The Bidder's Curse*

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Abstract

Traditional explanations for the popularity of auctions are efficiency and revenue maximization. We argue that another reason is the potential for overbidding, i.e., buyers bidding above their willingness to pay outside the auction. The auction mechanism ensures that, even if only few buyers overbid, they affect prices and allocations. We employ a novel approach to identify overbidding in the field. Comparing auction prices to simultaneous fixed prices for identical items on the same eBay webpage, we argue that fixed prices provide an upper bound for auction bids. In a detailed data set of board game auctions, we find that the final price exceeds the simultaneous fixed price in 42 percent of the auctions. The result is not explained by differences in item quality, shipping costs, or seller reputation. Prior auction experience does not eliminate overbidding. The finding replicates in a second, broad data set of a cross-section of auctions (48 percent overbidding). The substantial fraction of overbid auctions is induced by a small number of bidders: only 17 percent ever bid above the fixed price. Using a simple model of second-price auctions with alternative fixed prices, we show that transaction costs of switching between auctions and fixed prices cannot explain the results, given that even the *expected* auction price is higher than the fixed price. Consistent with limited attention, the closer the fixed price is listed relative to an auction, the less likely are overbids. This effect is strongest for bidders' first bids, when they are likely to examine the auction and fixed-price listings more closely.

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1 Introduction

Auctions have been widely used for centuries (Cassidy, 1967). In ancient Rome, auctions were used to sell everyday household objects, war spoils, or even tax collection rights.[1] Today, objects as diverse as spectrum rights, treasury bills, and cars are regularly auctioned off. The auction literature suggests that revenue maximization and the efficiency of auctions under incomplete information are core explanations for their popularity.[2] Auctions identify the bidder who values a good the most and who is thus willing to pay the highest price.

We consider another reason for the popularity of auctions among sellers, the potential for overbidding. Auctions maximize the price impact of 'overbidders', i.e., buyers who bid above their willingness to pay outside the auction. Even if only few buyers overbid, they affect prices and allocations since auctions systematically pick those bidders as winners. Unlike the winner's curse, such overbidding affects both private-value and common-value settings. We denote this phenomenon as the "bidder's curse."

Concerns about overbidding are as old as auctions. In ancient Rome, legal scholars debated whether auctions were void if the winner was infected by "bidder's heat" (*calor licitantis*).[3] Previous literature in economics has raised the possibility of overbidding in auctions and auction-like settings as diverse as bidding for free agents in baseball (Blecherman and Camerer, 1996), drafts in football (Massey and Thaler, 2006), auctions of collateralized mortgage obligations (Bernardo and Cornell, 1997), auctions of initial public offerings (Sherman and Jagannathan, 2006), real estate auctions (Ashenfelter and Genesove, 1992), the British spectrum auctions (Klemperer, 2002) and contested mergers (Hietala, Kaplan, and Robinson, 2003; Malmendier and Moretti, 2006). In all of these field settings, however, it has been difficult to prove that a bidder paid "too much" given the value of the object.

In this paper, we propose a novel research design to detect overbidding in the field. We examine auctions in which the identical good is also continuously available for immediate purchase at a fixed price on the same webpage. We show that, under the standard bidding model, no bid exceeds the fixed price. This provides a non-parametric test of overbidding, independent of bidders' valuations. This identification strategy is related to previous research which compares auction prices to retail prices on other online sites (Ariely and Simonson, 2003). Our approach helps to rule out explanations based on switching costs, other transaction costs,

[1] Livy (2,16,8 ff.) and Plutarch (Vitae parallelae, Poplikos 19,10) mention auctions of prisoners of war in the 6th century B.C. In the 2nd century B.C., Cato (De agr. 2,7) recommends agricultural auctions for the harvest and for tools and, in Orationum reliquae 53,303 (Tusculum), for any household good. Malmendier (2002), p. 94 ff.; Girard and Senn (1929), p. 305 f.

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

[3] The classical legal scholar Paulus argues that "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." (Corpus Iuris Civilis, D. 39,4,9 pr.) See Malmendier (2002).

and lack of information about the alternative sites, as we discuss further below.

To motivate the empirical test, we present a simple model that introduces fixed prices into standard second-price auctions.[4] In the basic framework, rational bidders never bid above the fixed price. We then consider a number of extensions. In the presence of switching costs between the auction and the fixed-price sale, rational bidders may bid above the fixed price conditional on entering the auction. However, the *expected* winning price will be strictly smaller than the fixed price. We also consider limited attention (or limited memory) regarding the fixed price and utility of winning an auction (bidding fever). Either model can explain bids above the fixed price and also *expected* winning prices above the fixed price.

We test for the occurrence of overbidding using two novel data sets. Our first data set contains all eBay auctions of Cashflow 101 from February to September 2004. Cashflow 101 is a popular board game designed to teach financial and accounting knowledge. A key feature of the data is the continuous presence of a stable fixed price for the same game on the same eBay website throughout the entire duration of the auctions. Two retailers continuously sold brand new games at a price of \$129.95 (later \$139.95). Their listings are shown together with the auction listings on the regular output screen for Cashflow 101, and eBay users can purchase the game at the fixed price at any point in time. Hence, the fixed price provides an upper limit to bidders' willingness to pay for the item under the standard model.

We find that 42 percent of the auction prices exceed the fixed price. If we account for the differences in shipping costs, 73 percent of the auctions end above the fixed prices. The overbidding is not explained by differences in item quality or seller reputation. The amount of overbidding is significant: 27 percent of the auctions exceed the fixed price by more than \$10 and 16 percent by more than \$20. The distribution also rules out that overbidders are mere shills.

We replicate the overbidding results in a second data set, which contains a broad cross-section of $1,929$ different auctions, ranging from electronics to sports equipment. Across three downloads in February, April, and May 2007, overbidding occurs with frequencies between 44 and 52 percent. The net overpayment is 9.98 percent of the fixed price and significantly different from zero (s.e. 1.85). The second data set addresses the concern that overbidding may be limited to a specific item. While the broader data does not provide for all the controls of the Cashflow 101 sample, the pervasiveness of the finding suggests that the result generalizes.

We consider a set of rational explanations based on transaction costs. A rational bidder may bid above the fixed price if switching is costly. This bidder, however, only enters the auction in

[4] Auctions with simultaneous fixed prices for identical items have not been analyzed much theoretically, but are a common empirical phenomenon. Examples are airline tickets (skyauction.com or priceline.com versus online sales, e.g., Orbitz), time shares (bidshares.com), cars (southsideautoauctions.com.au), equipment and real estate (General Services Administration, treasury.gov/auctions, usa.gov/shopping/shopping.shtml, and gsasuctions.gov), online ads (Google's AdSense versus advertising agencies' fixed prices), or concert tickets (ticketauction.net or seatwave.com versus promoters' fixed prices).

the first place if the *expected* price is significantly lower than the fixed price. We find, instead, that the average auction price exceeds the fixed price. Another type of transaction costs is the cost of understanding the buy-it-now system. Unexperienced eBay users might not take BIN listings into account since they are still learning about auction and fixed-price features. We find, however, that the extent of overbidding is essentially the same for bidders with high experience and with low experience.[5] Hence, rational transaction-cost models fail to explain the observed bidding patterns.

Our second main result pertains to the debate about the relevance of biases in market settings. We show that few overbidders suffice to affect the majority of prices and allocations. While 42 percent of the CashFlow 101 auctions exceed the fixed price, only 17 percent of bidders ever bid above the fixed price. It is inherent in the nature of auctions as a price mechanism that few overbidders have a large impact on market prices and allocations, suggesting that auctions are a tool to "search for fools."[6] We further illustrate the influence of few overbidders in a simple calibration that allows for the simultaneous presence of rational bidders and overbidders. For even slight increases in the fraction of overbidders above 0.1-0.2, the fraction of overpaid auctions increases disproportionately.

Having established the extent of bidding above the fixed price and ruled out rational, friction-based explanations, we consider alternative explanations. One explanation is 'joy of winning.' Bidders may gain extra utility from winning an item in an auction relative to purchasing it at a fixed price. While it is difficult to test a general model of utility from winning, we present some evidence on one specific form, the quasi-endowment effect. According to the quasi-endowment effect, bidders become more endowed to auction items, and hence more likely to submit high bids, the longer they participate in the auction, in particular as the lead bidder (Heyman, Orhun, Ariely, 2004; Wolf, Arkes, Muhanna, 2005). However, we find no evidence of a positive correlation between overbidding and time spent on the auction or as the leading bidder. While bidders who ultimately win the auction with an overbid enter the auction 1.27 days before the auction ends, those who win without overbidding enter the auction earlier, 1.52 days before the auction ends. The same pattern emerges if we only consider the time a bidder has been the lead bidder.

A second explanation for our findings is limited attention towards the fixed price. Bidders may not pay attention to alternative prices for the identical good, even if offered on the same screen. According to this explanation, an auction should be less likely to receive an overbid if the fixed price is listed very closely on the same screen since the fixed price is more likely to capture the attention of the bidder. Using a conditional logit framework, we find that, indeed, greater distance between auction and fixed-price listings predicts significantly higher

[5]Bajari and Hortacsu (2003) and Garratt, Walker, and Wooders (2007) also find that bidders' experience has only a very small effect on overbidding in the field and the laboratory.

[6]We would like to thank Danny Kahneman for suggesting this description.

probability that the auction receives a bid. This relationship is strongest for bids just above the buy-it-now price, suggesting that limited attention is a determinant of overbidding. The effect of nearby fixed prices is particularly strong for a bidder's first bid. This is consistent with one form of inattention, limited memory: bidders may account for the lower-price outside option initially, but fail to do so when eBay's outbid notice ('You have been outbid!') comes in and they rebid.

This paper relates to several different strands of literature. First, it contributes to the literature on biases in markets. Also dubbed Behavioral Industrial Organization, this literature asks: Are biases less relevant in markets, e.g., due to experience, learning, and sorting (List, 2003; Levitt and List, 2006)? Or does market interaction with profit-maximizing sellers exacerbate their relevance (cf., Ellison, 2006)? Gabaix and Laibson (2006), for example, analyze firms' incentives to suppress information about add-on prices when consumers fail to account for these costs ex ante.[7] Our paper emphasizes firms' response to consumers' limited attention ex post (rather than ex ante), once they are engaged in a transaction. Hirshleifer and Teoh (2003) model firms' choice of earnings disclosure when investors display limited attention. Limited memory, and consumers' naiveté about their memory limitations has been modelled in Mullainathan (2002), along with market implications such as excess stock market volatility and over- and underreaction to earnings surprises. Hirshleifer and Welch (2002) show that limited memory may induce excessive continuation of previous behavior (in our context, bidding). Daniel, Hirshleifer, and Teoh (2002) provide a broad overview of the literature relating investor inattention to financial decision-making. In this paper we provide evidence on bidders being affected by the salience of auction and fixed-price listings and displaying limited memory of alternative fixed prices. Most closely related to the application in this paper, Compte (2004) argues that an alternative explanation for the winner's curse is that bidders make estimation errors and competition induces the selection of overoptimistic bidders. In another related paper, Simonsohn and Ariely (2007) document that sellers respond to buyers' preference for auctions with more bids by setting low starting prices.

This paper also relates to the growing literature on online auction markets, surveyed in Bajari and Hortacsu (2004). Roth and Ockenfels (2002) interpret last-minute bidding as either a rational response to incremental bidding of irrational bidders or rational equilibrium behavior when last-minute bids fail probabilistically. Neither hypothesis, however, explains overbidding beyond the eBay fixed price. The neglect of shipping costs, observed in our main data set, was first documented in Hossain and Morgan (2006). Most relatedly to our paper, Ariely and Simonson (2003) document that 98.8 percent of eBay prices for CDs, books, and movies are higher than the lowest online price found with a 10 minute search.[8] However, the design details

[7]Other applications include DellaVigna and Malmendier (2004, 2006), Heidhues and Koszegi, (2005), and Oster and Scott-Morton (2005).

[8]Pratt, Wise, and Zeckhauser (1979) find similar price variation when searching by phone.

and objective of the study are different. The overpayment may reflect lower transaction and information costs (search costs, creating new online logins, providing credit card information, site awareness etc.) and higher trustworthiness of using eBay. Our design addresses these explanations, given that all prices are on the same website and that the fixed-price sellers have significantly higher reputation and better shipping, handling, and return policy. Differently from Ariely and Simonson, our approach also disentangles the observed overbidding from mere shipping-cost neglect. Our setting also guarantees that the alternative fixed price is available simultaneously for the entire duration of the auction rather than only after the auction.

The continuous presence of a fixed price on the same webpage is also the main distinguishing feature relative to the field experiments of Anderson, Friedman, Milan, and Singh (2007) and Standifird, Roelofs, and Durham (2004). These studies evaluate the price impact of a 'hybrid' buy-it-now price, which disappears after the first bid. Here, final prices may exceed the buy-it-now price since early bidders' willingness to pay lies below the buy-it-now price and the winning bidder typically enters the auction after the fixed price has disappeared.

The observed overbidding on eBay is also related to overbidding in laboratory auctions. Experiments have documented large and persistent overbidding in second-price auctions. For example, 62 percent of bidders overbid in Kagel and Levin (1993) and 76 percent of bidders in Cooper and Fang (2006). However, in laboratory ascending (first-price) auctions, which are the closest in framing to eBay auctions, the observed overbidding largely disappears.[9] This discrepancy confirms that the source of overbidding in the laboratory is different from the causes we identify in the field.[10] In particular, limited attention is unlikely to play a role in prior laboratory experiments, where subjects are directly confronted with their induced value.

There is a large theoretical and empirical literature on the winner's curse in auctions, extensively discussed in Kagel and Levin (2002). The findings on winner's curse in online auction are mixed, cf. Jin and Kato (2006) and Bajari and Hortacsu (2003).[11] Differently from the winner's curse, the phenomenon analyzed in this paper is not restricted to common-value settings. Recent, belief-based explanations proposed for "cursedness" in common-value and private-value settings, e.g. Eyster and Rabin (2005) and Crawford and Iriberri (2007), cannot easily explain the overbidding observed in our data since it is suboptimal not to switch to the fixed price, once the auction price moves above, independently of the belief system.

[9] Kagel, Harstad, and Levin (1987) suggests that the difference in information flows between the two auction formats explains why erroneous overbidding does not disappear in SPAs.

[10] A number of experiments explore the causes for overbidding in the laboratory, such as spite motives, joy of winning, fear of losing, or bounded rationality (Cooper and Fang, *forthcoming*; Morgan, Steiglitz, and Reis, 2003; Delgado, Schotter, Ozbay, and Phelps, 2007). Bids above the risk-neutral Nash equilibrium in first-price auctions are commonly attributed to risk aversion (Cox, Smith, and Walker, 1988; Goeree, Holt, and Palfrey, 2002).

[11] Bajari and Hortacsu (2003) argue that buyers account for winner's curse since bids decline with the number of bidders. However, this is also consistent with a partially cursed equilibrium à la Eyster and Rabin (2003).

Finally, the paper relates to the literature comparing auctions to other price mechanisms, such as negotiations and posted prices (Bulow and Klemperer, 1996; Bajari, McMillan and Tadelis, 2002; Wang, 1993; Kultti, 1999). Zeithammer and Liu (2006) document stylized facts about sellers who use auctions and fixed prices on eBay. Halcoussis and Mathews (2007) study the correlation between auction and fixed prices for similar products (different concert tickets).

The remainder of the paper proceeds as follows. In Section 2, we present a simple model of bidding in second-price auctions with simultaneous fixed prices. Section 3 describes the data and some institutional background about eBay. In Section 4, we present the core empirical results. Section 5 discusses broader applications of the bidder's curse and concludes.

2 Model

Overbidding is difficult to identify since it is hard to measure a bidder's valuation. Our empirical identification strategy overcomes this hurdle by exploiting the availability of a fixed price at which the auction object is simultaneously sold in the same (virtual) outlet. In this Section, we extend a standard auction model to the availability of fixed prices. We show under which assumptions the fixed price provides an upper bound to bidders' willingness to bid. We then examine alternative assumptions, which may explain bidding above the fixed price: transaction costs of switching, inattention (including limited memory), and non-standard utility of winning (including pre-endowment effect and bidding fever). While the theoretical analysis considers the case of homogeneous bidders, the calibration in Section 4.3 allows for the interaction of heterogeneous bidders.

2.1 Benchmark Model

The bidding format on eBay is a modified second-price auction. Bidders can bid repeatedly within a specified time limit. The highest bid at the end of the auction wins, and the winner pays the second-highest bid plus an increment. Instead of bidding, buyers can also purchase at fixed prices. We model the second-price aspect and the availability of the fixed price. For simplicity, we neglect the discrete increments, the time limit in bidding, and reserve prices. We also abstract from the more complex, progressive-bid framing of eBay auctions. While these features are important to explain strategies such as sniping (Roth and Ockenfels, 2002), they do not rationalize bidding above the simultaneously available fixed price for the identical item on the same website.

We extend the standard second-price auction to a two-stage game, which incorporates the option to purchase the same good at a fixed price. Let the set of players be $\{1, 2, \ldots, N\}$, with $N \geq 2$, and denote their valuations as $v_1, v_2, \ldots, v_N$. The vector v of valuations is drawn from a distribution with no atoms and full support on R_+^N. Valuations are private information.

The first stage is a second-price auction. Each bidder i bids an amount $b_i \in R_+$. The highest bidder obtains the object and pays a price p_w equal to the second-highest bid. Ties are resolved by awarding the item to each high bidder with equal probability. In the second stage, players can purchase the good at a fixed price $\overline{p} \geq 0$. There is unlimited supply of the good in the second stage but only one unit is valuable to a player; the value of additional units is 0. We assume that, if indifferent, players purchase the good. Conditional on winning the auction, player i's payoff is $v_i - p_w$ if she does not purchase in the second stage and $v_i - p_w - \overline{p}$ if she purchases an additional unit (valued at 0). Conditional on losing the auction, her payoff is $v_i - \overline{p}$ if she purchases and 0 otherwise. We now characterize the equilibrium strategies b^*.

Proposition 1 (Benchmark Case). *(a) The following strategy profile is a Perfect Bayesian equilibrium (PBE): In the first stage (the second-price auction), each player i bids her valuation up to the fixed price: $b_i^* = \min\{v_i, \overline{p}\}$. In the second stage (the fixed-price transaction), player i purchases if and only if she has lost the auction and her valuation is higher than the posted price ($v_i \geq \overline{p}$). (b) For all realizations of valuations v and in all PBEs, the auction price is weakly smaller than the fixed price: $p_w(v) \leq \overline{p} \quad \forall v \in \mathbb{R}_+^N$.*

Proof. See Appendix A.

Proposition 1.(a) illustrates the impact of a fixed price option on bidding in second-price auctions. Rather than simply bidding their valuations, as in the classic analysis of Vickrey (1961), bidders bid at most the fixed price. If they do not win the auction they then purchase at the fixed price if their value is high enough. The strategy profile described in Proposition 1.(a) is unique if we rule out degenerate equilibria. An example of a degenerate PBE is that, for all realizations of v, one person, say bidder 1, always bids an amount above $\overline{p}$, $b_1 > \overline{p}$, in the first stage and does not purchase in the second stage; all others bid 0 in the first stage and purchase in the second stage if and only if their valuation is weakly higher than $\overline{p}$. Proposition 1.(b) states that, even if we allow for degenerate equilibria, the auction price never exceeds $\overline{p}$.

2.2 Transaction Costs of Switching

One explanation for auction prices above the fixed price are transaction costs of switching. Once a consumer has started bidding, it might be costly to return to the webpage with all auctions and fixed prices and to click on the fixed price. We show that, if transaction costs are high, rational bidders may bid more than the fixed price but that the *expected* auction price will be lower than the fixed price. Rational bidders enter the auction only if they expect the final price, conditional on winning, to be smaller than the fixed price.

For simplicity, we assume infinite switching costs: players have to choose between the auction and the fixed price. We model this case with a simple change to the game: player i can purchase in the second stage if and only if $b_i = 0$. Thus, bidder i enters the auction for all valuations v_i for which the expected surplus conditional on winning, $E\left[v_i - p_w \,|v_i, i \text{ wins}\right]$, times the probability of winning, $\Pr(i \text{ wins}|v_i)$, is larger than the (deterministic) surplus from purchasing at the fixed price, $\max\{v_i - \overline{p}; 0\}$, where b is the vector of bidding strategies including the zero bids of those bidders who do not enter the auction. We assume that bidders enter the auction if indifferent between the auction and the fixed price.

It is easy to see that, in this game, switching costs may explain bidding above the fixed price: Once a player has decided to enter the auction she may bid up to her valuation. Proposition 2, however, qualifies this conclusion:

Proposition 2 (Transaction Costs of Switching). *In all PBEs of the game with switching costs, the expected winning price is strictly smaller than the fixed price: $E[p_w] < \overline{p}$.*

Proof. See Appendix A.

Hence, though bids above the fixed price may occur, the auction price cannot exceed the fixed price in expectations. In any PBE, players enter the auction only if they expect that, conditional on winning, they pay a price below the fixed price. This is trivially true for players with a low $v_i \in [0, \overline{p})$. They would not enter the auction if they expected to pay more than their valuation, conditional on winning. But it is also true for players with a valuation above the fixed price, $v_i \geq \overline{p}$. For them, the difference between fixed price and expected auction price has to be large enough to compensate for the times that they lose the auction (and earn utility 0). Since the expected price conditional on winning is lower than $\overline{p}$ for all realizations of v and for all players, the (unconditional) expected auction price is also strictly smaller. Hence, switching costs imply that the average auction price is lower than the fixed price.

2.3 Limited Attention and Limited Memory

Another explanation for auction prices above the fixed price is that inattentive bidders overlook the fixed price even though they are available on the same webpage throughout the auction. The simplest way to model this situation is to assume that bidders neglect the fixed price in the second stage and only play the first-stage game, which reduces the game to a standard Vickrey auction.

Proposition 3 (Limited Attention). *If players neglect the second-stage fixed price game, each player i bids her valuation, $b_i^* = v_i$, in the unique PBE. Hence, the auction price exceeds the fixed price if and only if $v_i > \overline{p}$ for at least two players.*

Proof. Since every player participates only in the first-stage auction, the proof follows directly from Vickrey (1961). **Q.E.D.**.

Closely related is the case of limited memory (forgetting). Bidders may notice the fixed price when they start bidding, but forget it over time. Our static model of limited attention can be interpreted as a reduced-form model of the forgetting dynamics.[12] The limited-memory interpretation has a direct empirical implication: It predicts that bidders are unlikely to exceed the fixed price in their first bid but are likely to do so in later bids, when the memory of the fixed price fades away. We will test this prediction in Section 4.3.

Both the limited-attention and the limited-memory interpretation differ from switching costs in that the expected price is not bounded above by $\overline{p}$ (cf. Proposition 2).

2.4 Utility of Winning and Bidding Fever

Another explanation is that bidders are willing to pay more in an auction than outside the auction because they enjoy winning the auction.[13] We assume that bidder i earns additional utility $\pi_i \in R$ if she acquires the item in the auction. All other assumptions are unchanged.

Proposition 4 (Utility of Winning). *If players obtain utility from winning the object in an auction, there exists a PBE in which each player i places a first-stage bid $b_i^* = \min\{v_i + \pi_i, \overline{p} + \pi_i\}$ and, in the second stage, purchases if and only if she has lost the auction and $v_i \geq \overline{p}$. Hence, auction prices can exceed the fixed price if $\min\{v_i + \pi_i, \overline{p} + \pi_i\} > \overline{p}$ for some i.*

Proof. The game differs from the benchmark case (Subsection 2.1) in the utility player i earns if she wins: $v_i + \pi_i - p_w$ instead of $v_i - p_w$. Hence, the proof of Proposition 1.(a) applies after substituting $v_i + \pi_i - p_w$ for $v_i - p_w$ and $\min\{v_i + \pi_i, \overline{p} + \pi_i\}$ for $\min\{v_i, \overline{p}\}$ with the resulting equilibrium bid $b_i^* = \min\{v_i + \pi_i, \overline{p} + \pi_i\}$. **Q.E.D.**

Proposition 4 shows that players with utility $v_i \geq \overline{p}$ will bid above the fixed price $\overline{p}$ by the extra amount of utility they get from winning the auction. The equilibrium is essentially unique if the π_i are drawn from a continuous distribution with full support on R_+^N or, more generally, if there is a positive probability of any player winning the auction. The proposition implies that a player may win the auction even though other bidders have a higher valuation of the object but lower utility of winning. The resulting allocation is still efficient since we consider π_i part of the surplus.

A reinterpretation of this set-up is the phenomenon commonly known as bidding fever. During the heat of the auction, bidder i perceives an additional payoff π_i if she acquires the object via the auction. However, once the auction is over, the player realizes that $\pi_i = 0$, i.e., that the utility from obtaining the same object via an auction and via a fixed-price transaction

[12] Alternatively, we can model forgetting explicitly and introduce intermediate stages of bidding before the final fixed-price stage, where the probability of forgetting increases over time. Another possibility is that, instead of forgetting the outside price, players simply do not know it, but can learn it by paying a cost. If (some) players have high costs or rely on other players learning about the outside price, overbidding can occur in equilibrium.

[13] Note that joy of bidding (rather than winning) does not suffice to generate overbidding. Fixed utility benefits just from bidding in the first stage do not affect the optimal strategies and reduces the game to the standard case (Proposition 1). Intuitively, players can get this utility also by placing a low bid.

are identical. From the perspective of the earlier or later selves, the additional valuation π_i is a mistake, similar to the valuation of addictive goods in Bernheim and Rangel (2004). This reinterpretation affects the welfare of the players and efficiency but not the optimal strategies. Hence, Proposition 4 applies and we can observe overbidding if $\min\{v_i+\pi_i, \overline{p}+\pi_i\} > \overline{p}$. Similar results hold if we assume that π_i depends explicitly on the play of the game, e.g. on the auction price, $\pi_i(p_w)$, the ascending-bid structure or the time structure of the auction.

A third interpretation of increased willingness to pay over the course of the auction is a form of endowment effect (Thaler, 1980): the longer a bidder is the leading bidder, the more she anticipates being the winner and owning the item, which in turn increases her willingness to pay. This interpretation explains bidding above the fixed price only if the bidder becomes attached specifically to the auction item and would not want the (identical) fixed-price item.

3 Data

Our main source of data is hand-collected auction and fixed-price data from eBay. We briefly introduce eBay's bidding system, followed by a detailed description of the data sets.

3.1 Background Facts on Online Auctions

Since their inception in 1995, online auctions have exploded in sales and revenues. In 2004, the year of our primary sample period, the largest market participant, eBay, reported \$3.27bn revenues, 135.5m registered users, 1.4bn listings, and \$34.2bn gross merchandise volume.[14] The success of online auctions has been linked to the low transaction costs of selling and bidding (Lucking-Reiley, 2000). Sellers use standardized online tools and do not have to advertise. Buyers benefit from low-cost online bidding, easy searching within and between websites, and receive automatic email updates during auctions. These benefits suggest that online auctions should increase price sensitivity and reinforce the law of one price.

To trade on eBay, users generate an ID, providing an email address and a credit card number. Sellers choose a listing category, a listing period (1, 3, 5, 7, or 10 days), and the starting price. They can also specify a secret reserve price. Sellers pay an insertion fee for the listing, a sales fee if the item is sold, and a PayPal fee if the winner pays through PayPal[15]. The last two fees are proportional to the transaction amount. Buyers do not pay any fees.

eBay follows a modified sealed-bid, second-price auction. Bidders submit their 'maximum willingness to pay,' and an automated proxy system increases their bids up to that amount as competing bids come in. The highest bidder wins the item but only pays the second-highest price plus an increment (\$1 for prices between \$25 and \$99.99, \$2.50 between \$100 and \$249.99).

[14]See the annual reports (10-K SEC filings) for 2004 and 2005.

[15]PayPal enables anyone with an email address to send and receive payments online.

eBay also allows fixed-price sales, so-called "Buy-it-now" (BIN) listings. Whoever pays the BIN price first acquires the item. BIN sales make up about one third of eBay transactions, mostly from small retailers who use eBay as an additional outlet.[16] More rarely used are hybrid "auctions with BIN." If the first bidder does not click on the BIN price but places a (lower) bid, the BIN option disappears.

The reliability of buyers and sellers is measured with the Feedback Score, calculated as the number of members who left a positive feedback minus the number of members who left a negative feedback. An additional measure, the "Positive Feedback Percentage," calculates the percentage of positive feedback out of the total feedback. This measure is naturally volatile for bidders with a short history.

3.2 Detailed Data on Cashflow 101 Auctions

Our identification strategy requires that homogeneous items are simultaneously auctioned and sold at a fixed price on the same webpage. The fixed price should be continuously present throughout the auction and stable so that any bidder who searches for the item at any time finds the same fixed price. Moreover, there should be multiple staggered fixed-price listings so that it is easy to infer that the option will be continuously available.

The market for Cashflow 101 satisfies all criteria. Cashflow 101 is a board game invented by Richard Kiyosaki "to help people better understand their finances." The manufacturer sells the game on his website *www.richdad.com* for \$195 plus shipping cost of around \$10.[17] Cashflow 101 can be purchased at lower prices on eBay and from other online retailers. In early 2004, we found an online price of \$123 plus \$9.95 shipping cost. Later in the year (on 8/11/2004), the lowest price we could identify was \$127.77 plus shipping cost of \$7.54.

Cashflow 101 is actively traded on eBay. In 2004, auction prices ranged from \$80 to \$180. At the same time, two professional retailers offered the game on eBay at the same fixed price of \$129.95 until end of July 2004 and of \$139.95 from August on. They charged \$10.95 and \$9.95, respectively, for shipping. Figure I displays an example of listings retrieved after typing "Cashflow" in the search window. (Typing "Cashflow 101" would have given a more refined subset.) As shown, the listings are pre-sorted by remaining listing time. On top are three smaller items, followed by a combined offering of Cashflow 101 and Cashflow 202. The fifth and sixth lines are two data points in our sample: a fixed-price listing of Cashflow 101 at \$129.95 by one of the professional retailers and an auction, currently at \$140.00.

We collected all eBay listings of Cashflow 101 between 2/11/2004 and 9/6/2004. Data is missing on the days from 7/16/2004 to 7/24/2004 since eBay changed the data format requiring an adjustment of our downloading procedure. Our initial search for all listings in U.S. currency,

[16]See *The Independent*, 07/08/2006, "eBay launches 'virtual high street' for small businesses" by Nic Fildes.

[17]The 2004 prices were \$8.47/\$11.64/\$24.81 for UPS ground/2$^{\text{nd}}$day air/overnight.

excluding bundled offers (e.g., with Cashflow 202 or additional books), yielded a sample of 287 auctions and 401 fixed-price listings by the two professional sellers. We eliminated 100 auctions that ended early (seller did no longer wish to sell the item) or in which the item was not sold. Out of the remaining 187 auction listings, 20 were combined with a BIN option, which was exercised in 19 cases. In the one remaining case, the first bidder bid below the BIN price and the listing became a regular auction, which is included in the sample. While we could have used lower BIN prices in the other 19 cases as a tighter bound for rational bidding behavior,[18] we chose to remove them from the sample in order to have a conservative and consistent benchmark with a forecastable price. For the same reason we dropped two more auctions during which a professional listing was not always available (between 23:15 p.m. PDT on 8/14/2004 to 8:48 p.m. on 8/20/2004). Our final auction sample consists of 166 listings with $2,353$ bids by 807 different bidders.

The summary statistics of the auction data are in Panel A of Table I. The average starting price is \$46.14. The average final price, \$132.55, foreshadows our first result: a significant subset of auctions end above the simultaneous fixed price. Shipping costs are reported for the 139 cases of flat shipping costs, \$12.51 on average; they are undetermined in 27 cases where the bidder had to contact the seller about the cost or the cost depended on the distance between buyer and seller location. The average auction attracts 17 bids, including rebids of users who have been outbid. The average Feedback Scores are considerably higher for sellers (262) than for buyers (37). At the time of purchase, 16.27 percent of the buyers had zero feedback. The seller scores translate into a mean positive feedback percentage of 62.9 percent.

The distribution of auction lengths shows a sharp drop after 7 days. While the percentage increases in days from 1.2 percent one-day auctions to 65 percent seven-day auctions, only 5.42 percent last ten days, which cost an extra fee of \$0.20. The most common ending days are Sunday (24.7 percent) and Saturday (18.7 percent). Within a day, 34 percent of the auctions end during "prime time", defined as 3-7 p.m. (Jin and Kato, 2006; Melnik and Alm, 2002).

Items are always brand new in the BIN listings. For the auctions, instead, 28.3 percent of the listing titles indicate new items, e.g., with the descriptions "new," "sealed," "never used," or "NIB," and 10.8 indicate prior use with the words "mint," "used," or "like new." And 28.4 percent of the titles imply that standard bonus tapes or videos are included. (The professional retailers always include both extras.) Finally, about one third mention the manufacturer's price of \$195.

Panels B and C provide details about the 807 bidders and $2,353$ bids. Due to the eBay-induced downloading interruptions, we have the complete bidding history only for 138 auctions out of 166. An example is in Figure II. The bidding history is pre-sorted by amount. It shows the 'maximum willingness to pay' a bidder indicated at a given time, except for the highest bid, for which the winning price is shown, typically the second-highest bid plus the increment. Panel

[18] Nine BIN prices were below \$100. Eight more BIN prices were below the retailers' BIN prices.

B shows that bidders bid on average twice in an auction and three times among all Cashflow 101 auctions. About 6 percent of bids come during the last hour of a listing, 3 percent during the last 5 minutes.[19] The vast majority of bidders, with only two exceptions, do not acquire a second game after having won an auction. We also collected the entire history of feedback for each of the bidders in our sample and verify that they are regular eBay participants who bid on or sell a range of objects, reducing concerns about shill bidding or mere scams.

3.3 Cross-section of Auctions

We also downloaded $3,863$ auctions of a broad range of items with simultaneous fixed prices. This data allows us to analyze whether the results in the first data set generalize to different item types and price ranges. By choosing products that appeal to different demographics (gender, age, and political affiliation), we can also estimate the robustness of the results across these demographics. The drawback of the larger data is that the fixed prices are not necessarily as stable as in our detailed Cashflow 101 set.

The primary selection criterion for the cross-sectional data was comparability of the items sold in auctions and those sold at fixed prices. Ensuring homogeneity is not trivial since items are identified only with verbal descriptions. Typical issues are separating used from new items, accessories, bundles, and multiple quantities. We repeatedly refined the search strings and used eBay's advanced search options to avoid such mismatches. All details are in Appendix B.

We undertook three downloads of auctions and matching fixed prices in February, April, and May 2007. The product lists contained 49, 89, and 80 different items with overlaps between the three sets, amounting to 103 different items. The items fall into twelve categories: consumer electronics, computer hardware, financial software, sports equipment, personal care, perfumes/colognes, toys and games, books, cosmetics, home products, automotive products, and DVDs. The distribution of items across categories and downloads is summarized in Table II. The full list of all items and the complete search strings are in Appendix-Table A.1.

We tracked all "ongoing" auctions at three points in time in 2007: February 22 (3:33-3:43 a.m.), April 25 (4:50-4:51 a.m.), and May 23 (9:13-9:43 p.m.).[20] From the resulting list of $3,863$ auctions, we dropped auctions that did not re-appear in our final download (e.g. since they were removed by eBay), that ended too shortly after the snapshot to allow capturing the simultaneous fixed price, that did not receive any bids, those in foreign currency, and those that were misidentified (wrong item), arriving at a final list of $1,926$ auctions. Appendix-Table A.2 summarizes the data construction and composition.

After extracting the auction ending times from our snapshot of auctions, we scheduled $2,854$

[19] Bidders can automatize last-minute bidding, using programs such as http://www.snip.pl.

[20] The resulting list of auctions ended between 5:42 a.m. on February 22 and 12:01 a.m. on March 1 (Download 1), between 2:22 a.m. on April 26 and 9:42 p.m. on May 4 (Download 2), and between 9:20 p.m. on May 23 and 9:29 a.m. on June 2 (Download 3).

downloads of fixed prices for identical items. The details are in Appendix B (BIN Extraction). We matched each auction to the buy-it-now listing of the same item that was downloaded closest in time to the auction ending time, typically within 30 minutes of the auction ending. We undertook this matching twice, accounting and not accounting for shipping costs.[21] Some auctions did not match because there were no BINs for the item. Also, in the case with shipping costs, ambiguous shipping fields (such as "See Description" or "Not Specified") prohibited some matches. We do account for "Free" shipping as $0.00. The resulting data set consists of 688 (571) auction-BIN pairs without (with) shipping in Download 1, 551 (466) pairs in Download 2, and 647 (526) pairs in Download 3.

3.4 Other Data Sources

Survey. We also conducted a survey, administered by the Behavioral Laboratory at Stanford GSB in four waves in 2005, on March 1, April 28 (in class), May 18/19, and July 13/14, with a total sample of 399. Subjects are largely Stanford undergraduate and MBA students. The six-minute survey inquires about their eBay bidding behavior and their familiarity with different eBay features. The subjects are not identical to those in our main data sets. The answers reveal common bidding patterns and motivations and allow us to gauge the effect of different design elements of the eBay auction. The full survey is available from the authors.

Choice Experiment. Finally, we conducted a choice experiment, also administered by the Behavioral Laboratory, with 99 Stanford students on April 17, 2006. Subjects had to choose one of three items from our Cashflow 101 data based on their description, two randomly drawn auction descriptions and one of the two professional BIN descriptions. The choice was hypothetical, and there was no payment conditional on the subjects' choice. The experiment allows us to test for unobserved wording differences. More details follow below. The instruction and item descriptions are available from the authors.

4 Results

4.1 Overbidding

In our detailed data set (Cashflow 101 auctions), we find a significant amount of bidding above the fixed price (Table III):

Finding 1 (Overbidding in Cashflow 101 Data). *In 42 percent of all auctions, the final price is higher than the simultaneously available fixed price for the same good.*

Hence, the bidding strategy of a significant number of auction winners is inconsistent with

[21] The median time differences between auction endings and BIN download in Downloads 1, 2, and 3 were 21, 22, and 25 minutes for the matches without shipping costs and 21, 21, and 26 minutes with shipping costs.

the equilibrium strategies of the simple benchmark model in Subsection 2.1. According to Proposition 1, rational bidders should never pay more than the fixed price in an auction. The observed behavior may, however, merely reflect frictions in the auction market rather than overbidding.

1. Noise. While a significant share of auctions end above the fixed price, it is possible that the difference between the auction price and the fixed price is small, possibly just cents, for example due to bidding in round numbers. The lower part of Table III shows, however, that more than a quarter of all auctions (and 64 percent of all overbid auctions) exceed the fixed price by more than \$10. In 16 percent of all auctions (39 percent of overbid auctions), the winner overpays by more than \$20.

The six graphs of Figure III display the full distribution of Final Prices in bins of \$5 width (Panel A) and in bins of \$1 width (Panel B). The histograms are overlaid with a kernel density estimate, using the Epanechnikov kernel with an "optimal" half-width.[22] A significant share of auction prices is above the fixed price both in the early sample period, when the fixed price is \$129.95, and in the later sample period, when the fixed price is \$139.95. We also observe some evidence of bunching just below the fixed price.

The distribution of bids also helps to further address concerns about shill bidding. Even if some of the overbids were submitted by shills, overbid auctions typically receive more than one overbid, leading to the final overbidding price.

2. Shipping Costs and Sales Taxes. Another hypothesis is that shipping costs are higher for the fixed-price items. We find the opposite. In the subsample of 139 auctions for which we can identify the shipping costs, the mean shipping cost is \$12.51, compared to \$9.95 for the fixed-price items of one of the professional retailers. Accounting for shipping costs strengthens the overbidding result: 73 percent of the auctions end above the fixed price plus the shipping cost differential. Table III shows that the entire distribution is shifted upwards: Almost half of the auctions are overpaid by more than \$10 and 35 percent by more than \$20.

Another explanation is that buyers from the same state as the professional sellers may not buy at the fixed price in order to avoid sales taxes.[23] The two fixed-price retailers are, however, located in different states, Minnesota and West Virginia. Since both have at least one listing most of the time, bidders from these states can choose the other fixed price. Moreover, even if we take into account sales taxes of 6-6.5 percent for the fixed-price retailers and assume no tax for the auction, overbidding remains substantial, as the distribution above illustrates.

3. Retrieval and Dislike of Fixed Prices. Another potential concern is that bidders' searches do not retrieve the fixed-price listings. However, regardless of whether a bidder searches by typing a core word or by first going to the appropriate item category, in this case

[22]The 'optimal' width minimizes the mean integrated squared error if the data is Gaussian and if a Gaussian kernel were to be used.

[23]Buyers owe their state's sales tax also when buying from another state, but they may not declare it.

'boardgames', and then searching within this category,[24] the output screen will show both fixed-price and auction listings. If the search includes additional qualifiers, fixed-price listings are *more* likely to be retrieved than most auctions since their descriptions are more detailed and without typos.

A related concern is that buyers may prefer auctions over buy-it-now offerings due to past (bad) experiences with fixed-price transactions. Our survey indicates that, generally, the opposite is the case. The 50.83 percent of respondents who are eBay users were well aware of the meaning of "buy-it-now" and, if anything, expressed a preference for buy-it-now transactions.

4. Seller reputation. Another explanation is lower seller reputation of the fixed-price retailers. Based on eBay's Feedback Scores[25], however, the two retailers have a considerably better reputation than other sellers: their scores were 2849 (with a *Positive Feedback Percentage* of 100 percent) and 3107 (99.9 percent) as of October 1, 2004. In contrast, the average score of auction sellers is 262. In addition, both fixed-price retailers allow buyers to use PayPal, which increases the security of the transaction, while several auction sellers do not.

5. Quality Differences. Finding 1 could also be explained by systematically higher quality of auction items relative to fixed-price items. However, the quality of auction items is, if anything, lower: some games are not new, others are missing the cassette tapes and other bonus items. The two retailers, instead, offer only new items that include all original bonus items and, occasionally, additional bonuses, such as free access to a financial-services website. In addition, the professional sellers offer the fastest handling and sending among all sellers (auction or fixed price) and a six month return policy, which is rarely offered in auctions.

A remaining concern is *unobserved* quality differences, such as differences in wording. To address this concern, we conducted an experiment with 99 Stanford students. Subjects were asked which of three items they would prefer to purchase, assuming that prices and listing details such as remaining time and number of bids were identical. Two descriptions were randomly drawn from auctions in our sample and one from the fixed-price items. The order of the descriptions was randomized, as shown in Appendix-Table A.3. Seller identification and prices were removed from the description, as was the indication of auction versus fixed price.

Three subjects did not provide answers. Among the remaining subjects, 35 percent expressed indifference, 50 percent chose the offer of the professional retailer, and 15 percent preferred one of the two auction items.[26] Hence, it is unlikely that unobserved quality differ-

[24] In our survey, 92 percent of respondents indicated that they start their searches by typing a core word, typically the item name, and 8 percent first go to the item category.

[25] Feedback Scores have been used as proxies for reputation and been linked to higher prices in Dewan and Hsu (2004), Houser and Wooders (2006), and Melnik and Alm (2002), among others.

[26] When asked to explain their choice, the 14 students who chose an auction item most commonly said that the fixed-price offer provided too much information – a reaction that may have been driven by time pressure in the six-minute experiment. Students who chose the retailer's offer most commonly mentioned the retailer's money-back-guarantee and more professional layout.

ence explain the bidding behavior.

Overbidding in the Cross-section. Our results so far indicate significant overbidding for a specific item, Cashflow 101. It remains, however, possible that overbidding is an isolated phenomenon that does not apply to most items. To address this concern, we explore the prevalence of overbidding in a cross-section of items offered both in auctions and at fixed prices. The results are in Table IV.

Finding 2 (Overbidding in Cross-Sectional Data). *In the cross-section of auctions, the final price is higher than the corresponding fixed price in* 48 *percent of the cases.*

Overbidding is even more prevalent in the cross-sectional data than in the Cashflow 101 data. It ranges from 44 to 52% across the three downloads and applies to different types of objects (Table IV, Panel A). As Figure IV, Panel A, illustrates, we observe at least 30 percent of overbidding in 10 out of 12 item categories, such as electronics, cosmetics, and books. No clear correlation with the price level emerges. Expensive hardware (around $150) triggers little overbidding, while overbidding for expensive sports equipment (exercise machines around $200) is frequent, 56% across the three downloads. The share of overbidding is slightly lower with than without shipping costs, differently from what we found in the Cashflow 101 data.

The results suggest that the pattern of overbidding identified in our first data set generalizes across auction items. We also explore differences in overbidding by demographics. While we do not observe *bidder* demographics directly, our data includes objects associated with a *consumer* demographic. To examine gender differences, we compare for example perfumes of the same brand for men and women. As shown in Panel B of Table IV, the frequency of overbidding is higher for products that target men than for those targeting women, though the difference is not large (38 percent versus 33 percent) and, in aggregate, not significant (s.e.= 5.03 percent). We also examine differences by target age groups, comparing toys for kids (Elmo), teenagers (games and playstations), and adults (electronics). We find no systematic differences. Comparing books of liberal versus conservative authors (Obama versus O'Reilly), we find again no systematic pattern. Finally, to capture the impact of income, we compare the prices for cheap versus expensive products, such as financial software (Quicken 2007 Basic versus Home Business). Again, overbidding is significant in each category and not systematically correlated with the price level. Overall, we do not detect any significant correlation with features of the target consumer. Overbidding is sizeable within each demographic subset.

As discussed above, the larger-scale cross-sectional data comes at the cost of some loss of control over the setting. In particular, differently from the Cashflow 101 data, we cannot be sure about the availability of the same buy-it-now prices in the future or about differences in seller reputation between the auction and the fixed-price listings.

Transaction costs. As a final step in establishing the overbidding result, we consider rational explanations based on different types of transaction costs. We first consider switching costs, as modeled in Subsection 2.2. Once a bidder has decided to enter the auction, it might be costly to return to the screen with all listings and to purchase the object at the fixed price. This explanation implies, however, that the expected auction price should be significantly lower than the fixed price (Proposition 2). We find the opposite pattern in the Cashflow 101 data.

Finding 3 (Overpayment on Average). *The average auction price is higher than the simultaneous fixed price, by* \$0.28 *without shipping costs and by* \$2.69 *with shipping costs.*

As Table III shows, the difference without shipping costs, \$0.28, is not significant (s.e.= \$1.30 and 95 percent confidence interval of [−\$2.27; \$2.84]), but the difference with shipping costs, \$2.69, is significant (s.e.= \$1.27 and 95 percent confidence interval of [\$0.19; \$5.20]). This comparison is, however, a conservative test of the switching cost explanation: the expected auction price should be significantly lower than the fixed price in order to induce a bidder to enter the auction rather than purchasing the fixed price. We perform calibrations of the expected auction price that would make a bidder indifferent assuming eight players per auction, corresponding to the mean number of bidders in the Cashflow 101 data. For the unobserved values, we assume either a uniform distribution between \$80 and \$180 or a $\chi^2(130)$ distribution, reflecting approximately the distribution of final prices. We calculate the optimal bidding region for each valuation.[27] The resulting calibrated average auction prices are \$4.48 lower than the fixed price for the χ^2-distribution and \$10.05 lower than the fixed price for the uniform distribution, both significantly different from the observed average auction prices.

We also estimate the parallel of Finding 3 for the cross-sectional data of auctions. In this data, the computation of the price differential is less straightforward because of the heterogeneity in prices across items. We calculate the percentage of over- (or under-)bidding for each item (final bid minus BIN, as a percentage of BIN) and then average over all percent differences. We find a net overpayment of 9.98 percent, significantly different from 0 percent (s.e.= 1.85 percent). Accounting for shipping costs, the net overpayment is 4.46 percent (s.e.= 1.99 percent). Overall, the prediction that on average auction prices are lower than the fixed prices is rejected in the data.

Another type of transaction costs is the cost of understanding the buy-it-now system. Complete unawareness is unlikely since buy-it-now listings are very common, representing over one third of eBay listings during our sample period. Moreover, they are intuitively designed and similar to any fixed price on the internet. Nevertheless, it is possible that inexperienced eBay users do not take BIN listings sufficiently into account. If overbidding is due to this type

[27] We use an iterative procedure to find the cutoff point, at which a player switches from bidding her valuation to purchasing at the fixed price. We start from the fixed price and check whether a player with this valuation would wish to bid this amount if she were facing seven other players employing the same bidding cutoff, namely the fixed price. (We run one million iterations of this bid against seven other players and calculate the average price and probability of winning.) If the expected gain in the auction is higher than from the fixed-price purchase, we increase the hypothetical cutoff. Once we reach equality, we have found the bidding threshold.

of transaction costs, it should be lower for high-experience users. We test this implication in the Cashflow 101 sample, using a median split by Feedback Scores as a proxy for experience (Panel B of Figure IV).[28]

Finding 4 (Effect of Experience). *There is no difference in the prevalence of overbidding among more experienced and among less experienced auction winners.*

The percentages of overbidding are almost identical for low-experience and high-experience users, 41 and 42 percent. Also if we partition auction experience more finely, we find no relationship between overbidding and experience. For example, we can split the sample of auction winners into winners with Feedback Scores of 0 (17% of winners), 1 (19%), 2-4 (14%), 5-14 (20%), 15-92 (20%) and higher (remaining 10% of winners). The respective propensities to overbid are 31%, 55%, 35%, 47%, 36%, and 44%, indicating no systematic pattern.

Finding 4 does not rule out that experience reduces overbidding since we do not have longitudinal bid histories for each bidder. However, it *does* rule out that only eBay novices overbid. The result also helps to further alleviate concerns about shill bids or 'fake bids,' e.g. the hypothesis that the overbidders are sellers who use fake IDs to buy their own goods at inflated prices. Such IDs are unlikely to be used for many transactions and, hence, have low feedback scores.

Finally, while we have addressed several simple transaction-cost explanations, more complex versions might explain the overbidding phenomenon. For example, it might be hard to form expectations about the future availability and prices of buy-it-now items.[29] We will discuss a related explanation, the transaction cost of 'finding' prices on the eBay output screen as a form of Limited Attention.

4.2 Disproportionate Influence of Overbidders

Our key finding so far is that we observe overbidding with high frequency. We now show that a high frequency of overbid auctions does not imply that the 'typical' buyer overpays. Instead, it is generated by a relatively small fraction of overbids (Table V). We document this phenomenon using the detailed bidder- and bid-level data of Cashflow 101 for 138 auctions. (Summary statistics are in Panels B and C of Table I.)

[28]Since the vast majority of ratings is positive (e.g., 99.4% in Resnick and Zeckhauser, 2002), Feedback Scores track the number of past transactions. The measure is imperfect since some users do not leave feedback, since the measure does not capture bids, and since users may 'manufacture reputation' (Brown and Morgan, 2006). However, the measure is sufficient to reject the hypothesis that only unexperienced bidders overbid; users with a high feedback score *do* necessarily have experience.

[29]Note, however, that information about current and past BIN prices is available via eBay Marketplace Research, which informs subscribers about average selling prices, price ranges, average BIN prices, and average shipping costs. Using this service, or researching past transactions themselves, bidders can easily find out that the fixed price is constant over long periods (or its upper ceiling).

Finding 5 (Disproportionate Influence of Overbidders). *The share of bidders who ever submit a bid above the fixed price is* 17 *percent and the fraction of overbids among all bids* 11 *percent, significantly less than the share of winners who pay more than the fixed price.*

The majority of bidders, 83 percent, submit one or more lower bids but drop out once the price crosses the buy-it-now threshold. This finding is, of course, not surprising given the auction mechanism. By definition, the highest bidder wins and will thus have a 'disproportionate influence' on the price. However, the traditional interpretation is that auctions identify the bidder with the highest valuation, who should determine the price. The insight from our data, instead, is that bidders may submit high bids for other, non-standard reasons, such as limited attention or bidding fever (which we will discuss in the next Subsection). Whatever the reason for their overbidding behavior, the auction design implies that the bidders with particularly high bids determine prices and allocations.

The calibrations at the end of the next Subsection further illustrate this point.

4.3 Explanations for Overbidding

Having established the extent of bidding above the fixed price and addressed rational explanations, we consider non-standard explanations for overbidding.

Limited Attention and Limited Memory. One possible explanation is that bidders do not pay attention to the fixed-price listings, even if offered on the same screen (Proposition 3). If inattention explains overbidding, we expect more overbidding when the fixed-price listing is less salient. The further apart the fixed-price listing is from a given auction listing, the more likely an inattentive bidder is to miss the fixed price listing when considering the auction. Salience also varies with the absolute position of a listing on the screen. The higher an auction is positioned, the more likely it is to capture the attention of a bidder, an effect known as "above the fold" in internet marketing.[30]

In order to test these two implications, we reconstruct, for each bid observed in our data, the set of all auctions and buy-it-now listings available at the time of the bid. We make the assumption that listings are ordered by remaining listing time, as it is the eBay default. We also assume that bidders only see the relevant listings (Cashflow 101). In reality, irrelevant listings may be retrieved as well, depending on the search words, and users may reorder listings, e.g., by lowest price. This is likely to introduce noise but not bias into our estimation.

We construct the data set of auction listings available at each bidding instance accounting for truncation from the left: we drop the first seven days of our sample period to ensure that we observe all simultaneous auctions. For the same reason, we drop the first seven days after the period of missing data (from 7/16/2004 to 7/24/2004). The resulting data set captures 2,187

[30]The expression was coined in reference to the newspaper industry where text above the newspaper's horizontal fold is known to attract significantly more attention from readers.

bids of the $2,353$ bids in our full sample and, including the simultaneous auction listings at each bid, consists of $14,043$ observations. The two main independent variables of interest are: (1) Distance to nearest BIN listing, coded as 0 if there are no rows between the auction and the closest BIN (one row above or one row below), 1 if there is one row between the auction and the closest BIN, etc.; and (2) Position on screen, coded as 1 for auctions listed on top of the screen, 2 for auctions in the second row, etc.

We use a conditional logit framework, relating the probability of receiving an auction bid to the closeness of the nearest buy-it-now listing and absolute screen position of the auction. We condition the estimation on one of the auction listing receiving a bid at a given time.[31] We model the utility from bidding on auction listing i in bidding instance b as $U_{ib} = \beta_1 D_{ib} + \beta_2 P_{ib} + X'_{ib}B + \varepsilon_{ib}$, where D is the distance to the nearest fixed-price listing, P is the screen position, and X are auction-specific controls.[32] Assuming that, conditional on the choice of making a bid at bidding instance b, ε_{ib} is i.i.d. extreme value, the probability of bidding in auction i is

$$P_{ib} = \frac{\exp(\beta_1 D_{ib} + \beta_2 P_{ib} + X'_{ib}B)}{\sum_j \exp(\beta_1 D_{jb} + \beta_2 P_{jb} + X'_{jb}B)}.$$

The null hypothesis of rational bidding (no limited attention) is that the distance to the fixed price listing D and the screen position P do not affect the probability of receiving a bid, that is, β_1 and β_2 equal zero. If the coefficient estimate β_1 is positive and β_2 negative, bidding behavior conforms with the predictions of limited attention.

In Table VI, Column 1, we present the baseline results. Coefficients are reported as odds ratios, and standard errors are clustered by bidding instance. We find a significantly positive effect of distance on receiving a bid, suggesting that nearby fixed-prices deter bids on auction items. We also find a significantly negative effect of screen position: an auction is less likely to receive a bid if its position on the output screen is lower. These results are robust to the inclusion of the following controls (Column 2): the price outstanding on the respective auction listing (and its square), the starting price of the auction, seller reputation (measured by feedback score), auction length (in days), a dummy for prime time (6-9 p.m. Pacific Time), and remaining auction time (measured in days and fraction of days). Also, the inclusion of more time controls (the square and cube of remaining auction time, dummies for the last auction day and the six last hours of the auction) does not affect the results. In all specifications, the coefficient estimates indicate that limited attention affects bidding behavior.

[31] We do not explicitly model the selection into the bidding process. One could embed the decision on which auction to bid as the lower nest of a nested logit where the upper nest involves the decisions to participate in the auction. Under the assumptions of McFadden (1978), the estimation of the lower nest is consistent for the selected subsample of consumers, conditional on the decision in the upper nest.

[32] In a standard nested logit model, consumers make one choice from a standard set of alternatives. In our setting, a bidder may make repeated choices. For the estimates to be consistent, we need to make the additional assumption of no serial correlation of errors in the bottom nest.

In order to link inattention specifically to *over*bidding, we estimate the effect of nearby fixed-price listings in the subgroup of auctions whose price outstanding exceeds the fixed price. If inattention explains overbidding, we expect the closeness of fixed-price listings to matter most for those auctions. In Columns 3 and 6 of Table VI, we introduce dummies for auctions with prices outstanding 'just below' the concurrent fixed-price, auctions with prices 'just above' the concurrent fixed price, and auctions with high prices outstanding (with 'very low' prices being the left out category) and test for an interaction effect with the Distance to nearest BIN listing. For prices 'just below or above' we use either $[-\$5; \$5]$ or $[-\$10, \$10]$. (Any range in between and up to \$30 lead to very similar results.) We also include the full range of additional auction controls. We find that the closeness of fixed-price listings has no significant effect for auctions whose prices are below the concurrent fixed price or far above it. For auctions with prices just above the BIN price, instead, a fixed price listed close to the auction has a significantly negative effect on the probability that the auction receives a bid. An increase in distance by one row increases the odds of an auction receiving a bid by 1.4-2 (depending on the choice of interval for prices 'just above'). Hence, closeness of fixed prices directly affects bidders' inclination to overbid.

We also find that the effect of nearby fixed prices is particularly strong for bidders' first bids in a given auction. When splitting the sample into first and later bids, we find that the interaction effect of Distance to nearest BIN listing and the dummy for Price just above is significant only in the subsample of first bids, whether we use the \$5-interval of 'prices just above' (Columns (4) and (5)) or the \$10-interval (Columns (7) and (8)). This finding is consistent with one particular form of inattention, limited memory. Bidders may account for the fixed price initially, but fail to do so when they increase their bids. Limited memory is particularly plausible because of the design of eBay's outbid notices: In the email informing bidders that they have been outbid, eBay provides a direct link to increase a bid, but no link to the page with all ongoing auctions and buy-it-now listings.

Note that the model of limited memory that can explain the above results also suggests bidder naiveté about their memory limitations. Rational bidders with limited memory, who are aware of their memory limitations, can easily remedy the memory constraint, for example by always submitting only one bid (up to the BIN price) and never responding to outbid notices.

Joy of Winning, Bidding Fever, and Quasi-Endowment Effect. Another explanation for the observed overbidding is that bidders gain extra utility from winning an item in an auction relative to purchasing it at a fixed price. As discussed in the Section 2.4, such non-standard utility may induce overbidding, whether the bidder actually obtains the extra utility (joy of winning) or mistakenly thinks so (bidding fever). This type of explanation is hard to test given that any type of observed bidder behavior can be interpreted as revelation of preferences for such behavior.[33] It is, however, possible to address specific forms of 'joy of

[33]Our survey evidence suggests that bidding fever applies to some extent. For example, of the 216 subjects

winning' such as the quasi-endowment effect.

The quasi-endowment effect postulates that bidders become more endowed to auction items, and hence more likely to submit high bids, the longer they participate in the auction, in particular as the lead bidder (Heyman, Orhun, Ariely, 2004; Wolf, Arkes, Muhanna, 2005).[34] One could argue that the quasi-endowment effect is not particularly plausible in our setting given that bidders can always obtain ownership of the identical item via the fixed-price listing. Nevertheless, we test the prediction of a positive correlation between overbidding and time spent on the auction or as the lead bidder. We do not find support for this prediction. While bidders who win the auction with an overbid enter the auction 1.27 days before the auction ends, those who win but do not overbid enter the auction earlier, 1.52 days before the auction ends. The same pattern emerges if we only consider the time a bidder has been lead bidder: Winners who overbid have been lead bidders for 0.55 days by the time of their last bid (1.03 days by the end of the auction); winners who do not overbid have been lead bidders 0.74 days (1.24 overall.)

The literature on the pre-endowment effect also predicts that it is reduced by experience. We found that more experienced bidders are no less likely to overbid (Finding 4).

Calibration. The findings in this Subsection provide some evidence in favor of limited attention (or memory) and not in favor of quasi-endowment. We cannot address utility from winning in general, given the lack of testable predictions. However, a simple calibration of utility from winning provides some insights into the plausibility of this explanation, which we contrast with a calibration of the limited attention (memory) model.

Our calibrations allow for bidder heterogeneity, with a share of bidders having non-standard preferences and the remaining bidders acting according to the standard model. We vary the share of the population that displays the non-standard behavior from 0 to 1. We consider a variety of distributions for the values, including χ^2, uniform, exponential, and logarithmic distributions, and a range of possible moments.

As in the transaction-cost calibration, we draw eight players from an infinite population. For each distribution of valuations, we draw 1,000,000 i.i.d. realizations for each player. We then draw another 1 million values, separately for each of the eight players, from a uniform distribution on $[0, 1]$, determining whether a player is a rational or a behavioral type. For example, when the proportion of behavioral players is 0.1, only player-auction pairs for which we draw values between 0 and .1 follow non-standard bidding strategies. In the Utility of Winning model, we make the additional assumption that the utility of winning is uniformly distributed

who have previously acquired an item on eBay, 42 percent state that they have sometimes paid more than they were originally planning to, and about half of those subjects later regretted paying so much.

[34] A similar endowment effect 'without actual endowment' has been found in the context of lottery tickets (Casey, 1995), coupons (Sen and Johnson, 1997), and by inducing subjects to think about an option (Carmon, Wertenbroch, and Zeelenberg, 2003).

between \$0 and \$10 and that the values are independently drawn. Hence, we generate a third (1 million x 8)-matrix of winning utilities drawn from a uniform $[0, 10]$ distribution. These values are added to the valuations in the first matrix if the player is a behavioral type in the respective auction. For each player-auction pair, we compute the equilibrium bid using the strategies specified in Propositions 1 for rational players and in Propositions 3 and 4 for behavioral players,[35] setting the simultaneous fixed price equal to \$130.

Figure V shows the calibrations for $\chi^2(130)$ and $U[80, 180]$, i.e., two distributions of valuations whose first moment is equal to the buy-it-now price and, in case of the uniform distribution, reflects the observed minimum and maximum prices.[36] The left graphs show the results for the Limited Memory model, the right graphs the results for the Utility from Winning model. In each graph, we show the percentage of auctions with a price above the fixed price (Percent overpaid) and the percentage of bidders who submit a bid above the fixed price (Percent overbidders). The leftmost values correspond to our benchmark rational model and the rightmost values correspond to everybody having non-standard preferences.

In all graphs, the 'Percent overpaid' increases steeply starting from a probability of forgetting around 0.1-0.2 and crosses the 45-degree line. The 'Percent overbidders', instead, increases more slowly in the probability of forgetting, and always has a slope below 1, illustrating the disproportionate impact of few overbidders. Both models match the observed frequency of overbidding (43%) and frequency of overbidders (17%) for plausible parameter values. They differ, however, in how well they match other empirical outcomes. Most importantly, the utility of winning model has the shortcoming that the maximum of overbidding is limited to the maximum amount of utility of bidding, i.e. in our calibration \$10, even though we allow for realizations of v_i above the fixed price plus \$10. More generally, the calibration illustrates that, a simple model of utility of winning that imposes an upper limit to bidders' willingness to pay for winning fails to produce price distributions similar to those in Figure III.A, unless we allow for a large maximum amount of utility of winning. Limited Attention or Limited Memory emerge as better suited to capture all aspects of the empirical distributions of outcomes since do not impose an upper bound on overbids relative to the fixed price $\overline{p}$.

5 Discussion and Conclusion

In this paper, we identify overbidding on eBay, exploiting the availability of fixed prices for identical items on the same webpage. The first main finding is that a significant fraction of bidders bid more than predicted by a simple rational model, even accounting for transaction costs. The second main finding is that a small fraction of bidders who bid too much affect a

[35]It is easy to see that Propositions 1, 3, and 4 hold under bidder heterogeneity, given that bidders' choices solely reflect whether they benefit from winning with a given bid, relative to the safe outside option.

[36]Alternative calibrations with the above mentioned distributions are available from the authors.

disproportionately large fraction of auction prices and allocations. Auctions select precisely those consumers as winners who overbid and thus amplify the effect of biases in the market. Our third main finding is that insufficient attention to the alternative fixed price explains part of the observed overbidding. In particular, a subset of bidder appear to pay attention initially, when submitting their first bid, but fail to do so later, when rebidding. Other explanations, such as joy of winning or 'bidding fever,' may also explain part of the observed overbidding, though not due to a pre-endowment effect.

Our findings suggest that design elements such as the wording of eBay's outbid message ("You have been outbid!") may have a larger effect on bidding behavior and prices than traditional auction theory suggests. Profit-maximizing sellers should account for consumers' behavioral preferences and beliefs when choosing auctions over other price mechanisms and when selecting a specific type of auction. In a similar spirit, Kagel and Levin (2006) suggest that the popularity of dynamic multi-object auctions, versus their one-shot counterparts, may be attributed to the bounded rationality of bidders. And Eliaz, Offerman, and Schotter (*forthcoming*) contrast the high revenues and the empirical popularity of "right-to-choose" auctions (where bidders compete for the right to choose an item from a set of heterogeneous items) with the predictions of lower revenues in a rational auction framework.

While our paper analyzes online auctions, overbidding and the disproportionate influence of few overbidders applies to auctions more broadly. Even in non-auction settings, the same logic may induce sellers to set exceedingly high prices (or to obfuscate item quality) in the hope of encountering one of the (few) consumers who, for behavioral or other reasons, is willing to pay such a price (Gabaix and Laibson, 2006; Liebman and Zeckhauser, 2004; Ellison, 2005; Ellison and Ellison, 2005). Anecdotally, a number of auctions are suspected to showcase overbidding, including wine, antiques, and car auctions, free agents in baseball (Blecherman and Camerer, 1996), drafts in football (Massey and Thaler, 2006), and even auctions of collateralized mortgage obligations, where sophisticated broker dealers and institutional investors display too high a dispersion in bids to be explicable by rational strategic bidding (Bernardo and Cornell, 1997). An example that compares closely to our empirical analysis and research design is real estate auctions. Ashenfelter and Genesove (1992) document auctions of 83 condominium apartments in New Jersey, which – when the auction sale unexpectedly fell through – sold at significantly lower prices in face-to-face negotiations. The findings in this paper suggest that the large number of auction participants was a key determinant. It ensured the presence of overbidders.

Even in mobile-phone auctions, such as the British 3G auctions in 2000-01, it has been argued that the winners "paid too much" (Binmore and Klemperer, 2002). Klemperer (2002) attributes the large revenues of the British auction to the low hurdles to entry[37] and argues that the large differences in revenues across different Western European 3G auctions strongly covary

[37] Similarly, McAfee and McMillan (1996) explain the variation in the 1994/5 FCC auction prices for broadband licenses across cities with variation in the number of competitors.

with the number of participants. This paper offers an alternative interpretation: facilitating entry is important to ensure that the auction attracts at least two overbidders.

Another example are mergers and acquisitions. Contested transactions, in which several bidders aim to acquire the same target, are often suspected to induce overpayment, such as the 2007 bidding war between Blackstone and Vornado Real Estate Trust to acquire Equity Office Properties, at the time the biggest leveraged buyout in history. In fact, Malmendier and Moretti (2006) show that winners of merger fights perform on average worse than the losers after the merger fight, while they did not perform significantly different before the merger fight. Their finding does not imply that the target company is overvalued by all market participants; but that few overbidders suffice to generate large average losses in contested mergers.

A last example are initial public offerings, some of which take place as actual auctions (e.g. in the case of Google) and all of which are bought and sold in the stock market and hence an auction-like procedure from then on. A long-standing view (Stoll and Curley, 1970; Ritter, 1991) is that the pattern of initial rise in stock price, right after the offering, and subsequent decline does not (only) reflect that the offering price is low but also that the aftermarket price is too high. Relatedly, Sherman and Jagannathan (2006) report that auctions of initial public offerings have been abandoned in virtually all of the 24 countries that have used them in the past and argue that overbidding was a major determinant of this development.

The evidence provided in this paper as well as the suggestive examples discussed above imply that, in order to maximize their revenues, sellers should pick the auction that maximizes their chances of attracting overbidders to participate in the auctions.

Appendix A

Proof of Proposition 1. **(a)** In the second stage, it is optimal for player i not to purchase if she has won the auction in the first stage since the payoff after purchasing, $v_i - p_w - \overline{p}$, is strictly smaller than the payoff after not purchasing, $v_i - p_w$. After losing the auction, it is optimal to purchase in the second stage if and only if $v_i \geq \overline{p}$ since the payoff from purchasing, $v_i - \overline{p}$, is weakly higher than the payoff from not purchasing, 0, if and only if $v_i \geq \overline{p}$.

Taking into account the second-stage behavior, we now show that bidding $b_i^* = \min\{v_i, \overline{p}\}$ in the first-stage game is part of a PBE. We distinguish two possible deviations:

Case 1: $b_i < \min\{v_i, \overline{p}\}$. There are three subcases. Either both b_i and b_i^* are the highest bid, or neither is, or b_i^* is the highest bid and b_i is not. In the first subcase, player i obtains the object at the same auction price and, hence, makes the same second-stage decision after both bids. In the second subcase, i does not win the auction and, again, makes the same second-stage decision after both bids. In the last subcase, b_i induces payoff $\max\{v_i - \overline{p}, 0\}$, while b_i^* induces $v_i - p_w$, where $p_w \leq \min\{v_i, \overline{p}\}$. Thus, i's payoff from bidding b_i is the same as after b_i^* in the first two subcases and is weakly lower in the third subcase. Hence, b_i induces lower expected utility than b_i^*.

Case 2: $b_i > \min\{v_i, \overline{p}\}$. By the same reasoning as before, i attains the same utility with b_i and b^* if either both are the highest bid or neither is. If, instead, b_i^* is not the highest bid but b_i is, then b_i induces payoff $v_i - p_w$ with $p_w \geq \min\{v_i, \overline{p}\}$, while b_i^* induces $\max\{v_i - \overline{p}, 0\}$. Thus, again, b_i leads to weakly lower expected utility than b_i^*.

Hence, i has no incentive to deviate from b_i^*, and bidding b_i^* in the first stage along with the second-stage strategies detailed above is a PBE.

(b) (By contradiction.) Assume that there is a PBE and a realization of valuations $\widehat{v} = (\widehat{v}_1, \widehat{v}_2, ..., \widehat{v}_N)$ such that $p_w(\widehat{v}) > \overline{p}$. Denote the winner in this case as w, her strategy as $s_w(v_w)$, and the strategies of all N players by s. We show that, under an alternative strategy $s'_w(v_w)$, w's payoff is weakly higher for all realizations of valuations and strictly higher for some realizations. (We denote the strategies of all players, with only w's strategy changed from s_w to s'_w, as s'.) We distinguish two scenarios.

First, if $\widehat{v}_w \geq \overline{p}$ we define s'_w to be identical to s_w for all realizations $v_w \neq \widehat{v}_w$ and, for $v_w = \widehat{v}_w$, to prescribe bidding $\overline{p}$ and, in case the auction is lost, purchasing in the second stage. The resulting payoffs are:

(i) For all $v \neq \widehat{v}$ with $v_w \neq \widehat{v}_w$, w's payoff is the same under s'_w and s_w.

(ii) For $v = \widehat{v}$, following strategy s_w, w wins the auction and earns $\widehat{v}_w - p_w(\widehat{v})$ or $\widehat{v}_w - p_w(\widehat{v}) - \overline{p}$, depending on the second-stage strategy. Under strategy s'_w, instead, w loses the auction (since $p_w(\widehat{v}) > \overline{p}$) and earns $\widehat{v}_w - \overline{p} > \widehat{v}_w - p_w(\widehat{v}) > \widehat{v}_w - p_w(\widehat{v}) - \overline{p}$, i.e. strictly more than under s_w.

(iii) For all remaining realizations $v \neq \widehat{v}$ with $v_w = \widehat{v}_w$, we distinguish three subcases. If both the bid prescribed by s_w, $b_w(\widehat{v}_w)$, and the bid prescribed by s'_w, $b'_w(\widehat{v}_w) = \overline{p}$, win the auction or if both lose the auction, w obtains the same payoff under s'_w and s_w (or a higher payoff under s'_w if s_w prescribes to purchase in the second stage after winning or not to purchase after losing). If, instead, b_w wins the auction and b'_w loses the auction, then the payoff under s'_w, $\widehat{v}_w - \overline{p}$, is weakly bigger than the payoff under s_w, where w wins the auction and pays at least $\overline{p}$.

Second, if $\widehat{v}_w < \overline{p}$, we define $s'_w(v_w)$ to be identical to s_w for all realizations $v_w \neq \widehat{v}_w$ and, for $v_w = \widehat{v}_w$, to bid $\widehat{v}_w$ and not to purchase in the second stage. The resulting payoffs are:

(i) For all $v \neq \widehat{v}$ with $v_w \neq \widehat{v}_w$, w's payoff is the same under s'_w and s_w.

(ii) For $v = \widehat{v}$, strategy s_w earns $\widehat{v}_w - p_w(\widehat{v})$ or $\widehat{v}_w - p_w(\widehat{v}) - \overline{p}$, depending on the second-stage strategy. With strategy s'_w, instead, w loses the auction (since $p_w(\widehat{v}) > \overline{p} > \widehat{v}_w$) and earns 0, i.e. strictly more than under s_w.

(iii) For all remaining realizations $v \neq \widehat{v}$ with $v_w = \widehat{v}_w$, we distinguish three subcases. If both the bid prescribed by s_w, $b_w(\widehat{v}_w)$, and the bid prescribed by s'_w, $b'_w(\widehat{v}_w) = \widehat{v}_w$, win the auction or if both lose the auction, the payoff is identical (or higher under s'_w if s_w prescribes to purchase in the second stage). If, instead, b_w wins the auction and b'_w loses the auction, then the payoff under s'_w, 0, is bigger than the payoff under s_w, where w wins the auction and pays at least $\widehat{v}_w$.

Under both scenarios, s'_w induces a weakly higher payoff than s_w $\forall v$ and a strictly higher payoff for some realizations of v. Hence, given full support of the continuous distribution of v, w's expected utility is higher under s'_w than under s_w, and w has an incentive to deviate from s_w. **Q.E.D.**

Proof of Proposition 2. We show that, in any PBE,

$$\int_v p_w(b_1(v_1), ..., b_N(v_N))dF(v) < \overline{p}$$

with $b(v) = (b_1(v_1), ..., b_N(v_N))$ denoting the bidding strategies and F the cdf of v. As before, the decision of a player i not to enter is denoted by $b_i = 0$. We also denote the marginal cdf of the ith component as F_i, the conditional cdf of all other components, given v_i, as $F_{-i|i}$, and the corresponding pdf's by f, f_i, and $f_{-i|i}$.

In any PBE, player i enters the auction iff the expected utility from bidding in the auction is higher than $\max\{v_i - \overline{p}, 0\}$. Thus, for all $v_i < \overline{p}$, player i enters and bids $b_i(v_i) > 0$ iff

$$\begin{aligned} \Pr(i \text{ wins}|v_i) \cdot E\left[v_i - p_w(b(v))|v_i, i \text{ wins}\right] &\geq 0 \\ \iff \int_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i)dF_{-i|i}(v_{-i}) &\leq \int_{\{v_{-i}|i \text{ wins}\}} v_i dF_{-i|i}(v_{-i}) \end{aligned}$$

For all $v_i \geq \overline{p}$, player i enters iff

$$\Pr(i \text{ wins}|v_i) \cdot E\left[v_i - p_w(b(v))|v_i, i \text{ wins}\right] \geq v_i - \overline{p}$$

$$\iff \int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i)dF_{-i|i}(v_{-i}) \quad \leq \quad \overline{p} - \int\limits_{\{v_{-i}|i \text{ loses}\}} v_i dF_{-i|i}(v_{-i})$$

Taking expectations with respect to v_i, we obtain

$$\begin{aligned}
& \int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v) \\
\leq \; & \int\limits_{\{v|i \text{ wins} \wedge v_i < \overline{p}\}} v_i dF(v) + \int\limits_{\{v|v_i \geq \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i \geq \overline{p}\}} v_i dF(v) \\
= \; & \int\limits_{\{v|i \text{ wins} \wedge v_i < \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i \geq \overline{p}\}} \overline{p} dF(v) + \int\limits_{\{v|i \text{ loses} \wedge v_i \geq \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i \geq \overline{p}\}} v_i dF(v).
\end{aligned}$$

Since the last two terms are strictly negative, given continuous support of v on R_+^N, we get

$$\begin{aligned}
\int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v) \quad & < \quad \int\limits_{\{v|i \text{ wins} \wedge v_i < \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i \geq \overline{p}\}} \overline{p} dF(v) \\
& = \quad \int\limits_{\{v|i \text{ wins}\}} \min\{v_i, \overline{p}\} dF(v) \\
& < \quad \int\limits_{\{v|i \text{ wins}\}} \overline{p} dF(v).
\end{aligned}$$

Adding up the left-hand side and the right-hand side for all i, we obtain

$$\int_v p_w(b(v))dF(v) < \overline{p}.$$

Q.E.D.

Appendix B
Search Criteria for Cross-sectional Auction Data

The primary selection criterion was that a given set of search words retrieves homogeneous items of exactly the same quality. We took several steps to avoid mismatches. First, we identified products with unique identifiers, such as model numbers or brand names (electronics, perfumes). Secondly, we focused on products that are highly likely to be new (hygiene products), or boxed products that could be easily identified as new (electronics). We also found that eBay users have conventions for denoting product quality (new, almost new, used, etc.). We required that the applicable naming convention for new products be present in the every item description. For example, items in boxes needed to be described with "new in box," "nib," "sealed," "unopened," or "never opened." We also employed a several advanced eBay search features:

1. Search title and description. We searched not only the item title (default), but also the item description. Product quality is often denoted in the description.

2. Browsing hierarchy. eBay assigns products to detailed categories. Narrowly chosen categories allowed us to eliminate differing products.

3. Minimum and maximum price. Minimum prices eliminated accessories and blatantly used products in the BIN results. Maximum prices eliminated bundled items in both the auctions and BIN results.

4. NOT. This eBay search feature allows specifying words that cannot be in the product description. We used this feature to eliminate related but different products.

5. OR. This eBay search feature allows specifying a group of words, at least one of which must be in the product description. We used this feature mainly to account for the multiple ways to refer to a new product. We also used it in cases of multiple descriptions of an identical feature such as "4gb" or "4 gb," "3.4oz" or "100ml."

BIN Extraction for Cross-sectional Auction Data

Buy-it-now downloads were usually scheduled to take place within 30 minutes of the respective auction close. For some auctions ending in the middle of the night the BINs were downloaded within a few hours of the auction close, most often within two hours. (The likelihood of the cheapest BIN changing within the space of two hours at that time of day was very low.) Overall, 91.86 percent of fixed prices were within 120 minutes of the auction ending time in Download 1, 94.56 percent in Download 2, and 94.28 percent in Download 3.

After removing a few mismatched items, we identified the cheapest fixed price for each item type without accounting for shipping costs and the cheapest fixed price accounting for shipping costs. We obtained a final data set of $5,708$ fixed-price listings, $1,876$ for the auctions of Download 1, $1,726$ for Download 2, and $2,106$ for Download 3.

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Table I. Summary Statistics: Cash-Flow 101 Data

Panel A. Auction-Level Data

The sample period is 02/11/2004 to 09/06/2004. Final Price is the price paid by the winner excluding shipping costs; it is equal 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 Hours are defined as 0 for the time interval from 12 am to 1 am, 1 for the time interval from 1 am to 2 am etc. Prime Time is a dummy variable and equal to 1 if the auction ends between 3 pm and 7 pm PDT. 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 item description mentions the $195 manufacturer price.

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
Number of Bidders	139	8.36	3.87	1	18
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
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 I. Summary Statistics: Cash Flow 101 Data (*continued*)

Panel B. Bidder-Level Data

Bids are submitted bids, except in the case of the winning bid which is displayed as the winning price (the second-highest bid plus the appropriate increment).

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Number of auctions per bidder	807	1.44	1.25	1	17
Number of bids per bidder (total)	807	2.92	3.35	1	33
Number of bids per bidder (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
Winning frequency per bidder (total)	807	0.17	0.38	0	2
Winning frequency per bidder (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
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	2,353	0.46	0.50	0	1
Bids on auction with bonus tapes/videos	2,353	0.25	0.43	0	1

Table II. Summary Statistics: Cross-sectional Data

The sample consists of all downloaded auctions in US currency for the items listed in Appendix-Table A.1 unless the auction was removed by eBay during the listing period, received no bids, ended before corresponding fixed-price data could be collected, or could otherwise not be downloaded.

	Download 1		Download 2		Download 3	
Item Category	# Items	# Auctions	# Items	# Auctions	# Items	# Auctions
Consumer electronics	16	197	28	129	26	140
Computer hardware	8	62	11	83	10	55
Financial software	7	125	3	15	3	12
Sports equipment	3	16	6	24	3	17
Personal care products	2	23	16	100	13	160
Perfume / cologne	3	18	4	23	4	36
Toys / games	4	99	5	24	5	42
Books	6	175	6	106	6	117
Cosmetics	0	0	2	16	2	5
Home products	0	0	2	8	2	21
Automotive products	0	0	1	3	1	6
DVDs	0	0	5	36	5	38
Total	49	715	89	567	80	649

Table III. Overbidding: Cashflow 101 Data

Overpayment (Final Price) is equal to Final Price minus the simultaneous buy-it-now price set by the professional retailers. 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 charged by the professional retailers.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Overpayment (Final Price)	166	0.28	16.70	-48.95	47.55
Overpayment (Total Price)	139	2.69	14.94	-28.91	45.60

	Obs.	Fraction of Total Number of Auctions	Fraction of Overbid Auctions
Overpayment (Final Price)			
> $0	166	42%	100%
> $10	166	27%	64%
> $20	166	16%	39%
> $30	166	6%	14%
Overpayment (Total Price)			
> $0	139	73%	100%
> $10	139	48%	66%
> $20	139	35%	48%
> $30	139	25%	35%

Table IV. Overbidding: Cross-sectional Analysis

Panel A. Frequency of Overbidding

The sample consists of all auctions matched to buy-it-now prices for the same item, available at the end of the auction period.

	Download 1				Download 2				Download 3			
Item Category	Sample	% Overbid	Sample (w/ship)	% Overbid	Sample	% Overbid	Sample (w/ship)	% Overbid	Sample	% Overbid	Sample (w/ship)	% Overbid
Consumer electronics	173	36%	145	41%	124	44%	108	39%	138	38%	111	31%
Computer hardware	62	29%	54	35%	73	32%	66	24%	55	35%	41	24%
Financial software	125	62%	94	49%	15	53%	13	38%	12	42%	12	25%
Sports equipment	13	8%	13	15%	25	68%	24	25%	17	76%	15	40%
Personal care	23	39%	14	50%	99	43%	74	38%	160	29%	127	39%
Perfume / cologne	18	67%	10	40%	23	30%	17	24%	36	31%	31	23%
Toys / games	99	48%	85	56%	23	43%	15	47%	42	36%	32	9%
Books	175	75%	156	69%	106	68%	93	55%	117	72%	96	60%
Cosmetics					16	44%	16	31%	5	60%	5	40%
Home products					8	13%	7	14%	21	29%	19	11%
Automotive products					3	0%	1	0%	6	0%	4	0%
DVDs					36	61%	32	50%	38	74%	33	64%
Total	688	52%	571	51%	551	48%	466	39%	647	44%	526	37%

Panel B. Overbidding by Demographics

Male products are electric shavers (Braun 8995/8985, Norelco 8140xl), hair tonics (Bumble & Bumble), colognes (Calvin Klein Eternity), and dark iPods (blue, green, silver); female products are hair straighteners (Fourk Chi, T3 Tourmaline), cosmetics (Lancôme Fatale/Definicils mascara), perfumes (Calvin Klein Eternity, Lovely Jessica Parker, Escada Island Kiss), and bright iPods (pink). Products for kids are toys (Tickle Me Elmo), for teenagers games and playstations (Super Mario Brothers, Sixaxis Wireless PS3 Controller, Wireless Xbox 360 Controller), and for adults all consumer electronics. The book "Audacity of Hope" by Obama is liberal, the book "Cultural Warriors" by O'Reilly conservative. Price level comparisons are made with financial software (Quicken 2007 Basic vs Home Business), navigation systems (Garmin C320, C330, and C550), iPods (shuffle, nano, and 80gb), and digital cameras (Canon A630, SD600, and SD630).

	Without Shipping		With Shipping	
Target Consumer	Sample	% Overbidding	Sample	% Overbidding
Male	212	38%	165	45%
Female	160	33%	136	29%
Kids	85	28%	68	54%
Teenagers	72	61%	58	31%
Adults	435	39%	364	37%
Liberal	20	40%	18	17%
Conservative	21	33%	16	38%
Cheap	114	45%	98	36%
Expensive	159	38%	133	48%
More expensive	34	41%	26	35%
Most expensive	10	40%	9	56%

Table V. Disproportionate Influence of Overbidders

		Observations	(Percent)
Auction-level sample			
Does the auction end up overbid?	No	78	56.52%
	Yes	60	**43.48%**
Total		138	100.00%
Bidder-level sample			
Does the bidder ever overbid?	No	670	83.02%
	Yes	137	**16.98%**
Total		807	100.00%
Bid-level sample			
Is the bid an over-bid?	No	2,101	89.29%
	Yes	252	**10.71%**
Total		2,353	100.00%

Overbidding is defined relative to the buy-it-now price (without shipping costs).

Table VI. Bidding and Limited Attention

McFadden conditional logit model where the dependent variable is equal to 1 for items that are bid on at a particular time, and 0 for items that are available but are not chosen by the bidder at that time. The sample consists of all auctions listed at each actual bidding instance. Reported are the exponentiated coefficients (odds ratios). Standard errrors are clustered by bidding instance. Auction controls include Seller reputation [measured by feedback score], Auction length [in days], a dummy for Prime time (6-9pm Pacific Time), and Remaining auction time [measured in days and fraction of days]. Extended time controls include Remaining auction time squared and cubed, dummies for Last day, six dummies for the six last hours of the auction.

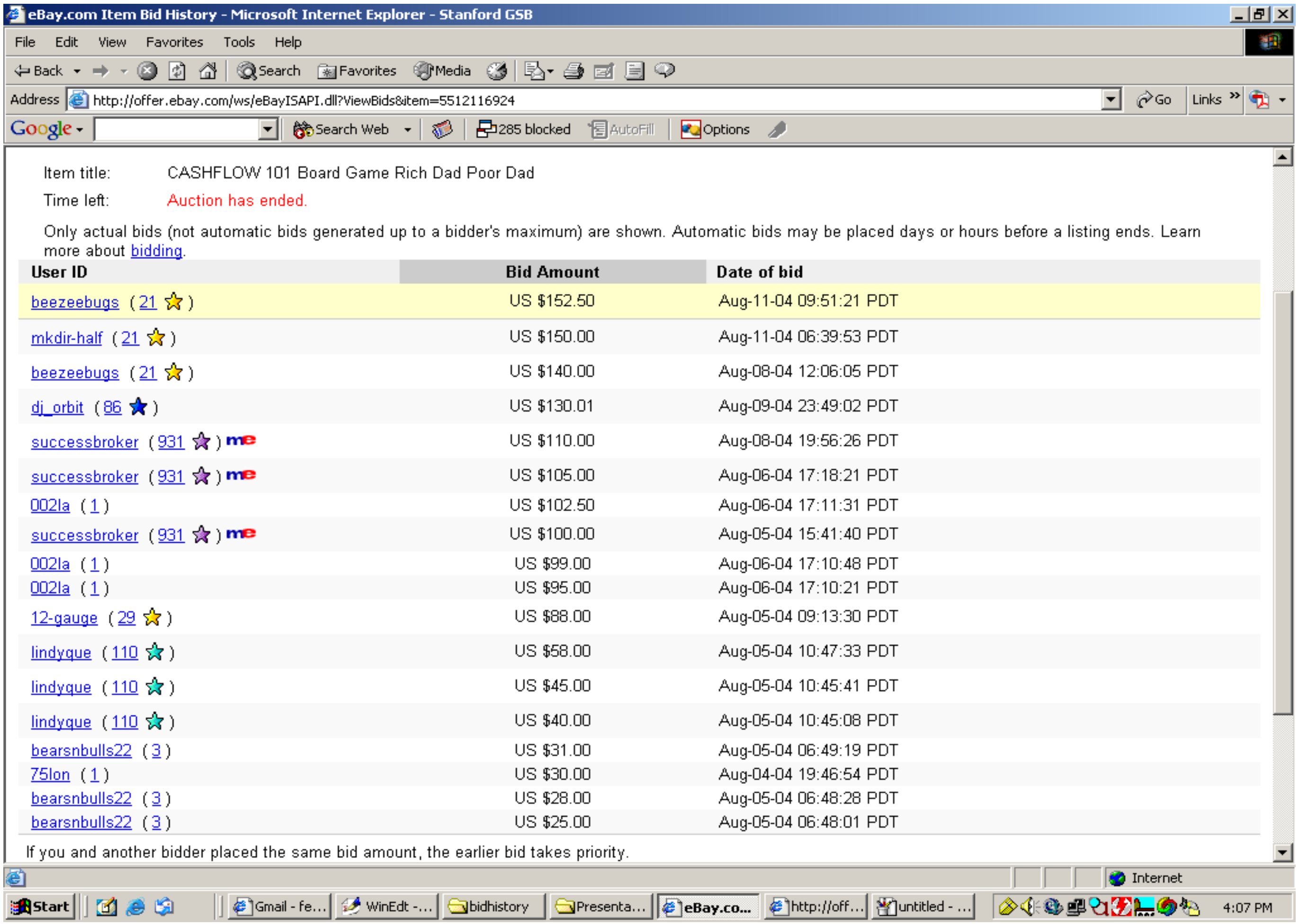
Dependent variable: binary variable equal to 1 for items bid on (at a given time)

	Full Sample		"Just above/below" = +/-$5			"Just above/below" = +/-$10		
			Full	First Bids	Later Bids	Full	First Bids	Later Bids
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to nearest BIN listing	1.176	1.106	1.021	1.061	1.006	1.025	1.056	1.013
[rows between]	[0.025]***	[0.029]***	[0.028]	[0.042]	[0.005]	[0.028]	[0.043]	[0.005]**
(Price just below)*(Distance to BIN)			0.894	0.868	0.939	0.822	0.933	0.752
			[0.160]	[0.245]	[0.204]	[0.128]	[0.232]	[0.147]
(Price just above)*(Distance to BIN)			2.083	2.948	1.785	1.372	1.538	1.469
			[0.487]***	[0.911]***	[0.670]	[0.239]*	[0.324]**	[0.421]
(Price far above)*(Distance to BIN)			1.159	0.640	1.325	1.231	0.861	1.261
			[0.137]	[0.236]	[0.152]**	[0.118]**	[0.346]	[0.133]**
Price outstanding just below BIN price			1.164	1.326	1.164	1.205	0.835	1.799
[dummy]			[0.207]	[0.357]	[0.279]	[0.179]	[0.198]	[0.347]***
Price outstanding just above BIN price			1.747	0.966	2.920	1.861	1.027	3.255
[dummy]			[0.453]**	[0.381]	[1.004]***	[0.412]***	[0.345]	[0.992]***
Price outstanding far above BIN price			2.152	1.761	2.844	2.746	1.213	5.922
[dummy]			[0.449]***	[0.617]	[0.781]***	[0.729]***	[0.575]	[2.057]***
Position on screen	0.988	0.918	0.974	1.000	0.983	0.973	0.998	0.977
[row number]	[0.005]**	[0.009]***	[0.013]**	[0.019]	[0.004]***	[0.013]**	[0.019]	[0.004]***
Price outstanding		0.975	0.99	0.983	1.006	0.991	0.981	1.013
		[0.003]***	[0.003]***	[0.004]***	[0.005]	[0.003]***	[0.005]***	[0.005]**
$(\text{Price outstanding})^2$		1.002	0.989	0.988	0.983	0.988	0.991	0.977
		[0.002]	[0.003]***	[0.004]***	[0.004]***	[0.003]***	[0.004]**	[0.004]***
Starting price		0.994	0.994	0.998	0.99	0.994	0.998	0.991
		[0.001]***	[0.001]***	[0.001]**	[0.001]***	[0.001]***	[0.001]*	[0.001]***
Auction controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended time controls			Yes	Yes	Yes	Yes	Yes	Yes
N	14,043	14,043	14,043	6,712	7,331	14,043	6,712	7,331
Pseudo R-squared	0.01	0.14	0.18	0.25	0.15	0.18	0.25	0.16

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 $ TRY IT TODAY, WITH ABSOLUTELY NO RISK,	$207.96	Buy It Now	1d 06h 47m
CASHFLOW® 101 Robert Kiyosaki Plus Bonuses! Your satisfaction is GUARANTEED, 100% $ back	$129.95	Buy It Now	1d 08h 02m
MINT Cashflow 101 *Robert Kiyosaki Game NR! It's easy to be rich. Brand New. Still sealed	**$140.00**	13	1d 08h 04m
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! Your satisfaction is GUARANTEED, 100% $ back	$129.95	Buy It Now	1d 14h 17m
CASHFLOW® 101 202 Robert Kiyosaki Best Pak $ TRY IT TODAY, WITH ABSOLUTELY NO RISK,	$207.96	Buy It Now	1d 15h 47m

Figure II. Bidding History Example



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.

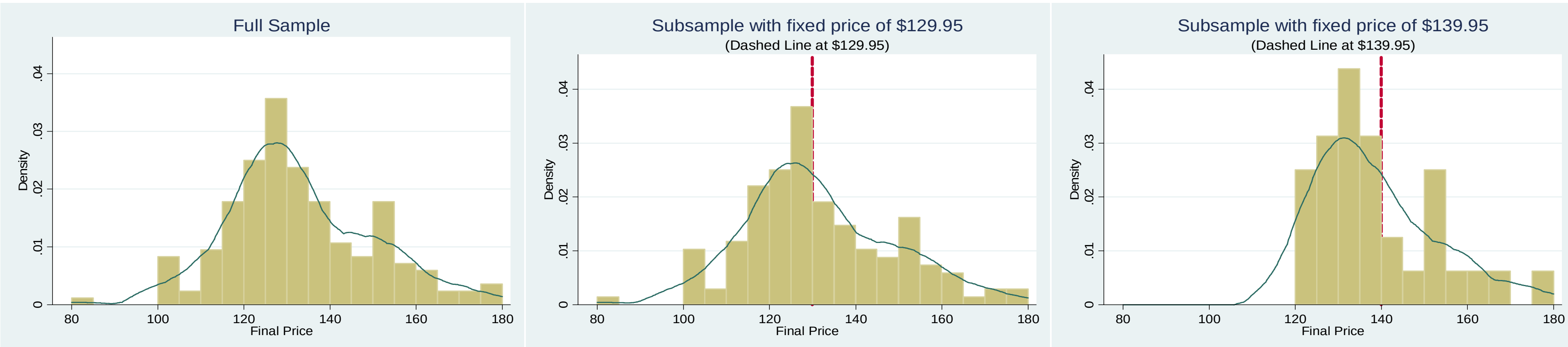
User ID	Bid Amount	Date of bid
beezeebugs (21)	US $152.50	Aug-11-04 09:51:21 PDT
mkdir-half (21)	US $150.00	Aug-11-04 06:39:53 PDT
beezeebugs (21)	US $140.00	Aug-08-04 12:06:05 PDT
dj_orbit (86)	US $130.01	Aug-09-04 23:49:02 PDT
successbroker (931) me	US $110.00	Aug-08-04 19:56:26 PDT
successbroker (931) 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 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

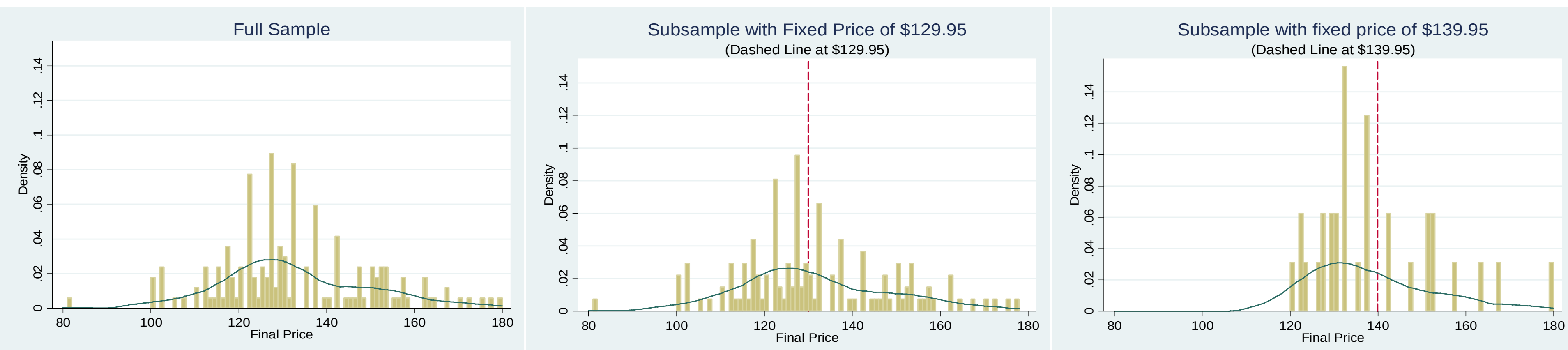
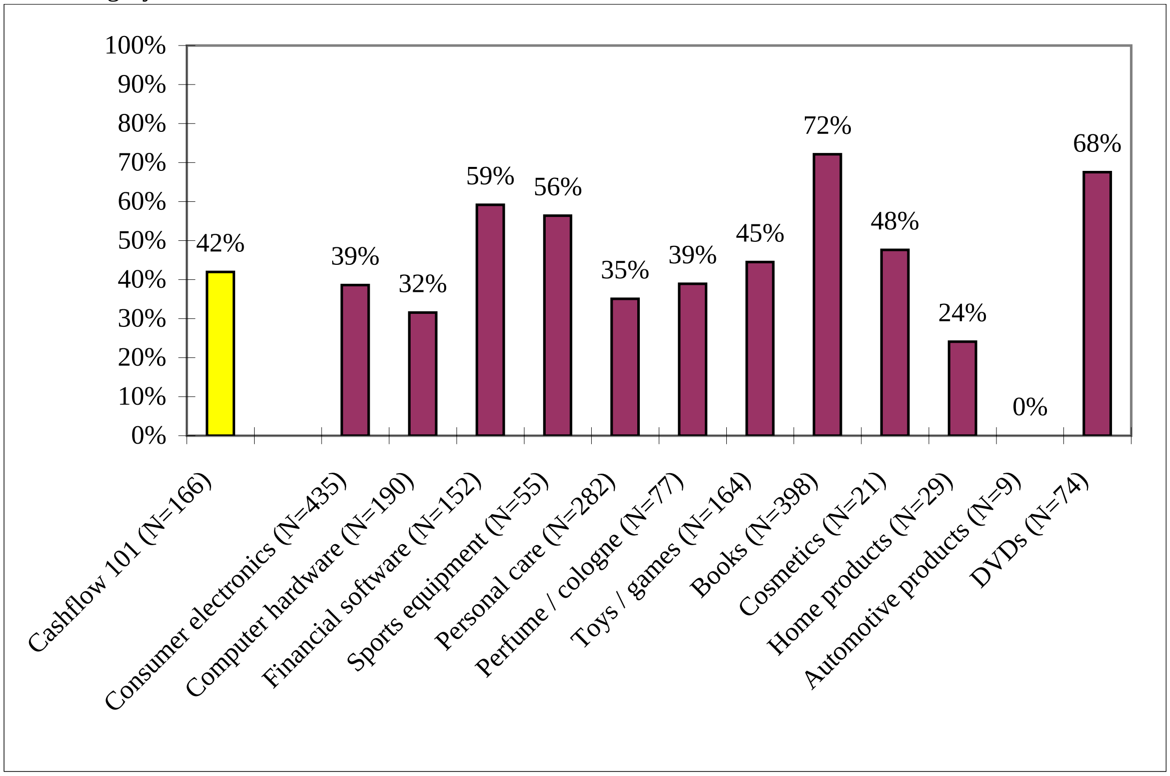


Figure IV. Overbidding

Panel A. Overbidding By Item Category

The leftmost column shows the percent of auction prices above the BIN in the Cashflow 101 data. The other columns show the percent of auction prices above the corresponding BIN in the cross-sectional data, split by item category.



Panel B. Overbidding By Experience

The sample consists of all Cashflow 101 auctions. The Below Median sample contains all winners with a Feedback Score of 4 or lower; the Above Median sample contains all winners with a Feedback Score above 4. Subsamples sizes are in the second pair of parentheses.

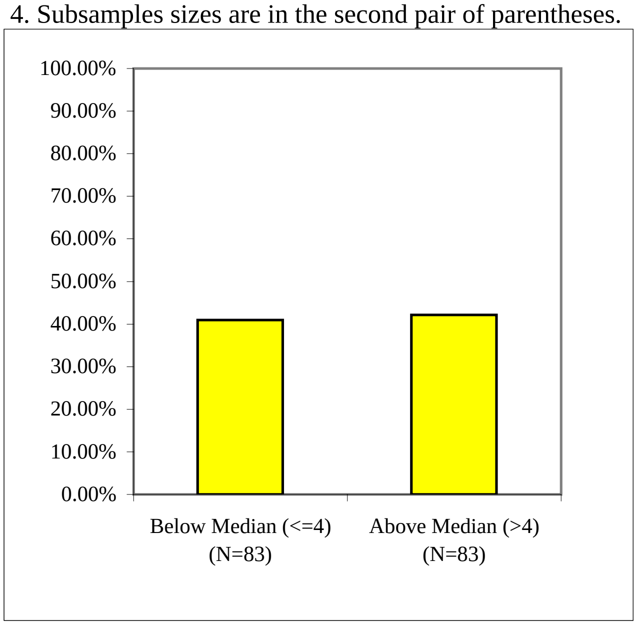
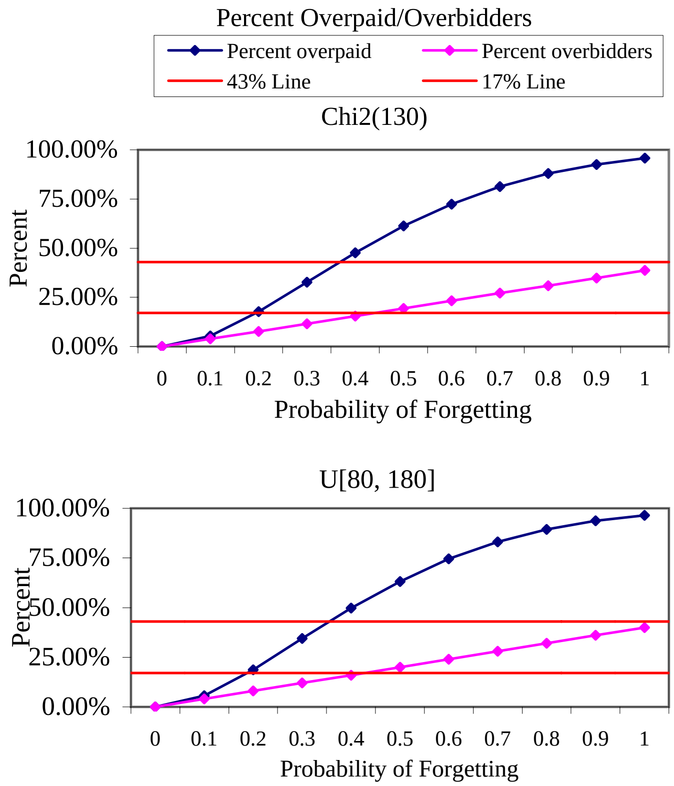
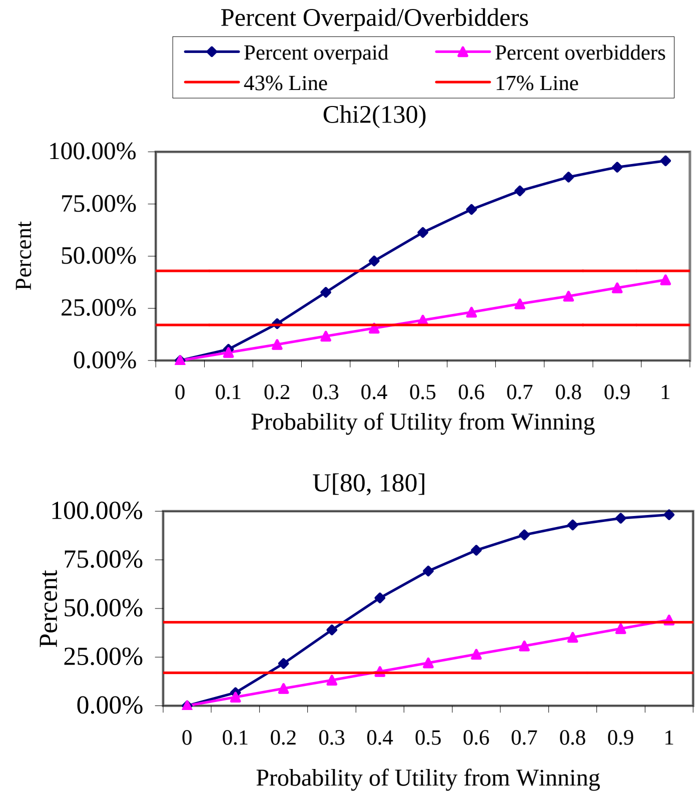


Figure V. Calibrations

Limited Memory



Utility of Winning



Appendix-Table A.1 List of All Items in Cross-sectional Data

Item Category		# Auctions Downld 1	Downld 2	Downld 3
Consumer electronics	Nokia N93 cell phone	7	2	2
	Motorola V3 Razr cell phone (gold)	14	7	9
	Motorola KRZR K1 cell phone (black)	4	0	2
	Motorola KRZR K1 cell phone (blue)	3	0	0
	Garmin StreetPilot c330 Vehicle GPS Navigator	12		
	Garmin StreetPilot c550 Vehicle GPS Navigator	2		
	1GB Apple iPod Shuffle (pink)	3	8	0
	1GB Apple iPod Shuffle (blue)	11	4	4
	1GB Apple iPod Shuffle (orange)	7	3	4
	1GB Apple iPod Shuffle (green)	5	1	1
	4GB Apple iPod Nano (blue)	30	2	3
	4GB Apple iPod Nano (green)	17	0	2
	4GB Apple iPod Nano (pink)	24	3	5
	4GB Apple iPod Nano (silver)	31	3	5
	80GB Apple iPod (black)	21	5	1
	80GB Apple iPod (white)	6	1	0
	30GB Microsoft Zune (black)		17	24
	30GB Microsoft Zune (white)		11	4
	XM2Go AC power cord for MyFi, Helix, Inno, Nexus		1	
	Texas Instruments TI-89 Titanium graphing calculator		16	15
	Texas Instruments TI-83 Plus graphing calculator		11	14
	InFocus Play Big 480p IN72 DLP projector		3	0
	Bose Lifestyle 48 speaker system (black)		0	4
	Garmin StreetPilot c320 Vehicle GPS Navigator		7	9
	Kenwood KDC-MP2032 automotive CD player		0	
	Canon PowerShot SD600 6 megapixel digital camera		0	2
	Canon PowerShot SD630 6 megapixel digital camera		1	3
	Canon PowerShot SD900 10 megapixel digital camera		8	2
	Canon PowerShot A630 8 megapixel digital camera		4	8
	T-Mobile Sidekick 3 cell phone		11	17
Computer hardware	Western Digital My Book 500GB external hard drive	21	10	10
	Western Digital My Book 400GB external hard drive	1		
	Western Digital My Book 320GB external hard drive	2		
	Sandisk 4GB Secure Digital Ultra USB flash drive	15		
	D-Link DI-524 wireless router	9	0	3
	Linksys WRT300N wireless router	7	6	10
	Omni Verifone 3750 credit card terminal	4		
	Nurit 2085 credit card terminal	3		
	Sandisk 1GB Cruzer Micro U3 USB flash drive		29	
	Belkin F5D7230 wireless router		8	5
	HP Laser Jet 3050 All in One printer/copy/scanner/fax		17	7
	Lexmark P450 photo printer		0	1
	Linksys WUSB11 wireless USB network adaptor		3	3
	Linksys WRE54G wireless router		5	7
	Netgear WGR614 wireless router		5	5
	Netgear WGR624 wireless router		0	4
Financial software	QuickBooks Premier Accountant Edition 2007	1		
	QuickBooks Premier Accountant Edition 2007 (5-User)	0		
	Quicken Basic 2007	38	8	5
	Quicken Deluxe 2007	12		
	Quicken Home Business 2007	28	5	6
	H&R Block Taxcut 2006 Premium Federal and State	44		
	QuickBooks Payroll 2007	2	2	1

Sports equipment	Callaway HX Tour golf balls (6 dozen)	11	0	
	Titleist Pro V1 golf balls (4 dozen)	3		
	Titleist Pro V1 golf balls (2 dozen)	2		
	Omron HJ-112 Premium digital pedometer		18	11
	Super Gym 3000 Total Fitness Model exercise machine		2	5
	Oakley Wisdom ski goggles (khaki, gold, iridium)		0	
	Oakley Wisdom ski goggles		0	
	Bones Reds skateboard bearings		4	1
Personal care products	Braun 8995 electric shaver	4	2	19
	Braun 8985 electric shaver	19	8	13
	T3 Tourmaline hair dryer		0	
	Farouk Chi Turbo Big 2” ceramic flat iron hair straightener		0	
	Murad Acne Complex kit		6	8
	Farouk Chi 1” ceramic flat iron hair straightener		12	22
	Farouk Chi 1” ceramic flat iron hair straightener (red)		1	
	T3 Tourmaline ceramic flat iron hair straightener		1	4
	Oral-B Vitality Sonic rechargeable toothbrush		8	8
	Oral-B Sonic S-320 power toothbrush		1	14
	Oral-B Professional Care 7850 DLX power toothbrush		9	8
	Oral-B Professional Care 9400 Triumph power toothbrush		25	31
	Sonicare 7300 power toothbrush		0	17
	Bumble & Bumble Hair Tonic (8oz)		5	11
	Norelco 8140 Speed XL shaver		5	4
	Proactive Renewing Cleanser		17	1
Perfume / cologne	Lovely by Sarah Jessica Parker perfume (3.4oz)	3	9	6
	Calvin Klein Eternity Cologne for Men (3.4oz)	6	9	5
	Calvin Klein Eternity Perfume for Women (3.4oz)	9	3	18
	Escada Island Kiss perfume		2	7
Toys / games	PlayStation3 Sixaxis wireless controller	12	4	10
	Nintendo Wii Play: 9 games, wireless remote, & nunchuck	3		
	Xbox 360 wireless controller	23	6	14
	Tickle Me Elmo TMX	61	10	14
	Parker Brothers Monopoly Here & Now		3	2
	Nintendo DS Super Mario Brothers game		1	2
Books	*You on a Diet* , by Craig Wynett and Lisa Mehmet	41	28	31
	The Audacity of Hope , by Barack Obama	11	4	5
	Culture Warrior , by Bill O'Reilly	14	6	1
	For One More Day , by Mitch Albom	6	1	1
	The Secret , by Rhonda Byrne	70	51	60
	The Best Life Diet , by Bob Greene	33	16	19
Cosmetics	Lancome Fatale mascara (black, full size)		6	2
	Lancome Definicils mascara (black, full size)		10	3
Home products	Roomba Scheduler 4230 robotic vacuum cleaner		5	16
	Yankee Housewarmer Christmas-cookie-scented candle (22oz)		3	5
Automotive products	Inline auto ignition spark plug tester		3	6
DVDs	*Teenage Mutant Ninja Turtles The Movie* DVD		0	0
	Scrubs Complete Fourth Season on DVD		10	12
	Lost First Season on DVD		10	10
	Grey's Anatomy Second Season on DVD		6	5
	Lost Second Season on DVD		10	11
Total		715	567	649

Appendix-Table A.2 Sample Construction of Data Set 2

	Downld 1	Downld 2	Downld 3	Total
Initially downloaded auctions	1,136	1,643	1,084	3,863
Auctions not retrieved at auction ending time (removed by eBay; outages in internet connection)	107	582	18	707
Ended before BINs downloaded	0	107	0	107
Auctions with no bids	307	378	372	1,057
Auctions in non-US currency	1	0	22	23
Auctions for items not on list	6	14	23	43
Final list of auctions (pre-matching)	715	562	649	1,926

Appendix-Table A.3 Wording Experiment

The order in which subjects received the item descriptions vary by Ordering and are indicated in *italics* below the number choosing that description.

	Ordering 1	Ordering 2	Ordering 3	Aggregate
First item description	14	2	3	
	(retailer)	*(individual 1)*	*(individual 2)*	
Second item description	1	5	19	
	(individual 1)	*(individual 2)*	*(retailer)*	
Third item description	1	15	2	
	(individual 2)	*(retailer)*	*(individual 1)*	
Indifferent	14	11	9	34
Did not answer	0	1	2	3
Total	30	34	35	99
Total (answered)	30	33	33	96
Percent Indifferent	47%	33%	27%	35%
Percent Preferring Retailer Item	47%	45%	58%	50%
Percent Preferring Auction Item	7%	21%	15%	15%