The Bidder's Curse*

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Abstract

Traditional explanations for the popularity of auctions are efficiency and revenue maximization. We argue that auctions also induce 'overbidding,' i.e., bidding above the buyer's willingness to pay for an item outside the auction. Even if only few buyers overbid, they affect prices and allocations since auctions systematically pick those buyers as winners.

We employ a novel approach to identify overbidding, using hand-collected data of eBay auctions with simultaneous fixed prices. We argue that fixed prices for identical items on the same webpage should provide an upper bound for bidders' willingness to pay in the auctions. In a first, detailed data set of board game auctions, we find that, in 42 percent of the auctions, the final price is higher than the simultaneous fixed price. The result is not explained by differences in item quality, shipping costs, or seller reputation. Auction experience, as measured by eBay's feedback score, does not eliminate overbidding. We also document that the large fraction of overbidding is induced by a small number of players: only 17 percent of bidders ever bid above the fixed price. The finding replicates in a broad cross-section of auctions (48 percent overbidding). Using a simple model of second-price auctions with a fixed price option, we show that transaction costs of switching between auctions and fixed prices are not sufficient to explain the results. Limited attention of bidders and utility of winning both contribute to explaining the empirical findings.

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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 this 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, the potential for overbidding. We argue that auctions help to identify buyers who overbid. The auction mechanism ensures that, even if only few consumers bid more than their valuation, overbidding affects prices and allocations: auctions systematically pick as winners those consumers whose bids are most excessive. 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] Experimental economics revived the debate about overbidding by documenting sizeable overbidding in laboratory second-price auctions (Kagel, Harstad, and Levin, 1987; Kagel and Levin, 1993; Harstad, 2000) and, relative to the risk-neutral Nash equilibrium, in first-price private-value auctions (Cox, Roberson, and Smith, 1982; Cox, Smith, and Walker, 1988). A number of experiments explore the pervasiveness, correlates, and causes for such overbidding (e.g., Cooper and Fang, forthcoming). Most commonly, risk aversion or non-standard utility of winning are proposed as explanations for bids above the risk-neutral Nash equilibrium (Cox, Smith, and Walker, 1988; Goeree, Holt, and Palfrey, 2002). Recent work in neuroeconomics (Delgado, Schotter, Ozbay, and Phelps, 2007) suggests that "fear of losing," rather than "joy of winning," explains overbidding in the laboratory.

Overbidding, however, is hard to identify outside the laboratory. A major hurdle is that we typically do not know buyers' private valuations. In this paper, we use a novel research design to detect overbidding in the field. We compare second-price auctions to fixed prices at which the same good is available for immediate purchase on the same webpage. We argue that bids above the fixed price for the same good are a sufficient criterion for overbidding. This approach

[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).

allows us to analyze overbidding without having to measure private valuations directly.

We first present a simple model that introduces fixed prices into a standard second-price framework. Auctions with simultaneous fixed-price offerings for identical items have become a common empirical phenomenon, both on eBay and beyond (e.g., for airline tickets, time shares, cars, houses, online ads, or concert tickets[4]), but have not yet been analyzed much theoretically. Our model allows us to distinguish different explanations for overbidding in auctions. In the basic framework, rational bidders should never bid above the fixed price. If we introduce transaction costs of switching between the auction and the fixed-price sale, rational bidders may bid above the fixed price conditional on entering the auction. However, they enter the auction only if the expected winning price is strictly smaller than the fixed price. Other explanations – limited attention or limited memory of the fixed price, utility of winning an auction, and bidding fever – do not impose this restriction on the expected auction price, but allow us to pin down other features of the empirical distribution of bids.

We test for the occurrence of overbidding using a novel data set of all eBay auctions of Cashflow 101, a popular board game designed to teach financial and accounting knowledge, from February to September 2004. A key feature of the data set is the continuous presence of a stable fixed price for the same game on the same eBay website. 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 if a user searches for Cashflow 101. Hence, the fixed price should provide an upper limit to bidders' willingness to pay for the item.

We find that 42 percent of the auctions end at prices above the fixed price. If we account for the differences in shipping costs, 73 percent of the auction prices are above the fixed prices. The observed overbidding is surprising since the quality of the fixed-price items is always equal or higher, and the reputation of the fixed-price sellers, as measured by the feedback from previous transactions (Feedback Score), significantly better. Conducting a complementary choice experiment and a survey of eBay users, we rule out unobserved wording differences between the listings or general unawareness of the fixed prices as explanations.

The amount of overbidding is significant: 27 percent of the auctions exceed the fixed price by more than \$10, 16 percent by more than \$20, and still 6 percent by more than \$30. Even the average auction price is above the fixed price, significantly so after accounting for shipping cost differences. The latter finding rules out switching costs as an explanation.

The overbidding phenomenon generalizes to a wide range of other objects. We collect a second data set containing a broad cross-section of $1,929$ different auctions (electronics, hard-

[4]See skyauction.com or priceline.com versus online sales (e.g., Orbitz) for flights; bidshares.com for auctions and fixed prices of timeshares; southsideautoauctions.com.au for auctions and fixed prices of cars; Google's AdSense versus advertising agencies' fixed prices for online banner ads; and ticket-auction.net or seatwave.com versus promoters' fixed prices for concert tickets. See also equipment and real estate auctions by the General Services Administration, treasury.gov/auctions, usa.gov/shopping/shopping.shtml, and gsasuctions.gov.

and software, sports equipment, personal care products and cosmetics, toys and games, books, home products, automotive products, and DVDs). Across three downloads in February, April, and May 2007, overbidding frequencies range from 44 to 52 percent. The net overpayment is 9.98 percent of the fixed price, significantly different from zero (s.e.= 1.85 percent).

These findings do not imply that most items sell at too high a price. Some items have many simultaneous fixed prices (e.g., 401 listings by the professional retailers for Cashflow 101 in our sample), and are sold outside eBay. Rather, the results suggest that, on the margin, auctions induce higher prices and allocate objects to those buyers who are willing to pay more than the simultaneous fixed prices.

Several additional results help to distinguish between the remaining explanations for overbidding. First, we show that experience does not eliminate overbidding. Bidders with high numbers of previous eBay transactions, as measured by eBay's Feedback Score, are no less likely to overbid. Hence, overpayment is not limited to auction novices, who might be less familiar with the eBay site and buy-it-now prices. Second, 89.9 percent of overbids are follow-up bids to earlier bids below the fixed price by the same bidder. Hence, it is plausible that bidders initially account for the lower-price outside option but fail to do so when eBay's outbid notice ('You have been outbid!') comes in, consistent with the limited-memory explanation.

Our second main result is that few overbidders suffice to generate the observed large fraction of overbid auctions: While overbidding is common across auctions, it is not as common across bidders. Only 17 percent of bidders ever overbid. Thus, a small number of consumers with non-standard bidding behavior has a disproportionate effect on auction outcomes. This auction selection effect applies regardless of the cause of overbidding, and mirrors the findings on the winner's curse in common-value auctions: On average, winners display a higher upward bias than the populations as a whole (see, e.g. Kagel and Levin, 1986).

We illustrate this influence of few overbidders in a simple calibration. We allow a fraction of bidders to have non-standard preferences that generate overbidding; all other bidders are rational. We show that, over a range of plausible distributions of private values, we can match the results if 30-40 percent of bidders display non-standard behavior. In this calibration, 10 to 20 percent of bidders overbid and 40 percent of the auctions end above the fixed price.

In summary, the observed overbidding is hard to explain in a simple rational framework, even with transaction costs. Both limited attention (or limited memory) and utility of winning (or bidding fever), instead, appear to explain part of the observed overbidding. Auctions amplify the non-standard behavior by selecting as winners those consumers who display the strongest deviations from the standard model. While our identification strategy relies on online auctions, overbidding applies more broadly. Previous literature has raised this possibility in the context of 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 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).

Our results speak to an ongoing debate in Behavioral Economics about the relevance of biases in markets: Do non-standard preferences and beliefs, as documented in experiments, matter in markets where biased agents interact with unbiased agents, learn from their mistakes, and can sort into those markets that are least affected by their biases (List, 2003; Levitt and List, 2006; Lazear, Malmendier, and Weber, 2006)? The literature in Behavioral Industrial Organization (cf., Ellison, 2006) points out that market interaction can exacerbate the relevance of biases if firms tailor their contracts and products to individual biases.[5] Applied to the context of online auctions, Simonsohn and Ariely (2007) document that sellers respond to buyers' bias towards auctions with more bids by setting low starting prices in order to attract more bids.

In this paper, we show that a specific set of market outcomes—auction prices and allocations—are affected by non-standard behavior. The overbidding reported in laboratory second-price auctions appears to mirror actual behavior in the field. Moreover, the popularity of the market mechanism itself (auctions) might reflect the importance of consumer biases. Auctions emerge as a tool to "search for fools."[6]

Our paper also relates to several strands of the auction literature. 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 Hortascu (2003).[7] Differently from the winner's curse, the phenomenon analyzed in this paper is not restricted to common-value settings. Moreover, some of the 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 independently of the belief system.

Related to our result on bidder experience, Bajari and Hortascu (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, consistent with the findings on experience in this paper.

The growing literature on online auction markets is surveyed in Bajari and Hortacsu (2004). The neglect of shipping costs, observed in our main data set, was first documented in Hossain

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

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

[7] Bajari and Hortascu (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).

and Morgan (2006). Most relatedly, Ariely and Simonson (2003) document that 98.9 percent of eBay prices for CDs, books, and movies are higher than the lowest online price found with a 10 minute search. Pratt, Wise, and Zeckhauser (1979) found similar variation in prices for identical items when searching by phone. Our empirical strategy of using only within-eBay comparisons helps to rule out transaction costs of using different websites.

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 those who (also) use fixed prices on eBay. Halcoussis and Mathews (2007) study the correlation between auction and fixed prices for similar products (different types of concert tickets). We can think of other selling mechanisms that "search for fools," such as the continuous 'sales' in tourist areas, or selling strategies in door-to-door sales. The optimality of one mechanism over another depends on circumstances such as the arrival process of consumers, sorting of consumers into different markets, and rationality assumptions. This paper does not compare different price mechanisms explicitly or analyze the choice between them. But our results illustrate an advantage of auctions for the seller: auctions help to identify those (potentially few) buyers who are most inclined to overbid.

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. We derive the equilibrium bidding strategies and distinguish different explanations for why bidders may deviate from this strategy. Section 3 describes the data and some institutional background about eBay. In Section 4, we present the core empirical results: a large fraction of auctions are overbid, but a relatively low fraction of bidders overbid. We also calibrate the potential explanations from our model, showing which frequencies of such deviations are needed to generate the observed overbidding. 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, which is a common empirical phenomenon but has not been studied in prior literature. We show under which assumptions the fixed price provides an upper bound to bidders' willingness to bid. We then examine alternative assumptions, under which we may observe bidding above the fixed price: transaction costs of switching, inattention, limited memory, utility of bidding and bidding fever. While the theoretical analysis considers the case of homogeneous bidders, we will consider the interaction of heterogeneous bidders in the calibration in Section 4.5.

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 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, $E\left[v_i - p_w \left| v_i, i \text{ wins}\right.\right]$, 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: $E[p_w] < \overline{p}$, even though the auction price may exceed the fixed price if $v_i > \overline{p}$ for some player i.*

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 bidders are not aware of the fixed price. Although the fixed prices are listed in eBay together with the auctions, players with limited attention may miss out on them. The simplest way to model this situation is to assume that bidders are unaware of the fixed price in the second stage and hence only play the first-stage game, which reduces the game to a standard Vickrey auction.

Proposition 3 (Limited Attention). *If players are not aware of the fixed price, each player i bids her valuation, $b_i^* = v_i$, in the unique PBE. Hence, the auction price may exceed the fixed price if $v_i > \overline{p}$ for some player i.*

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 be aware of 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. 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. This 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.(b)).

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.[8] 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

[8] Note that 'joy of bidding' (rather than winning) does not suffice to generate overbidding. Fixed utility benefits just from bidding in the first stage does 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.

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 $b_i^* = \{v_i + \pi_i, \overline{p} + \pi_i\}$. **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. If $\pi_i = 0\ \forall i$, we are in the standard case. However, if some $\pi_i > 0$, a player may obtain the good in 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 $\pi_i = 0$: the utility from obtaining the same object via an auction and via a fixed-price transaction 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). In our setting, this reinterpretation affects the welfare of the players 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 in the auction, the more she anticipates being the winner and owning the item, which in turn increases her willingness to pay. This interpretation, however, explains bidding above the fixed price if the bidder gets specifically attached to the auction item and would not want the (identical) fixed-price item.

The simple model in this Subsection suggests another empirical test to distinguish different explanations for overbidding. The model implies an upper bound for bids relative to the fixed price. For example, if we assume that π_i cannot plausibly exceed \$20, then bids on an item with a fixed price of \$130 should not exceed \$150, even if the realization of v_i can be higher than \$150. Limited attention and limited memory as well as the transaction-cost explanation, instead, do not impose an upper bound on overbids relative to the fixed price $\overline{p}$.

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

Online auctions have undergone an explosion in sales and revenues since their inception in 1995. 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.[9] 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[10]. 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).

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.[11] 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. Ideally, the fixed price should be stable and continuously present so that any bidder who searches for the item at any time finds the same fixed-price offering. Moreover, there should be multiple staggered fixed-price listings so that

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

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

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

it is easy to infer that the seller intends the offer to be continuously present at a stable price.

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.[12] 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, 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 or where 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,[13] 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 pm PDT on 8/14/2004 to 8:48 pm 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

[12]The 2004 prices were $8.47/$11.64/$24.81 for UPS ground/2ndday air/overnight.

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

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 pm (Jin and Kato, 2006; Melnik and Alm, 2002).

Items are always brand new in the BIN listings. For the auctions, 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. The correlation between *Starting Price* and *Number of Bids* is -0.73.

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 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.[14] 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,

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

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 am), April 25 (4:50-4:51 am), and May 23 (9:13-9:43 pm).[15] 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 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. We undertook this matching twice, accounting and not accounting for shipping costs.[16] 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

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

[16] 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.

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

We first document that auction prices frequently exceed the fixed prices and argue that this indicates overbidding. We then discuss several explanations for overbidding, based on the additional empirical implications derived in Section 2. Finally, we show that a relatively small number of users who overbid suffice to generate a high likelihood of overbidding. This discussion includes the calibration of the model in Section 2.

4.1 Overbidding

In our detailed data set on Cashflow 101 auctions, evidence of auction prices above the fixed prices is already implicit in the summary statistics (Table I, Panel A). The average final price amounts to $132.55, with a maximum of $179.30. In Table III, we show:

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.

The bidding strategy of a significant number of auction winners is inconsistent with the equilibrium strategies of the simple benchmark model in Subsection 2.1. According to Proposition 1, rational bidders never pay more than the fixed price in an auction.

Alternative Interpretations. Before discussing different possible explanations for overbidding, we consider a number of explanations that do not involve 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 end 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. The histograms in Panel A are in bins of $5 width; those in Panel B of $1 width. The histograms are overlaid with a kernel density estimate, using the Epanechnikov kernel with an "optimal" half-width.[17] 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. We will explore these distributional details in our discussion of alternative explanations.

2. Shipping Costs and Sales Taxes. Another hypothesis is that the overbidding is due to higher shipping costs for the fixed-price items. 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. Hence, 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, 35 percent by more than \$20, and still a quarter by more than \$30.

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.[18] 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 add the general sales tax of 6.5 percent for Minnesota and 6 percent for West Virginia to the fixed price and 0 percent to the auction prices, overbidding is substantial. For example, a buyer from Minnesota would pay \$138.45, including sales tax, for an item purchased from the Minnesota-based retailer; 28 percent of final prices lie above this threshold.

3. Unawareness or Misunderstanding of Fixed Prices. Bidders may bid above the fixed price if their search does not retrieve the fixed-price listings or if they do not understand how the buy-it-now option works. The first explanation is implausible. In our survey, 92 percent of respondents indicated that they start their search by typing a core word, typically the item name, and 8 percent first go to the appropriate item category, in this case 'boardgames', and then search within this category. With either method, the fixed-price listings are retrieved. If the search includes additional qualifiers, the fixed-price listings are *more* likely to be retrieved than most auctions since their descriptions more detailed and without typos.

Unawareness of the functioning of BIN is more difficult to address. It appears unlikely since buy-it-now listings are very common, representing over one third of eBay listings during our sample period. They are intuitively designed and similar to any fixed price on the internet. In addition, our survey indicates that 90.5 percent of subjects who have used eBay have come across the buy-it-now feature, and 100 percent of those who have used the buy-it-now feature

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

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

say that they were satisfied with their experience.[19] We will further address costs of "learning" about BIN, together with other transaction-cost explanations, in the next Subsection.

4. Quality Differences. Finding 1 could also be explained by systematically higher quality of auction items relative to fixed-price items. However, the observed quality of the BIN items is (if anything) systematically higher. In the auctions, some board 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 bonuses of the original board games and, occasionally, additional bonuses, such as free access to a financial-services website. In addition, the professional sellers offer 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. After having made their choice, subjects were asked to explain their preference. Among the 14 students who chose an auction item the most common explanation was that the fixed-price offer provided too much information – a reaction that may have been driven by time pressure in the six-minute experiment. Among the students who chose the retailer's offer, the most common explanation was the retailer's money-back-guarantee and more professional layout. Hence, it is unlikely that unobserved quality difference explain why bidders bid more than the simultaneously available fixed price.

5. Seller reputation. Another explanation is lower seller reputation of the fixed-price retailers. Based on eBay's Feedback Scores[20], 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.

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.

[19] This question was added only in the last wave of the survey ($N = 89$).

[20] 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.

We conclude that Finding 1 reveals significant overbidding in our data.

4.2 Overbidding in Cross-Section of Auctions

So far, we have documented overbidding for a specific item. It is 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 with different price levels and different target buyers. Our cross-sectional data set contains a broad set of items that are offered both in auctions and at fixed prices. The data was obtained in three downloads between February and May 2007 and is described in Subsection 3.3 and Table II. 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 for the Cashflow 101 item generalizes across auction items. As discussed above, the larger-scale cross-sectional data comes at the cost of some loss of control over the setting. In particular, the matched fixed-price are the lowest buy-it-now prices available around the time of auction ending. They were typically downloaded within 30 minutes of the auction ending; between 91.86 percent and 94.56 percent were downloaded within 2 hours of the auction close. However, 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.

The advantage of the cross-sectional data is that it allows us to show the generalizability of our findings across item types, even if measured with more noise. An additional advantage is that we can explore differences in overbidding by demographics. While we do not observe bidder demographics directly, our data includes objects that are identical for all but one feature, which is associated with a demographic. For example, to examine gender differences, we compare perfumes of the same brand for men and women, and personal care products for men (electric shaver, hair tonic) and women (hair straighteners, cosmetics). We also compare iPods of different colors (blue, green, silver versus pink). 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. The large amount of overbidding for teenagers is not robust to including shipping costs. Comparing books of liberal versus conservative authors (Obama versus O'Reilly), we find again no systematic pattern. Finally, returning to the correlation with price levels, we compare the prices for cheap versus expensive financial software (Quicken 2007 Basic versus Home Business), navigation systems (Garmin Streetpilot C320, Garmin GPS C330 Navigation System, and Garmin GPS C550 Navigation System), iPods (shuffle, nano, and 80gb), and digital cameras (Canon A630, SD600, and SD630). 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, holding constant other product characteristics. One caveat is that the consumers may not be bidding themselves. We conclude that consumer demographics do not appear to be strongly associated with overbidding; overbidding is sizeable within each demographic subset.

4.3 Additional Results and Explanations

Guided by the additional predictions of our model, we now discuss several explanations for the observed overbidding: transaction costs, limited attention or limited memory, and utility of winning or bidding fever.

Transaction costs. Consider first switching costs, as modeled in Subsection 2.2. Once a bidder has started bidding on an object, it might be costly to return to the screen with all listings and to purchase the object at a fixed price. Such switching costs can explain overbidding: Once a bidder has decided to enter the auction, she may bid up to her valuation and hence possibly more than the fixed price.

The switching-cost explanation implies, however, that the expected auction price is significantly lower than the fixed price (Proposition 2). Otherwise no bidder would enter the auction. In Subsection 4.5, we will provide a calibration of the switching-costs model suggesting that the average auction price should be \$10.05 lower than the fixed price, if we assume a uniform distribution of item valuations between \$80 and \$180, and \$4.48 lower if we assume a $\chi^2(130)$ distribution. The predicted difference between fixed price and auction price is even larger if we take into account the opportunity costs of waiting for the auction result and, in the case of Cashflow 101, the higher quality of the fixed-price item. Finding 3 documents that this prediction is not supported 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 average auction price is higher than the fixed price in the Cashflow

101 data. 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 $[\$0.19; \$5.20]$). Moreover, if we compare the average auction price to the calibrated expected auction price the differences are significant both accounting for and not accounting for shipping costs.

We also find higher auction prices in the cross-sectional data. Here the difference is significant both with and without shipping costs. In this data, however, the computation of the price differential is less straightforward because of the heterogeneity in prices across items. We construct an equal-weighted portfolio assuming that a consumer invests an equal amount in each sample auction. We compute how much the consumer would have saved or lost had she purchased at the BIN price rather than in the auction. This amounts to calculating the percentage of overbidding for each item (final bid minus BIN, as a percentage of BIN) and then averaging over all percent differences. We find a net overpayment of 9.98 percent, significantly different from 0 percent (s.e.= 1.85 percent). Applied to a baseline BIN of \$130 similar to the Cashflow 101 auctions, consumers overpay by \$12.97. Accounting for shipping costs, the net overpayment is 4.46 percent (s.e.= 1.99 percent) or, applied to a \$130 BIN, \$5.80. The variation across different categories is sizeable, ranging from -65.44 percent (automotive products, $N = 9$) to $+50.21$ percent (sports equipment, $N = 55$), though the category-level calculations are to be treated with caution because of the small subsample sizes. Overall, the prediction that auction prices are lower than the fixed prices on average is rejected in the data.

Another type of transaction costs is the cost of understanding how the buy-it-now system works. Unexperienced eBay users might not take BIN listings into account since they do not (yet) understand how they work or have a harder time identifying them on the screen. If overbidding is due to this type of transaction costs, it should decreases with experience.

We test this implication empirically in the sample of Cashflow 101 items, using eBay's Feedback Scores as a proxy for experience. As discussed in Subsection 3.2, Feedback Scores summarize all ratings from previous eBay transactions. Since the vast majority of ratings is positive (e.g., 99.4% in the analysis of Resnick and Zeckhauser (2002)), the scores mostly count the number of past transactions.[21]

Panel B of Figure IV shows the percentage of auction prices above the fixed price, separately for winners with below-median experience and winners with above-median experience.

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

[21]The Feedback Score is an imperfect measure of experience for several reasons: some users do not leave feedback; the measure captures purchases, not bids; and users may invest in 'manufacturing reputation' as suggested by Brown and Morgan (2006). However, users with a high feedback score *do* necessarily have experience, so that the measure is sufficient to reject the hypothesis that only unexperienced bidders overbid

users, 41 and 42 percent. Also if we partition auction experience more finely, we find no relationship between overbidding and experience. For example, splitting the sample of auction winners into $10 - 20\%$ quantiles, namely 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), we find that their propensity to overbid is 31%, 55%, 35%, 47%, 36%, and 44% respectively. Notably, winners with the lowest experience have the lowest propensity to overbid. We find the same results in a logit regression predicting overbidding after controlling for all available auction characteristics: auction length, ending time (dummies for day and hour or prime time), starting price, shipping cost, seller Feedback Scores, extras (dummies for bonus video/tape and delivery insurance), and whether the seller mentions the manufacturer price of $195.

Finding 4 does not rule out that experience reduces overbidding. Such learning from experience may simply not be detectable in the data since overbidders win more often and thus build up higher experience scores. On the other hand, it is also conceivable that bidders truly do not learn given that they do not get information about their overbids unless they actively compare prices after having won the auction. Only longitudinal data would allow to estimate the persistence of overbidding among individuals across auctions over time. However, our results *do* rule out that overbidding is restricted to eBay novices.

The results also alleviate concerns about 'fake bids,' e.g. the hypothesis that the overbidders are sellers who buy at inflated prices, e.g. using a fake eBay ID in an attempt to drive up prices for their own goods or even using their true ID in an attempt to build up a high feedback score. Buyers with a long experience are unlikely to fall into this category.

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.[22] We will discuss a related explanation, the transaction cost of 'finding' prices on the eBay output screen as a form of Limited Attention.

Limited Attention and Limited Memory. Overbidding is consistent with limited attention (users do not pay attention to the BIN listings) or limited memory (users forget them when rebidding), as stated in Proposition 3. 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 the item page, which bidders can use to increase their bid, but no link to the page with all ongoing auctions and buy-it-now listings.

We distinguish between two versions of limited memory. First, rational bidders with limited memory are aware of their memory limitations. Such bidders can easily remedy this constraint

[22]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).

by deciding to always submit only one bid (up to the BIN price) and to never respond to the outbid notice. Hence, a rational model of limited attention is unlikely to explain the observed overbidding if we allow for pre-commitment to one bid. Second, naive bidders with limited memory do not anticipate that they will forget the fixed price. These bidders account for the fixed price when submitting their first bid, but ignore it in later bids. Hence, a naive model of limited attention predicts overbidding. It also predicts that bidders do not overbid in the first round, but may overbid in the later rounds.

One way to test this prediction of the Limited Memory model is to measure the discontinuity in bid density around the BIN price. The discontinuity should be larger in the first round (when subjects still remember the BIN) than in later rounds.

We find only weak evidence of this prediction. Figure V shows the distribution of bidders' initial and subsequent bids in the Cashflow 101 data. The sample includes all bids, not just the winning bid. Out of the full sample of $2,353$ bids (Table I, Panel C), 11 percent are above the buy-it-now price. The two graphs in Panel A of Figure V display, separately, the histograms of all initial and all non-initial bids. We see that few bidders exceed the buy-it-now price in their initial bid (8.96 percent), but that the frequency overbids is higher among the non-initial bids (12.42 percent). If we exclude the bids of snipers, who enter in the last minute, and of users who bid only once and analyze only those who, at least one day (24 hours) after their initial bid, make another bid, we observe stronger differences. As shown in the two histograms in Panel B, these bidders overbid rarely initially (1.97 percent [3 out of 152 bids]), but much more commonly later (21.42 percent [63 out of 294 bids]).

The observed shift is consistent with limited memory/attention. On the other hand, we cannot draw strong inferences since initial bids are mechanistically lower than later bids.

Utility of Winning and Bidding Fever. Utility of winning and bidding fever are also consistent with all findings. Our data does not allow for a direct test separating these interpretations. Our survey evidence suggests that bidding fever applies to some extent. For example, of the 216 subjects 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.

The calibrations in Subsection 4.5, however, will illustrate that these explanations are unlikely to be the only cause of overbidding. A simple model of utility of winning or of bidding fever, which imposes an upper limit to bidders' willingness to pay for winning, say \$10, cannot explain the observed distribution. Another indication is that few overbids occur during the last minutes of an auction, as one may have suspected for bidding fever. In our Cashflow 101 data, only 8% of all bids above the fixed price occur during the last minute of an auction (13% during the last 2 minutes; 17% during the last 5 minutes). The percentages are similar for *winning* bids above the fixed price: 10% occur during the last minute; 13% during the last 2 minutes, and 19% during the last 5 minutes.

We also tested for a third related interpretation of the results, an anticipated 'endowment effect' (Thaler, 1980). As discussed in the Subsection 2.4, this interpretation does not explain why the 'endowed' bidder would not switch to the fixed price. Moreover, our data provides no robust evidence of a correlation between being the leading bidder for a longer time and higher auction prices, controlling for the initial price outstanding and the full set of auction controls.

4.4 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.

Finding 5 (Disproportionate Influence of Overbidders). The share of bidders who ever submit a bid above the fixed price is 17 percent, significantly less than the share of winners who pay more than the fixed price.

Table V documents Finding 5 using the detailed bidder- and bid-level data of Cashflow 101, which is available for 138 auctions and includes 2,353 bids of 807 bidders. (Summary statistics are in Panels B and C of Table I.) In this subset, 43 percent of auctions have a price above the concurrent fixed price. However, only 17 percent of the bidders ever submit a bid above the fixed price. The majority, 83 percent, submit one or more lower bids but drop out once the price crosses the buy-it-now threshold. The percentage of overbidders might be even lower if we could account for potential bidders whose valuations are below the current price. The percentage is also lower if we consider each bid separately. Only 11 percent of all bids are higher than the simultaneous buy-it-now price.

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 reasons, such as limited attention or bidding fever. The auction design implies that the bidders with particularly high bids determine prices and allocations.

The calibrations in the next Subsection further illustrate this point.

4.5 Calibration

The empirical findings are consistent with at least two sets of explanations: (1) Limited Attention and Limited Memory, and (2) Utility of Winning and Bidding Fever. We calibrate both types of models to illustrate a typical set of predicted outcomes and to further evaluate the plausibility of those explanations. We also calibrate the Transaction Cost model to illustrate how much lower than the fixed price the average auction price needs to be if transaction costs were to explain the overbidding results. (As we have already seen, the average auction price in our data is *higher* than the fixed price, rejecting the simple Transaction Cost model.)

We start from the calibrations of the remaining sets of explanations, Limited Attention/Memory and Utility of Winning/Bidding Fever. We consider a range of possible distributions of valuations, including χ^2, uniform, exponential, and logarithmic distributions, and a range of possible moments. Importantly, we allow for bidder heterogeneity, with a share of bidders having non-standard preferences and the remaining bidders acting according to the standard model. Thus, the calibrations show how the distribution of auction prices varies with the proportion of the player population that displays non-standard behavior. We let the proportion range from 0 to 1, in 0.005 steps.

The calibrations draw eight players from an infinite population, corresponding to the mean number of players in our Cashflow 101 data. For each distribution of valuations, we draw 1,000,000 realizations for each player. We then simulate draws from the distributions of model parameters. First, we draw another 1 million values, separately for each of the eight players, from a uniform distribution on $[0, 1]$, determining whether a player conforms to the standard rational model or displays non-standard behavior. 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/Bidding Fever model, we make the additional assumption that the utility of winning is uniformly distributed between \$0 and \$10 and that the values are independently drawn. Hence, we generate a third (1 million x 8)-matrix with the additional values from winning drawn from a uniform distribution on $[0, 10]$. The values are added to the valuations in the first matrix only if the player is a behavioral type for the respective realization. Finally, we set the simultaneous fixed price equal to \$130. 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.[23]

Figure VI 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.[24]

The left graphs show the results for the simple model of Limited Attention/Memory presented in Subsection 2.3. 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 model with no Limited Attention/Memory and the rightmost values correspond to everybody having Limited Attention/Memory.

In both 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' increases more

[23]It is easy to see that Propositions 1, 3, and 4 hold under bidder heterogeneity for the respective types, given that bidders' choices solely reflect whether or not they would benefit from winning with a given bid, relative to the safe outside option.

[24]A large number of other calibrations with the above mentioned distributions are available from the authors.

slowly in the probability of forgetting, and always has a slope below 1. For both distributions, 30-40 percent of bidders with non-standard behavior suffice to generate the empirically observed frequency of overpaid auctions. In both cases, this corresponds to 12-16 percent of bidders actually overbidding, slightly below the 17 percent we observe empirically.

The graphs for the Utility of Winning or Bidding Fever model are similar. Again, we observe that the fraction of overpaid auctions increases much more than the fraction of overbidders. For the $\chi^2(130)$ distribution, a fraction of 20-30 percent of bidders with utility of winning match the empirical frequency of overpayment, corresponding to 10-15 percent of overbidders. For the $U[80, 180]$ distribution, a fraction of 30-40 percent of bidders with utility of winning match the empirical frequency of overpayment, corresponding to 13-18 percent of overbidders.

Hence, the two simple calibrations of the models of Limited Attention and Utility of Winning can match the empirically observed percentages of overpayment and overbidding for plausible parameter values. They differ, however, in how well they match other empirical outcomes. For example, the mean amount of overbidding in the Limited Attention/Memory model with 30-40 percent of behavioral bidders is \$2.86-\$4.52 if we use the χ^2-distribution and \$6.48-\$10.06 for the uniform distribution. Both are slightly too high.

In the Utility of Winning calibrations, probabilities of 20-30 percent and the χ^2-distribution are closer to the observed outcome: mean overbidding ranges from \$0.78 to \$1.57, while probabilities of 30-40 percent under the uniform distribution generate mean overbidding ranging from \$1.31 to \$2.08. Most importantly, though, 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. Hence, unless we allow for a large maximum amount of utility of winning or bidding fever, the latter model fails to produce price distributions similar to those in Figure III. Limited Attention or Limited Memory emerge as better suited to capture all aspects of the empirical distributions of outcomes.

Finally, we return to the Transaction Costs calibration and gauge how much lower than the fixed price the average auction price needs to be if transaction costs were to explain the overbidding results. We then compare the predicted average auction price to the actual one.

In this calibration, we assume that all players are rational but incur prohibitively high transaction costs from switching between auctions and fixed-price transactions. We first calculate the optimal bidding region for each valuation given a particular distribution of player valuations.[25] We then create the matrix of bids. Players bid their valuation if inside the

[25] We use an iterative procedure to find the cutoff point, at which a player switches from bidding her valuation to not bidding and 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 check this by running one million iterations of this bid against seven other players and calculating 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 designated bidding threshold.

bidding region, and 0 otherwise.

Our calibrations converge, implying that there is indeed a symmetric equilibrium for those distributions. The resulting average auction prices are significantly lower than the fixed prices: \$125.52 for the χ^2-distribution (median \$127.03) and \$119.95 for the uniform distribution (median \$122.48). The percent of auction prices above the fixed price is 27.1%, generated by 12.7% of players overbidding, in case of the χ^2-distribution, and 26.6%, generated by 12.6% of players, in case of the uniform distribution. Hence, the calibrations produce counterfactual results, with average auction prices significantly below the observed values.

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 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.

One leading interpretation of our findings is that a subset of bidders pay insufficient attention to the alternative fixed price. They may pay attention initially, when submitting their first bid, but fail to do so later, when rebidding. A second explanation is utility of winning or 'bidding fever.' We provide some empirical and calibrational evidence in favor of the Limited Memory model, but both sets of explanations appear to account for part of the results.

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, consistent with the experimental and neuroeconomics findings on the role of 'contemplating losses' (Delgado, Schotter, Ozbay, and Phelps, 2007). More broadly, 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.

Our argument applies to auctions beyond the online setting. 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.

Another example are mobile-phone license auctions. In the British 3G auctions in 2000-01, bidders paid about five to ten times more than estimated ex ante, \$34 billion for five licenses, and many people believe that the five winners "paid too much" (Binmore and Klemperer, 2002). However, five of the other eight serious candidates withdrew after about two thirds of the auction duration. Hence, even if auction prices were indeed 'too high' from an ex-ante perspective, the typical market participant might not have overbid. It suffices that two bidders (per object) fail to limit their bids to the appropriate upper limit.

Relatedly, Klemperer (2002) attributes the large revenues of the British auction to the low hurdles to entry in this auction.[26] He argues that the large differences in revenues across the different Western European 3G auctions strongly covary with the ease of entry and the resulting numbers of participants. This paper offers a different interpretation of the same determinant: 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 that the first aftermarket price is too high. The interpretation of these stock price movements is subject to debate. However, even if it reflects overbidding during the first trading days, the median owner of new issues may not be overvaluing the stock. Relatedly, Sherman and Jagannathan (2006) report that auctions of initial public offerings have been abandoned in virtually all of the 24 countries

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

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 have important implications for auction design. 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

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

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

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

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

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

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

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

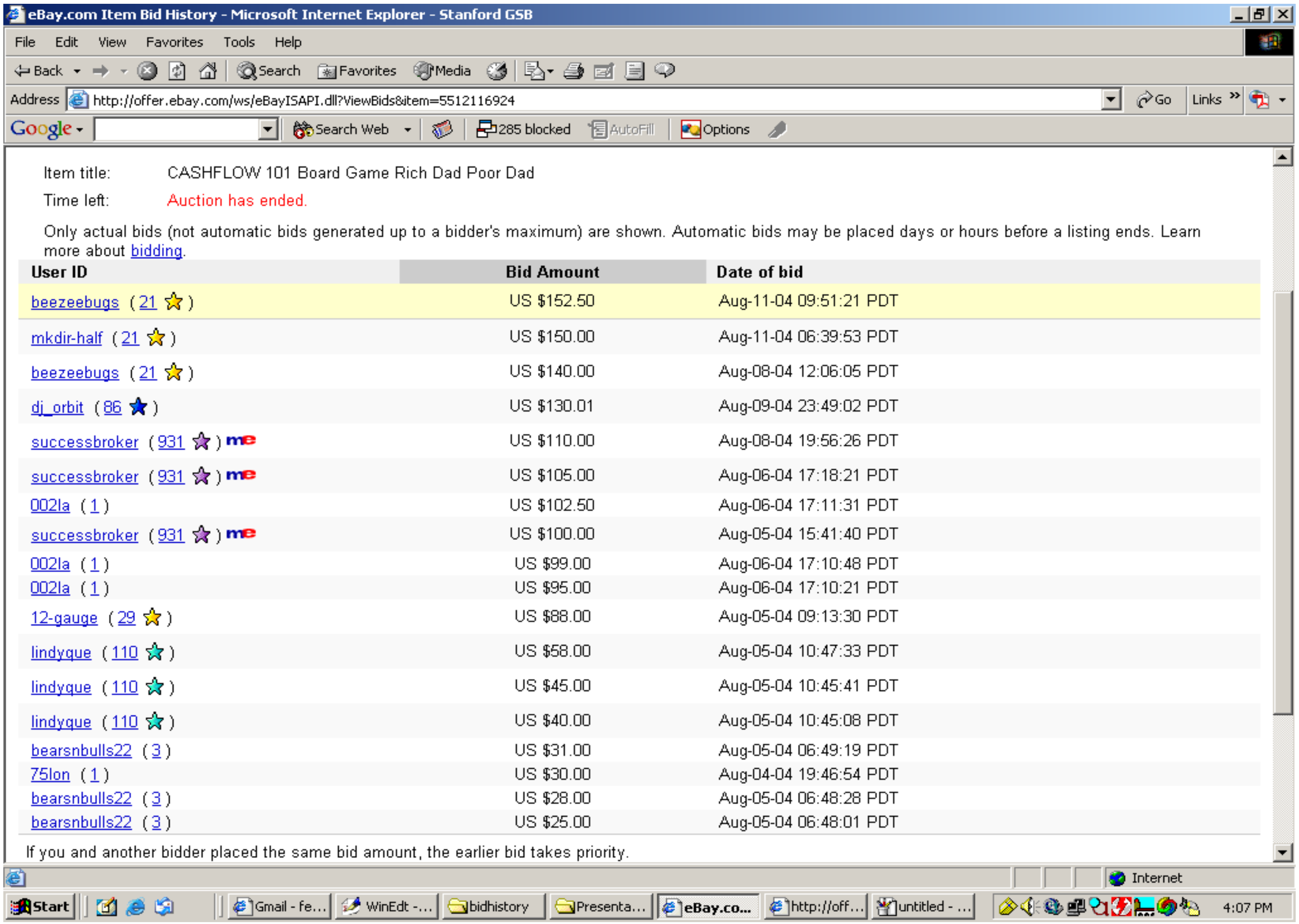
		Observations	(Percent)
Auction-level sample			
Does the auction end up overbid?	No	78	56.52%
	Yes	60	**43.48%**
Total		138	100.00%
Bidder-level sample			
Does the bidder ever overbid?	No	670	83.02%
	Yes	137	**16.98%**
Total		807	100.00%
Bid-level sample			
Is the bid an over-bid?	No	2,101	89.29%
	Yes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

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

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



eBay.com Item Bid History - Microsoft Internet Explorer - Stanford GSB

Address http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=5512116924

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.

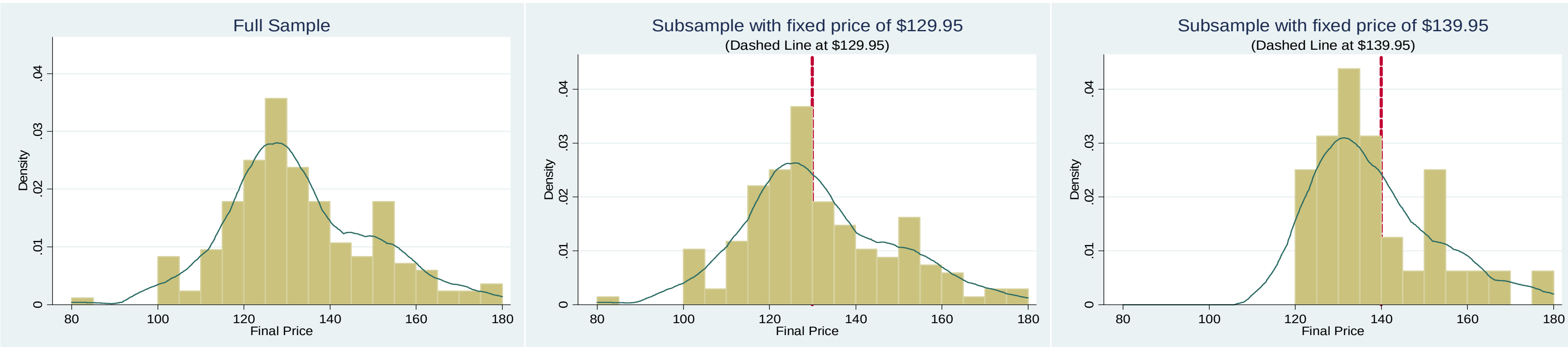
User ID	Bid Amount	Date of bid
beezeebugs (21)	US $152.50	Aug-11-04 09:51:21 PDT
mkdir-half (21)	US $150.00	Aug-11-04 06:39:53 PDT
beezeebugs (21)	US $140.00	Aug-08-04 12:06:05 PDT
dj_orbit (86)	US $130.01	Aug-09-04 23:49:02 PDT
successbroker (931) me	US $110.00	Aug-08-04 19:56:26 PDT
successbroker (931)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

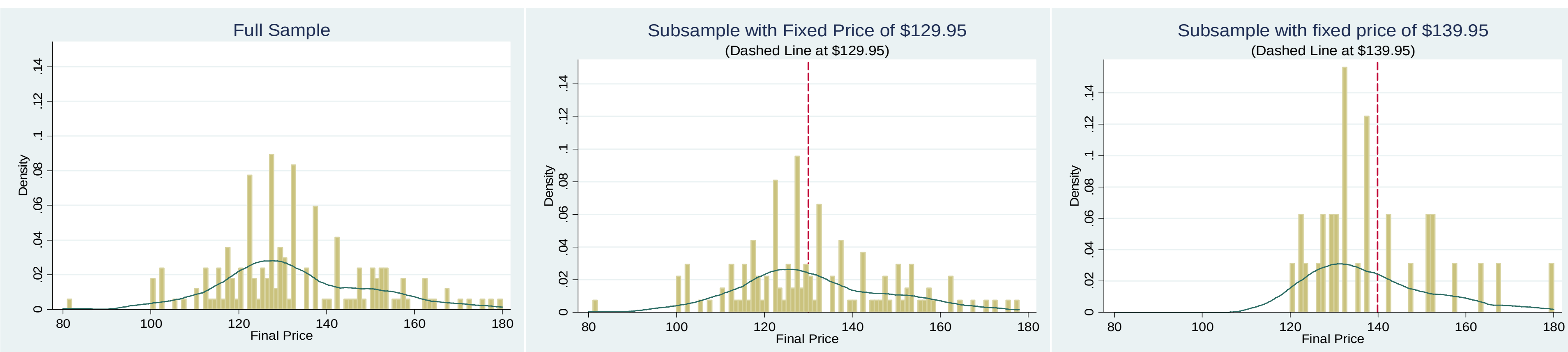
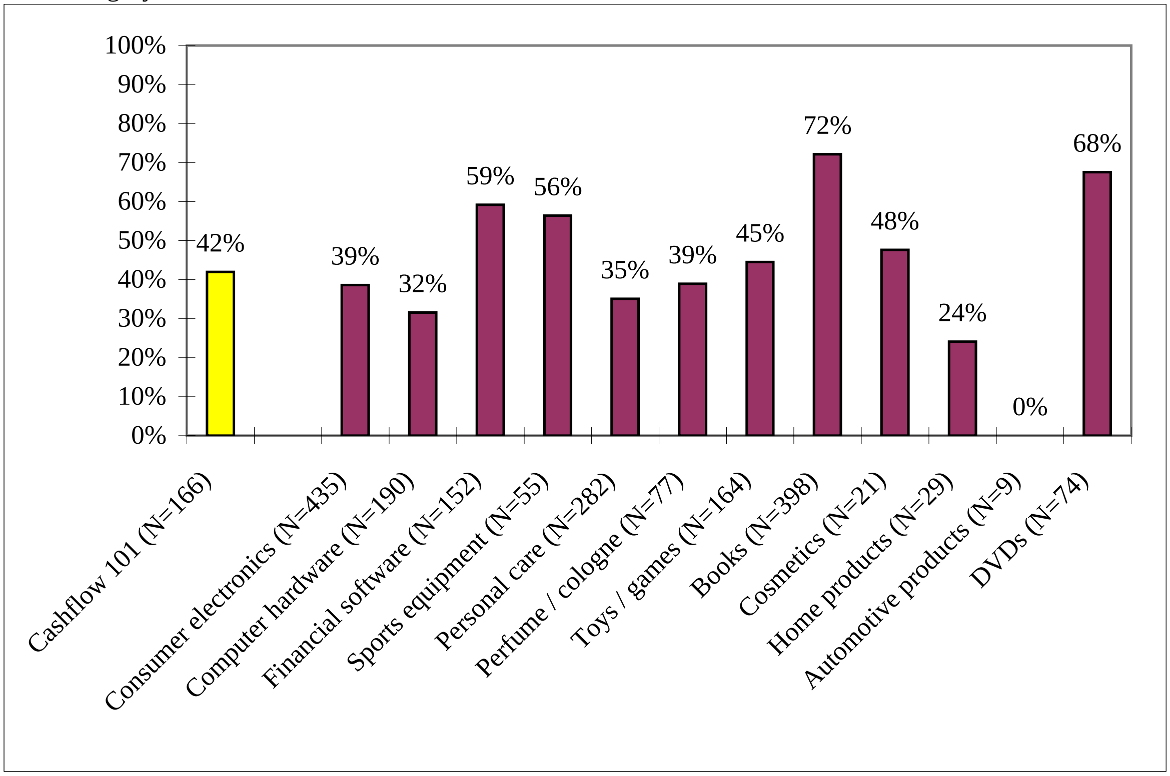


Figure IV. Overbidding

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.

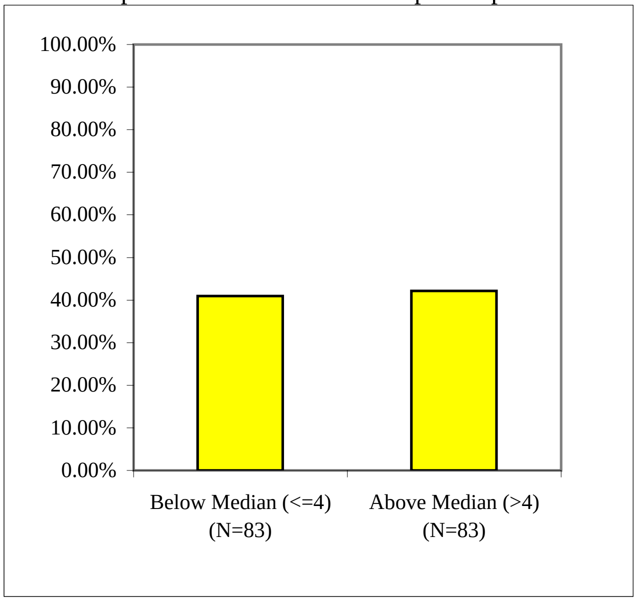
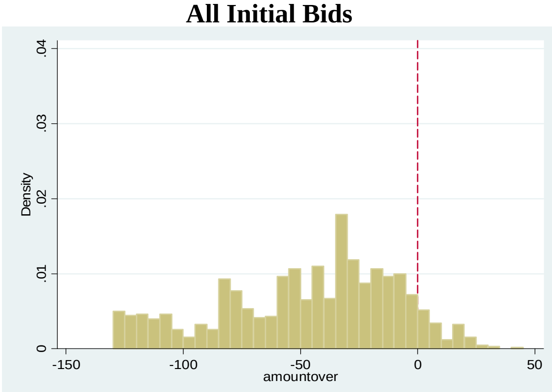


Figure V. Distribution of First Bids and Later Bids (Net of Fixed Price)

The two graphs in Panel A display histograms of all initial bids and all non-initial bids. The two graphs in Panel B display histograms of initial bids and bids made at least one day (24 hours) after the initial bid. The sample in Panel B consists of all bidders who make at least one bid one day after their initial bid or later. Bids are displayed net of the simultaneous fixed price ('amountover').

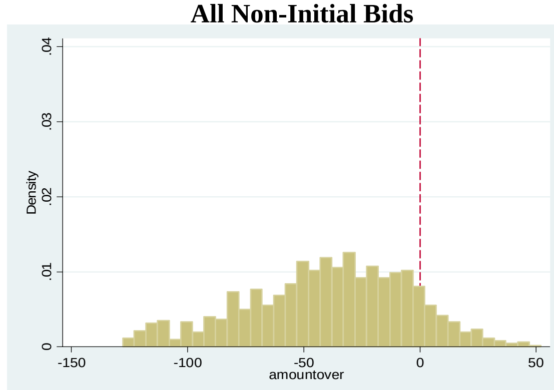
Panel A. Full sample

All Initial Bids



Number of observations: 1,162.

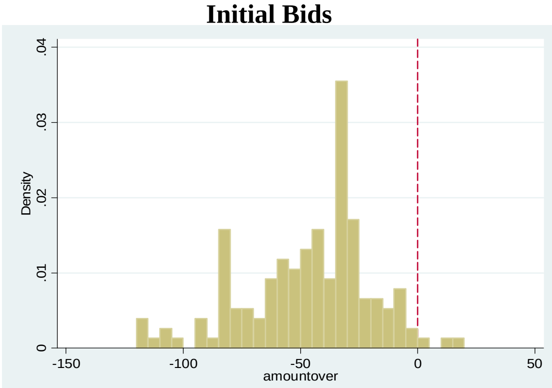
All Non-Initial Bids



Number of observations: 1,192.

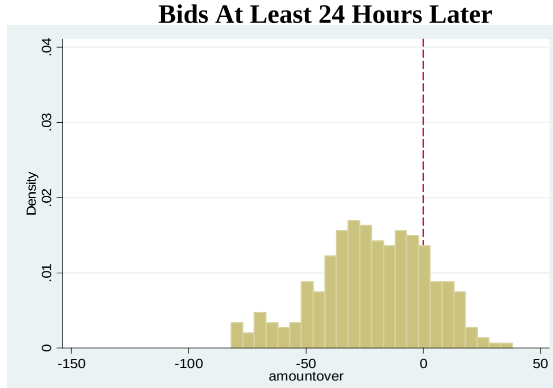
Panel B. All bidders who bid again 24 hours after initial bid or later

Initial Bids



Number of observations: 152.

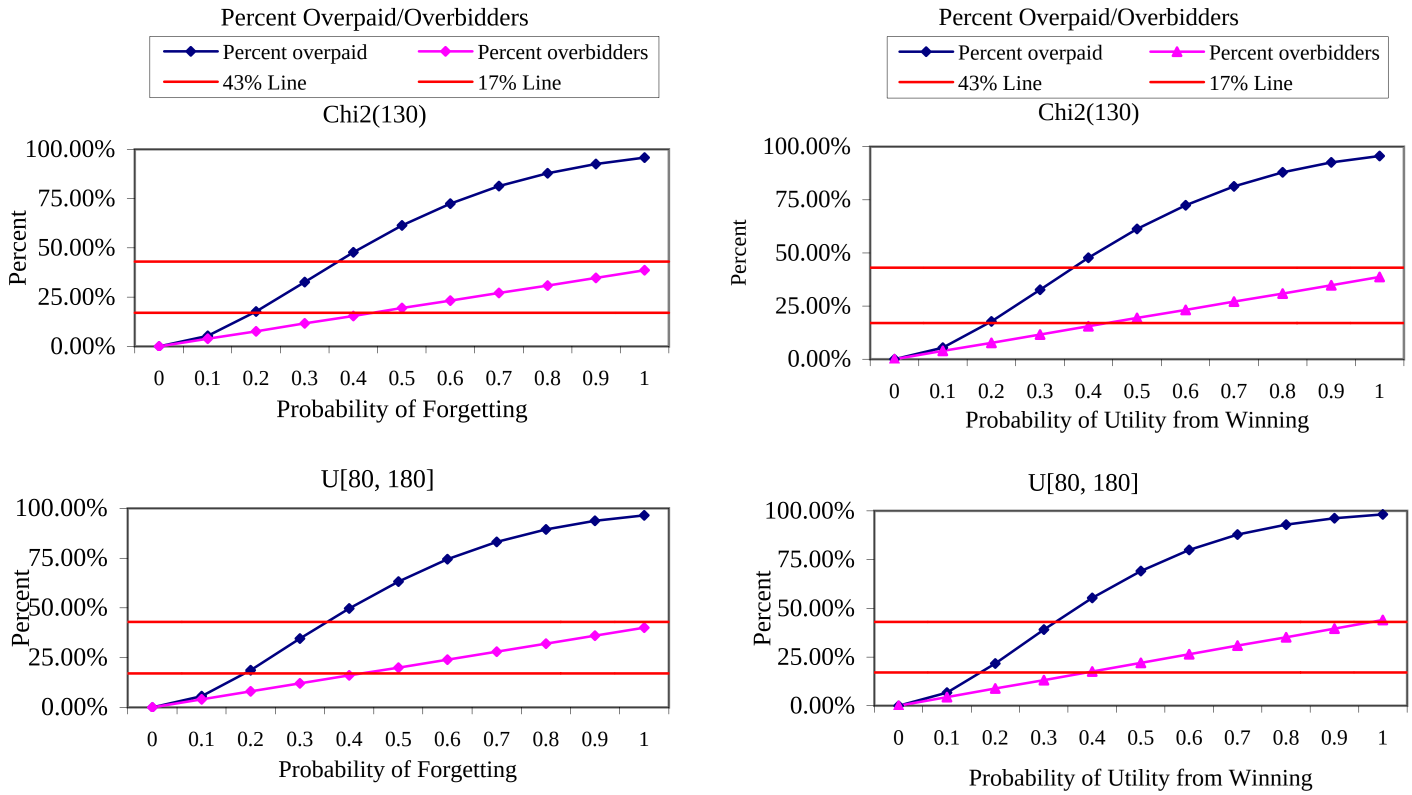
Bids At Least 24 Hours Later



Number of observations: 294.

Figure VI. 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 *(retailer)*	2 *(individual 1)*	3 *(individual 2)*	
Second item description	1 *(individual 1)*	5 *(individual 2)*	19 *(retailer)*	
Third item description	1 *(individual 2)*	15 *(retailer)*	2 *(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%