The Bidder's Curse

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Abstract

We employ a novel approach to identify overbidding in the field. We compare auction prices to fixed prices for the same item on the same webpage. In detailed board-game data, 42 percent of auctions exceed the simultaneous fixed price. The result replicates in a broad cross-section of auctions (48 percent). A small fraction of overbidders, 17 percent, suffices to generate the overbidding. The observed behavior is inconsistent with rational behavior, even allowing for uncertainty and switching costs, since also the expected auction price exceeds the fixed price. Limited attention to outside options is most consistent with our results.

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Concerns about overbidding are as old as auctions. Already in ancient Rome, legal scholars debated whether auctions were void if the winner was infected by "bidder's heat" (*calor licitantis*).[1] Previous literature in economics has raised the possibility of overbidding in auctions and auction-like settings as diverse as sports, real estate and mortgage securitization, corporate finance, and privatization.[2] However, it has been difficult to prove that bidders pay too much, relative to their willingness to pay outside the auction, given the value of the object.

We propose a novel research design to detect overbidding in the field. We examine online auctions in which the exact same item is continuously available for immediate purchase on the same webpage. At any point during the auction, bidders can acquire the same object at a fixed price. To motivate the empirical test, we present a simple model with fixed prices as an alternative to standard second-price auctions. In the basic framework, rational bidders never bid above the fixed price. When we allow for uncertainty about the availability of the fixed price or for switching costs between auction and fixed price, bidders may bid above the fixed price, but the expected auction price is still strictly smaller than the fixed price. Two leading behavioral explanations can explain that even the *expected* auction price exceeds the fixed price: limited attention regarding the fixed price and utility from winning an auction (bidding fever).

The theoretical analysis illustrates that comparing auction prices to fixed prices provides a test of overbidding independent of bidders' valuations, especially if it is frequent enough to raise even the *average* auction price above the fixed price. We denote the overbidding phenomenon as "bidder's curse." Unlike the winner's curse, such overbidding affects both private-value and common-value settings. Moreover, even if only a few buyers overbid, they affect prices and allocations since auctions systematically pick those bidders as winners.

We test for the occurrence of overbidding using two novel data sets. Our first data set contains all eBay auctions of a popular board game, Cashflow 101, from February to September 2004. A key feature of the data is the continuous presence of a stable fixed price for the same game on the same eBay website throughout the entire duration of the auctions. Two retailers continuously sold brand new games for \$129.95 (later \$139.95). The fixed prices are shown together with the auction listings in the results for any Cashflow 101 search on eBay, and users can purchase the game at the fixed price at any point. Hence, the fixed price provides an upper limit to rational bids under the standard model. It is a conservative limit for two reasons. First, the auction price exceeds the fixed price only if at least two bidders overbid. Since winners who bid above the fixed price pay a price below the fixed price if the second-

[1]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 Ulrike Malmendier (2002).

[2]See Barry Blecherman and Colin Camerer (1996) on free agents in baseball, Cade Massey and Richard Thaler (2006) on football drafts, Antonio E. Bernardo and Bradford Cornell on collateral mortgage obligations. Details on all other examples are in Section IV.

highest bid is below, we underestimate the frequency and the amount of overbidding. Second, even if no bid exceeds the fixed price, bidders may overbid relative to their private value.

We find that 42 percent of auctions exceed the fixed price. If we account for differences in shipping costs, which are on average higher in the auctions, even 73 percent are overbid. The overbidding is not explained by differences in item quality or seller reputation. We also show that the overbids are unlikely to represent shill bids. The amount of overbidding is significant: 27 percent of the auctions are overbid by more than \$10, and 16 percent by more than \$20.

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

Our empirical findings allow us to rule out the standard rational model as well as rational explanations based on uncertainty and transaction costs of switching. Another type of transaction costs is the cost of understanding fixed prices, so-called buy-it-now prices. Inexperienced eBay users might not take the simultaneous fixed prices into account since they are still learning about auction and fixed-price features. We find, however, that bidders with high and low experience overbid with identical frequencies.

Our second main result pertains to the debate about the relevance of biases in markets. We show that a few overbidders suffice to affect the majority of prices and allocations. While 42 percent of the Cashflow 101 auctions exceed the fixed price, only 17 percent of bidders ever overbid. The auction mechanism allows the seller to identify the "fools" among the bidders, who then have an overproportional impact. We further illustrate the disproportionate influence of few (at least two) overbidders in a simple calibration that allows for the simultaneous presence of rational bidders and overbidders. For even slight increases in the fraction of overbidders above 0.1-0.2, the fraction of overpaid auctions increases disproportionately.

Having ruled out standard explanations for the observed overbidding, we consider two leading behavioral explanations. One is that bidders gain extra utility from winning an auction relative to purchasing at a fixed price. This explanation is hard to falsify; it can justify almost any behavior with a "special utility" for such behavior. However, we can test one specific form, the quasi-endowment effect. Bidders might become more attached to auction items – and hence willing to pay more – the longer they participate in the auction, in particular as the lead bidder (James Heyman, Yesim Orhun, Dan Ariely, 2004; James Wolf, Hal Arkes, Waleed Muhanna, 2005). Even though it is questionable whether the quasi-endowment effect can explain bidding *above the fixed price* for identical items, we test for a positive relation between overbidding and time spent on the auction, both overall and as lead bidder. We find no evidence. We also provide a simple calibration, which illustrates that utility from winning, more generally, cannot easily match the empirically observed distribution of bids.

A second explanation is limited attention towards the fixed price. Limited attention implies that an auction should be less likely to receive an overbid if the fixed price is listed very closely on the same screen and, hence, more likely to capture bidders' attention. Using a conditional logit framework, we find that, indeed, smaller distance to fixed-price listings predicts a significantly lower probability that an auction receives a bid. This relationship is strongest for bids just above the fixed price. It is also particularly strong for a bidder's first bid, consistent with one form of inattention, namely limited memory: bidders may account for the lower-price outside option initially, but fail to do so when they rebid after seeing eBay's outbid notice ('You have been outbid!'). In summary, the strongest direct evidence points to limited attention. At the same time, we cannot rule out that other explanations for overbidding are also at work.

This paper relates to several strands of literature. First, it contributes to the debate about the role of biases in markets, "Behavioral Industrial Organization": Are biases less relevant in markets, e.g., due to experience, learning, and sorting (John A. List, 2003)? Or does market interaction with profit-maximizing sellers exacerbate their relevance (cf., Glenn Ellison, 2006)?[3] Our findings illustrate that a few behavioral bidders can have a large impact on market outcomes. Relatedly, David Hirshleifer and Siew Hong Teoh (2003) model firms' choice of earnings disclosure when investors display limited attention. Limited memory and consumers' naiveté about their memory limitations have been modelled in Sendhil Mullainathan (2002), along with market implications such as excess stock market volatility and over- and underreaction to earnings surprises. Uri Simonsohn and Ariely (2008) document that eBay bidders tend to herd on auctions with lower starting prices and more bids, even though they are less likely to win and pay higher prices conditional on winning. Sellers respond by setting low starting prices. Note that herding alone cannot explain our results since bidders should still choose the fixed price once the auction exceed the fixed price. Anna Dodonova and Yuri Khoroshilov (2004) and Nicholas Shunda (2009) suggest that sellers set high 'buy-it-now' prices in (hybrid) auctions to move bidders' reference points.[4] While an interesting example of market response to biases, reference dependence does not explain bidding above fixed prices. Moreover, fixed prices in our data are stable and, hence, cannot explain variation in overbidding.

This paper also relates to the growing literature on online auction markets, surveyed in Patrick Bajari and Ali Hortacsu (2004) and in Axel Ockenfels, David Reiley, and Abdolkarim Sadrieh (2006). Alvin Roth and Ockenfels (2002) interpret last-minute bidding as either a rational response to incremental bidding of irrational bidders or rational equilibrium behavior when last-minute bids fail probabilistically. Neither hypothesis, however, explains bids above

[3] Applications include Stefano DellaVigna and Malmendier (2004, 2006), Paul Heidhues and Botond Kőszegi (2005), Sharon Oster and Fiona Scott-Morton (2005), and Xavier Gabaix and David Laibson (2006).

[4] See also Stephen Standifird, Matthew R. Roelofs, and Yvonne Durham (2004).

the fixed price. Most relatedly, Ariely and Itamar Simonson (2003) document that 98.8 percent of eBay prices for CDs, books, and movies are higher than the lowest online price found with a 10 minute search.[5] However, the overpayment may reflect lower transaction and information costs (search costs, creating new online logins, providing credit card information, site awareness etc.) and higher trustworthiness of eBay relative to other online sites. Our design addresses these explanations, given that all prices are on the same website and the fixed-price sellers have higher reputation and better shipping, handling, and return policy. Our approach also disentangles overbidding from mere shipping-cost neglect,[6] and guarantees, in the first data set, that the fixed price is available for the entire duration of the auction rather than only after the auction.

Large and persistent overbidding has also been documented in laboratory second-price auctions (e.g., John Kagel and Dan Levin, 1993; David Cooper and Hanming Fang, 2008). It is smaller and not persistent in laboratory ascending auctions (Kagel, Ronald Harstad, and Levin, 1987). Oliver Kirchkamp, Eva Poen, and J. Philipp Reiss (2009) find that outside options increase bidding in laboratory first-price auctions but have no impact on laboratory second-price auctions. The latter finding suggests that we can use outside options as a benchmark in second-price auctions and make inferences for second-price auctions without outside options. The cause of overbidding in the laboratory is likely to be different from the field.[7] In particular, limited attention should not play a role in the laboratory, where subjects are directly confronted with their induced value.

There is a large theoretical and empirical literature on the winner's curse, extensively discussed in Kagel and Levin (2002). The findings on winner's curse in online auctions are mixed (Bajari and Hortacsu, 2003; Zhe Jin and Andrew Kato, 2006). Olivier Compte (2004) argues that an alternative explanation for the winner's curse is that bidders make estimation errors and competition induces the selection of overoptimistic bidders. Differently from the winner's curse, the bidder's curse is not restricted to common values. Belief-based explanations for "cursedness" in common-value and private-value settings (Erik Eyster and Matthew Rabin, 2005; Vincent P. Crawford and Nagore Iriberri, 2007) cannot explain the overbidding in our data since it is suboptimal not to switch to the fixed price once the auction price exceeds the fixed price, independently of the belief system.

The remainder of the paper proceeds as follows. In Section I, we present a simple model

[5] Dennis Halcoussis and Timothy Mathews (2007) study auction and fixed prices for similar products (different concert tickets).

[6] Shipping-cost neglect, as observed in our first data set, was first documented in Tanjim Hossain and John Morgan (2006).

[7] Experiments explore spite, joy of winning, fear of losing, bounded rationality (Cooper and Fang, *forthcoming*; Morgan, Ken Steiglitz, and George Reis, 2003; Mauricio R. Delgado, Andrew Schotter, Erkut Ozbay, and Elizabeth A. Phelps, 2008) and, for bids above the RNNE in first-price auctions, risk aversion (James C. Cox, Vernon L. Smith, and James M. Walker, 1988; Jacob K. Goeree, Charles A. Holt, and Thomas R. Palfrey, 2002).

of bidding in second-price auctions with simultaneous fixed prices. Section II provides some institutional background about eBay and describes the data. Section III presents the core empirical results. Section IV discusses broader applications of the bidder's curse and concludes.

I Model

Overbidding is difficult to identify empirically since it is hard to measure a bidder's valuation. Our empirical strategy overcomes this hurdle by using fixed prices as a threshold for overbidding. Auctions with simultaneous fixed prices have not been analyzed much theoretically, but are a common empirical phenomenon.[8] In this Section, we extend a standard auction model to the availability of fixed prices. We show the assumptions under which the fixed price provides an upper bound to rational bids. While the theoretical analysis considers the case of homogeneous bidders, the calibration in Section III.C allows for the interaction of heterogeneous bidders.

A Benchmark Model

The bidding format on eBay is a modified second-price auction. The highest bidder at the end of the auction wins and pays the second-highest bid plus an increment. Buyers can also purchase at a fixed price. For simplicity, we neglect the discrete increments, repeated bidding within a time limit, reserve prices, and the progressive-bid framing of eBay auctions. While these features help explain strategies such as sniping, they do not rationalize bids above the fixed price. Unless noted otherwise, proofs are in Appendix A.

Let the set of players be $\{1, 2, \ldots, N\}$, $N \geq 2$, and their valuations $v_1, v_2, \ldots, v_N$. The vector v of valuations is drawn from a distribution with no atoms and full support on R_+^N. Valuations are private information. We extend the standard second-price auction to a two-stage game. The first stage is a second-price auction. Each bidder i bids an amount $b_i \in R_+$. The highest bidder wins 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 $\overline{p} > 0$. There is unlimited supply of the good in the second stage, but only one unit is valuable to a player. 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. Conditional on losing the auction, her payoff is 0 if she does not purchase in the second stage and $v_i - \overline{p}$ if she purchases.

[8] For airline tickets see skyauction.com and priceline.com versus online sales, e.g., Orbitz; for time shares bidshares.com; for cars southsideautoauctions.com.au; for equipment and real estate the General Services Administration, treasury.gov/auctions, usa.gov/shopping/shopping.shtml, and gsasuctions.gov; for online ads Google's AdSense versus advertising agencies' fixed prices; and for concert tickets ticket-auction.net or seatwave.com versus promoters' fixed prices.

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 weakly 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: $p_w(v) \leq \overline{p} \quad \forall v \in \mathbb{R}_+^N$.*

Proposition 1.(a) illustrates that, rather than simply bidding their valuations as in the classic analysis of William Vickrey (1961), bidders bid at most the fixed price if there is a fixed-price option. 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 in degenerate equilibria, the auction price never exceeds $\overline{p}$.

One extension of the benchmark model is uncertainty about the future availability of the fixed price. In the eBay case, the initial search results screen shows both the ongoing auctions and the fixed prices for a given item. However, if a bidder bids in the auction but later wants to return to the fixed price, it might have disappeared. To incorporate such uncertainty, we assume that, at the beginning of the game, the item is available both in the auction and at the fixed price $\overline{p}$. Once the auction is over, however, the fixed price $\overline{p}$ remains available only with probability $\alpha \in [0, 1)$. Formally, we add an "initial stage" to the game, called stage 0. (Stage 0 was redundant in the benchmark case because the utility of buying initially is identical to the utility of buying after the auction.) All bidders can purchase the item at $\overline{p}$ in stage 0. In stage 1, players submit auction bids and, in stage 2, they decide again whether or not to purchase at the fixed price — if the item is still available. We capture the decision of a player i not to enter the auction with $b_i = 0$.[9] Proposition 1' characterizes the equilibrium strategies in the subgame after bidders have entered the auction and the resulting auction prices.

Proposition 1' (Uncertainty). *(a) The following strategy profile is a PBE in the subgame after entering the auction: each player i who enters the auction bids $b_i^* = \min\{v_i, (1-\alpha)v_i + \alpha\overline{p}\} = v_i - \alpha \max\{v_i - \overline{p}, 0\}$ and then purchases at the fixed price, insofar still available, if and only if she has lost the auction and her valuation is weakly higher than the fixed price ($v_i \geq \overline{p}$). (b) In all PBEs of the (full) game with uncertainty, the expected winning price is strictly smaller than the fixed price: $E[p_w] < \overline{p}$.*

Proposition 1' illustrates that, under uncertainty, bidders do not necessarily bid less than the fixed price. Instead, bidders with a valuation above the fixed price may bid up to a

[9]Note that, in any PBE, a player will never enter and bid 0, because not entering is weakly better.

convex combination of fixed price and own valuation, where the weights are determined by the probability of the fixed price remaining available. However, the expected auction price still does not exceed the fixed price. As we show in the proof of part (b), players with a low $v_i \in [0, \overline{p}]$ do not purchase in the first stage, but also do not submit bids such they would pay a price of $\overline{p}$ or higher, and hence more than their valuation, conditional on winning. Players with a valuation above the fixed price, $v_i > \overline{p}$, are willing to forego the initial fixed price and enter the auction only if the expected price is strictly smaller than $\overline{p}$, given that there is a chance of losing the fixed-price option after the auction. Note that our findings imply that not all high-value players necessarily enter the auction, depending on the PBE. In any PBE, however, the expected auction price has to be lower than $\overline{p}$ for all realizations of v and for all players. Hence, the (unconditional) expected auction price is also strictly smaller.

Empirically, we will present a first data set in which the fixed price remains available with certainty after the auction and where the persistent availability is easy to anticipate for any bidder. We will also use a second, broader data set, where we cannot ensure the permanent availability of the same fixed price. There, we will rely on part (b) of Proposition 1' to differentiate rational bidding above the fixed price due to uncertainty from overbidding.

B Transaction Costs of Switching

Another explanation for auction prices above the fixed price is transaction costs of switching. Bidders incur switching costs if it is costly for them to return to the webpage that lists all auctions and fixed prices after they have previously bid in an auction. Such switching costs are not too plausible in the online setting. If they exist, players may bid above the fixed price: Once a player has decided to enter the auction she may bid up to her valuation.

We model switching costs using the three-stage structure of the game with uncertainty. In stage 0, players can purchase at the fixed price. In stage 1, they can bid for the good. In stage 2, they can again purchase at the fixed price, but incur a transaction cost $c > 0$. The sequential game structure is a simplified way to capture that bidders initially have the choice between purchasing or bidding and incur transaction costs only if they return to the fixed price after the auction. As before, the vector of bidding strategies b include zero bids of those who do not enter the auction. Bidders enter if indifferent between the auction and the fixed price.

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:* $E[p_w] < \overline{p}$.

Proposition 2 states that even though bids above the fixed price may occur, the auction price does not exceed the fixed price in expectations. The intuition is similar to the uncertainty case. In any PBE, players with low valuations $v_i \leq \overline{p}$ never purchase at the fixed price, but also do not submit bids such that they would pay a price of $\overline{p}$ or higher, and hence more than their valuation, conditional on winning. Players with a high valuation $v_i > \overline{p}$ forego the initial fixed price and enter the auction only if the expected auction price is smaller than the fixed price. The difference in prices has to be large enough to compensate for the times that they lose the auction and either do not purchase in stage 2 because of the transaction cost or do purchase and incur cost c. Since the expected price conditional on winning is lower than $\overline{p}$ for all realizations of v and all players, the expected auction price is also strictly smaller.

We obtain the same result if we add uncertainty to the setting with switching costs. Consider the case that, once the auction is over, the item remains available at the fixed price $\overline{p}$ only with probability $\alpha \in [0, 1)$ and, if available, only at an additional cost c.

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

Uncertainty affects only players who would consider purchasing in stage 2, i.e., players with valuations $v_i > \overline{p} + c$. With uncertainty, these players demand an even higher compensation for foregoing the fixed price in stage 0 and entering the auction, since they may not get the item in stage 2. As a result, the expected auction price is even lower.

There are several interesting variations of the switching-cost model if we allow for irrationality. One example is that bidders also systematically underestimate the expected winning price. In this case, they enter the auction more frequently, and we observe more frequent bidding above the fixed price. Thus, biased expectations plus transaction costs could explain our empirical findings. An extension is that some bidders are rational and anticipate the presence of irrational bidders. Hence, they have further incentive not to enter the auction, increasing the proportion of biased bidders. Either variation relies on irrational overbidding of some bidders, which is the baseline fact we aim to distinguish from traditional models, including uncertainty or switching costs. If we do find empirical evidence of non-standard behavior, it is possible that it is exacerbated by such traditional frictions.

C Limited Attention

One behavioral explanation is that inattentive bidders overlook the fixed price, even though it is available on the same webpage. A simple way to model inattention in the two-stage game structure of the benchmark case is neglect of the fixed price in the second stage. Hence, they only play the first-stage game, which reduces the game to a standard Vickrey auction.

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

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

Closely related is the case of limited memory (forgetting). Bidders may notice the fixed price when they start bidding, but forget it over time. Our static model of limited attention can be interpreted as a reduced-form model of the forgetting dynamics.[10] Limited attention and limited memory differ from switching costs in that the expected price is not bounded above by $\overline{p}$. In addition, the limited-memory interpretation 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 test this prediction in Section III.C. Finally, note that our inattention model is a naive model: players are not aware of their limitations. In an alternative model, rational bidders anticipate their inattention and adjust their strategies. The rational model of uncertainty introduced above can be re-interpreted as bidders' rational response to anticipating the possibility of forgetting about the fixed-price option when placing a bid.

D Utility of Winning

Another explanation for overbidding relative to the fixed price is that bidders enjoy winning the auction. Assume that bidder i earns additional utility $\pi_i \in R_+$ if she acquires the item in the auction. All other assumptions are as in the benchmark case.

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 exceed the fixed price if $\min\{v_i + \pi_i, \overline{p} + \pi_i\} > \overline{p}$ for at least two bidders.*

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

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

This set-up can be reinterpreted as bidding fever, including the opponent effect described by Heyman, Orhun, and Ariely (2004). During the heat of the auction, bidder i believes that she gets an additional payoff π_i if she acquires the object in the auction. Once the auction is over, the player realizes that $\pi_i = 0$, i.e., that the utility from obtaining the same object at a fixed price is identical. From the perspective of the earlier or later selves, the additional

[10] Another possibility is that players learn the outside price only at a cost. If (some) players have high costs or rely on other players learning about the outside price, overbidding can occur in equilibrium.

valuation π_i is a mistake, similar to the valuation of addictive goods in Douglas Bernheim and Antonio Rangel (2004). This reinterpretation affects welfare and efficiency but not the optimal strategies. Hence, Proposition 4 applies. Similar results hold if π_i depends explicitly on the play of the game, e.g. the auction price, the ascending-bid structure, or the time structure of the auction.

Another reinterpretation is quasi-endowment. Over the course of an auction, bidders become attached to the item and are willing to bid above their (original) willingness to pay. However, if auction and fixed price are for identical, commodity-like items, quasi-endowment should not induce bids above the fixed price; the bidder simply purchases the item to which she is attached at the fixed price. Still, we will test for quasi-endowment in Section III.C.

II Data

The success of online auctions has been linked to their low transaction costs (David Lucking-Reiley, 2000). Sellers use standardized online tools and do not have to advertise. Buyers benefit from low-cost bidding, easy searching within and between websites, and automatic email updates. Hence, online auctions should increase price sensitivity and reinforce the law of one price.

Our main source of data is eBay auctions and fixed prices. EBay offers modified sealed-bid, second-price auctions. 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 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 offers fixed price, so-called "Buy-it-now" (BIN) listings. BIN sales make up about one third of eBay transactions, mostly from small retailers.[11] Rarer are hybrid "auctions with BIN," where the BIN option disappears if the first bidder does not click on it but places a bid. The reliability of buyers and sellers is measured with the Feedback Score, calculated as the number of members who left positive feedback minus the number who left negative feedback for that buyer or seller, and the "Positive Feedback Percentage" relative to total feedback.

A 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 throughout the auction so that any bidder who searches for the item at any time finds the same fixed price. Moreover, there should be multiple staggered fixed-price listings so that it is easy to infer that the option will be continuously available.

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

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 auctioned off on eBay. 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.[13] 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 refined subset.) The listings are pre-sorted by remaining listing time. On top are three smaller items, followed by a combined offering of Cashflow 101 and 202. The fifth and sixth lines are two data points in our sample: a fixed-price listing of Cashflow 101 at \$129.95 by a 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 are missing on the days from 7/16/2004 to 7/24/2004 since eBay changed the data format requiring an adjustment of the downloading procedure. Our automatized process retrieved bids and final price from the final page after an auction finished. 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 288 auctions and 401 fixed price listings by the two professional sellers. We eliminated 100 auctions that ended early (seller did no longer wish to sell the item) or in which the item was not sold.[14] Out of the 188 auction listings, 20 were combined with a BIN option, which was exercised in 19 cases. The remaining case, which became a regular auction, is included in the sample. We dropped the other 19 cases, instead of using their lower BIN prices,[15] in order to have a conservative and consistent benchmark with a forecastable price. For the same reason we dropped two more auctions during which a professional listing was not always available (between 23:15 p.m. PDT on 8/14/2004 to 8:48 p.m. on 8/20/2004). Our final auction sample consists of 167 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 \$46.56. The average final price, \$131.95, foreshadows our first result: a significant subset of auctions end above the simultaneous fixed price. Note that the winning bid is recorded as the final price, i.e., the second-highest bid plus increment, instead of the true (higher) bid. Shipping costs are reported for the 140 cases of flat shipping costs, \$12.51 on

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

[13] There were no other fixed price sellers during the sample period, and fixed-price sellers never used auctions.

[14] Dropping the (few) auctions in which the item was not sold might inflate the percentage of overbid auctions. Unfortunately, the downloads did not store starting prices to check whether they were above the fixed price. Thus, all results are conditional on a sale taking place.

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

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 16.84 bids including rebids. The average Feedback Scores are considerably higher for sellers (296.17) than for buyers (37.86). Sellers' mean positive feedback percentage is 59.81 percent. We also find that 33.53 percent of auctions end during "prime time", defined as 3-7 p.m. PDT (Jin and Kato, 2006; Mikhail Melnik and James Alm, 2002). Fixed-price items are always brand new, but only 16.77 percent of the listing titles for auctions indicate new items, e.g., with "new," "sealed," "never used," or "NIB." 27.54 percent of titles imply that standard bonus tapes or videos are included. (The professional retailers always include both extras.) Finally, about one third mention the manufacturer's price of $195.

Panels B and C provide details about the 807 bidders and 2,353 bids. Due to the eBay-induced downloading interruptions, we have the complete bidding history only for 138 auctions out of 167. 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.[16] 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.

B Cross-sectional Auction Data

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, price ranges, and buyer demographics (gender, age, and political affiliation). The drawback is that the fixed prices are not necessarily as stable as in our detailed first data set.

The primary item selection criterion was comparability across auctions and fixed prices. Ensuring homogeneity is not trivial since items are identified verbally. Typical issues are separating used from new items, accessories, bundles, and multiple quantities. We repeatedly refined the search strings using eBay's advanced search options. Details are in Appendix B.

We undertook three downloads of all "ongoing" auctions at three points in time in 2007: February 22 (3:33-3:43 a.m.), April 25 (4:50-4:51 a.m.), and May 23 (9:13-9:43 p.m.).[17] 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

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

[17] The resulting auctions ended between 5:42 am on 2/22 and 12:01 am on 3/1 (Download 1), between 2:22 am on 4/26 and 9:42 pm on 5/44 (Download 2), and 9:20 pm on 5/23 and 9:29 am on 6/2 (Download 3).

list of all items and the complete search strings are in Online-Appendix Table 1. From the resulting $3,863$ auctions, we dropped those that did not reappear in our final download of the auction outcome page (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 misidentified (wrong item). As summarized in Online-Appendix Table 2, we arrived at a final list of $1,926$ auctions. After extracting the auction ending times from our snapshot of auctions, we scheduled $2,854$ downloads of fixed prices. The details are in Appendix B. We matched each auction to the fixed price of the same item that was downloaded closest in time to the auction ending, typically within 30 minutes of the auction ending. We undertook this matching twice, accounting and not accounting for shipping costs being available.[18] Ambiguous shipping fields such as "See Description" or "Not Specified" prohibited some matches. Some auctions did not match because there were no BINs. The resulting data consists of 688 (571) auction-BIN pairs without (with) shipping in Download 1, 551 (466) in Download 2, and 647 (526) in Download 3.

C Other Data Sources

Survey. We also conducted a six-minute survey about eBay bidding behavior and familiarity with different eBay features, administered by the Stanford Behavioral Laboratory 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 student and are not identical to those in our main data sets. The full survey is available from the authors.

Choice Experiment. 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. More details follow below. The instruction and item descriptions are in the Online Appendix.

III Results

A Overbidding

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

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

[18] 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.

Hence, the bidding strategy of a significant number of auction winners is inconsistent with the simple benchmark model in Section I.A. According to Proposition 1, rational bids never exceed the fixed price. As discussed, the estimated 42 percent is conservative since, first, we only observe overbidding if at least two bidders exceeded the fixed price and, second, even auction prices below the fixed price may exceed the winner's private value.

The construction of the data set rules out that buyers bid more than the fixed price due to uncertainty about the future availability of the fixed price. The observed behavior may, however, reflect other frictions not accounted for in the benchmark model.

1. Noise. Even if a significant share of auctions exceeds the fixed price, the difference in price could be 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 overbid auctions) exceed the fixed price by more than $10. In 16 percent of all auctions (39 percent of overbid auctions), the winner overpays by more than $20.

The six graphs of Figure II display the full distribution of Final Prices in bins of $5 width (Panel A) and in bins of $1 width (Panel B). The histograms are overlaid with a kernel density estimate, using the Epanechnikov kernel and a bandwidth of 4.8. A significant share of auction prices is above the fixed price both in the early sample period, when the fixed price is $129.95, and in the later sample period, when the fixed price is $139.95. We also observe some evidence of bunching just below the fixed price.

The distribution of bids further addresses concerns about shill bidding for the seller. Even if some overbids were shills, overbid auctions typically receive more than one overbid, leading to the final overbidding price. A shill bidder, who tries to artificially drive up the price, would have little incentive to place multiple bids over the fixed price and risk the loss of a sale.

2. Shipping Costs and Sales Taxes. Another hypothesis is that shipping costs are higher for the fixed-price items. We find the opposite. In the subsample of 139 auctions for which we can identify the shipping costs, the mean shipping cost is $12.51, compared to $9.95 for the fixed-price items of one of the professional retailers. Accounting for shipping costs, 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 have closing prices that exceed the fixed price by $10 and 35 percent by more than $20.

Another explanation is that buyers from the same state as the professional sellers do not buy from them to avoid sales taxes.[19] The two fixed-price retailers are, however, located in different states, Minnesota and West Virginia. Moreover, even if we add 6-6.5 percent sales tax to the fixed prices and no tax to the auction, overbidding remains substantial.

3. Retrieval of Fixed Prices. Another concern is that bidders do not retrieve the fixed prices. However, regardless of whether they search by typing a core word or by going to the

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

item category and then searching within this category, the output screen shows both fixed prices and auctions. If the search includes additional qualifiers, fixed prices are *more* likely to be retrieved than most auctions since their descriptions are more detailed and without typos.

A related concern is that buyers may not take the fixed prices into account due to past (bad) experiences with such transactions. Our survey indicates the opposite. The 50.83 percent of respondents who are eBay users were well aware of the meaning of "buy-it-now" and, if anything, expressed a preference for buy-it-now transactions.

4. Seller reputation. Another explanation is lower seller reputation. The two fixed-price retailers have, however, Feedback Scores of 2849 (with a *Positive Feedback Percentage* of 100 percent, i.e., zero negative feedback) and 3107 (with a 99.9 percent *Positive Feedback Percentage*) as of October 1, 2004. In contrast, the average score of auction sellers is 262 (with only 63 percent positive feedback).[20] In addition, both retailers allow buyers to use PayPal, which increases the security of the transaction, while several auction sellers do not.

5. Quality Differences. Finding 1 could be explained by higher item quality in auctions. However, the quality of auction items is, if anything, lower. Some games are not new; others are missing the bonus items. The two retailers, instead, offer only new items with all original bonus items and, occasionally, additional bonuses, such as free access to a financial-services website. The retailers also offer the fastest delivery and a six month return policy.

A remaining concern is *unobserved* quality differences, such as wording differences. Our choice experiment addresses this concern. Subjects were asked which of three items they prefer, 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 same three listings were shown to all subjects but the order was randomized. (See Online-Appendix Table 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. Hence, it is unlikely that unobserved quality difference explain the bidding behavior.

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

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

Overbidding is even more prevalent in the cross-sectional data, ranging from 44 percent

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

to 52 percent across the three downloads (Table IV). As Figure III, Panel A, illustrates, we observe at least 30 percent overbidding in 10 out of 12 item categories. We find no significant relation between price level and overbidding. Expensive hardware (around $150) triggers little overbidding, while overbidding for expensive sports equipment (exercise machines around $200) is frequent, 56 percent across the three downloads. Detailed scatterplots of the frequency of overbidding for different price levels in the Online-Appendix show that it is no less prevalent for more expensive goods. Overbidding is slightly lower after accounting for shipping costs, differently from what we found in the Cashflow 101 data. We also explore differences in overbidding by bidder demographics, as far as we can infer from the auction object (gender, age group, liberal versus conservative). A detailed analysis in the Online -Appendix finds that overbidding is sizeable and significant within each demographic subset. The results suggest that the pattern of overbidding identified in our first data set generalizes across auction items.

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

Uncertainty and Transaction costs. As a final step in establishing the overbidding result, we consider rational explanations based on uncertainty about the future availability of the fixed price, transaction costs, and a combination of both. As modeled in Section I.A, a fixed price may not remain available after the corresponding auction. We have argued that such uncertainty is not present in data set 1, but it is in data set 2. And, as modeled in I.B, it might be costly for a bidder to return to the screen with the fixed-price listings after having bid in the auction. In either case, however, the expected auction price will be significantly lower than the fixed price (Propositions 1' and 2). We find the opposite:

Finding 3 (Overpayment on Average). *The average auction price is higher than the simultaneous fixed price, in data set 1 by* $0.28 *without shipping costs and by* $2.69 *with shipping costs, and in data set 2 by* 9.98 *percent without and by* 4.46 *percent with shipping costs.*

In the first 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]), as shown in Table III. This comparison is, however, a conservative test: the expected auction price should be significantly lower than the fixed price in order to induce a bidder to enter the auction rather than purchasing at the fixed price. In the second, cross-sectional data, the computation of the price differential is less straightforward because of the heterogeneity in prices across items. We calculate the percentage of over- or underbidding for each item (final bid minus BIN, as a percentage of BIN) and then average over all percent differences. Here, the net overpayment of 9.98 percent is significantly different from 0 percent (s.e.= 1.85 percent), also if accounting for shipping costs, 4.46 percent (s.e.= 1.99 percent). Overall, the prediction that on average auction prices are lower than the fixed prices is rejected in the data.

Finding 3 rejects all rational "frictions" modeled in the theory section, which require that the average auction price is significantly lower than the fixed price.

Another type of transaction costs is the cost of understanding the buy-it-now system. We have already argued – and confirmed in our survey – that complete unawareness is unlikely since fixed prices are very common, intuitively designed, and similar to any fixed price on the internet. Still, inexperienced eBay users may not yet take them sufficiently into account. We test whether overbidding is lower for high-experience users using the Cashflow 101 sample and a median split by Feedback Scores (Panel B of Figure III).[21]

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

The percentages of overbidding are almost identical for low-experience and high-experience users, 41.7 and 42.2 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 those with Feedback Scores of 0 (17 percent of winners), 1 (19 percent), 2-4 (14 percent), 5-14 (20 percent), 15-92 (20 percent) and higher (remaining 10 percent of winners), we find propensities to overbid of 31 percent, 55 percent, 35 percent, 47 percent, 36 percent, and 44 percent, indicating no systematic pattern.[22]

Finding 4 does not rule out that experience reduces overbidding; we do not have longitudinal bid histories for each bidder. However, it *does* rule out that only eBay novices overbid. The result also helps to further alleviate concerns about shill bids since fake IDs are unlikely to be used for many transactions and, hence, have low feedback scores.

The results so far indicate that the standard rational framework does not explain the observed behavior, even if we allow for a wide range of possible frictions. Our findings do not rule out that these frictions exist. In fact, they may exacerbate overbidding if interacted with consumer biases, as we emphasized in the Section I. Also, there are behavioral twists of the above explanations, which can explain the overbidding phenomenon. For example, it might be hard to form expectations about the future availability and prices of buy-it-now items.[23] The conclusion so far is that, without allowing for non-standard preferences or beliefs, we are not

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

[22] Our results are consistent with Bajari and Hortacsu (2003) and Rod Garratt, Mark Walker, and Wooders (2007).

[23] 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 (or its upper bound) is constant over long periods.

able to explain the observed overbidding.

B Disproportionate Influence of Overbidders

Before we turn to the leading behavioral explanations for the observed overbidding, we show that a high frequency of overbid auctions does not imply that the 'typical' buyer overpays. Instead, it is generated by a relatively small fraction of overbids (Table V). We document this phenomenon returning to our first data set, in which we have detailed bidder- and bid-level data for 138 auctions. (Summary statistics are in Panels B and C of Table I.)

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

The reason why 42 percent of overbid auctions involve only 17 percent of overbidders is that there are many more bidders than auctions. The vast majority of bidders submit bids below the fixed price and drop out of the auction once the price crosses the fixed-price threshold. Each auction only needs two overbidders for the auction price to end above the fixed price. Therefore, the existence of a few overbidders suffices to generate a significant amount of overbidding.

This finding reflects, of course, the nature of auctions. 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. The insight from our data is, instead, that bidders may submit high bids for other, non-standard reasons. Whatever the reason for their overbidding, the auction design implies that the bidders with particularly high bids determine prices and allocations. The calibrations at the end of the next subsection further illustrate this point.

C Explanations for Overbidding

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

Limited Attention and Limited Memory. One possible explanation is that bidders do not pay attention to fixed prices, even if listed on the same screen (Proposition 3). In that case, we expect more overbidding when fixed prices are less salient. The further apart fixed prices are listed from an auction, the more likely is an inattentive bidder to miss them. Salience also varies with absolute screen position: The higher an auction is positioned, the more likely will it capture the attention of a bidder, an effect known as "above the fold" in internet marketing.[24]

To test these two implications, we reconstruct, for each bid observed in our data, the set of

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

all auctions and fixed prices available at the time of the bid. That is, we augment the sample of bids by all listings that were simultaneously available but did not receive a bid, separately for each bid. We drop the first seven days of our sample period and after the period of missing data (7/16-7/24/2004) to ensure that we observe all simultaneous auctions. The resulting data set captures $2,187$ of the $2,353$ bids of the full sample and, including the simultaneous listings, consists of $14,043$ observations. We assume that listings are ordered by remaining listing time, as it is the eBay default, and that bidders only see Cashflow 101 listings. In reality, users may reorder, e.g., by price, and irrelevant listings may show up, depending on the search. This is likely to introduce noise but not bias. The two independent variables of interest are (1) Distance to nearest BIN listing, coded as 0 if there are no rows between the auction and the closest BIN (one row above or below), 1 if there is one row between them, etc.; and (2) Position on screen, coded as 1 for auctions on top of the screen, 2 for auctions in the second row, etc.

We use a conditional logit framework, relating the probability of receiving an auction bid to the closeness of the nearest fixed price and to the absolute screen position of the auction. We condition the estimation on one of the auctions receiving a bid at a given time.[25] The utility from bidding on auction i in bidding instance b is $U_{ib} = \beta_1 D_{ib} + \beta_2 P_{ib} + X'_{ib} B + \varepsilon_{ib}$, where D is the distance to the nearest fixed-price listing, P is the screen position, and X are auction-specific controls.[26] Assuming that, conditional on the choice of making a bid at bidding instance b, ε_{ib} is i.i.d. extreme value, the probability of bidding in auction i is

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

The null hypothesis of rational bidding is that the distance to the fixed price listing D and the screen position P do not affect the probability of receiving a bid, that is, β_1 and β_2 equal zero. Limited attention predicts that the coefficient estimate β_1 is positive and β_2 negative.

In Table VI, Column 1, we present the baseline results. Coefficients are reported as odds ratios. Standard errors are clustered by bid. We find a significantly positive effect of distance on receiving a bid. The odds that an auction receives a bid are 1.176 times greater when there is one more row between the between fixed price and auction. We also find a significantly negative effect of screen position. An auction is less likely to receive a bid if its position on the output screen is lower (odds 0.988 lower). The results are robust to controlling for the price outstanding (and its square), starting price, seller feedback score, auction length, a prime-time

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

[26]In a standard nested logit model, consumers make one choice from a standard set of alternatives. In our setting, a bidder may make repeated choices. For the estimates to be consistent, we need to make the additional assumption of no serial correlation of errors in the bottom nest. This assumption does not hold to the extent that bidders tend to bid again on the same auctions.

dummy (3-7 p.m. Pacific Time), and remaining auction time; see Column 2. Also the inclusion of more time controls (the square and cube of remaining auction time, dummies for the last auction day and the six last hours of the auction) does not affect the results.

In order to link inattention to *over*-bidding, we estimate the effect of nearby fixed prices in the subgroup of auctions whose price outstanding exceeds the fixed price. We introduce dummies for auctions with prices outstanding 'just below' the concurrent fixed price, auctions with prices 'just above,' and auctions with 'very high' prices. 'Very low' is the left out category. For prices just below or above we use either $[-\$5;\$5]$ or $[-\$10,\$10]$. (Any range in between and up to \$30 leads to similar results.) We test for an interaction effect with Distance to nearest BIN and include the full set of controls. Columns 3 and 6 show that Distance to BIN has no significant effect on auctions with prices below or far above, but a significantly positive effect on the probability of receiving a bid for auctions with prices just above the fixed price. An increase in distance by one row increases the odds of receiving a bid by 1.4-2 (depending on the interval for 'just above'). Hence, closeness of fixed prices directly affects overbidding.

We also find that the effect of nearby fixed prices is particularly strong for bidders' first bids in a given auction. After splitting the sample into first bids and later bids, the interaction of Distance to BIN and Price just above is significant only in the subsample of first bids (Columns 4-5 and 7-8).[27] This finding is consistent with limited memory: Bidders account for the fixed price initially, but fail to do so when they increase their bids. Limited memory is plausible because of the design of eBay's outbid notices, in which eBay provides a direct link to increase a bid, but no link to the page with all ongoing auctions and buy-it-now listings.

In summary, limited attention and limited memory emerge as plausible explanations for the observed overbidding. Note that the results also suggest that bidders are naive about their memory limitations. If they were aware of their memory constraint they could easily remedy it, for example, by always submitting only one bid (up to the fixed price) and never responding to outbid notices. The bidding behavior described in the (rational) model of uncertainty introduced in Section I.C can be re-interpreted as bidders' rational response to forgetting the fixed-price option. Hence, Finding 3 about the average auction price exceeding the fixed price also rejects the rational model of limited attention or limited memory.

Utility from Winning, Bidding Fever, and Quasi-Endowment Effect. Another behavioral explanation is utility from winning an item in an auction relative to purchasing it at a fixed price.[28] This type of explanation is hard to falsify empirically given that any behavior can be interpreted as revelation of preferences for such behavior. We can address specific

[27]Column 5 also shows a negative interaction effect of Position on screen in the subsample of later bids, but not in the subsample of first bids. This finding is not easily explained by limited attention.

[28]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.

forms, though, such as the quasi-endowment effect. The quasi-endowment effect postulates that bidders become psychologically more endowed to auction items, and hence more likely to submit high bids, the longer they participate in the auction, in particular as the lead bidder (Heyman, Orhun, Ariely, 2004; Wolf, Arkes, Muhanna, 2005). One could argue that the quasi-endowment effect cannot explain bidding above the fixed price, given that bidders can always obtain the identical item at the fixed price. Still, we test whether bidders become more attached to auction items, and submit higher bids, the longer they participate, in particular as the lead bidder.

A simple comparison of means reveals no relation between overbidding and the length of bidding. Winners who overbid enter the auction 1.27 days before the auction ends; winners who do not overbid enter the auction earlier, 1.52 days before the auction ends. The same pattern emerges for time as lead bidder: Winners who overbid have been lead bidders for 0.55 days by the time of their last bid (1.03 days by the end of the auction); winners who do not overbid have been lead bidders for 0.74 days (1.24 overall).

We then test in a regression framework whether the time a bidder has spent as the leader affects overbidding, conditional on having been outbid. The regression framework allows us to control for the value of the bidder's last lead bid and the time and price outstanding when she is outbid for the final time. Appendix-Table A.1 shows a probit estimation where the binary dependent variable equals 1 if the bidder ultimately overbids. We find no significant relationship between the total time a bidder has led the auction and the probability of overbidding. The same holds if we restrict the sample to bidders whose first bid in the auction is not an overbid or whose first lead bid is not an overbid. Another prediction in the literature on the quasi-endowment effect is that it is reduced by experience. We have already shown that more experienced bidders are no less likely to overbid (Finding 4).

In summary, we find no direct evidence for quasi-endowment explaining overbidding *relative to the fixed price.* The lack of a positive relation between time spent in the auction and overbidding also rules out other stories based on sunk-cost sensitivity and escalation of commitment (Barry Staw, 1976; G. Ku, D. Malhotra, and J. Keith Murnighan, 2005), which should both be increasing in time. However, our findings do not rule out more general versions of utility from winning.

Calibration. In a simple calibration, we provide more insights into the plausibility of limited attention and utility from winning. Our calibration allows for bidder heterogeneity, with only a fraction of bidders having non-standard preferences. We vary this fraction from 0 to 1. We consider a variety of distributions of bidder valuations, including χ^2, uniform, exponential, and logarithmic distributions, and a range of possible moments. We draw eight players from an infinite population, corresponding to the empirical moment. For each distribution of valuations, we draw 1,000,000 i.i.d. realizations for each player. We then draw another 1 million values, separately for each of the eight players, from a uniform distribution on $[0, 1]$, determining whether a player is a rational or a behavioral type. For example, when the proportion of behavioral players is 0.1, only player-auction pairs for which we draw values between 0 and 0.1 are behavioral. We assume that the utility of winning is uniformly distributed between \$0 and \$10. Values are independently drawn. Hence, we generate a third (1 million x 8)-matrix of winning utilities drawn from a uniform $[0, 10]$ distribution. These values are added to the values in the first matrix if the player is behavioral in the respective auction. We compute the equilibrium strategies as specified in Propositions 1 for rational players and in Propositions 3 and 4 for behavioral players,[29] setting the simultaneous fixed price equal to \$130.

Figure IV shows the calibrations for $\chi^2(130)$ and $U[80, 180]$, i.e., two distributions whose first moment is equal to the fixed price and, in the case of the uniform distribution, reflects the observed minimum and maximum prices.[30] The left graphs show the results for Limited Memory, the right graphs for Utility from Winning. In each graph, we show the percentages of auctions with a price above the fixed price (Percent overpaid) and of bidders who submit a bid above the fixed price (Percent overbidders). The leftmost values correspond to our benchmark rational model and the rightmost values to everybody having non-standard preferences.

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

IV Discussion and Conclusion

In this paper, we provide clean evidence on overbidding in the field. We exploit the availability of fixed prices for identical items on the same eBay webpage. A significant fraction of bidders bid more than predicted by a simple rational model, even accounting for uncertainty and transaction costs. We provide evidence that bidders fail to pay sufficient attention to their outside options, especially when re-bidding. The leading behavioral alternative, utility from

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

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

winning, is hard to test in the data, though we can rule out the quasi-endowment effect. We also provide a calibrational argument that utility from winning cannot easily match the empirically observed distribution of bids. The second main finding is that a small fraction of bidders who overbid affect a disproportionately large fraction of auction prices and allocations. Auctions select overbidders as winners and thus amplify the effect of biases in the market.

Our findings suggest that design elements such as the wording of eBay's outbid message ("You have been outbid!") may have a larger effect on bidding behavior and prices than traditional auction theory suggests. Profit-maximizing sellers should account for consumers' behavioral preferences and beliefs when choosing auctions over other price mechanisms and when selecting a specific type of auction. This implication is explored by Malmendier and Adam Szeidl (2009), who compare different auction formats and auction designs from the revenue and welfare perspective after accounting for overbidding biases.[31]

While our paper analyzes online auctions, overbidding and the disproportionate influence of few overbidders apply to auctions more broadly. For example, Orley Ashenfelter and David Genesove (1992) document overbidding in real estate auctions in New Jersey relative to face-to-face negotiations. A large number of auction participants appears to be key to ensure the presence of overbidders. Even in mobile-phone auctions, such as the British 3G auctions in 2000-01, it has been argued that the winners "paid too much" (Ken Binmore and Paul Klemperer, 2002). Klemperer (2002) attributes the large revenues of the British auction to the low hurdles to entry[32] and argues that the large differences in revenues across different Western European 3G auctions strongly covary with the number of participants. This paper offers an alternative interpretation: facilitating entry is important to ensure that the auction attracts at least two overbidders. Another example is mergers and acquisitions. Contested transactions, in which several bidders aim to acquire the same target, are often suspected to induce overpayment. Malmendier and Enrico Moretti (2006) show that winners of merger fights perform on average worse than the losers after the merger fight. While not all firms overvalue the target, a few overbidders suffice to generate large losses. A last example are initial public offerings, some of which are actual auctions (e.g. Google) and all of which are later bought and sold in the auction-like stock market setting. A long-standing view (Hans Stoll and Anthony Curley, 1970; Jay Ritter, 1991) is that the pattern of initial stock-price rise and subsequent decline reflects that the initial aftermarket price is too high. Relatedly, Ann Sherman and Ravi Jagannathan (2006) argue that IPO auctions have been abandoned in the 24 countries that have used them in the past because of overbidding. While IPO underwriters might favor

[31] In a similar spirit, Kagel and Levin (2009) attribute the popularity of dynamic multi-object auctions, versus their one-shot counterparts, to bidders' bounded rationality. Kfir Eliaz, Theo Offerman, and Schotter (2008) contrast the high revenues and the empirical popularity of "right-to-choose" auctions with the predictions of lower revenues in a rational auction framework.

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

overbidding, it appears to discourage informed investors and prevent price discovery. Even in non-auction settings, the same logic may induce sellers to set exceedingly high prices in the hope of encountering a consumer who, for behavioral or other reasons, is willing to pay such a price (Ellison, 2005; Ellison and Sara Fisher Ellison, 2009).

Our findings have more general implications about consumer choices. They suggest that consumers might not always choose the lowest-price good, even when the goods are homogeneous and search costs are low. Understanding the extent of this phenomenon could help us understand the large and persistent price dispersion documented, for example, by John Pratt, David Wise, and Zeckhauser (1979) when searching by phone, or by Michael R. Baye, Morgan, and Patrick Scholten (2004) and (2006), including online searches. In the long run, a better understanding of this phenomenon might help us make our models of competition more accurate.

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, $v_i - p_w$. If she has lost the auction in the first stage, 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 $b_i \neq b_i^*$.

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 $p_w \leq b_i^* = \min\{v_i, \overline{p}\}$. 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 weakly 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 bidder who wins the auction in this case, i. e., under realization $\widehat{v}$ in this equilibrium, 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'.) For all realizations v where $v_w \neq \widehat{v}_w$, we define s'_w to be identical to s_w. For $v_w = \widehat{v}_w$, we prescribe bidding $\min\{\widehat{v}_w, \overline{p}\}$ and not purchasing in the second stage unless the auction is lost and $\widehat{v}_w \geq \overline{p}$. 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 $p_w(\widehat{v}) > \overline{p}$) and earns $\max\{\widehat{v}_w - \overline{p}, 0\}$, 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, $b'_w(\widehat{v}_w) = \min\{\widehat{v}, \overline{p}\}$, 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, to purchase after losing even though $\widehat{v}_w < \overline{p}$, or not to purchase after losing even though $\widehat{v}_w > \overline{p}$). If, instead, b_w wins the auction and b'_w loses the auction, then the payoff under s'_w, $\max\{\widehat{v}_w - \overline{p}, 0\}$, is weakly higher than the payoff under s_w, where w wins the auction and pays at least $\min\{\widehat{v}_w, \overline{p}\}$.

Thus, s'_w induces a weakly higher payoff than s_w $\forall v$ and a strictly higher payoff for some realizations of v. 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.

Proof of Proposition 1'. (a) In the proof of Proposition 1(a), substitute $b_i^* = \min\{v_i, \overline{p}\}$ with $b_i^* = v_i - \alpha \max\{v_i - \overline{p}, 0\}$. The optimal second-stage strategy is unaltered if the item is available. (If the item is not available the player does not choose an action.) To show that $b_i^* = v_i - \alpha \max\{v_i - \overline{p}, 0\}$ is part of a PBE in the subgame after entering the auction, distinguish the two possible devitiations $b_i < v_i - \alpha \max\{v_i - \overline{p}, 0\}$ (Case 1) and $b_i > v_i - \alpha \max\{v_i - \overline{p}, 0\}$ (Case 2), and the proof of Proposition 1(a) applies.

(b) 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 $f_{-i|i}$. The fixed price sale is available before the auction and remains after the auction with probability $\alpha \in [0, 1)$.

In any PBE, player i enters the auction iff the expected utility from bidding in the auction is higher than $\max\{v_i - \overline{p}, 0\}$, i.e., the utility of either never purchasing nor bidding (a positive amount) or purchasing in the first stage. Thus, all players i with $v_i \leq \overline{p}$ enter and bid a positive amount $b_i(v_i) > 0$, iff $\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] \geq 0$, i.e.,
$\int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i)dF_{-i|i}(v_{-i}) \leq \int\limits_{\{v_{-i}|i \text{ wins}\}} v_i dF_{-i|i}(v_{-i})$.
And all players i with $v_i > \overline{p}$ enter iff
$\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] + \alpha \Pr(i \text{ loses}|v_i) \cdot (v_i - \overline{p}) \geq v_i - \overline{p}$,
that is, $\int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i)dF_{-i|i}(v_{-i}) \leq \overline{p} - \int\limits_{\{v_{-i}|i \text{ loses}\}} v_i dF_{-i|i}(v_{-i}) + \alpha \int\limits_{\{v_{-i}|i \text{ loses}\}} (v_i - \overline{p}) dF_{-i|i}(v_{-i})$.
Taking expectations of p_w with respect to v_i, including both types of players, we obtain

$$\int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v)$$
$$= \int\limits_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} p_w(b(v))dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} p_w(b(v))dF(v)$$
$$\leq \int\limits_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int\limits_{\{v|v_i > \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} v_i dF(v) + \alpha \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} (v_i - \overline{p}) dF(v)$$
$$= \int\limits_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + (1 - \alpha) \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} \overline{p} dF(v) - (1 - \alpha) \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} v_i dF(v).$$

$= \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + (1-\alpha) \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} (\overline{p} - v_i) \, dF(v).$

Since the last term is strictly negative, given continuous support of v on R_+^N, we get
$\int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v) < \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v)$
$= \int\limits_{\{v|i \text{ wins}\}} \min\{v_i, \overline{p}\} dF(v) \le \int\limits_{\{v|i \text{ wins}\}} \overline{p} dF(v).$
Adding up the left-hand side and the right-hand side for all i, we obtain $\int_v p_w(b(v))dF(v) < \overline{p}$.

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 $f_{-i|i}$. We denote with c the cost of switching, i.e., of purchasing at the fixed price after having bid in the auction.

In any PBE, player i enters the auction iff the expected utility from bidding in the auction is higher than $\max\{v_i - \overline{p}, 0\}$, i.e., the utility of either never purchasing nor bidding (a positive amount) or purchasing in the first stage. Thus, all players i with low valuations $v_i \le \overline{p}$ enter and bid $b_i(v_i) > 0$ iff $\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] \ge 0$,
that is, $\int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i) dF_{-i|i}(v_{-i}) \le \int\limits_{\{v_{-i}|i \text{ wins}\}} v_i dF_{-i|i}(v_{-i}).$
Players i with medium valuations $\overline{p}+c \ge v_i > \overline{p}$ enter iff $\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] \ge v_i - \overline{p}$, that is, $\int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i) dF_{-i|i}(v_{-i}) \le \overline{p} - \int\limits_{\{v_{-i}|i \text{ loses}\}} v_i dF_{-i|i}(v_{-i}).$
And players i with high valuations $v_i > \overline{p} + c$ enter iff
$\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] + \Pr(i \text{ loses}|v_i) \cdot (v_i - \overline{p} - c) \ge v_i - \overline{p}$,
i.e., $\int\limits_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i) dF_{-i|i}(v_{-i}) \le \overline{p} - \int\limits_{\{v_{-i}|i \text{ loses}\}} v_i dF_{-i|i}(v_{-i}) + \int\limits_{\{v_{-i}|i \text{ loses}\}} (v_i - \overline{p} - c) \, dF_{-i|i}(v_{-i}).$

Taking expectations of p_w with respect to v_i, including all three types of players, we obtain
$\int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v)$
$= \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} p_w(b(v))dF(v) + \int\limits_{\{v|i \text{ wins} \wedge \overline{p}+c \ge v_i > \overline{p}\}} p_w(b(v))dF(v) + \int\limits_{\{v|v_i > \overline{p}\}} \overline{p} dF(v)$
$\le \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|v_i > \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} (v_i - \overline{p} - c) \, dF(v)$
$= \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge \overline{p}+c \ge v_i > \overline{p}\}} v_i dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} (\overline{p} + c) \, dF(v).$
$= \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) - \int\limits_{\{v|i \text{ loses} \wedge \overline{p}+c \ge v_i > \overline{p}\}} (v_i - \overline{p}) \, dF(v) - \int\limits_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} c dF(v).$
Since the sum of the last two terms is strictly negative, given continuous support of v on R_+^N, we get $\int\limits_{\{v|i \text{ wins}\}} p_w(b(v))dF(v) < \int\limits_{\{v|i \text{ wins} \wedge v_i \le \overline{p}\}} v_i dF(v) + \int\limits_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v)$

$$= \int_{\{v|i \text{ wins}\}} \min\{v_i,\overline{p}\}dF(v) \leq \int_{\{v|i \text{ wins}\}} \overline{p}dF(v).$$

Adding up the left-hand side and the right-hand side for all i, we obtain $\int_v p_w(b(v))dF(v) < \overline{p}$.

Proof of Proposition 2'. Following the proof of Proposition 2, the uncertain availability of the fixed price after the auction affects only the auction participation condition for players with high valuations $v_i > \overline{p} + c$. They enter iff $\Pr(i \text{ wins}|v_i) \cdot E[v_i - p_w(b(v))|v_i, i \text{ wins}] + \alpha \Pr(i \text{ loses}|v_i) \cdot (v_i - \overline{p} - c) \geq v_i - \overline{p}$,

that is, $\int_{\{v_{-i}|i \text{ wins}\}} p_w(b(v)|v_i)dF_{-i|i}(v_{-i}) \leq \overline{p} - \int_{\{v_{-i}|i \text{ loses}\}} v_i dF_{-i|i}(v_{-i}) + \alpha \int_{\{v_{-i}|i \text{ loses}\}} (v_i - \overline{p} - c)\, dF_{-i|i}(v_{-i})$.

The other two participation constraints (for players with low valuations $v_i \leq \overline{p}$ and for players with medium valuations $\overline{p}+c \geq v_i > \overline{p}$) are unaffected. Taking expectations of p_w with respect to v_i, including all three types of players, we now obtain

$$\int_{\{v|i \text{ wins}\}} p_w(b(v))dF(v)$$

$$\leq \int_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int_{\{v|v_i > \overline{p}\}} \overline{p} dF(v) - \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} v_i dF(v) + \alpha \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} (v_i - \overline{p} - c)\, dF(v)$$

$$= \int_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} \overline{p} dF(v) - \int_{\{v|i \text{ loses} \wedge \overline{p}+c \geq v_i > \overline{p}\}} v_i dF(v)$$

$$- (1-\alpha) \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} v_i dF(v) - \alpha \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} (\overline{p} + c)\, dF(v).$$

$$= \int_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + (1-\alpha) \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} \overline{p} dF(v) + \alpha \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} \overline{p} dF(v)$$

$$- (1-\alpha) \int_{\{v|i \text{ loses} \wedge \overline{p}+c \geq v_i > \overline{p}\}} v_i dF(v) - \alpha \int_{\{v|i \text{ loses} \wedge \overline{p}+c \geq v_i > \overline{p}\}} v_i dF(v)$$

$$- (1-\alpha) \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} v_i dF(v) - \alpha \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} \overline{p} dF(v). - \alpha \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} c dF(v).$$

$$= \int_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v)$$

$$- (1-\alpha) \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}\}} (v_i - \overline{p})\, dF(v) - \alpha \int_{\{v|i \text{ loses} \wedge \overline{p}+c \geq v_i > \overline{p}\}} (v_i - \overline{p})\, dF(v) - \int_{\{v|i \text{ loses} \wedge v_i > \overline{p}+c\}} c dF(v).$$

Since the sum of the last three terms is strictly negative, given continuous support of v on R_+^N, we get $\int_{\{v|i \text{ wins}\}} p_w(b(v))dF(v) < \int_{\{v|i \text{ wins} \wedge v_i \leq \overline{p}\}} v_i dF(v) + \int_{\{v|i \text{ wins} \wedge v_i > \overline{p}\}} \overline{p} dF(v)$

$$= \int_{\{v|i \text{ wins}\}} \min\{v_i,\overline{p}\}dF(v) \leq \int_{\{v|i \text{ wins}\}} \overline{p}dF(v).$$

Adding up the left-hand side and the right-hand side for all i, we obtain
$\int_v p_w(b(v))dF(v) < \overline{p}$.

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 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. For each item in our cross-sectional data, we carefully determined a price below which a brand new item could not possibly be listed, and a price above which it could never sold. Minimum prices eliminated accessories and blatantly used products in the BIN results. Maximum prices eliminated bundled items in both the auctions and BIN results. We conducted test downloads where we simply searched for the item names, then hand-checked for false positives (e.g. an iPod case instead of an iPod). This allowed us to derive boundaries for the item prices.

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.) The purpose of extracting the BIN prices right before the close of the auction is to find the cheapest fixed-price match to each auction item. 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 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	167	46.56	43.96	0.01	150
Final Price	167	131.95	16.84	81.00	179.30
Shipping Cost	140	12.51	3.81	4.95	20.00
Total Price	140	144.27	14.96	110.99	185.50
Number of Bids	167	16.84	9.21	1	39
Number of Bidders	138	8.41	3.84	1	18
Feedback Score Buyer	167	35.90	102.68	0	990
Feedback Score Seller	167	254.40	1427.83	0	14730
Positive Feedback Percentage Seller	167	61.35	48.52	0	100
Auction Length [in days]	167	6.27	1.69	1	10
one day	167	1.20%			
three days	167	11.38%			
five days	167	17.37%			
seven days	167	65.27%			
ten days	167	4.79%			
Auction Ending Weekday					
Monday	167	11.98%			
Tuesday	167	7.78%			
Wednesday	167	15.57%			
Thursday	167	11.98%			
Friday	167	9.58%			
Saturday	167	18.56%			
Sunday	167	24.55%			
Auction Starting Hour	167	14.84	5.21	0	23
Auction Ending Hour	167	14.84	5.21	0	23
Prime Time	167	33.53%			
Title New	167	16.77%			
Title Bonus Tapes/Video	167	27.54%			
Explicit195	167	31.14%			

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	2.03	1.76	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	0.14	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. The exact auction date is missing for one auction, reducing the sample to 166 (from 167 in Table I).

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

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

Table V. Disproportionate Influence of Overbidders

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

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

Table VI. Bidding and Limited Attention

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

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

	Full Sample		**"Just above/below" = +/-$5**			**"Just above/below" = +/-$10**		
			Full	First Bids	Later Bids	Full	First Bids	Later Bids
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to nearest BIN listing	1.176	1.106	1.021	1.061	0.995	1.025	1.056	1.006
[rows between]	[0.025]***	[0.029]***	[0.028]	[0.042]	[0.037]	[0.028]	[0.043]	[0.038]
(Price just below)*(Distance to BIN)			0.894	0.868	0.939	0.822	0.933	0.752
			[0.160]	[0.245]	[0.204]	[0.128]	[0.232]	[0.147]
(Price just above)*(Distance to BIN)			2.083	2.948	1.785	1.372	1.538	1.469
			[0.487]***	[0.911]***	[0.670]	[0.239]*	[0.324]**	[0.421]
(Price far above)*(Distance to BIN)			1.159	0.640	1.325	1.231	0.861	1.261
			[0.137]	[0.236]	[0.152]**	[0.118]**	[0.346]	[0.133]**
Price outstanding just below BIN price			1.164	1.326	1.164	1.205	0.835	1.799
[dummy]			[0.207]	[0.357]	[0.279]	[0.179]	[0.198]	[0.347]***
Price outstanding just above BIN price			1.747	0.966	2.920	1.861	1.027	3.255
[dummy]			[0.453]**	[0.381]	[1.004]***	[0.412]***	[0.345]	[0.992]***
Price outstanding far above BIN price			2.152	1.761	2.844	2.746	1.213	5.922
[dummy]			[0.449]***	[0.617]	[0.781]***	[0.729]***	[0.575]	[2.057]***
Position on screen	0.988	0.918	0.974	1.000	0.983	0.973	0.998	0.945
[row number]	[0.005]**	[0.009]***	[0.013]**	[0.019]	[0.004]***	[0.013]**	[0.019]	[0.018]***
Price outstanding		0.975	0.99	0.983	1.006	0.991	0.981	1.013
		[0.003]***	[0.003]***	[0.004]***	[0.005]	[0.003]***	[0.005]***	[0.005]**
(Price outstanding)^2		1.002	0.989	0.988	0.983	0.988	0.991	0.977
		[0.002]	[0.003]***	[0.004]***	[0.004]***	[0.003]***	[0.004]**	[0.004]***
Starting price		0.994	0.994	0.998	0.99	0.994	0.998	0.991
		[0.001]***	[0.001]***	[0.001]**	[0.001]***	[0.001]***	[0.001]*	[0.001]***
Auction controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended time controls			Yes	Yes	Yes	Yes	Yes	Yes
N	14,043	14,043	14,043	6,712	7,331	14,043	6,712	7,331
Pseudo R-squared	0.01	0.14	0.18	0.25	0.15	0.18	0.25	0.16

Figure I. Listing Example

Rich Dad's Cashflow Quadrant, Rich dad ...	**$12.50**	4	1d 00h 14m
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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
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MINT Cashflow 101 *Robert Kiyosaki Game NR! It's easy to be rich. Brand New. Still sealed	**$140.00**	13	1d 08h 04m
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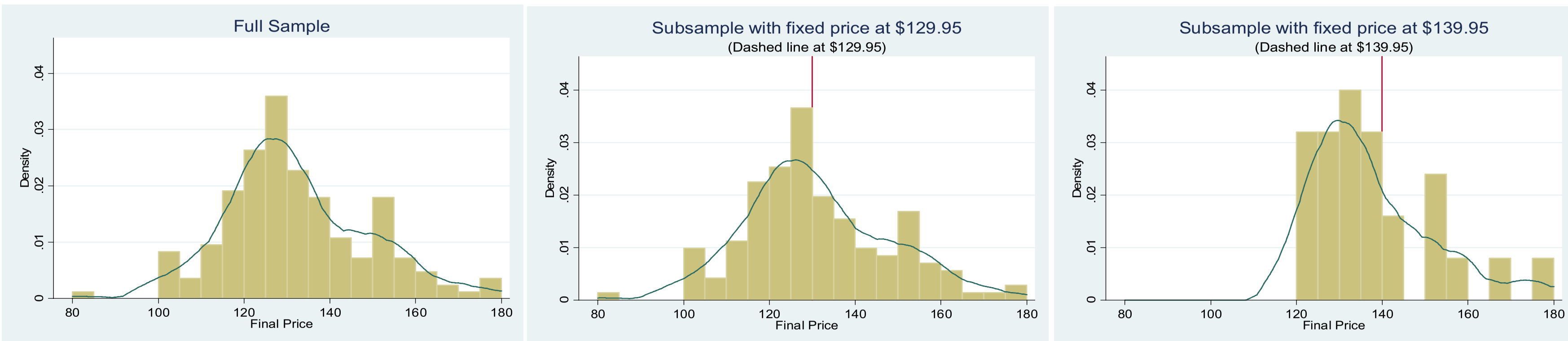
Figure II. Distribution of Final Prices

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 and a bandwidth of 4.8.

Panel A. Bin-width $5



Panel B. Bin-width $1

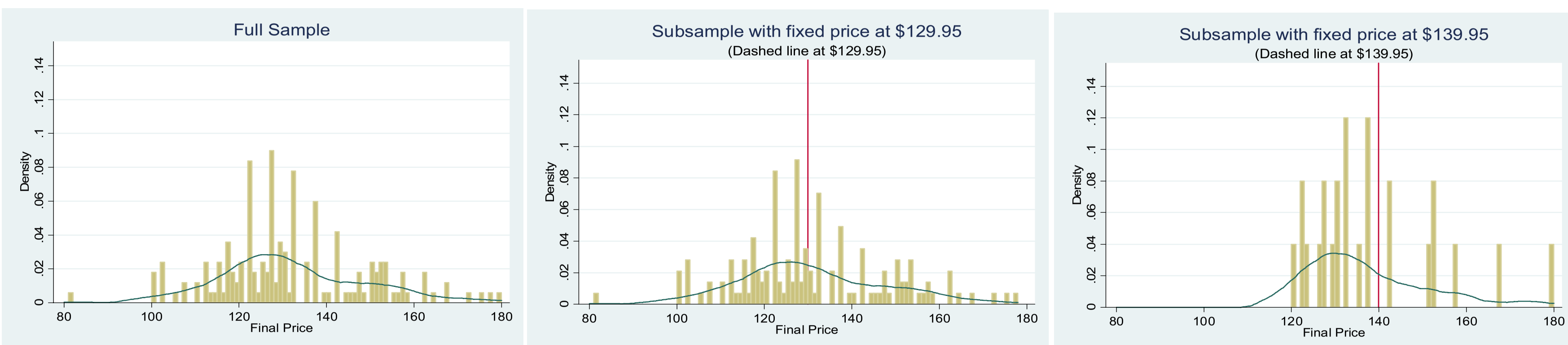
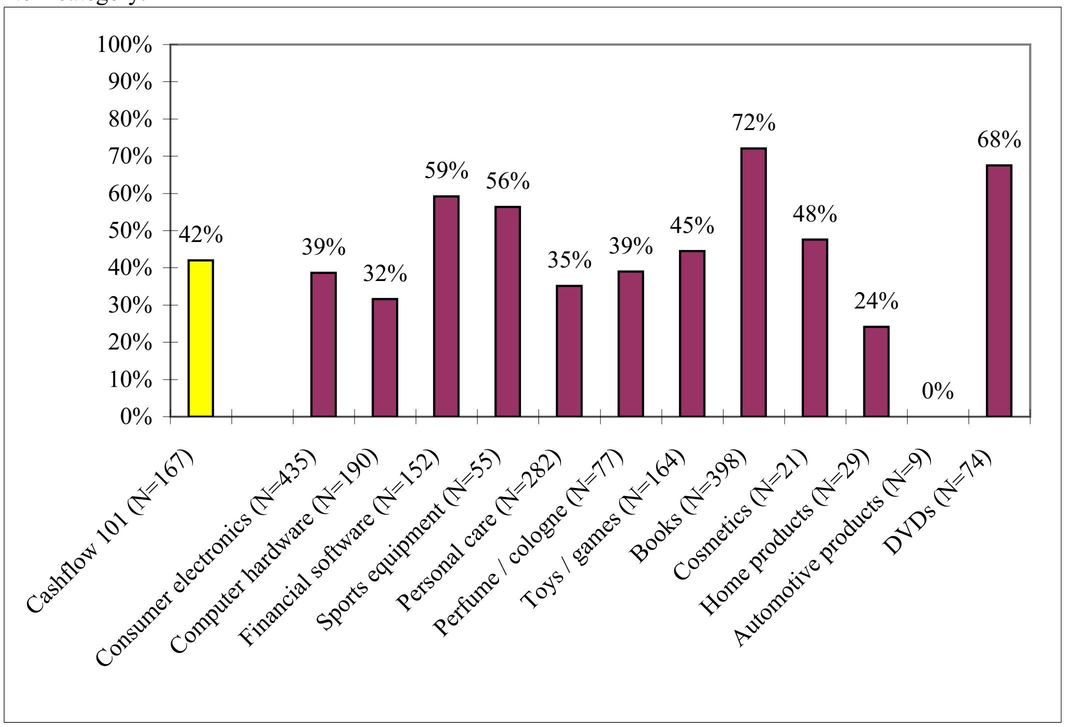


Figure III. Overbidding

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.



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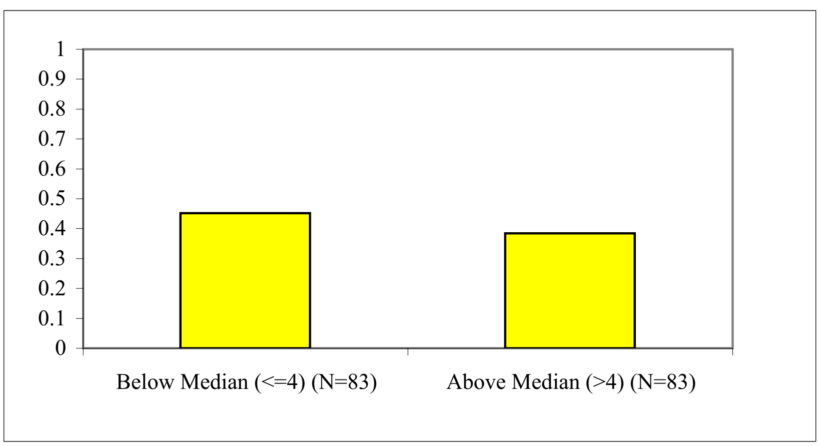
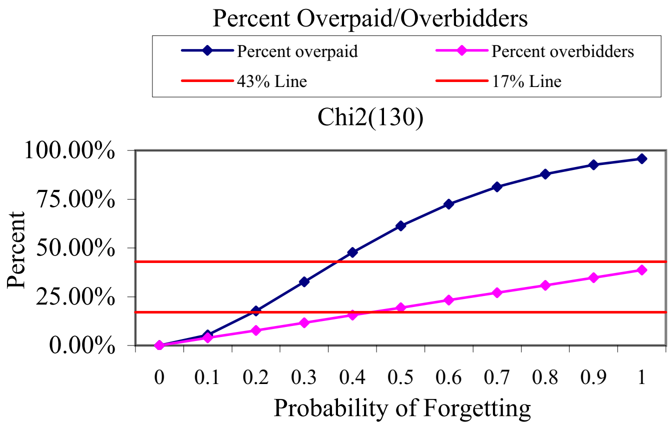
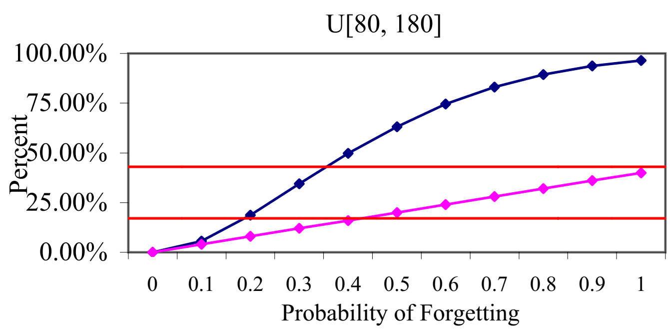


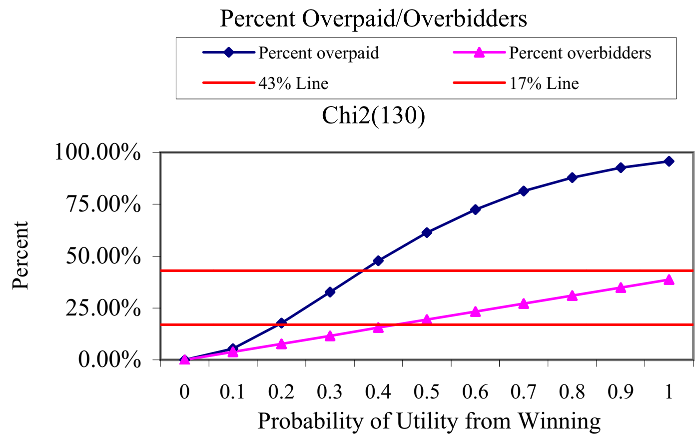
Figure IV. Calibrations

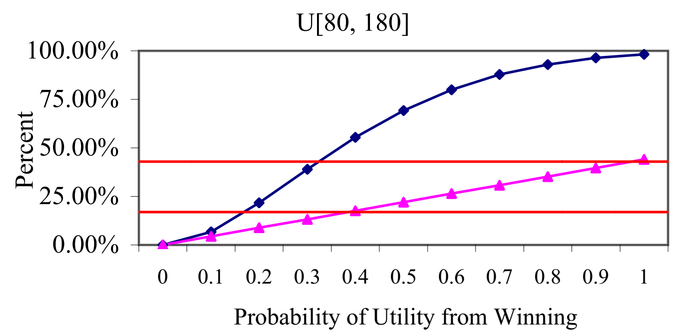
Limited Memory





Utility of Winning





Appendix - Table A.1 Overbidding and Quasi-endowment

Probit model where the binary dependent variable is 1 if the bidder ultimately overbids. In Column 1, we consider the sample of all bidders who have been lead bidder at some point and who have been outbid at some point. Column 2 restricts the sample of Column 1 to those bidders whose first bid was not an overbid. Column 3 restricts the sample of Column 1 to those bidders whose first bid that made the lead bidder was not an overbid. Total lead time is the total length of the times a bidder was lead bidder. We also control for the value of the bidder's last lead bid and the time and price outstanding when she is ultimately outbid. Coefficients are reported as marginal effects.

	(1)	(2)	(3)
Total lead time	0.123	0.161	0.139
	(0.220)	(0.207)	(0.201)
Value of last lead bid	0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)
Time of the last outbid	0.000	-0.001	0.000
	(0.004)	(0.004)	(0.004)
Price outstanding at the time of the last outbid	0.000	0.002	0.002
	(0.004)	(0.004)	(0.004)
N	784	742	732
Pseudo R-squared	0.2232	0.1889	0.1902

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 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	167	46.56	43.96	0.01	150
Final Price	167	131.95	16.84	81.00	179.30
Shipping Cost	140	12.51	3.81	4.95	20.00
Total Price	140	144.27	14.96	110.99	185.50
Number of Bids	167	16.84	9.21	1	39
Number of Bidders	138	8.41	3.84	1	18
Feedback Score Buyer	167	35.90	102.68	0	990
Feedback Score Seller	167	254.40	1427.83	0	14730
Positive Feedback Percentage Seller	167	61.35	48.52	0	100
Auction Length [in days]	167	6.27	1.69	1	10
one day	167	1.20%			
three days	167	11.38%			
five days	167	17.37%			
seven days	167	65.27%			
ten days	167	4.79%			
Auction Ending Weekday					
Monday	167	11.98%			
Tuesday	167	7.78%			
Wednesday	167	15.57%			
Thursday	167	11.98%			
Friday	167	9.58%			
Saturday	167	18.56%			
Sunday	167	24.55%			
Auction Starting Hour	167	14.84	5.21	0	23
Auction Ending Hour	167	14.84	5.21	0	23
Prime Time	167	33.53%			
Title New	167	16.77%			
Title Bonus Tapes/Video	167	27.54%			
Explicit195	167	31.14%			

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	2.03	1.76	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	0.14	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. The exact auction date is missing for one auction, reducing the sample to 166 (from 167 in Table I).

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

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

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

Table V. Disproportionate Influence of Overbidders

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

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

Table VI. Bidding and Limited Attention

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

Dependent variable: binary variable equal to 1 for items bid on (at a given time)								
			"Just above/below" = +/-$5			**"Just above/below" = +/-$10**		
	Full Sample		Full	First Bids	Later Bids	Full	First Bids	Later Bids
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to nearest BIN listing	1.176	1.106	1.021	1.061	0.995	1.025	1.056	1.006
[rows between]	[0.025]***	[0.029]***	[0.028]	[0.042]	[0.037]	[0.028]	[0.043]	[0.038]
(Price just below)*(Distance to BIN)			0.894	0.868	0.939	0.822	0.933	0.752
			[0.160]	[0.245]	[0.204]	[0.128]	[0.232]	[0.147]
(Price just above)*(Distance to BIN)			2.083	2.948	1.785	1.372	1.538	1.469
			[0.487]***	[0.911]***	[0.670]	[0.239]*	[0.324]**	[0.421]
(Price far above)*(Distance to BIN)			1.159	0.640	1.325	1.231	0.861	1.261
			[0.137]	[0.236]	[0.152]**	[0.118]**	[0.346]	[0.133]**
Price outstanding just below BIN price			1.164	1.326	1.164	1.205	0.835	1.799
[dummy]			[0.207]	[0.357]	[0.279]	[0.179]	[0.198]	[0.347]***
Price outstanding just above BIN price			1.747	0.966	2.920	1.861	1.027	3.255
[dummy]			[0.453]**	[0.381]	[1.004]***	[0.412]***	[0.345]	[0.992]***
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[dummy]			[0.449]***	[0.617]	[0.781]***	[0.729]***	[0.575]	[2.057]***
Position on screen	0.988	0.918	0.974	1.000	0.983	0.973	0.998	0.945
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Price outstanding		0.975	0.99	0.983	1.006	0.991	0.981	1.013
		[0.003]***	[0.003]***	[0.004]***	[0.005]	[0.003]***	[0.005]***	[0.005]**
$(\text{Price outstanding})^2$		1.002	0.989	0.988	0.983	0.988	0.991	0.977
		[0.002]	[0.003]***	[0.004]***	[0.004]***	[0.003]***	[0.004]**	[0.004]***
Starting price		0.994	0.994	0.998	0.99	0.994	0.998	0.991
		[0.001]***	[0.001]***	[0.001]**	[0.001]***	[0.001]***	[0.001]*	[0.001]***
Auction controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended time controls			Yes	Yes	Yes	Yes	Yes	Yes
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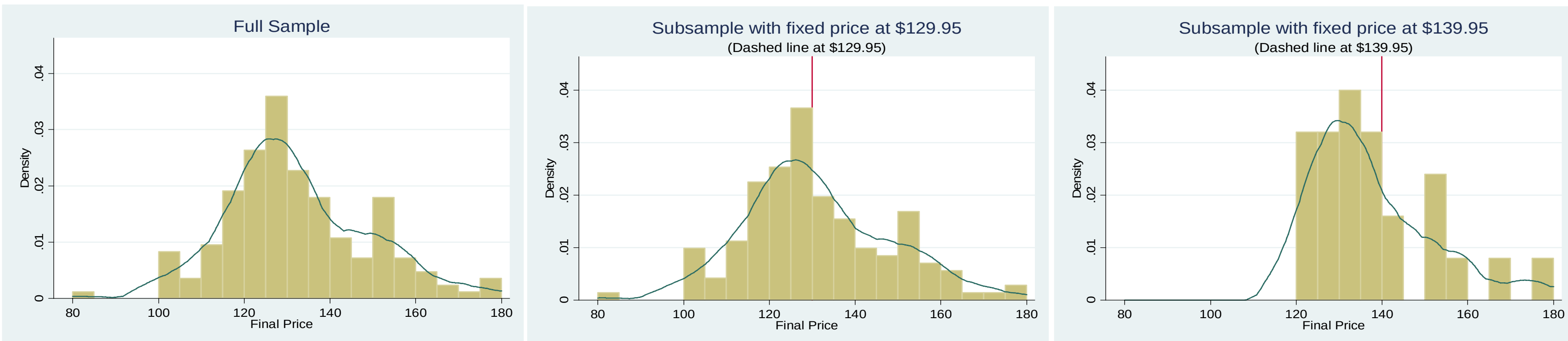

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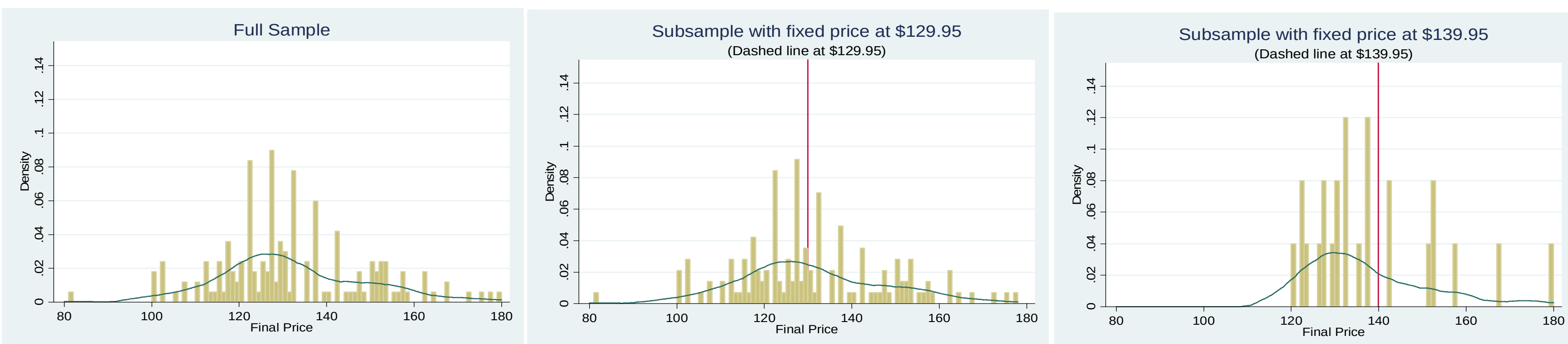

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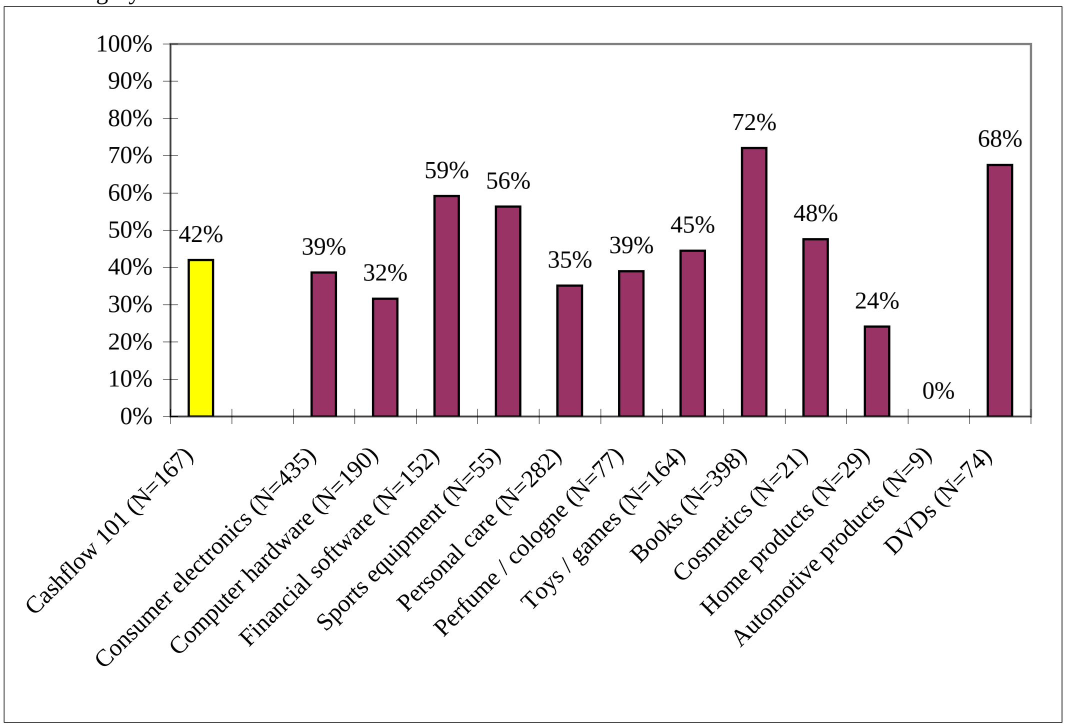

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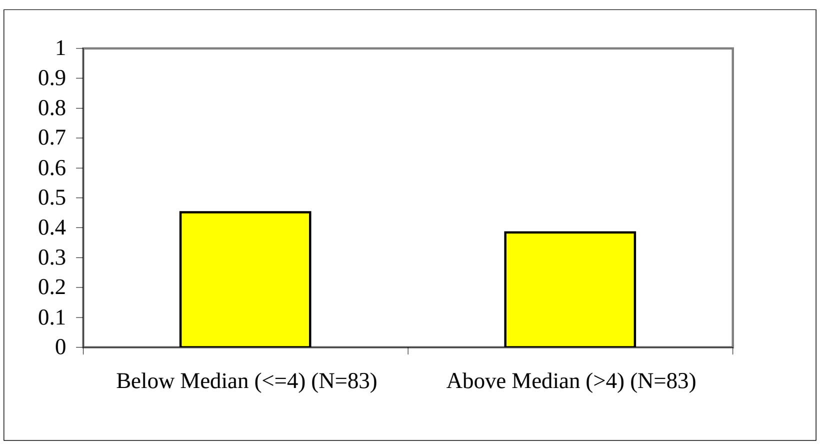

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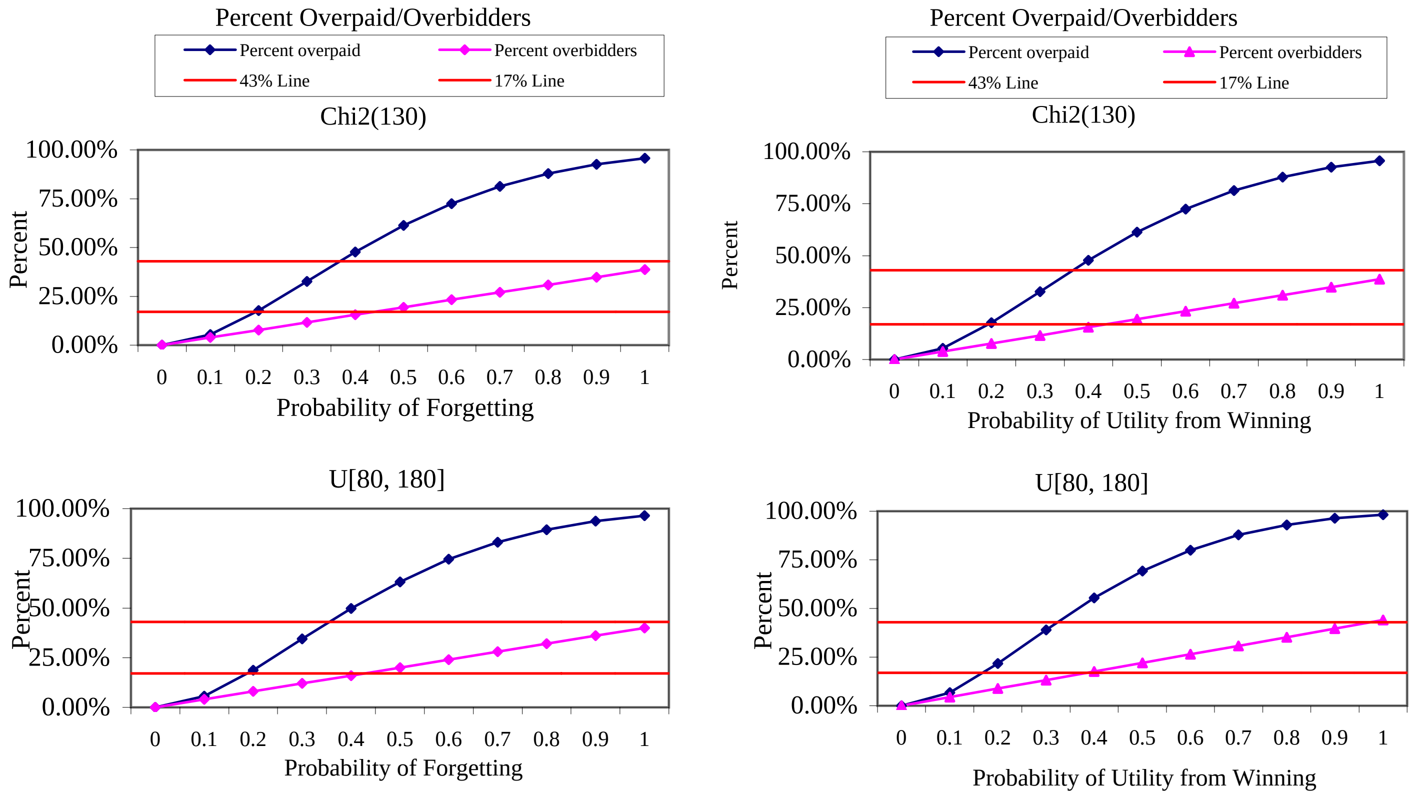
Utility of Winning



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Value of last lead bid	0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)
Time of the last outbid	0.000	-0.001	0.000
	(0.004)	(0.004)	(0.004)
Price outstanding at the time of the last outbid	0.000	0.002	0.002
	(0.004)	(0.004)	(0.004)
N	784	742	732
Pseudo R-squared	0.2232	0.1889	0.1902