-it-now price, and the listing became a regular auction, which is included in the sample. In the other 19 cases we could have used the (low) buy-it-now price as a tighter bound for rational bidding behavior in simultaneous auctions.¹³ We chose to simply removed them from the sample. In order to have a conservative and consistent benchmark of high-quality buy-it-now options with anticipated price we consider only the professional buy-it-now listings. For the same reason we dropped two more auctions during which, for a few hours no professional listing was available (8/14/2004 at 15:00:00 PST to 8/20/2004 at 20:48:22 PST). in which none of the professional retailers had a listing. Our final auction sample consists of 166 listings, with details of 2,353 bids by 806 different bidders.

In summary, every bidder in our sample of auctions who checked at any time during one of these 166 auctions the website of Cashflow 101 listing would have found the identical item, offered for immediate purchase at the buy-it-now price. Figure I displays an example of a listing webpage after the eBay member typed “Cashflow” in the search window. (Typing “Cashflow 101” would have given a more refined subset.) As shown, the listings are pre-sorted by their remaining listing time. On top are three smaller items, followed by a combined offering of Cashflow 101 and Cashflow 202. The fifth and the sixth lines contain Cashflow 101 only and are two data points of our sample. In the fifth line, we have a fixed-price listing by one of the professional retailers. In the sixth line, we have a standard auction. The availability of both types of formats on the same webpage allows us to use the buy-it-now prices as a benchmark for the maximum willingness to pay a buyer should display under standard assumptions of preferences and rationality.

The summary statistics of the auction data are displayed in Panel A of Table II. The starting price in an auction is \$46.14, well below the fixed prices. The average final price, \$132.55, points already to our first result, that a substantial subset of auctions end up above the simultaneous fixed prices. We also recorded shipping cost. However, in 27 cases, the shipping cost vary with the location of the buyer, which we could not determine. Thus, we report only the cost of the 139 cases, in which the seller set fixed shipping costs. The average auction attract 17 bids, with a standard deviation of 9 bids and the maximum number as high as 39 bids. These number

¹³Nine items had buy-it-now prices below \$100. In those cases, the items were sold within a few hours. Eight more buy-it-now prices were below the simultaneous buy-it-now prices of the professional retailers.

includes unsuccessful attempts (bids which fail to exceed the highest submitted bid until that time). Thus, a high number of bids does not necessarily mean that there was much competition. It may indicate that some bidders did not submit their highest willingness to pay immediately, but made many bids in a row, which did not outbid the highest bid at that moment. The interpretation of the number of bids recorded is therefore noisy.

We also obtained the data on feedback scores. The average seller score is considerably higher (262) than the average buyer score (37). 16.27% of the buyers have zero feedback at the time of purchase; the median is 5. The seller score translates into a positive feedback percentage of 62.9% on average.

The distribution of auction lengths chosen by the seller shows a sharp drop after 7 days. While the percentage of sellers continuously increases with the number of days, from only 1.2% choosing one day to the vast majority (65%) choosing a seven-day listing, only 5.42% choose 10 days. The drop is likely related to the small extra fee of \$0.20.

The most common ending day is Sunday (24.7%) followed by Saturday (18.7%). Tuesday has the lowest volume, followed by Friday. 34% of the auctions end during “prime time”, defined as 3 to 7 p.m. PST (following the convention of Jin and Kato (2004) and Melnik and Alm (2002)).

We also collected details in any quality differences. In 28.3% of the auctions, the listing title indicates that the board game is new, as indicated by “new,” “sealed,” “never used,” or “NIB.” In 10.8%, the title indicates prior use with the words “mint,” “used,” or “like new.” 28.4% of the titles imply that the standard bonus tapes or videos are included. Note that both are granted by the professional sellers. Finally, about one third mention that the (higher) retailer price of the board game if purchased from the manufacturer.

We also examine the correlations among key variables. *Starting Price* and *Number of Bids* have a correlation of $\rho = -0.72836$. The strong negative correlation raises concerns about collinearity. We will thus include *Starting Price* and *Number of Bids* only alternatively in our regressions. *Final Price* and *Explicit195* have a correlation 0.25143, already indicating the effect of explicitly mentioning the retail price. The starting price does not seem to be related to the final price. Their correlation is 0.01720.¹⁴

The remaining two panels of Table II provide details about the 807 bidders and 2,353 bids in our sample. Note that, due to the eBay-induced downloading interruptions, we have the complete data only for 138 auc-

¹⁴The starting price and the total price have a correlation of -0.02464 .

tions. This information is extract from the bidding history of each auction. An example is in Figure II. The bidding history is pre-sorted by amount, and display the maximum willingness to pay, indicated by a bidder at given point in time. The only exception is the highest bid, which is not revealed. Instead, the bidding history displays the winning price, i.e. typically the second-highest bid plus increment next to the winner’s ID.

In addition to recasting the information from Panel A in a bidder-level format (Panel B) and a bid-level format (Panel C), Panel B also reveals that bidders bid on average twice in a given auction and thrice overall (on any Cashflow 101 auction). About 6% of the bids come in within the last hour of a listing, more than 3% during the last 5 minutes.¹⁵

The vast majority of bidders does not acquire another Cashflow 101 after having won an auction. There are only 2 exception.

4 Overbidding

Our empirical analysis proceeds as follows. We first provide evidence of overbidding relative to the simultaneously available fixed-price on the same website, and discuss a number of alternative explanations for this empirical finding. We then analyze the circumstances under which overbidding occurs. In the following Section, we trace the significant amount of overbidding to a relatively small number of “overbidders.” We show that few users who bid beyond the buy-it-now price suffice to generate overbidding on average. We also show that experience does not eliminate such suboptimal bidding behavior.

Evidence of overbidding was already implicit in the summary statistics of Table II. The average starting price is \$46.14, is far below the simultaneous fixed-price offering of the board game. The most common range for the starting price (about 45%) is below \$20, indicating that sellers think that a low starting price can attract more bidders. However, the average final price amounts to \$132.55. In Table III, we show:

Fact 1. In 43% of all auctions, the final price is higher than the simultaneously available fixed price for the same good.

¹⁵Bidders can automatize last-minute bidding, using software programs to automatically place a bid in the closing seconds of an online auction, e. g. from <http://www.snip.pl>. EBay originally prohibited the use of automated programs on its auction site and sued some of the providers. The company now acknowledges the existence of automated bid programs, and refers to them as “outbid” services in its help section.

Thus, a significant number of auction winners deviate from the optimal bidding behavior – to buy the item either at a price below the fixed-price in an auction or, else, at the fixed price. Notice that such a better bidding strategy is easy to implement. Bidder can submit a willingness to pay that is identical to (or lower than) the buy-it-now price. If they receive an outbid notice, they can return to the fixed-price offering.¹⁶ Thus, a large portion of winners appears to choose a bidding strategy that is inconsistent with our standard model of preferences and beliefs.

Robustness. Before we explore the determinants and consequences of such behavior, we explore a number of alternative explanations for this phenomenon.

1. Noise. As indicated in Table III, the *average* price resulting from an auction lies only \$0.80 above the concurrent fixed price. Thus, overbidding may appear small – in absolute and relative to the value of the object – and could be justified by the transaction cost of returning to the buy-it-now item after having been outbid.

To test whether overbidding is constrained to cents in order of magnitude we study the entire distribution of the amount overbid. As shown in Table III, overbidding exceeds the magnitude of cents for a significant subset of auction winners. More than a quarter of all auctions end up \$10 above the alternative fixed price. 16% imply overpayment by more than \$20.

The six graphs of Figure III display histograms and kernel densities of the Final Prices. The histograms in Panel A are in bins of \$5 width. The histograms in Panel B are in bins of \$1 width. The histograms are overlaid with a kernel density estimate, using the Epanechnikov kernel with an “optimal” halfwidth. (The optimal width is the width that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel were used.)

2. Shipping cost. Another hypothesis is that the overbidding result disappears once we take shipping cost into account.

¹⁶It is also noteworthy that the information about current and past buy-it-now prices is available from eBay via the so-called eBay Marketplace Research. This eBay service requires a subscription fee (e.g. \$2.99 for one-time access) and offers information about average selling prices, price range, average buy-it-now price, and average shipping cost (http://pages.ebay.com/marketplace_research/detailed-comparison.html). Using this service (or researching past transactions themselves), bidders can easily find out that the BIN is constant over long periods.

The opposite is the case. This result becomes even sharper if we consider difference in shipping costs between auctions and the fixed-price offering of the professional sellers. The majority of sellers, 84% (in 139 auctions), choose the option to charge flat shipping costs. For the other 27 cases, either the bidder had to contact the seller or the cost depended on the distance from the seller’s location.¹⁷ The mean shipping cost is \$12.51. The average total price (including shipping costs) amounts to \$144.68. Accounting for shipping costs, 72% of the auctions end above the simultaneously available buy-it-now price and corresponding (lower) shipping costs.

Accounting for shipping cost, we also find that almost half of the auctions lead to overpayment by more than \$10. In 35% of all cases, the overpayment amounts to more than \$20; and still a quarter of final prices are \$30 higher than the concurrent fixed-price option.

3. Quality Differences. A third concern is that differences in quality between the items in high-price auctions and the items in the fixed-price offering explain the differences in price.

It is indeed the case that the quality of the boardgame varies somewhat between the different listings. Some boardgames are entirely new, in exactly the same condition as those offered by the manufacturer. In other cases, the boardgame was opened and played several times. Cassette tapes and other bonus items may be missing. Some sellers list the boardgame only. However, the two professional sellers offers only brand new items that include all “bonuses” of the original boardgames such as three audio cassettes and one VHS. They sometimes include even more bonuses such as a fake one-million-dollar bill, a handout with boardgame playing tips, or free access to some financial service websites. In addition, the professional sellers offer a six month return policy. The return policy in individual auctions was typically worse.¹⁸

Thus, the item quality of professionally sellers is (if anything) systematically higher. The buy-it-now price is therefore an even more conservative

¹⁷As alternative to setting a “flat shipping cost” the seller can opt for variable shipping costs that depend on the winner’s location. Typically, the seller opts for the “shipping cost calculator” of eBay. The buyer can type his or her zip code into the calculator and learns the approximate shipping cost. There are also cases where the seller simply states that “the winner should contact the seller regarding the shipping cost.” In both cases, the information is not available to us.

¹⁸The item descriptions say “6 Month No Risk Return Policy” for one retailers and “Your Bullet-Proof Protection... If, by the 180th day (six months) of evaluating CASHFLOW[®] 101, you are not absolutely delighted with the game, we want you to send the game back to us and we will gladly refund your entire purchase price - no questions asked.” for the other retailers.

comparison for the final price in the individual auctions.

4. Seller reputation. Another potential explanation regards the reputation of the sellers. Consumers may be willing to pay more for items they can buy from a trustworthy seller.

Using the eBay feedback score of sellers as a measure of trustworthiness, however, differences in seller reputation strengthen our results. The two professional retailers have considerably better *Feedback Scores* than ordinary individual users. One retailer had a score of 2849, with a *Positive Feedback* rate of 100% as of October 1, 2004. This seller received one neutral feedback which does not affect the *Feedback Scores* and no negative feedback at all. The overall positive feedback received was 2959. The other seller had an even higher feedback score of 3107 as of 10/1/2004, with a *Positive Feedback* rate of 99.9%. There were 3111 members who left positive feedback and four members who left negative feedback. The total positive feedback received was 3333. Negative feedback was received once in the previous 12 months.

A related concern is that buyers may prefer auctions of non-professional sellers over the buy-it-now offerings of professional retailers, for example due to past (bad) experiences.

To address this concern of a bad “buy-it-now reputation”, we conducted a large survey among 306 Stanford students.

(Details about the survey to be filled in.)

We found that the opposite is the case. The eBay users in our sample (50.83%) were well aware of the meaning of a buy-it-now offering and expressed a preference for buy-it-now transactions.

5. Unobserved quality differences. All of the measurable differences between auctions and buy-it-now transactions, discussed above, suggest that buyers should be willing to pay weakly more for the buy-it-now items than for the auction items.

A remaining concern is that unmeasured (i.e. unobserved) wording differences may explain our findings. For example, some aspect of the item description of the professional seller may turn potential buyers away and stir them towards the auction.

To address this concern, we conducted a hypothetical experiment with 99 Stanford students. The students received two randomly drawn item descriptions from auctions in our sample and one of the two item descriptions by a professional retailer. Any seller identification and prices were removed from the description. The order of the descriptions was randomized among the subjects. Subjects were asked which of the items they would prefer to purchase, assuming that prices and all eBay listing details (remaining time,

number of bids) were identical. It was also possible to express indifference between different items. Over 77% chose the buy-it-now item. After they made their choice, the students were also asked to explain their preference. Most commonly, they mentioned the more professional description and the money-back guarantee of the professional seller.

Given the significant amount of overbidding, we perform basic regression analyses to test for the features of an auction setting that trigger overbidding.

Fact 2. Overbidding is positively related to (i) auction length, (ii) mentioning of the (higher) manufacturer price in the item description, (iii) the number of bids, (iv) the number of simultaneous auctions, and (v) the position of an auction on top of the webpage.

In Table IV we relate the amount of *Overpayment*, defined as *Total Price* - ('buy-it-now' price) - (buy-it-now shipping cost) to the auction characteristics described in the summary statistics of Table II.

The most important and consistent determinant is the explicit statement in the description that the retail price is \$195. Only the dummy variable *Explicit195* has a positive coefficient with 95% statistically significant t-statistics. The total price is positively related to the auction length. However, Table IV also implies that one additional day of auction duration increases the final price by \$1.2 in most specifications. The latter finding suggests that it would increase sellers' profits to pay the extra fees for a 10-day auction period (at most \$0.20 as of 2004). The data suggests that buyers may not fully account for the potential increase. While it is the case that the vast majority (65.0%) chooses the maximum number of free days, only 4.7% are incurring the \$0.20-fee and choose a ten-day listing period. While the data is evidently insufficient to test whether the optimality of sellers' choice of auction length (both due to the lack of sufficient variation and, most importantly, exogenous variation), the sharp contrast between the frequency of free listing days (95.3%) and the frequency of auction lengths with an additional fee (4.7%) allows for the question whether buyers may underestimate the value of additional days of listing.

What is the relationship between a starting price and the final price? One view is that a low starting price can induce more number of bidders, and thus would push the price up with more competition. Another view is

that a low starting price will have an *anchoring effect*¹⁹ so that the final price will be low as well. The effect of the starting price on the final price is not clear in our analysis, with the regression coefficient virtually 0.

We also observe that a winner’s *Feedback Score* is negatively related to the final price, though not significantly so. The interaction of buyer feedback and *explicit195*, shown in Column IV, is positive and significant. This implies that the effect of explicitly stating that the retail price is \$195 is driven by experienced buyers. This result suggest that experience and sorting do not ameliorate overbidding. To the opposite, those with most market experience display the biggest overreaction to an (irrelevant) higher outside price. To examine the effect of the auction end day, we also include dummy variables for each day but Tuesday in addition as regressors. Column IV shows that the regression coefficients for the day dummies are insignificant. Adding these dummies (all or one by one) has little impact on the results.

Robustness. Using overpayment in terms of final prices, rather than accounting for shipping costs, yields similar results. The results are also similar if we use the subset of data that were collected before the “buy-it-now” price increase (Feb. 20th to the end of July, 2004). Adding the number of bids as independent variable decreases the coefficient of *Explicit195* somewhat, produces positive coefficients for *Starting Price*, and increases the R-square. This specification also leads to a larger negative intercept compared to the regression without *Number of bids*.

Finally, instead of using the log transformation of the buyers and sellers’ *Feedback scores*, the actual raw scores were used, and the results were similar.

The linear regression framework above shows which determinants lead to how much of a higher price. Alternatively, we may ask which determinants trigger bidders to cross the threshold of the buy-it-now price. For the latter analysis, we use a logit model. The dependent variable is an indicator equal to 1 if the total price is above “buy-it-now” and 0 otherwise. As shown in Table V, *Explicit195* still has a large positive coefficient, though it does not reach conventional levels of statistical significance. Only the effect of *Auction Length* remains statistically significant.

Table VI confirms that the effect of *Explicit195* is driven by bidders with high rather than low experience and is statistically significant for the group of bidders with highest experience (top 15%).

¹⁹People sometimes have a bias towards the number that was initially given to them when estimating true value of something. The initial number can be arbitrary and not directly related with the true value (Kahneman, Tversky (1974)[42]).

To be added: Description of conditional logit analysis. See Table V.

Bidders are more likely to bid on an item if eBay’s automatic pre-sorting by “time remaining” puts the listing on top of the webpage. This holds controlling for the time remaining.

Most aspects can be explained in a model of limited attention. In fact, 89.9% of overbids are follow-up bids to earlier bids below the fixed price by the same bidder in the same auction (only 77.2% if accounting for shipping cost). This suggests that bidders may originally choose the auction in hope for a lower price than the fixed price. At a later stage, however, they might not remember or be unwilling to return to the buy-it-now offering.

5 Market Amplification of Overbidding

This Section describes that, while the majority of auctions end up at too high a price, only few bidders display the inclination to overbid.

See Table VII.

We then describe that frequent market interaction does not eliminate the bias.

Buyers with the highest feedback scores choose, if anything, worse bidding strategies.

Thus sorting and experience does not eliminate the relevance of this bias for real-world market interaction studied in this paper.

The latter result also implies that the non-standard bidding behavior, analyzed in this paper, does not reflect standard search cost. Those users who are most familiar with the display format and who are most likely to have seen numerous buy-it-now offerings before, are most likely to be induced to overbid.

6 Conclusion

Our results suggest that a subset of bidders pay insufficient attention to alternative lower prices for the identical item on the same website. At the same time, mentioning the irrelevant higher retail price of \$195 does attract attention and affects bidding. The latter results may reflect an anchoring effect (see Kahneman, Tversky (1974)[42] or Rabin (1998)[38]). Previous psychology literature argues that the insufficient adjustment (here: to market prices) after anchoring is not reduced by much even when people are

aware of its influence, or when subjects' payoffs depended on their responses. (Chapman and Johnson (2002)[10]). It is also possible that some fraction of the final price is impacted by competitive bidding, or 'bidding fever.' Or, bidders may gain utility from the gambling process and therefore bid more. Our research design does not allow us to disentangle these explanations. Our findings do, however, indicate that standard rational models of bidding behavior, even accounting for search cost, are insufficient to explain overbidding. Moreover, while only a minority of consumers displays overbidding behavior, the nature of the auction selects precisely those consumers as winners and, thus, amplify the effect of biases in the market.

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Table I. Bid Increments

The bid increment is the amount by which an outstanding bid will be raised if it is outdone unless the winning bidder's maximum bid beats the second-highest maximum by an amount less than the full increment.

(Source: <http://pages.ebay.com/help/buy/bid-increments.html>, as of 10/02/2004.)

Current Price		Bid Increment
\$0.01-	\$0.99	\$0.05
\$1.00-	\$4.99	\$0.25
\$5.00-	\$24.99	\$0.50
\$25.00-	\$99.99	\$1.00
\$100.00-	\$249.99	\$2.50
\$250.00-	\$499.99	\$5.00
\$500.00-	\$999.99	\$10.00
\$1000.00-	\$2,499.99	\$25.00
\$2500.00-	\$4,999.99	\$50.00
\$5,000.00	and up	\$100.00

Table II. Summary Statistics**Panel A. Auction-Level Data**

The sample period is 02/11/2004 to 09/06/2004. Final Price is the final payment of the winner excluding the shipping cost and amounting to the second-highest bid plus the bid increment. Shipping Cost is the flat-rate shipping cost set by the seller. Total Price is the sum of Final Price and Shipping Cost. Auction Starting and Ending Time are defined in hours and fraction of hours, where [0; 1) is the time interval from 12am to 1am, [1,2) is the time interval from 1am to 2am etc. Prime Time is a dummy variable and equal to 1 if the auction ends between 3 p.m. and 7 p.m. PST. Delivery Insurance is a dummy variable and equal to 1 if any delivery insurance is available. Title New is a dummy and equal to 1 if the title indicates that the item is new. Title Used is a dummy and equal to 1 if the title indicates that the item is used. Title Bonus Tapes/Video is a dummy and equal to 1 if the title indicates that the bonus tapes or videos are included. Explicit195 is a dummy variable equal to 1 if the seller mentions the (high) manufacturer price in the description.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Starting Price	165	46.14	43.81	0.01	150
Final Price	166	132.55	17.03	81.00	179.30
Shipping Cost	139	12.51	3.75	4.95	20.00
Total Price	139	144.68	15.29	110.99	185.50
Number of Bids	166	16.91	9.13	1	39
Feedback Score Buyer	166	36.84	102.99	0	990
Feedback Score Seller	166	261.95	1,432.95	0	14,730
Positive Feedback Percentage Seller	166	62.92	48.11	0	100
ln(Feedback Score Buyer + 1)	166	2.04	1.68	0.00	6.90
ln(Feedback Score Seller + 1)	166	2.47	2.39	0.00	9.60
Auction Length [in days]	166	6.30	1.72	1	10
one day	166	1.20%			
three days	166	11.45%			
five days	166	16.87%			
seven days	166	65.06%			
ten days	166	5.42%			
Auction Ending Weekday					
Monday	166	11.45%			
Tuesday	166	7.83%			
Wednesday	166	15.66%			
Thursday	166	12.05%			
Friday	166	9.64%			
Saturday	166	18.67%			
Sunday	166	24.70%			
Auction Starting Hour	166	14.78	5.20	0	23
Auction Ending Hour	166	14.80	5.21	0	23
Prime Time	166	34.34%			
Title New	166	28.31%			
Title Used	166	10.84%			
Title Bonus Tapes/Video	166	21.08%			
Explicit195	166	30.72%			

Table II. Summary Statistics (continued)

Panel B. Bidder-Level Data

The sample period is 02/11/2004 to 09/06/2004.

Bids are submitted bids except the winning price for the winning bid.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Number of auctions a bidder participates in	807	1.44	1.25	1	17
Number of bids per bidder (total)	807	2.92	3.35	1	33
Number of bid per bidder (total per auction)	807	2.13	1.85	1	22
Average bid per bidder [in \$]	807	87.96	38.34	0.01	175.00
Maximum bid per bidder [in \$]	807	95.14	39.33	0.01	177.50
Maximum average bid per bidder [in \$]	807	92.48	38.72	0.01	177.50
Average number of auctions won	807	0.17	0.38	0	2
Frequency of winning per auction	807	0.15	0.34	0	1

Panel C. Bid-Level Data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Bid value [in \$]	2,353	87.94	36.61	0.01	177.5
Bid price outstanding [in \$]	2,353	83.99	38.07	0.01	177.5
Leading bid [in \$]	2,353	93.76	35.18	0.01	177.5
Feedback Score Buyer	2,353	32.40	104.65	-1	1,378
Feedback Score Seller	2,353	273.23	1422.55	0	14,730
Positive Feedback Percentage Seller	2,353	64.72	47.40	0	100
ln(Feedback Score Buyer + 1)	2,353	1.87	1.65	-1	7.23
ln(Feedback Score Seller + 1)	2,353	2.67	2.36	0	9.60
Starting time of auction	2,353	15.63	4.91	0.28	23.06
Ending time of auction	2,353	15.68	4.93	0.28	23.41
Bidding time	2,353	13.70	5.54	0.20	24.00
Last-minute bids					
during the last 60 minutes	2,353	6.25%			
during the last 10 minutes	2,353	4.25%			
during the last 5 minutes	2,353	3.48%			
Bid on auction with Explicit195	2,353	0.32	0.47	0	1
Bid on auction with delivery insurance option	2,353	0.46	0.50	0	1
Bids on auctions with bonus tapes/videos	2,353	0.25	0.43	0	1

Table III. Overbidding

Overpayment (Final Price) is equal to Final Price minus the simultaneous "buy-it-now" price set by a professional retailer. Overpayment (Total Price) is equal to Total Price minus the sum of the simultaneous "buy-it-now" price and the cheapest shipping cost for the "buy-it-now" item as set by a professional retailer.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Overpayment (Final Price)	166	0.80	16.86	-48.95	47.55
Overpayment (Total Price)	139	2.98	15.11	-28.91	45.60
Overpayment (Final Price)					
> \$0	166	43%			
> \$10	166	27%			
> \$20	166	16%			
> \$30	166	6%			
Overpayment (Total Price)					
> \$0	139	72%			
> \$10	139	48%			
> \$20	139	35%			
> \$30	139	25%			

Table IV. Determinants of the Amount of Overpayment

OLS regression with dependent variable is Overpayment (Total Price), i.e. the difference between the winning price and the simultaneously available buy-it-now price. Variable definitions as in Table II. In the third column, all the weekday variables except Tuesday are included in addition to the independent variables.

	(I)	(II)	(III)	(IV)
Explicit195	8.26*** (2.64)	7.39*** (2.76)	7.44** (2.90)	0.63 (4.45)
Shipping Cost	0.36 (0.36)	0.37 (0.36)	0.23 (0.38)	0.10 (0.39)
Auction Length	1.19* (0.71)	1.20* (0.71)	1.20 (0.73)	0.74 (1.28)
Starting Price	0.02 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
Ln(Feedback Score Buyer + 1)	-0.22 (0.74)	-0.27 (0.76)	-0.33 (0.78)	-2.76 (3.29)
Ln(Feedback Score Buyer + 1)*Explicit195				3.30** (1.65)
Ln(Feedback Score Buyer + 1)*(Auction Length)				0.20 (0.48)
Ln(Feedback Score Seller + 1)	0.31 (0.58)	0.29 (0.60)	0.19 (0.62)	0.02 (0.63)
Prime Time		1.26 (2.69)	1.52 (2.75)	1.46 (2.73)
Delivery Insurance		1.26 (2.69)	0.96 (2.74)	1.67 (2.76)
Bonus Tapes/Video		3.41 (2.91)	4.27 (2.97)	2.90 (3.03)
Auction Ends Monday			-1.86 (5.77)	-2.92 (5.74)
Auction Ends Wednesday			0.59 (5.62)	-0.85 (5.62)
Auction Ends Thursday			5.98 (5.93)	5.60 (5.89)
Auction Ends Friday			1.61 (6.38)	-0.10 (6.42)
Auction Ends Saturday			4.22 (5.44)	2.75 (5.45)
Auction Ends Sunday			-2.31 (5.16)	-3.42 (5.15)
Constant	-13.25* (7.44)	-14.37* (7.54)	-13.31 (9.22)	-4.45 (12.18)
<i>N</i>	140	140	140	140
<i>R</i> ²	0.10	0.11	0.14	10

Standard errors appear in parentheses.

Asterisks denote statistical significance at the 1%(***), 5%(**), and 10%(*) level.

Table V. Overpayment and Experience

We estimate Logit models and Probit models where the dependent variable is equal to 1 if the total price is greater than the simultaneously available buy-it-now price plus shipping cost. Variable definitions as in Table II. Coefficients are displayed as marginal effects.

	Logit	Logit	Logit	Logit
Explicit195	0.118 (0.092)	0.094 (0.095)	0.059 (0.103)	0.190 (0.159)
Shipping Cost	0.007 (0.012)	0.008 (0.013)	0.001 (0.013)	-0.004 (0.014)
Auction Length	0.051** (0.026)	0.053** (0.026)	0.054* (0.028)	0.050 (0.051)
Starting Price	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Ln(Feedback Score Buyer + 1)	-0.016 (0.026)	-0.019 (0.027)	-0.027 (0.028)	-0.092 (0.135)
Ln(Feedback Score Buyer + 1)*Explicit195				0.124 (0.064)*
Ln(Feedback Score Buyer + 1)*(Auction Length)				0.003 (0.020)
Ln(Feedback Score Seller + 1)	-0.010 (0.021)	-0.010 (0.021)	-0.016 (0.022)	-0.022 (0.023)
Prime Time		0.048 (0.096)	0.060 (0.098)	0.062 (0.100)
Delivery Insurance		0.032 (0.095)	0.013 (0.100)	0.036 (0.102)
Bonus Tapes/Videa		0.112 (0.101)	0.142 (0.105)	0.099 (0.110)
Auction Ends Monday			-0.296* (0.173)	-0.325* (0.166)
Auction Ends Wednesday			-0.153 (0.194)	-0.209 (0.191)
Auction Ends Thursday			0.137 (0.206)	0.136 (0.207)
Auction Ends Friday			-0.126 (0.221)	-0.183 (0.216)
Auction Ends Saturday			-0.009 (0.196)	-0.052 (0.201)
Auction Ends Sunday			-0.129 (0.183)	-0.173 (0.183)
<i>N</i>	140	140	140	140
<i>Pseudo-R</i> ²	0.04	0.04	0.08	0.10

Standard errors appear in parentheses.

Asterisks denote statistical significance at the 1%(***), 5%(**), and 10%(*) level.

Table VI. Which items do people bid on?

We estimate a McFadden conditional logit model where the dependent variable, *madebid*, is equal to 1 for items which were bid on at a particular time, and 0 for items available but which were not chosen by the bidder at that time. Reported here are the exponentiated coefficients, ie the odds ratios. The odds ratio indicates the change in the odds of an item receiving a bid if the independent variable increases by 1. For instance, if the rank of the remaining time on an item changes from 1 to 2, the odds that the item is bid on decrease by 11.5% (1-0.885) in

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current price	0.975 (23.73)***	0.975 (23.81)***	0.975 (24.00)***	0.972 (22.73)***	0.975 (23.79)***	0.976 (21.42)***	0.975 (23.85)***	0.972 (20.77)***
Remaining time on item	0.993 (11.50)***	0.997 (2.52)**	0.997 (2.71)***	0.997 (2.27)**	0.997 (2.59)***	1.000 (0.38)	0.997 (2.54)**	1.000 (0.16)
Starting price	0.995 (7.32)***	0.995 (7.69)***	0.995 (7.04)***	0.996 (5.78)***	0.995 (7.52)***	0.997 (4.70)***	0.995 (7.78)***	0.998 (2.36)**
Rank of remaining time on item (Rank on website)		0.885 (4.93)***	0.886 (4.88)***	0.873 (5.04)***	0.887 (4.85)***	0.862 (5.61)***	0.884 (4.98)***	0.837 (6.11)***
Seller feedback							1.000 (1.95)*	1.000 (3.78)***
Bidder feedback						0.999 (2.12)**		0.999 (2.50)**
After July 31, 2004					3.872 (1.73)*			4.724 (1.92)*
Shipping cost				0.997 (0.37)				0.987 (1.21)
Explicit195			1.279 (4.16)***					1.092 (1.23)
<i>N</i>	14760	14760	14760	11006	14760	12328	14760	9208
<i>Pseudo R-squared</i>	0.11	0.12	0.12	0.14	0.12	0.10	0.12	0.13

Table VII. Market Amplification

What % of <u>auctions</u> end up overbid?	(Auction-level sample)				
	0	74	53.62	53.62	
	1 	64	46.38	100.00	
	Total	138	100.00		
What % of <u>bidders</u> ever overbid?	(Bidder-level sample)				
	0	663	82.16	82.16	
	1 	144	17.84	100.00	
	Total	807	100.00		
What % of <u>bidders mostly</u> overbid?	(Bidder-level data)				
	0	708	87.73	87.73	
	1 	99	12.27	100.00	
	Total	807	100.00		
What % of <u>bids</u> are overbids?	(Bid-level data)				
	0	2,087	88.70	88.70	
	1 	266	11.30	100.00	
	Total	2,353	100.00		

Table VIII. Overbidding and Experience

Bidder-level data. The dependent variable is binary and equal to 1 if a bidder ever overbids.

	Probit	Probit
Number of auctions bidder participates in	0.021** (0.009)	0.019 (0.010)
Average starting price	0.002*** (0.001)	0.001* (0.001)
Average number of bidders	0.008 (0.005)	0.008 (0.006)
Average number of auctions won	0.294*** (0.034)	0.292*** (0.040)
Explicit 195	0.073** (0.030)	0.032 (0.037)
Seller feedback	0.000* (0.000)	0.0002* (0.000)
Top 15% of Bidder Feedback	0.020 (0.037)	-0.089 (0.093)
Bottom 15% of Bidder Feedback	0.011 (0.038)	-0.125 (0.082)
(top 15%)*(Number of Auctions)		-0.003 (0.024)
(bottom 15%)*(Number of Auctions)		-0.015 (0.111)
(top 15%)*(Average number of bidders)		0.004 (0.010)
(bottom 15%)*(Average number of bidders)		0.010 (0.010)
(top 15%)*(Number of Auctions Won)		0.036 (0.095)
(bottom 15%)*(Number of Auctions Won)		-0.015 (0.111)
(top)*(Explicit195)		0.204 (0.085)**
(bottom)*(Explicit195)		0.049 (0.075)
<i>N</i>		807
<i>Pseudo-R</i> ²		0.17

Standard errors appear in parentheses.

Asterisks denote statistical significance at the 1%(***), 5%(**), and 10%(*) level.

Figure I. Listing Example

Rich Dad's Cashflow Quadrant, Rich dad...	\$12.50	4	1d 00h 14m
Rich Dad's Cashflow Quadrant by Robert T. ...	\$9.00	9	1d 00h 43m
Real Estate Investment Cashflow Software \$\$\$!	\$10.49	2	1d 04h 36m
CASHFLOW® 101 202 Robert Kiyosaki Best Pak \$	\$207.96	=Buy It Now	1d 06h 47m
TRY IT TODAY, WITH ABSOLUTELY NO RISK,			
CASHFLOW® 101 Robert Kiyosaki Plus Bonuses!	\$129.95	=Buy It Now	1d 08h 02m
Your satisfaction is GUARANTEED, 100% \$ back			
MINT Cashflow 101 *Robert Kiyosaki Game NR!	\$140.00	13	1d 08h 04m
It's easy to be rich. Brand New. Still sealed			
cashflow Hard Money Funding 101 real estate	\$14.99	=Buy It Now	1d 09h 28m
BRANDNEW RICHDAD CASHFLOW FOR KIDS E-GAME	\$20.00	1	1d 13h 54m
CASHFLOW® 101 Robert Kiyosaki Plus Bonuses!	\$129.95	=Buy It Now	1d 14h 17m
Your satisfaction is GUARANTEED, 100% \$ back			
CASHFLOW® 101 202 Robert Kiyosaki Best Pak \$	\$207.96	=Buy It Now	1d 15h 47m
TRY IT TODAY, WITH ABSOLUTELY NO RISK,			

Figure II. Bidding History Example

The screenshot shows a Microsoft Internet Explorer browser window displaying the eBay bidding history for the item "CASHFLOW 101 Board Game Rich Dad Poor Dad". The browser's address bar shows the URL: <http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=5512116924>. The page indicates that the auction has ended. Below this, a table lists the bidding history, showing the user ID, bid amount, and date of bid for each bid. The highest bid is from user 'beezeebugs' for \$152.50 on August 11, 2004. Other users include 'mkdir-half', 'beezeebugs', 'dj_orbit', 'successbroker', '002la', '12-gauge', 'lindyque', and 'bearsnbulls22'. A note at the bottom of the table states: "If you and another bidder placed the same bid amount, the earlier bid takes priority."

Item title: CASHFLOW 101 Board Game Rich Dad Poor Dad
Time left: **Auction has ended.**

Only actual bids (not automatic bids generated up to a bidder's maximum) are shown. Automatic bids may be placed days or hours before a listing ends. Learn more about [bidding](#).

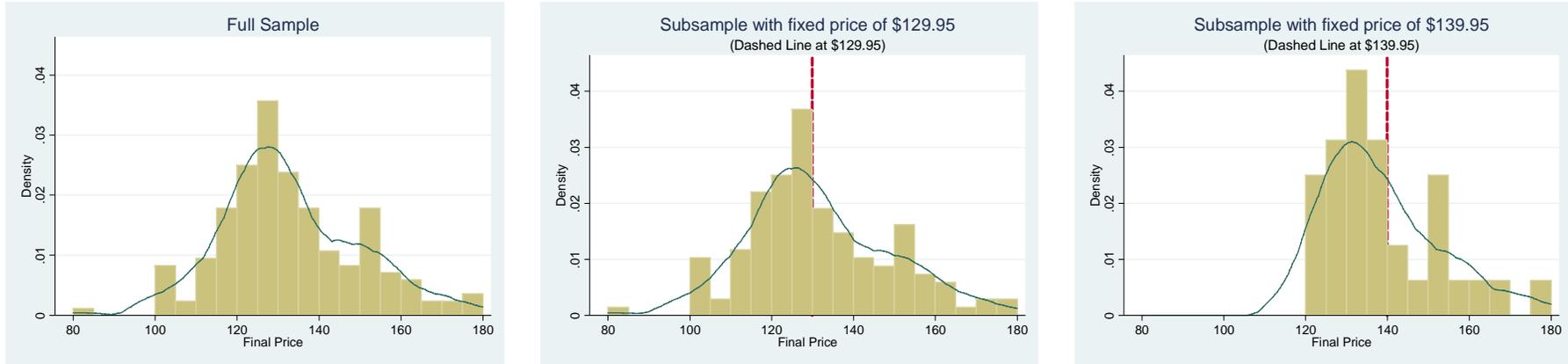
User ID	Bid Amount	Date of bid
beezeebugs (21 ★)	US \$152.50	Aug-11-04 09:51:21 PDT
mkdir-half (21 ★)	US \$150.00	Aug-11-04 06:39:53 PDT
beezeebugs (21 ★)	US \$140.00	Aug-08-04 12:06:05 PDT
dj_orbit (86 ★)	US \$130.01	Aug-09-04 23:49:02 PDT
successbroker (931 ★) me	US \$110.00	Aug-08-04 19:56:26 PDT
successbroker (931 ★) me	US \$105.00	Aug-06-04 17:18:21 PDT
002la (1)	US \$102.50	Aug-06-04 17:11:31 PDT
successbroker (931 ★) me	US \$100.00	Aug-05-04 15:41:40 PDT
002la (1)	US \$99.00	Aug-06-04 17:10:48 PDT
002la (1)	US \$95.00	Aug-06-04 17:10:21 PDT
12-gauge (29 ★)	US \$88.00	Aug-05-04 09:13:30 PDT
lindyque (110 ★)	US \$58.00	Aug-05-04 10:47:33 PDT
lindyque (110 ★)	US \$45.00	Aug-05-04 10:45:41 PDT
lindyque (110 ★)	US \$40.00	Aug-05-04 10:45:08 PDT
bearsnbulls22 (3)	US \$31.00	Aug-05-04 06:49:19 PDT
75lon (1)	US \$30.00	Aug-04-04 19:46:54 PDT
bearsnbulls22 (3)	US \$28.00	Aug-05-04 06:48:28 PDT
bearsnbulls22 (3)	US \$25.00	Aug-05-04 06:48:01 PDT

If you and another bidder placed the same bid amount, the earlier bid takes priority.

Figure III. Distribution of Final Prices

The six graphs of Figure III display histograms and kernel densities of the Final Prices. The histograms in Panel A are in bins of \$5 width. The histograms in Panel B are in bins of \$1 width. The histograms are overlaid with a kernel density estimate, using the Epanechnikov kernel with an "optimal" halfwidth. The optimal width is the width that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel were used.

Panel A. Bin-width \$5



Panel B. Bin-width \$1

