Fishing for Fools*

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Abstract

How big is the effect of a few fools on market outcomes? We argue that in auctions, even a small share of overbidding behavioral agents have a large effect, because the auction format "fishes" for the highest-bidding behavioral buyers. Through this fishing mechanism, behavioral agents disproportionately increase auction profits. They also generate a large welfare loss by crowding out the demand of rational agents, who obtain the good with delay or not at all. The welfare effect of a few fools can be further amplified when the market mechanism is endogenous: even with a small share of behavioral agents, sellers may prefer inefficient auctions over efficient fixed-price markets. Evidence from eBay supports the existence of overbidding and confirms its amplified effect on allocation and profits. Sellers who adjust the details of auctions to exploit buyer inattention earn higher revenue. Our predictions about sellers' market choice match stylized facts on the use of auctions versus fixed-price markets.

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How large is the effect of behaviorally biased agents on market outcomes? The literature in behavioral economics and psychology has documented a number of systematic deviations from the standard economic model.[1] While the evidence that such deviations exist is hard to dispute, less is known about the extent to which behavioral biases affect economically relevant decisions and market outcomes (Camerer, 2006; Ellison, 2006). In markets, several forces operate that can reduce the impact of agents with behavioral biases. High-stake incentives and repeated transactions discipline deviations (Stigler, 1958; Becker, 1957). Opportunities to learn and sort reduce the impact of biases relative to their measurement in laboratory experiments (Levitt and List, 2007). Moreover, the impact of any remaining behavioral agents is likely to be small because market outcomes are determined primarily by the large mass of rational agents. These arguments suggest that behavioral biases may not be important for allocations and welfare in practice.

In this paper, we make two contributions to this discussion. First, we argue that there exist market mechanisms that amplify, rather than reduce, the effect of behavioral biases. Specifically, we show that in auction markets, even a small share of overbidding behavioral agents can have a large effect on allocation, profits and welfare because auctions select highest-bidding behavioral buyers as winners. Second, sellers will optimally choose, when available, market mechanisms that amplify the impact of behavioral types, to maximize profits by exploiting these agents. For example, even if only a small share of agents tend to overbid, sellers may endogenously shift to allocate goods through inefficient auctions rather than efficient fixed-price markets. This endogenous choice of market mechanism further amplifies the welfare effect of behavioral agents. As a result of these two mechanisms, behavioral biases can have substantial influence on market outcomes and welfare in some environments.

These observations also suggest a new explanation for the widespread use of auctions for allocating goods in practice. The economics literature links the success of the auction format to profit maximization and efficiency under incomplete information.[2] Auctions identify the bidder who values the good the most, and is thus willing to pay the highest price. Bidders may, however, be willing to pay a high price for reasons other than a high valuation. Such concerns about participants bidding "too much" are as old as auctions: In ancient Rome, legal scholars debated whether auctions were void if the winner was infected by *calor licitantis*, i.e., "bidder's heat."[3] As we document in Section 1, laboratory studies and field data provide evidence that auction participants sometimes bid too much, due to psychological mechanisms such as bidding fever, joy of winning, loss aversion, and inattention towards, or limited memory of, alternative purchase opportunities. For example, we show that a large fraction of eBay auctions end at a price above the fixed price at which the

[1] See the surveys by Rabin (1998) and DellaVigna (2008).
[2] See, e.g., Milgrom (1987).
[3] Corpus Iuris Civilis, D. 39,4,9 pr. See Malmendier (2002).

same item is available for purchase on the very same webpage at the same time. In the presence of such overbidding, the popularity of auctions may be explained in part by the additional profits generated from exploiting behavioral agents.

To explore these ideas formally, we develop a simple dynamic model where a population of agents bid in several rounds of second-price auctions. A small fraction of agents are subject to a behavioral bias which induces overbidding. We show that the impact of behavioral agents on profits is amplified: due to overbidding, a disproportionately large share of behavioral agents end up as high bidders. For example, if the behavioral bias affects each buyer with 10% probability, in an auction with 15 participants, the probability of having the two fools required for high profits in the second price auction is as high as 45%. Effectively, the auction allows sellers to "fish for fools" who are willing to pay too much. Having a sequence of auctions results in further amplification, by allowing the seller to "fish over time" for the occasional behavioral bias and overbidding. Due to these forces, even a small share of behavioral agents can have a large effect on profits.

What are the welfare implications of having behavioral agents in auctions? By paying a high price, behavioral agents simply redistribute wealth to sellers, without affecting efficiency. However, overbidding can substantially reduce welfare by creating misallocation. By bidding too high, behavioral agents with low true values can crowd out the demand of rational agents with high values. This effect on welfare is even more powerful than the effect on revenue, because it only requires one fool in the auction, to whom the object is inefficiently allocated. For example, in our model, if each of 15 auction participants experiences the overbidding bias with 10% probability, 79% of auctions are won by a behavioral agent. Even if only a quarter of these auctions result in misallocation, we still end up with about 20% of all objects allocated inefficiently.

The endogenous choice of price mechanism by the seller further amplifies these welfare effects. Our model predicts that the higher the share of behavioral agents, the more sellers prefer auctions over fixed-price markets. However, auctions can be less efficient. In each auction, there is only one winner, and many buyers obtain the good with delay or, if they exit the market, not at all. By choosing the high-profit auction environment, the seller thus creates efficiency losses associated with exit, delay, as well as misallocation, the magnitude of which can be larger than the share of behavioral agents who generated the shift in market mechanism.

Endogenous sorting of agents into different markets need not attenuate these effects. When auctions and fixed-price markets are both available, rational buyers will self-select to fixed-price markets, and hence behavioral agents may be over-represented in auctions even relative to their share in the general population, resulting in further amplification.

Sellers can also increase profits by fine-tuning the auction mechanism to particular behavioral biases, for example by choosing the auction format. We show that when biases affect agents' bids, the seller prefers the first-price auction over the second-price auction, because it requires only one fool per auction to create high profits. It follows that with behavioral agents, the famous revenue equivalence result no longer holds: the auction format can influence seller profits. In a similar fashion, sellers can also fine-tune details of the auction that would not affect revenue in a world with only rational buyers. If overbidding is due to limited attention, sellers can tailor the information provided to buyers to maximize inattention; if agents are subject to bidding fever, sellers may instigate this bias using salient messages informing the buyer that he has been outbid. These observations suggest that explicitly modelling behavioral biases can be useful for thinking about optimal auctions, and more generally, mechanism design.

How relevant are our theoretical findings for auction markets in practice? At the end of the paper, we document three pieces of evidence consistent with the predictions of the model. (1) We show in data from eBay that a small number of overbidding agents generate a large fraction of overbid auctions. While only 17% of buyers submit bids above the fixed price at which the good is also available, these bids result in irrationally high prices in 43% of all auctions. This magnitude of amplification exactly matches the quantitative predictions of our model, providing external validity to our theoretical framework. (2) We document new evidence about sellers' fine-tuning of auctions to cater to behavioral biases. Both the design of eBay's outbid messages and the referencing of *high* manufacturer prices are profit-increasing policies if overbidding occurs because of inattention or limited memory. We show that the only significant predictor of overpayment in our eBay data is whether the seller mentions the high manufacturer price in the item description. Drawing attention to this high price consistently increases overbidding by \$7−\$9, an effect primarily driven by experienced eBay participants. (3) We provide stylized evidence consistent with the prediction that auctions should be more common when the share of potential overbidders is higher. While we do not have an unambiguous proxy for the share of biased buyers, we show that auctions are more frequent for used, unique, antique or just "vague" objects such as art, coins, and other collectibles and memorabilia, which are perceptible to potential overestimates in values. In contrast, commodity-type goods with clear market prices such as cameras, cell phones, PDAs, consumer electronics, books or computers are items with the lowest relative auction frequency. We also discuss the extent to which these findings can be explained in a model with only rational agents.

Our findings relate to several strands of the prior literature. A body of work in auction theory shows that sellers may prefer auctions to fixed-price markets even in the absence of behavioral biases. Milgrom (1987) and Bulow and Klemperer (1996, 2008) develop models with rational agents that compare auctions to other allocation mechanisms; Bajari, McMillan and Tadelis (2002), Wang (1993), and Kultti (1999) combine theory with empirical work. While we believe that these rational mechanisms are important in practice, they are shut down in our stylized model to better focus on the effect of behavioral agents. As a result, in the absence of biases fixed-price markets are always at least as profitable as auctions in our model. There is also a large theoretical and empirical literature on the winner's curse in auctions, extensively discussed in Kagel and Levin (2002) and Bajari and Hortacsu (2003). Differently from the winner's curse, we consider overbidding that occurs even in private-value settings.

We also build on previous research in behavioral and experimental economics. We survey the empirical literature on overbidding in auctions in the next section. In the theoretical literature, Eyster and Rabin (2005) and Crawford and Iriberri (2007) develop belief-based models for overbidding in common- and private-value settings, but do not study the amplification effects that we focus on. Also related is the work in behavioral finance, including DeLong, Shleifer, Summers, and Waldmann (1990) and Hong and Stein (1999), who study the effect of behavioral traders on asset prices. Unlike in the auctions we consider, these papers find that in financial markets, the impact of behavioral agents is proportional to their numbers.

Finally, our paper is a contribution to the literature in behavioral industrial organization. DellaVigna and Malmendier (2004), Gabaix and Laibson (2006), and Grubb (2008) study firms' response to consumer biases in their design of contracts and pricing. Differently from this work, we emphasize that even a small share of behavioral consumers can have large effects on profits and welfare through sellers' endogenous choice of market mechanism.

The rest of the paper is organized as follows. We present motivating evidence on overbidding in auctions in Section 1. In Section 2, we develop a model of dynamic auctions, and in Section 3 we study the seller's choice of market mechanism. Section 4 discusses empirical facts consistent with the predictions of our model, and Section 5 concludes. All proofs are presented in the Appendix.

1 Motivating Evidence

Our theoretical analysis rests on the assumption that auction participants sometimes overbid, i.e., are willing to pay more than their true valuation. A body of empirical work in economics has raised the possibility of overbidding in settings as diverse as bidding for free agents in baseball (Blecherman and Camerer, 1996), drafts in football (Massey and Thaler, 2006), auctions of collateralized mortgage obligations (Bernardo and Cornell, 1997), auctions of initial public offerings (Sherman and Jagannathan, 2006), real estate auctions (Ashenfelter and Genesove, 1992), the British spectrum auctions (Klemperer, 2002) and contested mergers (Hietala, Kaplan, and Robinson, 2003; Malmendier and Moretti, 2006). The central difficulty in these field settings has been to prove that a bidder paid "too much" given the value of the object.[4] We now turn to discuss, in more detail,

[4] For example, Ku, Malhotra, and Murninghan (2005) rely on the discrepancy between initial estimates and final prices and on survey evidence to argue that bidders displayed bidding fever in live auctions.

some evidence where the identification of overbidding is explicitly addressed.

Experimental evidence. Laboratory experiments, where valuations can be assigned randomly to subjects, allow clean and precise measurement of overbidding in auctions. The consensus finding in the literature seems to be that there is sizeable overbidding in second-price auctions, which does not disappear over time. For example, as much a 62% of bidders overbid in the experiment of Kagel and Levin (1993). In Cooper and Fang (2008), the share of overbidders is even higher at 76%.[5] The evidence on first-price auctions is less clear: while some studies find overbidding, this may also reflect risk-aversion; and overbidding seems to disappear over time.[6]

The clean measurement of overbidding in laboratory experiments comes at a cost of external validity. Induced-value auctions are unlikely to generate the same excitement in bidders as auctions for items they are actually interested in; and some potential explanations for overbidding, such as limited attention, are excluded in the laboratory set-up. Evidence from the field on overbidding is helpful in addressing these concerns.

Field evidence from eBay. We now introduce and discuss field evidence from eBay, first presented in Lee and Malmendier (2008), where a simultaneously available fixed-price market on the auction website helps the identification of overbidding.[7] The core data set contains all eBay auctions of a popular educational board game, Cashflow 101, during a seven month period in 2004.[8] During this time, two retailers continuously sold brand new games at a price of \$129.95 (since August, \$139.95) through eBay, and their fixed-price (buy-it-now, or BIN) listings were shown together with the auctions on the regular output screen for Cashflow 101. Given the availability of the game at this fixed-price throughout the auctions, rational eBay participants should never submit bids exceeding the fixed price. Thus the number of agents who bid above the simultaneous fixed price can be used as a conservative measure of overbidding, which may exclude some behavioral buyers who bid above their value but below the fixed price.

Table I provides summary statistics of these data. The sample consists of 166 listings with 2,353 bids by 807 different bidders. The average final price is \$132.55. The average auction attracts 17 bids, including rebids of users who have been outbid, and the average number of auction participants is 8.4. Items are always brand new in the BIN listings; for the auctions, 10.8% of the listing titles indicate prior use with the words "mint," "used," or "like new." About 28% of the titles imply that

[5] See also the work of Kagel, Harstad, and Levin (1987) and Harstad (2000).

[6] See Cox, Roberson, and Smith (1982), Cox, Smith, and Walker (1988), and Goeree, Holt, and Palfrey (2002). Kagel, Harstad, and Levin (1987) argue that the difference in information flows between the two auction formats can explain why overbidding does not disappear in second price auctions.

[7] This identification strategy is related to Ariely and Simonson (2003) who compare auction prices and retail prices on other online sites, and Ashenfelter and Genesove (1992) who compare prices in real estate auctions and in face-to-face negotiations.

[8] The exact time period is 2/11/2004 to 9/6/2004. Data is missing on the days from 7/16/2004 to 7/24/2004 since eBay changed the data format. Two 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) were also dropped.

standard bonus tapes or videos are included; the professional retailers always include both extras. Thus, the goods auctioned on eBay are, if anything, of somewhat lower quality than those sold on eBay by the fixed-price retailers.

The main result from this data is that 43% of auctions end up at prices above the simultaneously available fixed price. This result is *not* due to differences in shipping costs: if those differences are also accounted for, 73% of auctions end above the fixed price. Simple regressions show that overbidding is not explained by differences in item quality or seller reputation. The amount of overbidding is significant: 27% of auctions exceed the fixed price by more than $10, and 16% by more than $20. Even the average auction price exceeds the fixed price, which helps rule out rational explanations based on switching costs, since a rational buyer only enters the auction if the expected price is below the fixed price.

Do these results extend to other goods besides board games? Figure 1 addresses this question using a second, broader data set that contains a cross-section of 1,929 different auctions, ranging from electronics to sports equipment, detailed in Lee and Malmendier (2008). The figure shows the proportion of overbid auctions by item category, with Cashflow 101 depicted as the baseline on the left. Cashflow 101 is not an outlier: the figure shows that overbidding in auctions is common across a wide variety of goods, with the proportion of overbid auctions ranging between 30% and 60% for most categories.

Sources of overbidding. Why do people overbid? The eBay data suggests that for online auctions, limited attention is part of the explanation. Lee and Malmendier (2008) report that greater distance between auction and fixed-price listings on the eBay output screen predicts higher probability of bidding in the auction, consistent with limited attention to alternative prices. Other potential explanations include spite motives, joy of winning, fear of losing, bidding fever, or bounded rationality, several of which have been tested in the laboratory (Cooper and Fang, 2008, Morgan, Steiglitz, and Reis, 2003; Delgado, Schotter, Ozbay, and Phelps, 2007).

To summarize, data from both experiments and the field support the view that a non-negligible share of agents overbid in auctions. We now turn to develop a framework to study the allocative, revenue and welfare implications of such overbidding. Our basic model is agnostic about the source of overbidding, although we will sometimes invoke arguments related to limited attention, where bidders ignore alternative purchase opportunities. In some applications we discuss the implications of different psychological mechanisms in more detail.

2 A Model of Auctions with Behavioral Agents

We consider auctions that allocate a single good to the winner of the auction. In order to increase the probability of a successful purchase, prospective buyers might bid in multiple auctions for the same good. For example, auction houses often run sequences of auctions on similar items, and on eBay, bidders often participate in a number of auctions for the same good until they either win or decide to move on. We formalize bidding in multiple auctions following Satterthwaite and Shneyerov (2007). We develop a dynamic framework where, in each period, a population of buyers participate in (static) auctions, and those failing to win stay for another round with positive probability.

2.1 Buyer Values and Behavioral Bias

We model the pool of prospective buyers as a large population by assuming that each period a unit mass of new agents enter the market.[9] To abstract away from standard asymmetric information-based arguments for the efficiency of auctions, we assume that the true value of every buyer i in every period t is the same constant X. We allow for a subset of agents who depart from full rationality and overestimate the value of the item by $Y - X > 0$. This simple reduced-form definition of a behavioral bias can represent several alternative psychological foundations of overbidding, including those discussed in Section 1. Consistent with the empirical findings about inattention, we also assume that behavioral agents, while bidding in an auction, fail to account for alternative prices at which they could purchase the same good, i.e., the option of participating in future auctions. This behavior could be rationalized either by limited attention, or by the bidder narrowly framing the particular auction environment.

We consider biases affecting buyers in two different ways. First, a share π_P of new entrants in each period are permanently affected. These bidders continue to overvalue the good in each auction that they participate in. One interpretation of this permanent bias is that it is a personality type – certain agents are by nature subject to overbidding via any of the mechanisms discussed above. Second, we assume that with independent probability π_T, each agent in the population can be temporarily affected by overbidding bias in each period. This temporary bias can be interpreted as a reaction to features of the environment, such as the competitiveness of the auction.

We assume that both rational and behavioral buyers know the distribution of opponents' equilibrium bidding behavior. This assumption captures the idea that agents may have seen or had experience with auctions in the past. However, rational agents are not aware of the fact that, with some probability, they may be subject to a behavioral bias. They believe that their current rational state will continue in the future. Thus, the key differences between behavioral and rational agents lie in their perceived values and their ability to account for future purchase opportunities.

Perturbations. To ensure that truthful bidding in the second-price auction is a strictly dominant strategy, we make the technical assumption that the actual values of both rational and behavioral agents are subject to small idiosyncratic shocks. Formally, the value of an agent i in period t is

[9] The continuum formulation allows us to use the law of large numbers.

given by $X + \varepsilon_t^i$, where ε_t^i is a mean zero random variable, independent across buyers and periods, with an absolutely continuous distribution, support $[-\overline{\varepsilon}, \infty)$, and standard deviation $\sigma_\varepsilon < \overline{\varepsilon}$ for some small $\overline{\varepsilon}$. This perturbation simply makes the distribution of values continuous, ruling out non-truthful best responses. Throughout the analysis, we assume that $\overline{\varepsilon}$ is much smaller than all payoff-relevant quantities; thus the perturbation is so small that it can safely be ignored for all computations. In order to focus on intuition, we do not explicitly incorporate the perturbation in notation in the main text, but we do treat it rigorously in the Appendix. Thus all subsequent expressions in the text should be interpreted modulo a small perturbation.

2.2 A Dynamic Auction

We assume that all agents in the marketplace participate in auctions each period. Each auction has n participants and a single winner, who is the highest bidder.[10] For most of the analysis, we assume that all auctions are second-price auctions; we discuss different auction formats later. Bidders' discount factor is δ, and losers stay in the market with probability λ.

Buyers determine their optimal bidding strategy taking into account their continuation values. Rational types know that everybody else has a valuation at least as high as theirs, and hence have zero continuation value. Behavioral agents only focus on the current auction, and therefore effectively behave as if they had zero continuation value. Given the second-price auction structure, it follows that all agents bid their perceived values for the good each period.[11]

Characterizing the steady state. We begin the analysis by characterizing the steady state of this dynamic auction environment. Because there are n bidders per auction, a share $1/n$ of all agents leave the marketplace each period after winning the good. Of the remaining share $1 - 1/n$, a proportion λ stay in the auction for another round, and a proportion $1 - \lambda$ exit for exogenous reasons. As a result, the total share of agents leaving the auction in a given period is $1/n + (1 - 1/n)(1 - \lambda)$. Denote the the steady-state population size by N, where N is measured in multiples of the per-period inflow of people. Then the mass of people leaving the auction in any given period is $N \cdot (1/n + (1 - 1/n)(1 - \lambda))$. Since this mass of outflow must equal the unit mass of inflow in the steady state, we obtain

$$N = \frac{n}{1 + (n-1)(1-\lambda)}. \tag{1}$$

The total mass of auctions per period is N/n, which is the total mass of agents divided by the number of people in an auction. Equation (1) implies that $N/n \leq 1$, i.e., the total mass of auction

[10] Due to the small perturbations, ties are zero-probability events. In the event when a tie does occur, we assume that the good is randomly allocated among the highest bidders.

[11] Formally, the continuation values of all rational agents are identical and of the order $\overline{\varepsilon}$, which measures the size of the perturbation.

winners per period is less than or equal to one. The closer this ratio is to one, the more buyers successfully obtain the good in a given period.

What fraction of agents are subject to behavioral bias in any given period in the steady state? We denote this fraction by π^*, and let π_P^* and π_T^* denote the steady-state shares of agents experiencing permanent and temporary behavioral bias, so that $\pi^* = \pi_P^* + \pi_T^*$ holds.[12] These quantities are endogenously determined in the steady state, accounting for the fact that permanent behavioral agents, by winning auctions, exit at a higher frequency than rational buyers.

Lemma 1 *[Steady state of dynamic auction]*

(i) π_P^*, π_T^* and π^* are uniquely determined in the steady state.

(ii) When π_P and π_T are small, to a first order approximation $\pi_P^* \approx \pi_P/N$ and $\pi_T^* \approx \pi_T$, and consequently $\pi^* \approx \pi_P/N + \pi_T$.

(iii) π^* is a monotone increasing function of both π_P and π_T, and satisfies $\pi_T \leq \pi^*$ and $\pi_P/N < \pi_P^*$.

Part (i) just states that the share of behavioral agents of different types are well defined measures. According to (ii), for small frequencies of bias, the effect of the temporary bias on the steady-state share of behavioral bidders is N times as large as the effect of the permanent bias. The intuition is straightforward. The permanent bias affects a fixed mass of agents, and consequently it gets diluted in a large population of size N. In contrast, the temporary bias affects each agent with a fixed probability in the current period, and hence the share of buyers experiencing it does not depend on the population size. Part (iii) extends the characterization of π^* for arbitrary levels of bias. To understand the inequalities, first note that $\pi^* \geq \pi_T$ holds because each agent has a behavioral bias with at least probability π_T. On the other hand, each period a mass of π_P new permanent types enter into a population of total mass N; it follows that the share of permanently biased agents is at least π_P/N.

2.3 Allocation and Profit

To analyze outcomes in the dynamic auction, we first specify the supply of goods. We assume that the marginal cost of each unit of the good is $0 \leq c < X$. We explore two specifications for the supply of goods. The first, which we call the monopolistic-seller environment, assumes that the good can only be provided by a single seller in the economy, who can produce any number of goods at a marginal cost of c. This setup captures some features of large auction houses, who represent a significant share of the market, sell regularly and can easily adjust the volume of sales.

[12] We assume that an agent experiencing permanent bias is never subject to temporary bias.

In the second specification, which we call the small-seller environment, each period there is a mass of S sellers, who each have a single unit of the good that they desire to sell. This specification may be a better description of online auctions like eBay, where many sellers have only a limited supply of the good. With this formulation, market clearing requires that each period, the demand and supply of goods is equal, i.e., $N/n = S$. In equilibrium, the number of bidders per auction n adjusts to satisfy this condition.[13]

We now turn to study the impact of behavioral biases on outcomes. Throughout the analysis, we denote with $q_k^n(\pi)$ the probability that at least k out of n independent coin-flips are heads, when the probability of heads for each coin-flip is π. If γ^* denotes the proportion of auctions where the seller earns high revenue Y, which we refer to as "overbid" auctions, then it is easy to see that $\gamma^* = q_2^n(\pi^*)$: we need at least two "fools" in a pool of n agents to have the second-highest bid equal to Y, and the probability of this event is given by $q_2^n(\pi^*)$. We also introduce γ_P^*, the share of "overbid" auctions where the winner is a permanent behavioral type and γ_T^*, the share of overbid auctions where the winner has a temporary bias.

Proposition 1 *[Allocation and profits]*

(i) The expected total per-period profit in the steady state of the dynamic auction is

$$\text{Total profit} = \frac{N}{n} \cdot (X - c) + \frac{N}{n} \cdot \gamma^* \cdot (Y - X). \tag{2}$$

(ii) If $\pi_T > 0$, then as $n \to \infty$, we have $\gamma^* \to 1$, that is, the share of "overbid" auctions converges to 1. If $\pi_T = 0$ but $\pi_P > 0$, then as $n \to \infty$, we have $\gamma^*/\pi^* \to \infty$, i.e., the ratio between the share of "overbid" auctions and the share of behavioral agents goes to infinity.

(iii) When π_T and π_P are small, we have, to a second-order approximation,

$$\frac{\gamma_T^*}{\pi_T} \approx N \cdot \frac{\gamma_P^*}{\pi_P}$$

so that the temporary bias is N times as powerful as the permanent bias.

This result characterizes revenue and allocation in auctions and identifies the "fishing effect" by which a small share of behavioral types can have a large effect on outcomes. The intuition for the per-period revenue (2) is as follows. The first term represents the "baseline" profit of $X - c$ earned from the mass of N/n agents who obtain the good in the current period. The second term in (2) captures what we call the "fishing" profit from the auction. This term represents the additional revenue obtained from auctions where the price is bid up to Y; and hence is proportional to $Y - X$,

[13] We ignore the constraint that n must be an integer for simplicity. Integer constraints could be incorporated with additional notation by assuming that some auctions have n and some have $n - 1$ participants, and the share of these auctions is determined so that the market clears.

the excess bid of behavioral types; N/n, the number of auctions; and γ^*, the share of auctions with at least two fools where the price is overbid.

Part (ii) in the Proposition formalizes the idea that the impact of behavioral traders can be much larger than their steady-state share in the population. One way of measuring this impact is with γ^*/π^*, i.e., the ratio between the share of "overbid" auctions and the share of behavioral agents. For any $\pi_T > 0$, when the size of auctions is large, almost all auctions generate high revenue Y, so that $\gamma^* \to 1$. The intuition is straightforward: given that $\pi^* \geq \pi_T$, the probability of behavioral types is bounded away from zero; it follows that when n is large enough, with high probability there are at least two fools among a pool of n bidders. As a result, behavioral types can have a disproportionately large effect on outcomes: even if π_T is small, they can create high revenue in almost all auctions, and in particular, the ratio γ^*/π^* can be arbitrarily large. In the case where $\pi_T = 0$, i.e., when there are only permanent behavioral types, it is no longer true that almost all auctions are overbid, because as n increases, the steady-state population N also increases, and hence the fixed number of permanent behavioral types gets diluted and π^* approaches zero. However, the fishing mechanism still operates, and hence the impact of behavioral traders continues to be much larger than their steady-state share.

The amplification mechanism is also illustrated in Figure 2A. The heavy line plots the probability that there are at least two fools in the auction, i.e. γ^*, as a function of n, under the assumption that the steady-state share of bias π^* is held fixed at 10%. For n small, the impact of 10% of fools on profits is negligible: for example, with $n = 4$, the probability of two fools in the auction is only 5.2%. However, this probability increases rapidly in n; with 15 participants in the auction, the probability of having two fools and hence generating high profits is 45%. While the figure plots γ^* only up to $n = 20$, we know from (ii) above that as n increases further, γ^* will converge to 100%. Figure 2B provides an alternative way of illustrating the amplification mechanism. Here the heavy line plots the probability of two fools γ^* as a function of the share of fools π^*, when the size of the auction is held fixed at $n = 10$. The probability of having two fools increases quickly: with only 20% of fools in the general population, the share of overbid auctions with at least two fools is 62%. Figure 2 thus confirms the intuition that even a few biased agents can have a large effect on profits.

Part (iii) of the Proposition quantifies the relative strength of the temporary and permanent biases in fishing for fools. To a first order approximation, a one percentage point increase in π_T is equivalent to a N percentage point increase in π_P in increasing the share of overbid auctions. The intuition for this result is that the temporary bias allows for "intertemporal fishing." Consider a unit mass of people entering at a given point in time. Each period, only a share π_T of these people experience the behavioral bias; but they stay in the marketplace for an average of N periods, and may experience the bias in each of these periods, amplifying the revenue generated. By keeping these agents in the marketplace for an extended time period, the dynamic auction maximizes the probability that they experience overbidding at some point in time.

2.4 Welfare

How do behavioral agents affect welfare in the dynamic auction? In the basic setup we have analyzed so far, there are two potential sources of inefficiency: some bidders may not obtain the good due to attrition, and bidders obtain the good with delay. A third potential source of inefficiency that we have not yet introduced is misallocation of goods: some behavioral buyers with low true values might crowd out the demand of rational buyers with higher values. Such concerns about misallocation due to overbidding are sometimes discussed in the empirical literature on auctions. For example, in the context of the FCC spectrum auctions, Fritts (1999) argues that in the C block auctions which were targeted at small firms, bidding frenzy ensued and likely resulted in misallocation.

To introduce this misallocation effect in a simple way, we assume that each period, a share α of behavioral agents have true value $X_L < X$ for the good being auctioned, but their perceived value and bid continues to be Y. This assumption can be justified by allowing for two, slightly different types of goods in the market, and assuming that a mass of agents have true value X for the first type and true value X_L for the second type, another mass of agents have the opposite valuation, and a third mass value both goods at X. Rational buyers self-select into the auctions where the good they have a high value for is being sold. However, agents experiencing a behavioral bias in the current period may make a mistake: with probability α they enter the auction for a good that they have a low value for.

Under this modification, allocation and profits are unaffected, and hence the results in Proposition 1 remain unchanged. However, auctions now generate misallocation which results in an efficiency loss. Each time a behavioral agent buys a good for which he has low valuation X_L, efficiency could be improved by re-allocating the same good to some agent who is currently exiting the marketplace and values the good at X. The welfare gain from this re-allocation of goods is $X - X_L$, the difference in values between the rational and the behavioral agent.

To measure aggregate inefficiency, we define the proportional welfare loss (PWL) in the auction to be the welfare loss relative to the total surplus that can be generated by the inflow of new entrants in our economy, respecting the supply constraint. In the monopolistic-seller environment, this total surplus is just $X - c$, because there is a unit mass of incoming agents who need to be supplied one unit of the good each. In the small-seller environment, the total surplus is reduced to $S(X - c)$, because the total supply of available goods is only $S < 1$.

Before characterizing welfare, we introduce some additional notation. Let $\overline{\gamma}^* = q_1^n(\pi^*)$ denote the probability that an auction is won by a behavioral agent. Note that $\overline{\gamma}^* > \gamma^*$ because γ^* is the probability that there are at least two fools, while $\overline{\gamma}^*$ is the probability of at least one fool. By our assumptions, a share $\alpha\overline{\gamma}^*$ of all auctions generate a welfare loss from crowding out, because a low-value agent experiencing bias ends up purchasing the good.

Proposition 2 *[Welfare]*

(i) In the large seller environment, the proportional welfare loss when $\delta = 1$ is

$$PWL = \left[1 - \frac{N}{n}\right] + \frac{N}{n} \cdot \frac{X - X_L}{X - c} \cdot \alpha \cdot \overline{\gamma}^*, \tag{3}$$

where the first term measures exit and the second term measures misallocation. In the small-seller environment with $\delta = 1$,

$$PWL = \frac{X - X_L}{X - c} \cdot \alpha \cdot \overline{\gamma}^* \tag{4}$$

which is the welfare loss of misallocation.

(ii) If $\pi_T > 0$, then as $n \to \infty$, we have $\overline{\gamma}^* \to 1$ and hence the share of inefficiently allocating auctions converges to the constant α for any $\pi_T > 0$. If $\pi_T = 0$ but $\pi_P > 0$, then as $n \to \infty$, we have $\overline{\gamma}^*/\pi^* \to \infty$, i.e., the ratio between the share of inefficiently allocating auctions and the share of behavioral agents goes to infinity.

(iii) When π_P and π_T are small, to a first order approximation

$$\overline{\gamma}^* \approx n\pi^* \approx n\left(\pi_T + \frac{\pi_P}{N}\right),$$

in particular, the impact of behavioral types is magnified by n relative to their population share.

(iv) The welfare loss is increasing in impatience $(1/\delta)$.

When $\delta = 1$, the welfare loss in the monopolistic-seller environment is the sum of two terms given in equation (3). The first term measures the efficiency loss from attrition, i.e., the exit of some consumers who could have obtained the good in the first-best allocation. This term is simply $1 - N/n$, because this is the mass of agents who exit each period without winning the good. The second term in (3) captures the efficiency cost of misallocation, which is the result of low-value behavioral agents outbidding high-value rational buyers. This term is proportional to N/n, i.e., the mass of auctions this period where misallocation may occur. The term is also proportional to $(X - X_L) / (X - c)$, which is the percentage welfare loss associated with each sale of the good to a low type behavioral agent; and to $\alpha\overline{\gamma}^*$, which is the share of auctions that generate a welfare loss from crowding out. In the small-seller environment, there is no welfare loss from attrition, because the entire supply S of goods is being auctioned off; hence with $\delta = 1$ the only welfare cost of the auction is misallocation.

Part (ii) establishes an amplification result for welfare: even a small share of behavioral types can generate a large welfare loss through misallocation. This result is analogous to part (ii) in Proposition 1, but focuses on welfare rather than profits. Note that to create a welfare loss, it is sufficient to have one fool in the auction, to whom the good is inefficiently allocated; while to generate high revenue, two fools are necessary. It follows that the welfare loss created by fools is potentially much larger than the revenue gain for the seller.

The theoretical results about amplification in welfare are also confirmed in Figure 2a, where the dashed line plots the probability of having at least one fool, i.e., $\overline{\gamma}^*$, as a function of the auction size n, when $\pi^* = 10\%$. The probability of at least one fool increases considerably faster than the probability of two fools: for example, with $n = 15$, there is a 79% probability that a behavioral agent wins the auction. This rapid growth in $\overline{\gamma}^*$ provides for a large potential scope for misallocation, even when α is small. A similar picture emerges from Figure 2b which plots $\overline{\gamma}^*$ as a function of the share of bias π^* when $n = 10$. Even when only 20% of agents are subject to bias, 89% of auctions are won by them! If only $\alpha = 1/3$ of these cases result in misallocation, we still have about 30% of all goods allocated inefficiently. It follows that the presence of behavioral agents can potentially generate large inefficiencies through misallocation.

Part (iii) quantifies the amplification for small values of the bias parameters, by showing that the share of auctions won by behavioral agents is approximately n times the share of these agents. This result is a good approximation when π^* is of smaller order than $1/n$, and is analogous to the amplification illustrated in Figure 2. Finally, part (iv) simply shows that with impatient buyers, welfare is further reduced, simply because some agents obtain the good that they desire with delay.

3 Sellers' Choice of Market Mechanism

3.1 Auctions and Fixed-Price Markets

We now explore sellers' choice of auctions versus fixed-price markets. In the monopolistic-seller environment, we model markets by assuming that the seller sets a price p and serves all customers willing to pay this amount. We assume that buyers enter the market, decide whether to purchase the object, and afterwards leave. Thus, the total number of potential sales per period is equal to the unit mass of new customers. In the small-seller environment, we assume that each seller meets a random buyer, and can individually set a price, at which the buyer may or may not buy.

Do behavioral biases operate in markets with a fixed price? The answer depends on the source of the bias. If people overbid in auctions because of bidding fever, it is less likely that they overvalue objects for which there is a fixed-price market. However, if overbidding is the result of loss aversion, then we might expect the same mechanism to operate in fixed-price markets as well. To allow for both of these possibilities, we assume that the probability of bias in the fixed-price market is reduced by a factor $\beta \in [0,1]$, where $\beta = 1$ means no reduction and $\beta = 0$ corresponds to zero bias in the fixed-price market.

What price should sellers charge in the fixed-price market? When the frequency of bias is small, the natural choice of fixed price is $p = X$, which is the valuation of rational agents. With a high share of behavioral buyers, another potential alternative is to charge $p = Y$; this price takes all surplus from the behavioral buyers, but is too high for rational types to make purchases. It is never optimal to charge any price between X and Y, because this avoids selling to rational types but does not take all the surplus from behavioral buyers. Denote the share of behavioral buyers in the entering unit mass of population of any period by $\pi = \pi_P + (1 - \pi_P)\,\pi_T$. Then the high fixed-price market generates a revenue of $\beta\pi Y$ each period, while the low fixed-price market generates a revenue of X because it sells to all prospective buyers. It follows that the low price market is better for the seller if $\pi < X/(\beta Y)$. Given that we are interested in the seller's market choice when the frequency of behavioral bias is small, in the following we assume that this inequality holds, i.e.,

Assumption 1. $\pi_P + (1 - \pi_P)\,\pi_T < X/(\beta Y)$.

Under this condition the high fixed-price market is never optimal. We later discuss qualitatively what happens when this assumption is relaxed.

Market choice. In the monopolistic-seller environment, we assume that the seller compares long-term profits in the steady states of the respective market forms, and hence we ignore transitional dynamics. This assumption can be justified by the seller being sufficiently patient. In the small-seller environment, we assume that each seller can either run a separate auction with n participants, or choose to sell at a fix price. For both of these environments, we characterize the optimal choice of the seller as a function of π^*, the steady-state share of behavioral types that obtains of all trade takes place through auctions. While π^* is an endogenous quantity, we have seen that it is a monotone function of our primitives π_T and π_P; as a result, our characterization can easily be rephrased in terms of exogenous quantities only. We choose to characterize the optimal policy using π^* because this is the true payoff-relevant quantity both for the large seller and for the marginal small seller, and both treat it as exogenous.

Proposition 3 *[Sellers' choice of market mechanism]*

(i) In the small-seller environment, if $\pi^* > 0$ than all sellers choose the auction.

(ii) In the monopolistic-seller environment, for λ high enough, there exists a threshold $\underline{\pi}^*$ such that when $\pi^* < \underline{\pi}^*$ the seller chooses the fixed-price market; and when $\underline{\pi}^* < \pi^*$, the seller chooses the auction. Moreover, as $\lambda \to 1$ we have $\underline{\pi}^* \to 0$.

In the small-seller environment, even with an arbitrarily small share of behavioral buyers, each seller prefers the auction over the market. Intuitively, under Assumption 1 the highest price the seller can obtain in the market is X, while in the auction he gets at least X, but possibly more if there are at least two fools among the bidders. Due to this higher revenue, all S sellers choose to auction their goods. This finding demonstrates our basic argument that even a few fools can have a large effect of market structure.[14]

The optimal market choice is somewhat different with the monopolistic seller, because he can adjust the quantity of goods supplied. In particular, the monopolistic seller may be able to sell a larger quantity in the fixed-price market than in the dynamic auction, where some agents leave due to attrition.[15] Due to the trade-off between larger quantity in the fixed-price market and higher average price in the auction, the optimal choice of the large seller depends on the steady-state share of behavioral types. For low levels of bias, the fixed price is environment is better because it sells the good to all prospective buyers, while in the auction there is some attrition as losers exit the market. But as π^* increases, the auction becomes more attractive: selling at a high price to some behavioral types compensates for the loss of some customers due to attrition. We need λ high for the auction to be successful, because otherwise attrition is too large to make the auction worthwhile: for λ close to zero, losing bidders are unlikely to stay for another round of auction, and hence attrition is too big to make the auction worthwhile for the large seller. As $\lambda \to 1$, we have diminishing attrition, and hence even a tiny share of biased agents makes the auction more profitable, explaining why the threshold $\underline{\pi}^*$ converges to zero.

Figure 3 illustrates the choice of market mechanism for the monopolistic seller as a function of π_T and π_P. The construction of this figure assumes that each auction has 10 participants, and λ is set such that the auction sells 10% fewer goods than the market.[16] We also assume that the relative profit gain from selling in an overbid auction is $(Y - X) / (X - c) = 100\%$; this could obtain for example if the true value of the good is $X = \$100$, the marginal cost of production is $c = \$90$, and behavioral types overbid by $Y - X = \$10$. For completeness, the high fixed-price market is also included in the figure, under the assumption that $\beta = 1$, i.e., that the same bias operates both in auctions and markets.

In the Figure, the region surrounded by the heavy solid curve describes the set of bias levels where the auction is optimal. Auctions are the dominant market form for a wide range of parameters. In this numerical example, the threshold level of bias at which the auction starts to

[14] The Proposition assumes that the fixed costs associated with setting up the auction and the market are identical. If setting up the auction is more expensive, then sellers will choose the market when the share of behavioral agents is sufficiently small; but as π^* increases, they will switch to the auction.

[15] This consideration about the volume of sales is absent in the small seller environment, both because small sellers do not take into account their effect on market outcomes, and because the total supply of goods is limited at $S < 1$.

[16] This requires $\lambda = 0.99$. Why this number may seem high for auctions such as eBay, note that λ governs the share of people who do not get the good from *any* sources. In reality, many people who do not buy the good in an auction buy it through other markets. In the monopolistic seller environment, those other markets are usefully thought of as *also the auction*, because the monopolist controls all possible ways of selling the good.

become more profitable than the fixed-price market is $\underline{\pi}^* = 5.8\%$. As we move along the vertical axis, with $\pi_P = 0$, we reach this threshold when $\pi_T = 5.8\%$, because $\pi^* = \pi_T$ with no permanent types. Moving further along the vertical axis, the auction continues to be dominant until π_T hits 90%; for even higher levels of bias, the market with high fixed-price is more profitable. The results are qualitatively similar as we move along the horizontal axis: as π_P increases, first the low-price market, then the auction, and finally the high-price market dominates. However, both the low-price and the high-price market are dominant for a wider range of parameters: auctions are optimal only when $41\% \leq \pi_P \leq 48\%$. The more powerful effect of π_T is again the result of the "intertemporal fishing" mechanism.[17]

Taken together, Proposition 3 and Figure 3 thus illustrate that even a small share of fools can have a large effect on market structure, particularly when there are many small sellers, or when buyers are subject to temporary biases. These results also provide a potential alternative interpretation of the popularity of auctions in practice. Auctions may not be sellers' preferred mechanism purely because of their efficiency under asymmetric information. In the presence of overbidding, their popularity may partly be explained by the additional profits generated from exploiting behavioral agents.

Welfare. In order to explore the welfare implications of sellers' market choice, we begin the answer by assuming that there is no misallocation ($\alpha = 0$). In this case, the fixed-price market is fully efficient, because it fills the demand of all agents up to the point where supply is exhausted.

Figure 4 illustrates the welfare effects of varying π^* in this environment, using the same numerical values as in Figure 3. For $\pi^* < 5.8\%$, the monopolistic seller prefers the fully efficient fixed-price market. For a slightly higher share of behavioral agents, the seller shifts to the dynamic auction. As the dashed line illustrates, in the absence of misallocation, the auction reduces efficiency by 10%, which is the reduction in sales relative to the fixed-price market. This loss in welfare is the consequence of the endogenous market choice of the seller, who shifts from the efficient fixed-price mechanism to the inefficient auction. Due to the discontinuous drop in efficiency at $\underline{\pi}^* = 5.8\%$, even a small increase in the equilibrium share of behavioral agents, from just below $\underline{\pi}^*$ to just above $\underline{\pi}^*$ can lead to a large welfare loss. We conclude that the impact of a few behavioral agents can be amplified by the endogenous market mechanism.

Introducing misallocation further amplifies the welfare effect of behavioral agents through the fishing mechanism identified in Proposition 2. To understand how this effect interacts with endogenous market choice, we begin by assuming that behavioral agents do not make misallocation mistakes in fixed-price markets ($\beta = 0$). In this case the fixed-price market remains fully efficient, and Proposition 2 continues to characterize the welfare loss of the auction relative to the market.

[17] While $\pi_P = 41\%$ is required for the auction to be dominant, this high probability of permananent bias translates into a steady-state share of fools of only $\pi^* = 5.8\%$, which is the threshold $\underline{\pi}^*$ of Proposition 3.

To compute the additional welfare loss of misallocation in Figure 4, we set $\alpha = 0.5$, i.e., assume that half of the auctions that behavioral agents win result in misallocation. We also set the proportional efficiency loss to be $(X - X_L) / (X - c) = 50\%$: if the efficiently allocated good is worth $X = \$100$ and the marginal cost is $c = \$90$, this corresponds to a \$5 efficiency loss of misallocation, i.e., $X_L = \$95$. As the solid line in Figure 4 shows, with these parameters, the additional welfare loss due to misallocation is another 10% at the point of switching to the auction. Further increasing π^* results in additional welfare losses, as this misallocation effect becomes more powerful.

Figure 4 thus summarizes the two amplification mechanisms discussed in the introduction. Welfare is reduced as sellers shift from efficient markets to inefficient but profitable auctions. Welfare is further reduced because a disproportionately large share of auctions are won by high-bidding behavioral agents to whom the goods are allocated inefficiently. We conclude that behavioral agents can have substantial effects on efficiency in our environment.

What happens if behavioral agents make misallocation mistakes in fixed-price markets as well ($\beta > 0$)? In that case the fixed-price markets are not efficient either, because some behavioral agents end up purchasing the wrong good. However, as we show in the Appendix, even with $\beta = 1$, auctions are still less efficient: they continue to have reduced sales and delay, and moreover, misallocation is more powerful in the auction than in the market due to the fishing mechanism. Hence we continue to have the result that a small increase in behavioral agents can result in a disproportionate welfare loss due to endogenous market choice.

3.2 Combining Auctions and Markets

Thus far, our model has not allowed for the coexistence of auctions and markets: either auctions or markets are preferred by all sellers. However, in a slightly more general setup, for example, with both small and large sellers or with heterogeneity in fixed costs, the two mechanisms may coexist. We now explore qualitatively what happens when both markets and auctions are available. Does the endogenous sorting of agents into different markets attenuate the effects of behavioral agents? To model this situation in a simple way, we assume that auction participants learn about the existence of a fixed-price market with independent probability θ each period. In certain contexts this assumption is realistic: as we have seen, eBay sometimes posts information on the fixed price at which the good available on the auction website. Assume that in the fixed-price market the good is sold at some price $p < X$: a price slightly below X can be justified by having some competition between fixed-price sellers. The timing of events each period is the following: first the realization about agents' behavioral bias takes place, and then agents might learn about the fixed-price market.[18]

[18] The realization of the small perturbation takes place after this, just before the auction.

Given our assumptions, a rational buyer who learns about the fixed-price market will strictly prefer to take advantage of it and leave the auction. We assume that agents subject to a behavioral bias in the current period ignore the fixed-price market and stay in the auction; this is consistent with narrow framing or limited attention, as well as with the evidence from eBay discussed in Section 1. It follows that rational agents leave the auction at a higher frequency than behavioral types, and hence the share of behavioral agents in the auction increases. In the special case where $\pi_P = 0$, this steady-state share can be explicitly computed:

$$\pi^* = \frac{\pi_T}{(1-\theta) + \theta\pi_T}.$$

When $\theta = 0$, i.e., when nobody learns about the fixed-price market, we obtain $\pi^* = \pi_T$, as in our basic setup with $\pi_P = 0$. But when $\theta > 0$, the share of behavioral buyers π^* increases: since rational agents are more likely to leave, auctions become the marketplace for fools. This logic implies that behavioral types may be overrepresented in auctions relative to their share in the population, due to the endogenous choice of the fixed-price market by rational agents. These findings show that endogenous sorting of agents into different markets may amplify, rather than attenuate, the impact of behavioral biases on outcomes.

Competition in the fixed-price market. What happens when there is increased competition in the fixed-price market? Such competition should result in a lower fixed price p, which makes it likely that a greater share of rational agents choose the fixed-price mechanism. A simple reduced form way of modelling this is to increase θ, which in turn has two effects in the auction. First, more rational agents leave the auction, reducing profits. Second, since the share of behavioral agents is now larger, the average auction price is higher, increasing profits. The net effect depends on parameters, but when the initial share of behavioral buyers is small, the second force can dominate. It follows that the auction can become more profitable when competition in the fixed-price market is higher, because the exit of rational buyers increases the share of fools.

3.3 Auction Format with Bidding Mistakes

Beyond the choice of the price mechanism, sellers can also increase profits by fine-tuning the auction to the behavioral bias of buyers, for example, by choosing the auction format. While we developed our model in a second price auction framework, in our environment the revenue equivalence theorem holds, and hence first price auctions generate the same profits to the seller. This follows simply because in our environment agents bid rationally given their perceived private values, and the auction mechanism allocates the good to the agent with highest perceived value. Since our auctions are (ex ante) symmetric, the first price auction also results in this allocation, and hence the two mechanisms generate the same revenue.[19]

We analyze a different specification for the behavioral bias, where the choice of auction format also matters. Assume that instead of mistakes in valuations, agents make bidding mistakes: they correctly compute their bids given their true value, but then experience fever at the moment of bidding and increase their bids. For a concrete example, imagine an English (ascending) auction, where the buyer has decided on his highest bid. As the price approaches and passes by this highest bid, this buyer may have second thoughts, and in the spur of the moment may decide to continue bidding. To formalize this idea, suppose the value of the mistake is $F = Y - X$. With this specification, in a second price auction we obtain identical results as in our earlier analysis. Since agents' perceived continuation values are zero, they want to bid truthfully X; but then a share of them experience a mistake and bid instead $X + F = Y$. However, the results in the first price auction are now different.

Proposition 4 *[Bids, revenue and welfare with bidding mistakes]*

(i) In the first price auction, rational agents bid X and behavioral agents bid Y (modulo a small perturbation).

(ii)The the total profit of the auction is given by

$$\textit{Total profit} = \frac{N}{n}(X - c) + \frac{N}{n}(Y - X) \cdot q_1^n(\pi^*).$$

In particular, since $q_1^n(\pi^*) > q_2^n(\pi^*)$, the first price auction is always more profitable than the second price auction.

(iii) Statements (ii) and (iii) of Proposition 1, as well as all parts of Proposition 2 continue to hold.

Loosely speaking, the intuition for (i) is that rational agents bid X because they prefer to win the good with positive probability relative to not winning it with certainty. Behavioral types also plan to bid X, but then they overbid by F due to the bidding mistake. Given these strategies, the expression for total revenue in (ii) differs from the second price auction only in the probability of generating high revenue. In a second price environment this required having two fools; with the first price auction one fool is sufficient, explaining the q_1^n term. It follows that the first price auction always generates higher revenue than the second price auction: in the presence of behavioral types, the famous revenue equivalence result (Vickrey, 1961; Myerson, 1981; Riley and Samuelson, 1981) no longer holds. As Figure 2 illustrates, the profit difference can be large: switching from the second price to the first price auction means that the dashed line rather than the solid line determines the

[19] This argument also relies on the perturbation: the smooth distribution of values ensures that the first price auction has an equilibrium and that revenue equivalence holds.

probability that the auction generates high revenue. Finally, part (iii) of the Proposition shows that our results about amplification for revenue and welfare hold identically in this environment as well.

We conclude that the with bidding mistakes, the first price auction is a particularly attractive mechanism for the seller, essentially because it maximizes the "efficiency of fishing." More generally, our findings suggest that exploring mechanism design with behavioral agents can be a useful direction for future research.

3.4 Fine-Tuning Auction Design

Sellers can further fine-tune auctions by adjusting details that would not matter in a world with only rational agents. For example, if overbidding is due to limited attention, sellers may choose to tailor the information provided to buyers to maximize inattention. Alternatively, if overbidding is due to bidding fever, sellers may attempt to instigate this bias, for example, by organizing the market in such a way that being outbid is highly apparent and allowing agents to repeatedly increase their bids. Consistent with this intuition, the ascending auction allows agents to see opponents bids as well as the identity of opponents, which can generate a competitive environment and potentially lead to bidding fever. Similarly, online auctions such as eBay often use salient warning messages informing the bidder that he has been outbid, which can strengthen bidding fever or create loss aversion in prospective buyers.

A careful theoretical analysis of such fine-tuning would require formally modelling the specific behavioral bias that drives overbidding. An alternative, simple reduced form approach is to allow the probability of bias π_T to depend on some "fine-tuning action" taken by the seller. As Figure 2b shows, the auction revenue can be highly responsive to even small changes in π_T; as a result, it is in the best interest of the auctioneer to make even costly investments that can increase the share of fools in the auction. Such investments are particularly profitable if the number of agents per auction n is not too high, so that a slight change in π_T can substantially increase the probability of two fools.

4 Amplification, Fine-Tuning and Market Choice: Evidence

How relevant are our theoretical findings for auction markets in practice? In this section, we document new evidence from eBay and present stylized facts from online and offline auctions consistent with our model's predictions.

4.1 Amplification in Allocation, Profits and Welfare

A key prediction of our model, formally established in Proposition 1 and summarized in Figure 1, is that a few biased agents can have amplified effects on allocation and profits, because they end up as high bidders with disproportionately high frequency. We can evaluate the validity of this hypothesis using the eBay data on board game auctions introduced in Section 1. In this data, we identify agents as "overbidding" if their bid is higher than the fixed price at which the good is available.

Table II presents evidence on amplification using the detailed bidder- and bid-level data of the board game Cashflow 101, available for 138 auctions that have on average 8.4 participants.[20] The fraction of buyers who overbid in these auctions is only about 17%; however, 43% of auctions are overbid in the sense that the final price is above the fixed price at which the good is available. The effect of behavioral agents is thus amplified by a factor of $0.43/0.17 = 2.5$ relative to their share in the population. This effect is a manifestation of the fishing mechanism: high-bidding behavioral agents are more likely to set the price in these auctions. The findings in Table II thus provide strong evidence for the basic amplification prediction.[21]

How well does our model explain the magnitude of amplification observed in the data? To answer, we calibrate the model by setting the share of behavioral buyers in the population at $\pi^* = 17\%$, and the average auction size at $n = 8.4$. With these parameters, the share of auctions with at least two fools is predicted to be $q_2^n(\pi^*) = 43\%$. This is exactly what we observe in the data: for this observation, the quantitative fit of our model is essentially perfect! The reason for this close quantitative fit is straightforward. Both in the theory and in the field, we count the share of auctions with at least two fools, given the baseline share of fools in the population. If fools are distributed evenly across auctions in the data, the law of large numbers predicts that the share of overbid auctions should be approximately $q_2^n(\pi^*)$. The fact that this prediction is verified in the data provides external validity for our model, and, as we show below, also makes it a useful tool for predicting other unobserved quantities. We conclude that the evidence strongly supports the basic amplification mechanism identified by the model.

Welfare. What are the welfare effects of the amplification observed in these auctions? Since in this specific environment there good is also available at a fixed price, the most plausible welfare cost in our view is that low-value behavioral agents outbid high-value rational agents, who must therefore obtain the good with delay in the fixed-price market. This effect is a variant of the misallocation mechanism highlighted in Section 2, and its magnitude is governed by the share of

[20] Summary statistics are in Panels B and C of Table I.

[21] The fraction of bids that exceed the fixed price (11%) is lower than the fraction of buyers who overbid (17%). The difference is due to the fact that in the data, unlike in the model, some buyers bid multiple times. The right comparison with the theory is to use the fraction of buyers, treating their final bid as equivalent to the single bid agents can submit in the model.

auctions where a behavioral type wins $q_1^n(\pi^*)$, multiplied by the probability that such a win results in misallocation (α).

Unfortunately, neither of these quantities are observed in our data. However, using the above calibration, we can predict the probability that there is at least one fool in an auction to be $q_1^n(\pi^*) \approx 79\%$. The fact that our calibrated model exactly matched the probability of at least two fools suggests that this prediction is also likely to be precise. Thus our model suggests that in this particular market, almost 80% of all auctions are won by a behavioral agent. To get a sense of magnitudes, assume that a quarter of these result in misallocation ($\alpha = 0.25$); this would imply that a full one-fifth of all auctions are inefficient due to amplified effect of behavioral agents in the allocation of goods. This finding suggests that the presence of behavioral agents can result in substantial welfare losses due to misallocation.

4.2 Fine-tuning of Auction Design

We now turn to present new evidence about the fine-tuning of auctions in response to behavioral biases that we discussed in section 3.4. We document two examples of fine-tuning, both of which take advantage of buyer inattention. Previous work has shown that inattention plays a central role in explaining overbidding on eBay: Lee and Malmendier (2008) test the prediction that there should be more overbidding when the alternative fixed price is less salient. To proxy for salience, they use variation in the on-screen distance between the fixed-price and the auction listing, and in the absolute screen position of the latter. The further apart the two listings, the more likely an inattentive bidder is to miss the fixed price; and the higher an auction is positioned on the output screen, the more likely it is to capture the attention of a bidder, an effect known as "above the fold" in marketing.[22] The data confirms both of these effects, supporting the hypothesis that inattention is an important determinant of overbidding.

Outbid messages. How can sellers exploit buyer inattention? A natural approach is to minimize bidders' exposure to alternative, lower purchase options. One feature of eBay, which is consistent with this prediction but would be payoff-irrelevant in a world with rational agents, is the design of so-called outbid messages. Prospective buyers who were the high bidder but are subsequently overbid automatically receive an email from eBay. The email starts with highlighted text in large bold print: "**You have been outbid. Bid again now!**" It then contains the details of the item in question and provides a direct link to the item listing, which allows the buyer to easily increase the bid. The email does not contain any information about or links to listings of identical or similar items, even though such links would be easy to include (especially since the introduction

[22] 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.

of Unified Product Codes on eBay). The encouragement to rebid, the provision of information about the auction, the simplification of the rebidding process, and the lack of information or links about alternative purchase options within eBay are consistent with the idea that eBay aims to take advantage of bidder inattention to maximize profits.[23,24]

Drawing attention to high outside prices. A second example of exploiting buyer inattention is the design of item descriptions by sellers. The flip-side of buyers' narrow focus on the auction is that they might be affected by information about higher outside prices if brought to their attention *within* the auction. While neglecting the relevant low purchase prices, bidders may respond to irrelevant high prices emphasized in the item descriptions, and as a result bid high higher, possibly due to an anchoring effect.[25]

During the sample period, the manufacturer of Cashflow 101 sells the game online at $195 plus shipping cost of around $10.[26] This is of course much higher than the fixed price of $129.95 at which the goods are available directly from the auction website. As shown in Table I, almost one third (30.72%) of sellers in our Cashflow 101 data mention the manufacturer price in their item description, consistent with the idea that they try to anchor buyer valuations at the high price.

Does drawing attention to the high $195 manufacturer price affect bidder behavior? Table III provides formal evidence on this question by regressing the amount of overpayment relative to the low fix price on the indicator variable Explicit195, which equals one if the item description explicitly mentions the retail price of $195. These regressions control for a wide range of auction characteristics, including auction length, timing (duration and ending time during the 'prime time' period), prior experience of buyers and sellers (feedback scores[27]), and bonus features such as the availability of delivery insurance and tapes or videos. We also separate out the amount of shipping costs. The variable Explicit195 emerges as the most important and consistent determinant of overpayment: depending on specification, mentioning the high manufacturer's price appears to raise auction price by $\$7-\$9$ and is at the significant at the 1-5% level. The results are also robust to logit and probit specifications using an indicator for overbidding as the dependent variable. (In those specifications, auction length is also significantly positive.)

While these results are strongly suggestive that drawing attention to the high price is an important determinant of overbidding, given the non-experimental nature of the data, they do not

[23] An alternative interpretation is that eBay creates switching costs, which induce even rational sellers to bid above alternative lower prices. However, as shown in Lee and Malmendier (2008), a rational switching cost model fails to explain the extent of the observed overbidding, namely, that even average auction prices exceed fixed prices.

[24] The highly visible outbid message in bold font may also help generate bidding fever.

[25] The anchoring effect posits that people are biased towards a number that is initially given to them when evaluating an object, even if the number is arbitrary and not directly related to the true value (Kahneman and Tversky, 1974).

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

[27] If a bidder receives only positive feedback, as it is common, the feedback score measures the number of transactions the bidder undertook.

provide conclusive evidence of a causal relationship. One important concern is that our results may be driven by inexperienced eBay novices. To address this, in column IV we include the interaction of buyer experience, measured as the feedback score, with both Explicit195 and with auction length. The interaction between buyer feedback and Explicit195 is positive and significant: the price impact of explicitly stating the high retail price appears to be driven by experienced buyers.

This finding also suggests that sorting consumers into markets of their choice does not remedy overbidding: agents with the most market experience display the biggest overreaction to an irrelevant high outside price. This is consistent with the prediction of the theory discussed in Section 3.2, which shows that rational agents are more likely to leave the auction and purchase at the low outside price, hence agents who stay in the auction for longer are more likely to have behavioral biases. Our findings thus suggest that in these eBay auctions, sorting actually helps further amplify the effects of behavioral bias.

4.3 Auctions versus Fixed-Price Markets

Finally, we discuss stylized facts related to our model prediction about the endogenous choice of market mechanism, formalized in Proposition 3: the higher the share of behavioral agents in a market, the greater the probability that sellers prefer to use auctions over fixed-price markets. The ideal empirical evidence testing this prediction would provide (1) estimates of the share of behavioral buyers for different goods; and (2) estimates of the market share of auctions and fixed prices for these goods. Such evidence is hard to find for a comprehensive set of goods because it is difficult to measure the share of behavioral agents. For a restricted set of goods, the evidence on overbidding in Section 1 (Figure 1) allows some inferences about the number of overbidding agents across items. The clean empirical methodology comes, however, at the cost of being applicable only to auction items for which we can identify comparable fixed-price listing, i.e., commodity-type goods that are new, have a model number or other clear identification of their type. This excludes used, unique, or antique items such as art, coins, and other collectibles and memorabilia, which seem to be more plausible candidates for attracting behavioral bidders.

For this broader set of goods, we can still get a sense of the importance of endogenous choice of market mechanism by tabulating the share of auctions versus fixed-price markets for each good. This stylized evidence would be inconsistent with the model if auctions are particularly common for items where which overbidding is implausible, e.g., because of well-known market prices.

We use data from two sources. First, we collect data from eBay, exploiting the fact that eBay allows both the auction format and the fixed-price format. Table IV presents the absolute and relative frequencies of auction and fixed-price listings for 33 categories of eBay items (as of June 6, 2008, 22:17pm PDT), sorted by decreasing auction frequency. We find that commodity-type items, such as tickets, cameras, cell phones, PDAs, consumer electronics, books, and computers, for which it is hard to imagine that a bidder would be induced to overbid or fail to note the standard (outside) price, have the lowest relative auction frequency. Items such as stamps, pottery, antiques, art, coins and paper money, collectibles, and sports memorabilia, instead, which provide the greater scope for differences (and mistakes) in value assessment, have the highest relative auction frequency. A similar picture emerges for online auctions more broadly: Lucking-Reiley (2000) provides evidence of the type of items sold and the revenues on 142 Internet auction sites, and finds that "by far the most common type of item is collectibles, which includes antiques, celebrity memorabilia, stamps, coins, toys, and trading cards." Lucking-Reiley also finds that most goods auctioned online are used items that are being resold.

While these findings are consistent with our model, plausible alternative explanations are higher asymmetric information or greater heterogeneity in values for the "vaguer" items. These rational interpretations are likely to explain at least part of the observed variation, though they are harder to reconcile with two facts. First, these goods are auctioned online; and second, many of the goods are used items. For a rational buyer, it is difficult to assess the quality of a used good that he does not see before the purchase; and in the presence of a lemons problem, he is likely to submit a relatively low bid. From the perspective of our model, instead, the incidence of some fools being off in their value assessment is likely to be higher for items where quality is harder to assess.

Our second source of evidence are traditional, offline auctions. We survey the categories of objects sold by five of the largest auction houses: Christie's, Sotheby's, Bonhams 1793, Stockholm Auction House, and Lyon and Turnbull. Again, we find that similar "vague" items including art and antiquities, furniture, collectibles, and photographs are among the most common categories.[28]

Sotheby's website also provides information about the ex-ante value assessment of auction objects, allowing us to calculate the extent to which final prices exceed prior appraisal. Bids above the appraisal are, of course, not evidence of irrational overbidding; but they indicate that items sold in auction houses are perceptible to a wide range of valuations, including potential overestimates. We collected the online descriptions, selling prices[29], and the appraisal ranges (high and low valuations) of all auctions conducted between January and July 2007. After discarding four auctions which lacked catalog descriptions and online appraisals, we obtained a sample containing 178 auctions, with a total of $43,107$ items sold. We classified items as Antiques, Art, Books, Jewelry, Sports, Stamps or Wine.

Table V summarizes these data. Of the 178 auctions, only ten generated less money than the most optimistic expectation, computed by assuming that each item sells for its high valuation. 14.71% of all items sell for at double the amount of the most optimistic appraisal, with the maximum

[28] See Appendix-Table A1 for a comprehensive listing

[29] Revenues in foreign currencies were converted to USD using the conversion rates on June 20, 2008.

being a 100-fold multiple.

While the evidence on the choice of auctions versus markets documented here is suggestive, taken together with our more specific findings on overbidding, amplification and the fine-tuning of auctions, it helps support the view that sellers choose the auction format where the probability of behavioral mistakes is higher.

5 Conclusion

This paper develops a simple model to study the effect of psychological biases in auctions. We find that auctions can amplify the effect of even a few agents with behavioral biases, because the auction mechanism selects the highest-bidding behavioral types as winners. When sellers endogenously choose the market mechanism, further amplification can result as they switch from efficient fixed-price markets to inefficient auctions. Evidence from online and offline markets is consistent with these predictions.

Our findings question the received wisdom of neoclassical economics that markets attenuate the effect of behavioral biases. There exist market mechanisms, like the auction, where behavioral biases are amplified. When such mechanisms are available, profit-maximizing sellers will often choose them to exploit behavioral agents. Our results may explain part of the popularity of auctions in allocating goods in practice.

We conclude with two questions to be explored in future research. The first is closely related to the auction environment studied in this paper. How large are the welfare costs of overbidding in practice? Our model suggests that they can be significant; but to settle this question, careful measurement of bidder behavior across different environments is needed. Our second question is broader. What other mechanisms besides auctions amplify the impact of behavioral biases? We know from the behavioral industrial organization literature that sellers often cater to biases in contract design. Do these or other mechanisms result in amplification analogous to auctions? Answering these questions can help make progress with the larger agenda of understanding behavioral agents in markets.

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Appendix A: Proofs

Characterizing optimal bidding with perturbation. Begin with the case when all bidders are rational, and denote the continuation value of a rational agent by V. Given the second price auction structure, his bid in period t is $X+ \varepsilon_t^i - V$, and his payoff if winning the auction is $\varepsilon_t^i - \varepsilon_t^j$ when ε^j is the second-highest perturbation realization. This difference is always bounded from above by $\sum_{i=1}^n \left(\varepsilon^i + \overline{\varepsilon}\right)$, because the support of each ε^i is $[-\overline{\varepsilon}, \infty)$. It follows that the total value earned by auction bidders each period is at most $\sum_{i=1}^n \left(\varepsilon^i + \overline{\varepsilon}\right)$, which has mean $n\overline{\varepsilon}$; hence the total expected value earned by participants as a whole in the current period is at most $n\overline{\varepsilon}$. Whoever wins the auction wins at most this expected value. Since an agent can only win once in his lifetime, and conditional on winning his expected payment is bounded by $n\overline{\varepsilon}$, it follows that $V \leq n\overline{\varepsilon}$. In the presence of behavioral agents, V decreases further, because the probability of winning is reduced. It follows that when $\overline{\varepsilon}$ is small, each rational agent has essentially zero continuation value and bids very close to X.

Proof of Lemma 1. (i) and (iii): First note that

$$\pi_T^* = (1 - \pi_P^*)\,\pi_T, \tag{5}$$

because out of the share $1 - \pi_P^*$ who are not subject to permanent bias, a proportion π_T experience temporary bias in the current period. To compute π^* and π_P^* we now make use of a steady-state condition that equates the inflow and outflow of permanent behavioral types. We begin this argument assuming away the small perturbation ($\overline{\varepsilon} = 0$), and then we explain how to extend the argument to the $\overline{\varepsilon} > 0$ case.

Each of the $N\pi_P^*$ permanent behavioral types exit with at least probability $1 - \lambda$ in the current period. However, some permanent types exit with higher probability one, because they win auctions. To compute these, note that in each of the N/n auctions, the probability that a behavioral type wins is the probability that a behavioral type is in, which is $1 - (1 - \pi^*)^n$. A share π_P^*/π^* of these behavioral winners are permanent behavioral types. The exit probability for these agents is higher by λ relative to the non-winning permanent types, because they leave with probability one. Combining these terms allows us the express the total mass of permanent behavioral types who leave the marketplace on the left hand side of the following equation:

$$N\pi_P^*\,(1 - \lambda) + \frac{N}{n}\left[1 - (1 - \pi^*)^n\right]\lambda\frac{\pi_P^*}{\pi^*} = \pi_P. \tag{6}$$

The first term on the left hand side is the effect of regular attrition on all permanent behavioral agents; and the second term is the additional exit probability affecting those permanent behavioral types who win auctions. In the steady state, the total outflow of permanent behavioral types must equal the total inflow π_P, explaining the right hand side of the equation. Combining (5) and (6), we have the following equation for π^*:

$$N\frac{\pi^* - \pi_T}{1 - \pi_T}(1-\lambda) + \frac{N}{n}\left[1 - (1-\pi^*)^n\right]\lambda\frac{1}{\pi^*}\frac{\pi^* - \pi_T}{1 - \pi_T} = \pi_P.$$

It is easy to verify that the left hand side is strictly increasing in π^*, equals zero when $\pi^* = 0$ and equals one when $\pi^* = 1$, as can be checked using the definition of N. This implies that π^* is uniquely defined. In addition, the left hand side is strictly decreasing in π_T, while the right hand side is strictly increasing in π_P, which shows that π^* is a monotone increasing function of both π_T and π_P.

When $\bar{\varepsilon} > 0$, the term $1 - (1-\pi^*)^n$ in equation (6) needs to be modified, to capture the probability of those events when a rational buyer has higher true value than behavioral agent. It is easy to verify that the appropriate term is

$$\sum_{k=1}^{n}(-1)^{k-1}\binom{n}{k}\pi^{*k}\cdot\phi(k,\bar{\varepsilon})$$

where $\phi(k,\bar{\varepsilon})$ measures the probability that out of k rational agents in an auction of n people, no one bids higher than all the $n-k$ irrational agents. By definition, when $\bar{\varepsilon} \to 0$ we have $\phi(k,\bar{\varepsilon}) \to 1$ for all k. It is now easy to see that for any fixed pair of values π_T and π_P, when $\bar{\varepsilon}$ is small enough, the left hand side of (6) is still strictly increasing in π^*, and hence the above argument extends.

To prove the inequalities in (iii), note that $\pi^* \geq \pi_T$ holds because each agent has a behavioral bias with at least probability π_T. On the other hand, $\pi_P^* \leq \pi_P$ because behavioral agents leave at a higher frequency than rational agents; and we also know that each period π_P new permanent types enter, implying that $\pi_P^* > \pi_P/N$.

(ii) The contribution of agents with permanent bias entering in the current period to π^* is π_P/N. The contribution of agents with permanent bias entering in the previous period is proportional to $\pi_P \cdot \pi^*$, because this is the probability of having another behavioral type in the auction, which is required for the permanent type not to exit. Since this term is second order when π_P and π_T are small, to a first order approximation $\pi_P^* = \pi_P/N$. From equation (5), $\pi_T^* = (1-\pi_P^*)\pi_T \approx \pi_T - \pi_P\pi_P/N \approx \pi_T$, and hence $\pi^* = \pi_T + \pi_P/N$.

Remark. In the rest of the proofs, we only discuss the small perturbation if extra care is needed beyond the basic arguments we already presented.

Proof of Proposition 1. (i) In an auction with at most one fool, the revenue is X plus a small perturbation governed by $\bar{\varepsilon}$. In an auction with two fools, revenue is Y plus a small perturbation governed by $\overline{\varepsilon}$. The probability of two fools is exactly $q_2^n(\pi^*)$; hence, ignoring the perturbation terms, the expected revenue in one auction is

$$\mathrm{E}[\text{revenue}] = X + q_2^n(\pi^*) \cdot (Y - X)$$

and there are N/n auctions per period, the total period revenue in the dynamic auction is simply

$$\text{Total revenue} = \frac{N}{n} X + \frac{N}{n} q_2^n(\pi^*) \cdot (Y - X)$$

as desired.

(ii) When $\pi_T > 0$, we have $\pi^* \geq \pi_T$ and hence $q_2^n(\pi^*) \geq q_2^n(\pi_T)$. By definition,

$$q_2^n(\pi_T) = 1 - (1 - \pi_T)^n - n\pi_T(1 - \pi_T)^{n-1} = 1 - (1 - \pi_T)^{n-1}[1 + (n-1)\pi_T],$$

and as $n \to \infty$ the second term converges to zero, establishing that $q_2^n \to 1$. When $\pi_T = 0$ but $\pi_P > 0$, as n goes to infinity, we have $N \to \infty$ and hence $\pi^* \to 0$ because most behavioral bidders win the good immediately and leave. When π^* is small, we have the first order approximation $\pi^* \approx \pi/N$. To a second order approximation, $\gamma^* = q_2^n(\pi^*) \approx (1/2)\, n(n-1)\pi^{*2}$ and hence $\gamma^*/\pi^* \approx (1/2)\, n(n-1)\pi/N$ which goes to infinity as $n \to \infty$ because $N \leq n$. Since $\pi^* \to 0$ this approximation becomes arbitrarily accurate, and the result follows.

(iii) By definition, $\gamma_T^* = \gamma^* \cdot \pi_T^*/\pi^*$ and since $\pi_T^* \approx \pi_T$ we have $\gamma_T^*/\pi_T \approx \gamma^*/\pi^*$. In contrast, $\gamma_P^* = \gamma^* \cdot \pi_P^*/\pi^*$ and using $\pi_P^* \approx \pi_P/N$ we obtain $\gamma_P^*/\pi_P \approx \gamma^*/(N\pi^*)$, establishing the desired result.

Proof of Proposition 2. (i) The total period welfare generated by the auction in the large seller environment is

$$\frac{N}{n}(X - c) - \frac{N}{n}(X - X_L)\,\alpha\overline{\gamma}^*$$

because there are N/n auctions, and while the first best surplus for each of these is $X - c$, a share $\alpha\overline{\gamma}^*$ of these generate a surplus reduced by $X - X_L$. Since the first-best surplus is $X - c$, the efficiency loss is

$$\left(1 - \frac{N}{n}\right)(X - c) + \frac{N}{n}(X - X_L)\,\alpha\overline{\gamma}^*$$

and equation (3) follows from dividing by $X - c$. An analogous argument works for the small-seller environment.

(ii) This follows directly from Proposition 1 (ii), because $\overline{\gamma}^* \geq \gamma^*$.

(iii) We have the first order approximation $q_1^n(\pi^*) \approx n\pi^*$ when π^* is small; since $\overline{\gamma}^* = q_1^n(\pi^*)$, the first part of the desired approximation follows, the second part is an immediate consequence of

Lemma 1 (i).

(iv) Reducing δ does not change the allocations, but weakly reduces the surplus generated for each trade in the auction.

Proof of Proposition 3. We begin by characterizing seller pricing and revenue in the fixed-price market when perturbations are explicitly introduced. First note that the seller's revenue in the low fixed-price market is at least $X - \overline{\varepsilon}$ because the lower bound of the support of ε is $-\overline{\varepsilon}$, and the seller can set $p = X - \overline{\varepsilon}$. If a seller sets price $p \geq Y - \varepsilon$ then his revenue is at most πY from behavioral agents, because given that ε is zero mean, their average perceived value is Y. With this high price the seller also obtains profits from some rational agents with high perturbation realizations; however the assumption that $\sigma_\varepsilon < \overline{\varepsilon}$ implies via Chebysev's inequality that this additional revenue is second order. It follows that when Assumption 1 holds, there is $\overline{\varepsilon}$ small enough such that $p \geq Y - \overline{\varepsilon}$ is never optimal.

For a price $X < p < Y - \overline{\varepsilon}$, the seller revenue is at most

$$p \cdot (1-\pi) \cdot \Pr\left[\varepsilon \geq p - X\right] \leq p \cdot (1-\pi) \cdot \min\left[\frac{\sigma_\varepsilon^2}{(p-X)^2}, 1\right] < p \cdot \min\left[\frac{\overline{\varepsilon}^2}{(p-X)^2}, 1\right]$$

again using Chebysev's inequality. This goes to zero for any fixed $p > X$ as $\overline{\varepsilon} \to 0$; it follows that for $\overline{\varepsilon}$ small, the optimal p will be close to X and hence revenue will also be approximately X. We now continue with the proof ignoring the perturbations; but it would be easy to introduce them explicitly using the tools we have developed.

(i) With small sellers, the per person revenue in the auction is

$$X + q_2^n\left(\pi^*\right) \cdot (Y - X)$$

while the revenue in the fixed-price market is only X; hence the auction clearly dominates.

In the large seller environment, the auction revenue

$$\frac{N}{n}X + \frac{N}{n}q_2^n\left(\pi^*\right) \cdot (Y - X)$$

is increasing in π^*, while the revenue of the fixed-price market, X, is a constant. It follows that if the auction dominates for some π^*, then it continues to dominate for higher values of π^* as well. The auction generates higher revenue if

$$\frac{N}{n}X + \frac{N}{n}q_2^n\left(\pi^*\right) \cdot (Y - X) > X$$

or equivalently, after substituting in for N

$$\frac{1}{1+(n-1)(1-\lambda)}\left[X+q_2^n\left(\pi^*\right)\cdot(Y-X)\right]>X.$$

Since $q_2^n\left(.\right)$ is always positive when $\pi^*>0$ and its value does not depend on λ, it is easy to see that for any π^* there is λ close enough to one such that this inequality is satisfied. Fix $\overline{\lambda}<1$ such that this inequality holds for some value of parameters that satisfy assumption 1; it follows that there exists a $\underline{\pi}^*$ with the desired threshold property for this value of λ. By monotonicity, for all λ above $\overline{\lambda}$, there continues to be a range of π parameters for which auctions generate higher revenue, and hence a $\underline{\pi}^*$ with the desired threshold property. To prove that $\underline{\pi}^*$ goes to zero, recall that for any $\pi^*>0$, the above inequality is satisfied when λ is close enough to one.

Proof for Section 3. In the large seller environment, the per-period welfare difference between the market and the auction is

$$\left(1-\frac{N}{n}\right)X+\alpha\left(X-X_L\right)\left[\frac{N}{n}\overline{\gamma}^*-\pi\right]$$

where the second term captures misallocation mechanism. The welfare difference between the auction and the market depends on the relative frequency of misallocation. In the market, the frequency of misallocation is governed by π, the share of behavioral types in the incoming population. In the auction, it is instead governed by $\overline{\gamma}^*$, which is the share of auctions won by behavioral agents. It is easy to verify that the auction is always less efficient than the fixed-price market, simply because due to the fishing mechanism, the auction selects more behavioral agents who purchase the wrong good. In particular, when π_T and π_P are small, we have

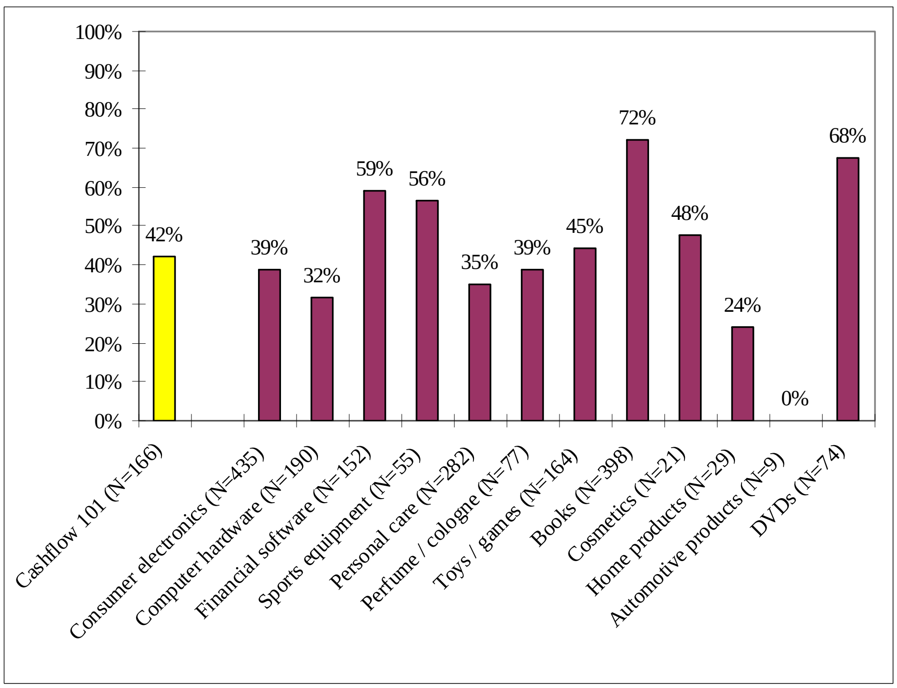
$$\frac{N}{n}\overline{\gamma}^*-\pi\approx\left(N-1\right)\pi_T.$$

Proof of Proposition 4. (i) Denote the continuation value of rational agents by V. We have seen that when the value perturbations are small, V is close to zero. Recalling that valuations are concentrated on the interval $[X-\overline{\varepsilon},\infty)$, suppose that in the symmetric equilibrium there is positive probability of bidding below $X-\overline{\varepsilon}-V$. Consider the agent with lowest realized current value $X-\overline{\varepsilon}$. Since equilibrium bids are monotonic, this agent must bid the lowest possible equilibrium bid, and he must earn zero profits today. But by bidding slightly above, he can earn profits exceeding V in the positive probability event in which he wins. This is an improvement over his current equilibrium strategy which generates V; this contradiction establishes the desired result.

(ii) This follows from (i) simply because there are N/n auctions each period, and a share $q_1^n\left(\pi^*\right)$ of these have at least one fool.

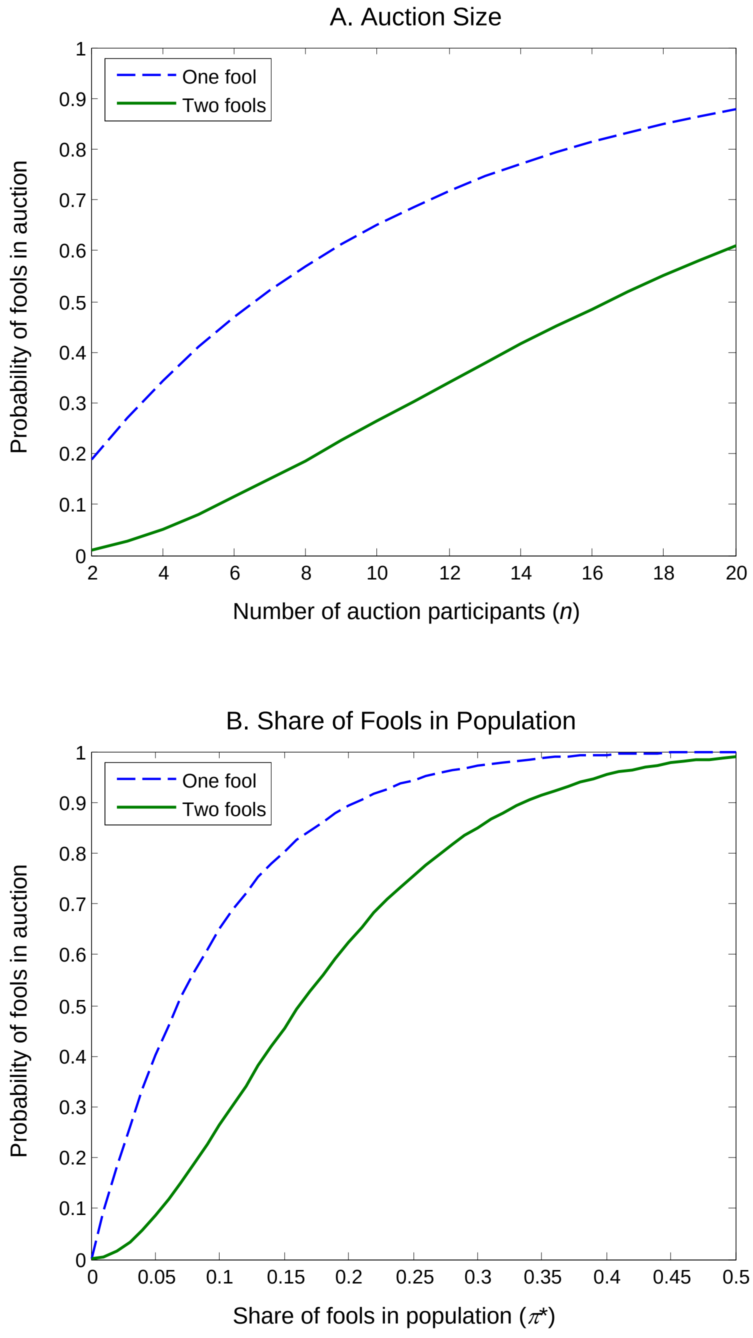
(iii) This can be directly verified the same way as in the respective Propositions.

Figure 1: Overbidding in a Cross-Section of Goods



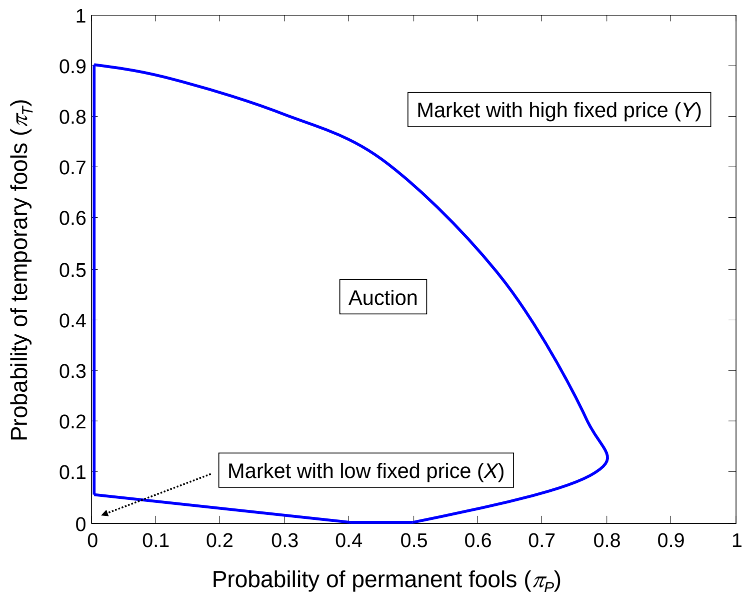
NOTE - This Figure shows the frequency of overbid auctions across different categories of goods on eBay. The leftmost column shows the percent of auction prices above the Buy-It-Now (BIN) price in the Cashflow 101 data. The other columns show the percent of auction prices above the corresponding BIN in the cross-sectional data, split by item category.

Figure 2: Amplification Effect in Auctions with Behavioral Agents



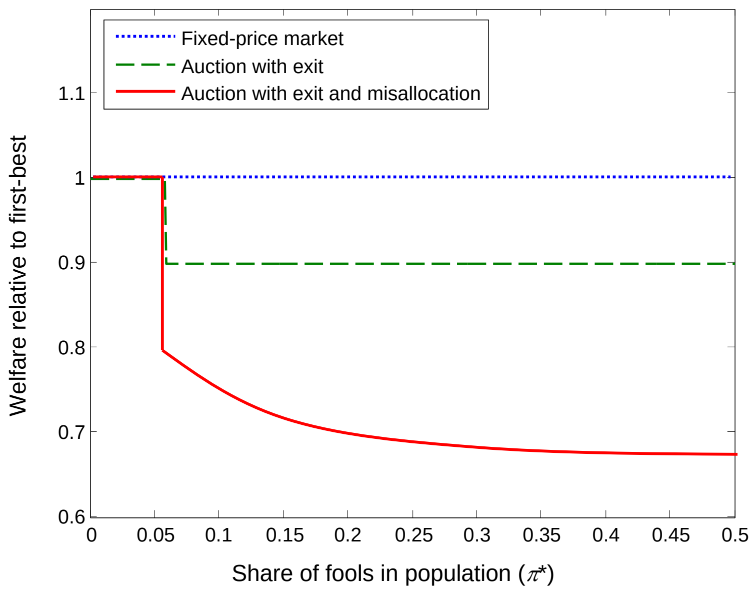
NOTE - Both panels plot the probability of one fool (dashed line) and the probability of two fools (solid line) in an auction. In Figure 1A, these probabilities are plotted as a function of auction size (n), with the share of behavioral agents in the population held fixed at $\pi^* = 10\%$. In Figure 1B the probabilities are plotted as a function of the share of behavioral agents (π^*), with the auction size held fixed at $n = 10$. Both panels show substantial amplification due to the fishing mechanism by which auctions select high-bidding behavioral agents.

Figure 3: Monopolistic Seller's Choice between Auctions and Markets



NOTE - Figure plots the monopolistic seller's choice of market mechanism as a function of the probability of permanent behavioral bias (π_P) and temporary behavioral bias (π_T). The true value of the good is $X = \$100$, the marginal cost is $c = \$90$ and the additional revenue from overbidding is $Y - X = \$10$. Each auction has $n = 10$ participants. The probability of staying in the auction $\lambda = 0.99$ is set so that each period a share 10% of agents exit without the good.

Figure 4: Welfare with Endogenous Market Choice



NOTE - Figure plots welfare with endogenous market choice as a function of the steady-state share behavioral agents (π^*). The parameters are the same as in Figure 2; the endogenous switch to auctions occurs at $\pi^* = 5.8\%$. The dotted line represents first-best welfare achived by the fixed-price market. The dashed line represents welfare with the endogenous shift to auctions, taking into account only the efficiency loss from reduced sales. The solid line also takes into account the efficiency loss from misallocation. We assume that 50% of all auctions won by behavioral agents result in misallocation, and the welfare cost of each misallocation is $5. See also the text for details.

Table I. Summary Statistics: Cash-Flow 101 Data

The sample period is 02/11/2004 to 09/06/2004. Final Price is the price paid by the winner excluding shipping costs; it is equal to the second-highest bid plus the bid increment. Shipping Cost is the flat-rate shipping cost set by the seller. Total Price is the sum of Final Price and Shipping Cost. Auction Starting and Ending Hours are defined as 0 for the time interval from 12 am to 1 am, 1 for the time interval from 1 am to 2 am etc. Prime Time is a dummy variable and equal to 1 if the auction ends between 3 pm and 7 pm PDT. Delivery Insurance is a dummy variable and equal to 1 if any delivery insurance is available. Title New is a dummy and equal to 1 if the title indicates that the item is new. Title Used is a dummy and equal to 1 if the title indicates that the item is used. Title Bonus Tapes/Video is a dummy and equal to 1 if the title indicates that the bonus tapes or videos are included. Explicit195 is a dummy variable equal to 1 if the item description mentions the $195 manufacturer price.

Panel A. Auction-Level Data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Starting Price	165	46.14	43.81	0.01	150
Final Price	166	132.55	17.03	81.00	179.30
Shipping Cost	139	12.51	3.75	4.95	20.00
Total Price	139	144.68	15.29	110.99	185.50
Number of Bids	166	16.91	9.13	1	39
Number of Bidders	139	8.36	3.87	1	18
Feedback Score Buyer	166	36.84	102.99	0	990
Feedback Score Seller	166	261.95	1,432.95	0	14,730
Positive Feedback Percentage Seller	166	62.92	48.11	0	100
Auction Length [in days]	166	6.30	1.72	1	10
one day	166	1.20%			
three days	166	11.45%			
five days	166	16.87%			
seven days	166	65.06%			
ten days	166	5.42%			
Auction Ending Weekday					
Monday	166	11.45%			
Tuesday	166	7.83%			
Wednesday	166	15.66%			
Thursday	166	12.05%			
Friday	166	9.64%			
Saturday	166	18.67%			
Sunday	166	24.70%			
Auction Starting Hour	166	14.78	5.20	0	23
Auction Ending Hour	166	14.80	5.21	0	23
Prime Time	166	34.34%			
Title New	166	28.31%			
Title Used	166	10.84%			
Title Bonus Tapes/Video	166	21.08%			
Explicit195	166	30.72%			

Table I. Summary Statistics: Cash Flow 101 Data (*continued*)

Panel B. Bidder-Level Data

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

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

Panel C. Bid-Level Data

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

Table II. Amplified Effect 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 III. Determinants of the Amount of Overpayment

OLS regression with overpayment, i.e. the difference between the winning price and the simultaneously available buy-it-now price, as the dependent variable. Variable definitions as in Table I. In the third and fourth column, all the weekday variables except Tuesday are included in addition to the independent variables.

	(I)	(II)	(III)	(IV)
Explicit195	8.26***	7.39***	7.44**	0.63
	(2.64)	(2.76)	(2.90)	(4.45)
Shipping Cost	0.36	0 .37	0.23	0.10
	(0.36)	(0.36)	(0.38)	(0.39)
Auction Length	1.19*	1.20*	1.20	0.74
	(0.71)	(0.71)	(0.73)	(1.28)
Starting Price	0.02	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Ln(Feedback Score Buyer + 1)	-0.22	-0.27	-0.33	-2.76
	(0.74)	(0.76)	(0.78)	(3.29)
Ln(Feedback Score Buyer + 1)*Explicit195				3.30**
				(1.65)
Ln(Feedback Score Buyer + 1)*(Auction Length)				0.20
				(0.48)
Ln(Feedback Score Seller + 1)	0.31	0.29	0.19	0.02
	(0.58)	(0.60)	(0.62)	(0.63)
Prime Time		1.26	1.52	1.46
		(2.69)	(2.75)	(2.73)
Delivery Insurance		1.26	0.96	1.67
		(2.69)	(2.74)	(2.76)
Bonus Tapes/Video		3.41	4.27	2.90
		(2.91)	(2.97)	(3.03)
Auction End Day-of-the-Week Dummies			X	X
N	139	139	139	139
R^2	0.10	0.11	0.14	0.14

Constant included. Standard errors appear in parentheses.
Asterisks denote statistical significance at the 1%(***), 5%(**), and 10%(*) level.

Table IV. Frequencies of Auctions versus Fixed Prices

Absolute and relative frequencies of auction listings and fixed-price listings on eBay by category as of June 6, 2008 (22:17pm PDT). Number denotes the absolute number of listings; Percent the percentage of lisitings of a given type out of all auction and fixed-price listings in the respective category. Categories are sorted by decreasing percentages of auction listings. Source: http://listings.ebay.com.

Category	Auction items		Fixed-price items	
	Number	Percent	Number	Percent
Stamps	151,720	93.3%	10,822	6.7%
Pottery & Glass	190,566	88.7%	24,397	11.3%
Antiques	169,983	86.5%	26,468	13.5%
Art	148,665	78.6%	40,411	21.4%
Coins & Paper Money	203,061	84.4%	37,608	15.6%
Collectibles	1,293,036	79.6%	330,434	20.4%
Sports Mem, Cards & Fan Shop	571,730	77.7%	164,440	22.3%
Clothing, Shoes & Accessories	2,198,045	68.9%	992,488	31.1%
Dolls & Bears	111,512	76.6%	34,087	23.4%
Music	390,900	74.5%	133,600	25.5%
Jewelry & Watches	980,948	74.8%	330,332	25.2%
Gift Certificates	9,874	75.6%	3,188	24.4%
Entertainment Memorabilia	157,926	68.6%	72,396	31.4%
Toys & Hobbies	568,978	72.8%	213,049	27.2%
Crafts	268,859	72.9%	100,013	27.1%
Sporting Goods	356,493	63.9%	201,339	36.1%
Video Games	216,644	56.6%	165,938	43.4%
Everything Else	111,625	69.6%	48,668	30.4%
Baby	45,658	64.4%	25,190	35.6%
Business & Industrial	195,441	59.6%	132,232	40.4%
Home & Garden	532,393	57.8%	388,437	42.2%
DVDs & Movies	315,195	54.7%	260,995	45.3%
Travel	7,727	56.9%	5,854	43.1%
Musical Instruments	104,559	54.9%	85,984	45.1%
Real Estate	2,939	75.7%	943	24.3%
Tickets	32,352	50.8%	31,331	49.2%
Health & Beauty	254,537	54.4%	212,988	45.6%
Cameras & Photo	134,871	44.2%	170,381	55.8%
Cell Phones & PDAs	237,793	37.4%	398,147	62.6%
Consumer Electronics	199,825	42.8%	266,653	57.2%
Books	495,422	47.0%	557,866	53.0%
Computers & Networking	251,442	40.2%	374,227	59.8%
Specialty Services	2,656	24.3%	8,260	75.7%

Table V. Bidding Relative to Appraisal

	Frequency of Auctions [Number (Percent)]		Revenues [$ (Percent of total revenues)]		Frequency of prices above the high valuation	Price as % of high appraisal	Price as % of low appraisal
Antiques	23	(12.92%)	$90,222,465	(3.15%)	52.33%	1.43	2.12
Art	117	(65.73%)	$2,535,543,690	(88.44%)	57.25%	1.45	2.09
Books	8	(4.49%)	$43,276,989	(1.51%)	53.55%	1.74	2.47
Jewelry	18	(10.11%)	$162,650,181	(5.67%)	56.47%	1.23	1.73
Sports	2	(1.12%)	$14,151,555	(0.49%)	48.82%	1.14	1.74
Stamps	2	(1.12%)	$3,136,188	(0.11%)	32.51%	1.10	1.40
Wine	8	(4.49%)	$17,846,897	(0.62%)	65.35%	1.35	1.81

Appendix-Table A1. Auction House Categories

Christie's

- Ancient Art & Antiquities
- Asian Art
- Collectibles
- Furniture & Decorative Art
- Photographs, Prints & Multiples
- Books, Manuscripts & Maps
- Fine Art
- Jewelry & Watches
- Wine, Spirits & Cigars

Sotheby's

- Ancient and Ethnographic Arts
- Asian Art
- Books and Manuscripts
- Ceramics and Glass
- Collectibles and Memorabilia
- Fashion
- Furniture and Decorative Arts
- Jewelry
- Musical Instruments
- Paintings, Drawings and Sculpture
- Photographs
- Prints
- Silver, Russian and Vertu
- Stamps, Coins and Medals
- Watches and Clocks
- Wine

Bonham's

- Angling & Fishing
- Antiquities
- Antique Arms & Armor
- Sporting Guns
- California and American Paintings
- Asian Art
- Blue Printed Earthenwares
- Books, Maps & Manuscripts
- Cameras
- Design 1860 - 1945
- Clocks & barometers
- Coins & Medals - Glendining's
- Contemporary Asian Art
- Contemporary Ceramics
- Entertainment Memorabilia
- Islamic & Indian Art
- Contemp. Indian & Pakistani Paintings
- Costume & Textiles
- Design 1860 - 1945
- European Pictures
- European Porcelain, Pottery & Glass
- 20th Century British Art
- Furniture
- 20th Century Decorative Art
- Jewelry
- Mechanical Music
- Motoring
- Contemporary Art
- Made In California
- Modern and Contemporary Art
- Musical Instruments
- Native American & Pre-Columbian Art
- Natural History
- Rugs & Carpets
- Pianos
- Photography
- Portrait Miniatures
- Prints
- Railwayana
- Rivercraft & Maritime
- Russian
- Scientific Instruments
- Sculpture & Works Of Art
- Silver
- Single Owner Sales
- Sports Memorabilia
- Staffordshire Figures
- Stamps
- Soma Estate Auctions
- Sunset Estate Auctions
- The Dog Sale
- Toys & Dolls
- Urban Art
- Watches & Wristwatches
- Wine

Stockholm Auction House

- Arms, Armor, Guns & Firearms
- Clocks & Watches
- City Auctions
- Fine Art & Antiques
- Modern Art & Works of Art
- Prints
- Rare Book & Manuscripts
- Russian Auction
- Selected Wine & Spirits
- Swedish Art Glasses
- Toys, Technica & Nautica

Lyon and Turnbull

- Asian Works of Art
- Books, Manuscripts & Photographs
- Ceramics & Glass
- Decorative Arts & Design
- Furniture, Works of Art & Clocks
- Jewellery & Watches
- Paintings & Prints
- Rugs & Carpets
- Silver & Objects of Vertu
- Sporting & Arms and Armour

Sources: www.christies.com ["Categories"]; www.sothebys.com/app/live/dept/DeptTopicAreaMainLive.jsp; www.bonhams.com/cgi-bin/public.sh/pubweb/publicSite.r?sContinent=EUR&screen=menuDepartments ["USA"]; www.auktionsverket.se/ramsidor_08/engelsk_ram.html ["Auctions"]; www.lyonandturnbull.com/departments.asp.