Sniping and Squatting in Auction Markets[*]

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Abstract

We conducted a field experiment to test the benefit from late bidding (*sniping*) in online auction markets. We compared sniping to early bidding (*squatting*) in auctions for newly-released DVDs on eBay. Sniping led to a statistically significant increase in our average surplus; however, this improvement was quite small. Nevertheless, the two bidding strategies resulted in a variety of other qualitative differences in the outcomes of auctions. We show that the small gain to sniping together with these other patterns in outcomes cannot be explained by a standard auction model with a single auction and payoff-maximizing opponents. Instead, all of the experimental results can be explained by a model in which multiple auctions are run concurrently and a fraction of our opponents are naïve in that they act as if eBay auctions are literally English auctions rather than dynamic second-price auctions. Our findings illustrate how the effects of behavioral biases identified in the lab may be substantially attenuated in real world market settings.

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1 Introduction

Online auction markets provide economists with an access to an almost textbook marketplace which serves as a natural laboratory for experimental research. In particular, there has been much recent research, bolstered by laboratory experiments, identifying the effects of documented behavioral biases. The online marketplace enables us to use field experiments to assess the extent to which these biases remain present in real world market settings and if so, to quantify their effect on economic outcomes.

We conducted a field experiment, participating in indigenous eBay auctions, to understand the well-documented phenomenon of "sniping," and to assess its effect on market outcomes. Sniping refers to the practice of bidding at the last opportunity in online auctions with fixed closing times.[1] The prevalence of sniping in private-value auctions is surprising because auction theory suggests that sniping would be, at best, no more profitable than bidding early if rival bidders follow undominated strategies. Explanations for sniping therefore focus on the presence of some behavioral bias.

While the practice of sniping has been documented and rationales proposed, surprisingly it has not been empirically verified whether sniping leads to any improvement in payoffs. Estimation of the benefit to sniping from field data or laboratory experiments would require inferring a bidders' valuation from her bidding behavior. This is complicated for two reasons. First, this entails imposing some assumptions about bidders' rationality (i.e. bidding your value) but the common rationalization for sniping in private-value auctions is to take advantage of some form of departure from the standard "rational" bidder paradigm in the behavior of typical online bidders. Second, even if we were to assume that bids reveal values, we cannot directly observe the values of winning bidders because online auction sites usually do not reveal the highest bid.

On the other hand, a field experiment enables a very simple test to compare the effect of sniping versus *squatting* (our term for early bidding) on a bidder's payoffs which does not require any assumption on distribution of bidder valuations or rationality. Briefly, we

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[1]See, for example, Roth and Ockenfels (2002), Bajari and Hortacsu (2003) and Hossain (2004) for evidence of sniping in online auctions of various goods.

bid in auctions of brand new movie DVDs. Randomly dividing the set of auctions of the same movie into two groups, we placed a bid on the first day of an auction (squatting) in the first group and a bid of the same amount five seconds before the closing of an auction (sniping) in the second group. For twenty popular recently released movies, we chose our induced valuation at four different levels that were expected to win 90%, 60%, 40% and 20% of the auctions respectively. In each case, we bid our value and in the event of winning, calculated our surplus to be the difference between our induced valuation and the final price including any shipping costs.

We find that sniping does lead to a small, but perhaps negligible, increase in a bidder's payoff. Controlling for auction characteristics, we find that sniping increases our payoffs by 16 cents, slightly more than 1% of our average induced valuation.

Additionally, we are able to identify the sources of benefits as well as costs to sniping behavior. Sniping is beneficial mainly because the typical online bidder bids naïvely: rather than treating the auction as a dynamic second-price auction and bidding her value once and for all, she acts as though she is involved in an English auction and continuously raises her bid whenever outbid until reaching some drop-out price. Bidding early against such a bidder induces a response and an escalating price. We call this the *escalation effect* and it explains the potential benefit to sniping over squatting. In the appendix we include bid pages from four illustrative auctions that exemplify naïve bidding behavior and its effects. See Figures 2-5.

On the other hand, there is an advantage to squatting that arises from a different source. Each individual auction is embedded within the broader eBay market. Entry by bidders into a given auction is endogenous and this is especially relevant for items such as DVDs where typically many auctions of near-perfect substitutes run concurrently. Bidding early in an auction signals to potential rivals that there is likely to be competition for this particular item, and this tends to deter entry. We find evidence for this *competition effect* which tends to favor squatting over sniping.

On the net, we find that these two effects roughly cancel out each other. In retrospect, it should not be surprising that the effects should be so neatly balanced. Free-entry into

eBay, and in particular into competing bidding strategies should equate the payoffs to those strategies. Indeed, our conclusion is that to explain the experimental requires a theoretical model where multiple auctions go on concurrently and bidders are naïve. We present such a model at the end of this paper.

We are not the first to identify naïve bidding as the rationale for sniping. Ariely, Ockenfels, and Roth (2006) performed a laboratory experiment intended to simulate the conditions on eBay and reproduce sniping behavior. While their primary focus was to compare the effect of alternative auction rules, they do draw some conclusions on sniping that relate to ours. They were the first to suggest that sniping arises as an optimal response to naïve bidding[2] and conclude that sniping significantly improves bidders' surplus. Our field experiment complements their findings from the lab. It allows us to test whether naïve bidding is relevant in a natural market setting with free-entry, and whether its effect remains strong enough there to produce noticeable bottom-line effects on outcomes. In addition, the greater control afforded by our experimental design gives us an improved test of the performance of sniping versus squatting.[3] We confirm that our bid level data is consistent with incremental or naïve bidding but the overall effect of naïveté is subsided by the large market effect eBay provides. This provides a nice example of a laboratory experiment providing an insight into a behavioral bias and then a field experiment providing a better and complete picture of the extent and impact of such behavioral biases in a large real world market.

1.1 Overview of Results

A striking summary of our experimental results is presented in Table 1. The table shows two effects of sniping vs. squatting. First, squatting reduces the number of opponents submitting competing bids. Indeed, the empirical distribution of the number of competitors is higher among auctions in which we sniped in the sense of first-order stochastic dominance. This is the competition effect and it is depicted graphically in Figure 1. Sec-

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[2]They refer to it as *incremental* bidding.

[3]Ariely, Ockenfels, and Roth (2006) caution that the conclusions from their laboratory setting should not be presumed to generalize to the natural market environment.

ond, in auctions with at least one opponent bidder, if we condition on a fixed number of competitors, our probability of winning was lower and the final price was higher in the auctions in which we squatted. This reflects the escalation effect.

Table 1: Auction outcomes by number of opponents.

# opps	surplus		win percent		final price		count	
	snipe	squat	snipe	squat	snipe	squat	snipe	squat
0	2.71	3.63	100%	100%	11.84	11.93	27	39
1	3.28	1.53	79%	61%	12.42	13.44	33	64
2	1.22	0.83	50%	47%	12.29	13.50	34	58
3	1.45	1.00	63%	45%	12.91	13.74	32	49
4	1.05	0.44	50%	20%	13.51	14.97	32	44
5	0.90	0.11	29%	9%	14.06	15.06	31	22
6	0.63	0.45	29%	9%	14.54	15.68	38	11
7+	0.64	0.34	38%	14%	14.81	16.13	45	7

Of course Table 1, while suggestive, is weak evidence in favor of our model. From an econometric point of view, we need to control for auction characteristics to determine the significance of the impacts of sniping. Auction theory suggests that the number of opponents is dependant on auction characteristics such as the opening price and our strategies. This implies that conditioning on the number of opponents would lead to endogeneity issues. Furthermore, as a theoretical matter, it turns out that the patterns exhibited in Table 1 can be generated by an entirely standard model of bidding in which bidders arrive in sequence and bid their private value if it exceeds the current price and stay out otherwise. We demonstrate this in Section 3.

In light of this, we look more closely at the data and highlight a set of results that are inconsistent with this benchmark model and point to a theory where naïve opponents and concurrent auctions play an important role. These include the effect of sniping on our winning probability and the seller's revenue. We also highlight a peculiar result from
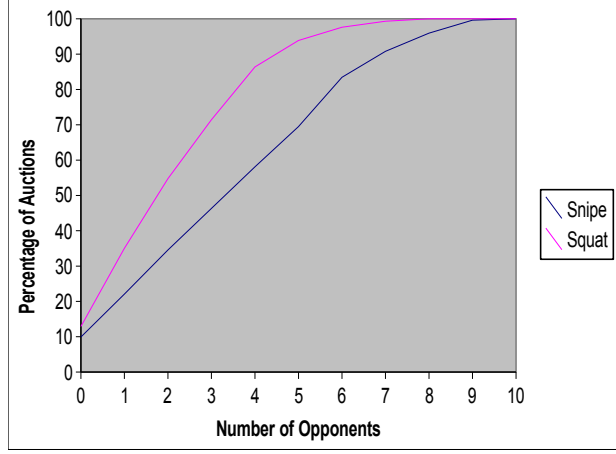
Figure 1: The competition effect of squatting.

auctions in which ours was the only bid placed. Our average surplus in such auctions was significantly higher when we squatted. This is inconsistent with our benchmark model and, as we discuss below, reinforces the significant influence of concurrent auctions.

Finally, we present and analyze a theoretical model of naïve opponents and concurrent auctions. Bidders view the objects as perfect substitutes and can participate in either auction (or both). In equilibrium, bidders will try to compete in the auction with the lowest price. We show how this gives rise to the competition effect, favoring squatting. Naïve bidders act as if they are competing in an English auction: they repeatedly submit bids just until they become the standing high-bidder. We show how this gives rise to the escalation effect, favoring sniping. More generally, the equilibrium of this model matches all of our empirical findings.

The remainder of this paper is organized as follows. In the next subsection we relate our work to the existing experimental and theoretical literature on online auctions and sniping in particular and to evidences of bounded rationality in online auctions. In Section 2 we describe our experimental design. In Section 3 we present the benchmark ascending single-auction model with standard bidders. Our empirical findings are detailed in Section 4. We reject some rationales behind sniping suggested in the literature in Sec-

tion 5. Finally, section 6 presents our main theoretical model with concurrent auctions and naïve bidders. Section 7 concludes. All the proofs are in the appendix.

1.2   Related Literature

This paper complements the theoretical literature on sniping in online auctions for a private-value object by empirically investigating the impact of sniping using field experiments. In one of the first papers in the online auction literature, Roth and Ockenfels (2002) present a model of eBay auctions in which sniping arises as part of a tacitly collusive equilibrium.

Rasmusen (2006) has a model with two bidders, one of which does not know her private valuation and can learn it exactly by paying a cost. An informed bidder with comparatively high valuation snipes in order to reduce the incentive of the uninformed bidder from value discovery. We discuss both models further in light of our data in Section 5.

In laboratory experiments, Ariely, Ockenfels, and Roth (2006) run dynamic second-price auctions with both fixed and extendable closing times. In their controlled environment, all auctions involve two bidders and the payoffs are designed to abstract away from the effects of concurrent auctions as in the eBay market. While their main focus is on the effect on outcomes of different ending rules, the prevalence and profitability of sniping is an underlying theme. Like us, they reject the Roth-Ockenfels model of implicit collusion and instead explain sniping as a response to incremental bidders (what we call the escalation effect).[4]

A paper that tests the impact of sniping using field experiments is Gray and Reiley (2005). They exclusively submitted high bids in order to ensure winning and focus on winning prices. They find a small benefit to sniping but the statistic is not significant due to a small data set. Our experimental design allows us to compare probability of

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[4] Ariely, Ockenfels, and Roth (2006) calculate a loss from early bidding in their experiments by demonstrating a negative correlation between a subject's surplus and the *number* of early bids placed by that subject. This understates the profitability of placing a single, truthful, early bid because it lumps together such a strategy with the inferior strategy of naïve bidding.

winning or analyze benefit of sniping for different levels of valuations. Moreover, a large data set of products from the same category (movie DVDs) enables us to get statistically significant results in many cases including the benefit from sniping.

Motivated by sniping and multiple bidding on eBay, Hossain (2004) proposes a dynamic second-price auction with uninformed bidders who do not know their valuations. During the auction, these bidders get more information about their valuations from the price and, in equilibrium, uninformed bidders place many bids to learn about their valuations. Bidding behavior of uninformed bidders can be observationally similar to those of naïve bidders suggested in this paper. An uninformed bidder perfectly understands that the auction is a second-price auction and she bids her expected valuation conditional on her current information as her final bid even if she is the high bidder towards the end of the auction. On the other hand, a naïve bidder knows her valuation perfectly but fails to bid that as her final bid when she is the high bidder.

2   Experimental Design

To test the benefit of sniping in a private-value setting, we bid the same amount on auctions of the same product using the two strategies: squatting and sniping. In one auction, we place a bid equaling our chosen valuation on the opening day. In the next one, we place a bid in the last minute using the same valuation. This experiment estimates the benefit (or loss) from sniping if a buyer randomly chooses whether to snipe or squat when she is bidding for a private-value good on eBay. One can also view it as a comparison between the payoffs of two bidders with identical valuations where one of them tends to bid early and the other tends to bid late in eBay auctions.

We bid on brand new DVDs for popular movies newly released to video. For these goods, two units are identical and bidders usually have unit demand. There is little uncertainty about the quality of the product in terms of both the content and the condition for new DVDs of popular movies.[5] Thus, DVDs can reasonably be assumed to approximate

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[5]Purchasing for the purpose of eventual resale is not very common. Average auction prices for these movies fall by 15%-20% one month after the DVD release. Considering the depreciation and shipping

the theoretical ideal of a private-value good. For all the titles we chose, a large number of auctions started during the period when we ran the experiment allowing us to get large enough samples for all treatments.

Via surveys of recently conducted auctions, we determined the most common movie DVDs being auctioned off on eBay. We also determined the probability of winning at different values for all the movies we considered. We placed bids at several levels of valuations to look at the effect of sniping for bidders with different levels of valuations. The 20 movie titles used in this experiment are presented in Table 12. We conducted the experiment in two separate runs and the table also presents the number of auctions we participated in and the bids we used in each run.

In each auction, we placed a single bid equalling our induced valuation. In the auctions in which we squatted, we bid our valuation on the first day. In the auctions in which we sniped, we bid our valuation using the sniping services provided by `bidnapper.com` Bidnapper charges a fixed fee for unlimited use of the service over a given time frame. Our bid was placed within the last 5 seconds of the auction.[6]

On eBay, the total price a bidder pays equals the sum of the final price from the auction and the shipping and handling cost. Therefore, if in auction k, our induced valuation was v_k and the shipping cost was s_k then our nominal bid b_k was $v_k - s_k$ so that our total bid equaled v_k. We assigned auctions to our treatment categories in alternating sequence according to the time the auctions were listed. Since the unobservable characteristics of an auction are presumably independent of the order in which they are listed by eBay, this effectively creates a random assignment.

We restricted our set of auctions in various ways in order to ensure uniformity across the auctions in our experiment. We participated only in 7-day auctions and did not participate in secret reserve price or buy-it-now auctions. We participated only in auctions that sold one movie, not a package of two or more movies. We disregarded the auctions that had a "total opening price," the sum of the opening price and the shipping cost,

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charges, it would not be very profitable to buy from eBay for resale.

[6]Out of 272 auctions in which we intended to snipe, our bid went through in all but two of them. This is further evidence against theories of sniping based on a substantial probability of lost late bids.

above our valuation. In all of our auctions, the sellers specified the shipping costs in the auction descriptions and accepted payments via "Paypal."

For the first run of the experiment, we chose the levels of bids that were likely to win approximately 90% and 60% of the time. We will refer these two levels of bids as valuation level 1 and valuation level 2 respectively. We placed bids assuming our induced valuation was at valuation level 1 in half of the auctions. For the other half, we used valuation level 2. The first run was conducted on all auctions of the 15 chosen titles that fitted the above mentioned criteria and started between August 12 and August 18 of 2004. There were 269 such auctions. Of those, we squatted in 141 and sniped in 128. In 141 auctions, we placed a bid using valuation level 1; that is, these bids were expected to be winning bids 90% of times. Our bids were from valuation level 2, bids expected to win 60% of times, in the remaining 128 auctions.

In the second run, we placed bids with relatively lower levels of valuations. Bids at valuation level 3 were likely to win 40% of times and bids at valuation level 4 were likely to win 20% of times. Once again, via a survey of recently completed auctions we chose the titles that had many auctions fitting our criteria going on. Of these 8 titles, 3 were included in the first run of the experiment and the other 5 were released after the first run of experiments started. Following the same criteria as in the first run, we placed bids in 297 auctions that started between September 9 and September 23 of 2004. We sniped in 144 auctions and squatted in 153 auctions. In 151 auctions, our bid was likely to win 40% times and in 146 auctions our bid was likely to win 20% times.[7]

We participated in 566 auctions in total. Of them, we sniped in 272 auctions and squatted in 294 auctions. The opening price in these auctions had a mean of $3.88 and a standard deviation of $3.31. The average shipping cost was $3.79 with a standard deviation of $1.23. The mean and standard deviation of the total opening price were $7.67 and $3.43 respectively. About 31% of all auctions started on a weekend.

We used the same eBay ID for all the auctions we participated in. As a result, our feedback number was not constant during the auction. For private-value goods such as

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[7]Table 13 in the appendix presents these summary statistics.

new movie DVDs, the reputation of a buyer should not significantly affect the bidding behavior of other bidders. We also do not find any evidence in our data to contradict this assumption. On the other hand, many studies have found that the reputation level of the seller positively affects bidder participation and revenues from auctions.[8] The average seller feedback score was 1277 in the auctions in our experiment. The seller had a feedback score of at least 100 in 433 auctions. In 12 auctions, the seller was a novice—she had been a member of eBay for less than a month at the start of the auction. The seller was located in the United States in 491 auction. We control for these auction characteristics in our empirical analysis.

2.1 A First Look at the Experimental Results

In this section we summarize the experimental findings that suggest the importance of the competition and escalation effects. We take a closer look at the experimental data in Section 4 following the development of our benchmark theoretical model.

We participated in 566 auctions and our average induced valuation in these auctions was \$14.05. The average final price including shipping cost was \$13.61. We won in 283 or exactly 50% of the auctions. Our winning percentage was 47.6% and 52.6% for squatting and sniping respectively. We made a total payment of \$3571.26 in the auctions we won.[9]

Surplus Sniping yielded a statistically significant, yet small, increase in our average surplus. Suppose our total bid, equaling our induced valuation, is v_k and the final price is p_k in auction k. If we lose the auction then our surplus is zero and if we win then our surplus in absolute and percentage terms are $(v_k - p_k)$ and $(v_k - p_k)/v_k$ respectively. Our average surplus was \$1.25 and \$1.41 in squatting and sniping treatments respectively, and \$1.32 averaged over all auctions.[10]

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[8]See Dellarocas (2003), Resnick, Zeckhauser, and Lockwood (2003) and Bajari and Hortacsu (2003) for surveys on effect of feedback scores on outcomes of eBay auctions.

[9]Table 14 in the appendix summarizes some statistics on auction outcomes.

[10]Table 16 in the appendix presents some additional data on the surpluses from the auctions in this experiment.

To estimate the impact of sniping on our surplus, we control for auction characteristics such as the opening price, shipping cost, reputation and location of the seller, valuation level of our bid etc. Throughout the paper we estimate equations of the form:

$$sr_k = \beta_0 + \beta_1 snipe_k + \beta_2 op_k + \beta_3 s_k + \beta X \tag{1}$$

Here sr_k stands for our surplus from auction k. That is, if we win auction k then $sr_k = v_k - p_k$ and $sr_k = 0$ otherwise. The dummy variable $snipe$ equals 1 when we sniped. The opening price is denoted by op and the shipping cost is denoted by s. The opening price and the shipping fee is chosen by the seller. Variables characterizing the auctions and fixed effects pertaining to valuation levels, movie specific variations and day specific variations are included as controls variables in X. Thus, all the right hand side variables are exogenous for all of our opponent bidders.

We ran our experiments in two different runs—run 1 in August of 2004 and run 2 in September of 2004. It is possible that error terms within a run are correlated but error terms from two different runs are uncorrelated. To rectify that, we use the Huber-White sandwich estimator of variance in calculating standard errors by clustering observations from the same run. Table 2 shows that, with robust errors, the impact of sniping on surplus is significant at 95% confidence level.[11] The surplus is higher by around 18 cents if we snipe. The coefficients for sniping stay significant when we look at surplus in percentage terms instead. Sniping increased our surplus by around 1.36% of our induced valuation. In column (1), we control for the auction characteristics and our valuation levels, but not for the heterogeneity arising from using many different movies. The results stay virtually unchanged when we include movie specific fixed effects.

We would like also to control for exogenous variation in the amount of competition, i.e. the total number of *potential* bidders including those who visited the auction but did not place a bid. However, this cannot be observed directly and we cannot use the number of *actual* bidders as that number is endogenous. Instead, by including fixed effects for the day that the auction started, we can control for any unmeasured difference in eBay traffic through the course of an auction to a limited extent. The results with these fixed

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[11]The coefficients are not significant at 95% confidence level without robust standard errors.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	0.18	0.16	0.17
	(1.99)	(2.67)	(2.17)
Opening Price	0.05	0.05	0.04
	(0.87)	(1.02)	(0.87)
Shipping Cost	−0.16	−0.18	−0.20
	(−3.35)	(−2.87)	(−2.42)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	566	566	566
Mean Dep. Variable	1.32	1.32	1.32
	(2.07)	(2.07)	(2.07)
Adjusted R-squared	0.55	0.60	0.60

Table 2: Effect of sniping on surplus.

effects included are reported in column (3). The fit does not improve in that case and the effect of sniping on surplus remains almost unchanged.

When we look at all the auctions together we find that the significant positive impact of sniping on our surplus is robust to many variations in empirical analysis. This is discussed in appendix A.3. However, if we look at auctions with different valuation levels separately, the impact of sniping stays positive but becomes statistically insignificant. As such, we do not consider the results on our surplus to be strong enough to reject the stand-alone auction model.

The small benefit of sniping could be a result of the fact that we have many data points with a low bid (bids at valuation level 4) where we were unlikely to win in either treatments. When we look at auctions where our bid was drawn from valuation levels 1 to 3 (bids that were expected to win at least 40% of times), the benefit to surplus jumps to 26 cents and stays significant.

Competition and Bids by Opponents An *opponent* in an auction refers to any bidder other than us who submitted at least one bid. The average number of opponents

we faced in an auction was 3.16. The average number of opponents were 2.48 and 3.90 when we squatted and sniped respectively.[12]

Table 1, which shows the frequencies of auctions with different numbers of opponents for sniping and squatting supports the hypothesis that a benefit from squatting is reduced competition. Indeed, using Poisson regressions of the number of opponents on auction characteristics, as presented in Table 3, we find that more opponents placed bids in sniping auctions. Given that the average number of opponents per auction was above 3, on average we faced almost 1.5 fewer opponents in auctions where we squatted. The coefficients are significant even without robust standard errors.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	0.43	0.43	0.42
	(3.96)	(3.90)	(3.56)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	566	566	566
Mean Dep. Variable	3.16	3.16	3.16
	(2.30)	(2.30)	(2.30)
Adjusted R-squared	0.24	0.27	0.27

Table 3: Effect of sniping on number of opponents.

Our hypothesis is that sniping pays because opponents are not provoked into bidding aggressively. Again, Table 1 is preliminary evidence of this. It shows that conditional on $n \geq 1$ opponent, the surplus was higher for auctions where we sniped. A stronger evidence of sniping reducing the aggressiveness of bidders is that, auctions where we squatted and had n opponents received lower surplus than auctions where we sniped and had $n + 1$ opponents in most cases.

We must emphasize that we view these results as suggestive, but not conclusive support of the role of competition and escalation effects in the performance of sniping. In both cases the reason is the same: the number of active opponents is endogenous and in

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[12]Table 15 in the appendix presents some more data on the numbers of bids, bidders and opponents.

particular affected by the auction price because higher prices early in the auction will mean that fewer bidders find it profitable to bid. Because the price always equals the second highest bid, the price is higher when we squat than when we snipe, other things equal. Even if opponent behavior is unaffected by our own strategy, this could make it look as if squatting reduced the number of opponents but made them bid more aggressively. Indeed, in the following section we formalize this point and show that the basic results outlined here are also consistent with an entirely standard model of bidding in which the competition and escalation effects are absent and there is no benefit to sniping.

3   Benchmark Model

In this section we develop an important theoretical benchmark model of a single private-value ascending auction with proxy bids. In the equilibrium of this model, opponents arrive in sequence and bid their value. Under this assumption, there can be no benefit from sniping and yet we show that the model generates the qualitative features from Table 1. This observation will require us to look more closely at the data to reveal evidence of these effects that are inconsistent with this benchmark model. These inconsistencies, presented in Section 4 will motivate our more general model of concurrent auctions and naïve bidders, to be presented in Section 6.

A single object is up for sale. We suppose that $N > 1$ potential opponents have values drawn independently from the same continuously differentiable strictly increasing distribution F on support $[0, 1]$. Let v_i denote the (private) value of bidder $i \in \{1, 2, \ldots, N\}$. In addition, we model the experimenter as an additional bidder whose private value is v_0. The auction starts at an opening price of $m \geq 0$. The auction takes place over $N + 2$ periods and proceeds as follows. In period 0, the experimenter may submit a bid. Then, in each subsequent period $i \leq N$, bidder i visits the auction. She observes the current price equal to the second highest among all bids previously submitted. The price is m if no bid has been placed. Bidder i can then submit a single bid of any value strictly greater than the current price. Finally, at date $N + 1$, the experimenter may bid. Arrival of bidders is uncorrelated with their valuations and bidders do not know in what sequence

they arrive at the auction site.

At the end of this sequence, the high bidder wins and pays the closing price, i.e. the second highest among all submitted bids (or zero if there were no bids). A losing bidder's payoff is zero and the winning bidder's payoff is equal to her private value minus the price paid.

When the experimenter bids at date 0 or $N + 1$, he is squatting or sniping, respectively. We will analyze separately these two cases, and we will always assume that the experimenter bids his value. Indeed, by standard arguments, for each bidder it is a weakly dominant strategy to bid her value whenever it exceeds the current price. In the subsequent analysis we focus on this undominated equilibrium.

The following proposition summarizes the qualitative features of the equilibrium of this game in the sniping and squatting treatments. Perhaps surprisingly, it shows that the patterns in Table 1 are replicated even though there is a single auction. Here the bidders are standard rational agents. We refer to them as *sophisticated* bidders.

Proposition 1 *In the benchmark single-auction model,*

1. *The distribution over the number of opponents who submit bids is larger in the sniping treatment than in the squatting treatment, in the sense of first-order stochastic dominance.*

2. *For any n, the probability that the experimenter wins conditional on n opponents submitting bids is larger in the sniping treatment than in the squatting treatment, strictly so iff $n \geq 1$.*

3. *For any n, conditional on the experimenter winning against n bidding opponents, the expected price paid is lower in the sniping treatment than in the squatting treatment, strictly so iff $n \geq 1$.*

4. *The overall expected surplus for the experimenter is the same in the sniping and squatting treatments.*

To gain some intuition for the result, note that for any given arrival sequence and valuation profile of players 1 to N, the price will be higher in the squatting treatment. This is because the price is always equal to the second highest among the set of bids submitted and in the squatting treatment the experimenter's bid is included in this set. As a result, on average, fewer bidders actually place bids. It follows that when we compare two auctions that received bids by the same number of opponent bidders (players 1 to N) these opponents will have higher values on average in the squatting treatment. Thus, conditional on a given number of bidders, the experimenter expects to earn a lower surplus and win with a lower probability when squatting.[13]

We see that the striking features of Table 1 are qualitatively consistent with a model of standard bidders in which there is no potential advantage to sniping.

4   Rejecting the Benchmark Model

Our hypothesis is that any benefit from sniping arises because some opponents bid naïvely, and that this benefit is offset and perhaps nullified by the competition effect which tends to favor squatting. Table 1 is tentative support for this hypothesis, but Proposition 1 shows that Table 1 is also qualitatively consistent with a completely standard bidding model with a single isolated auction and sophisticated bidders. In this section we show that a closer look at the experimental results can clearly reject the benchmark model. We present additional evidence of the competition and escalation effects that are not consistent with the benchmark model and motivate the concurrent auctions model that we present in Section 6.

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[13]While the result is intuitive, the proof is complicated by the fact that the valuations of those opponents who actually bid is endogenous and affected by the treatment, sniping vs squatting. It is easy to show that conditional on any given sequence of opponent bidders' valuations, the price will be lower when we snipe, but the endogenous distribution of these sequences are different in the two treatments even after conditioning on the number of opponents who bid.

4.1 Final Outcomes

If the benchmark model were an accurate description of the eBay market, then there would be no significant difference in the final outcomes of auctions in which we squatted and sniped. As discussed earlier, sniping did have an effect on our final surplus, but this effect was quite small and significant only for some specifications. Thus, on the basis of surplus alone, we cannot reject the hypothesis that the benchmark model is a reasonable approximation of bidder behavior on eBay, and that Proposition 1 is the explanation for Figure 1. However, sniping had very different effects on the two components of final surplus: winning probability and expected price conditional on winning.

Table 4 presents marginal effects coefficients for probit analysis of a dummy showing whether we won an auction. We once again use standard errors robust to correlations in error terms within a given run. We find that sniping increases the probability of winning and the increase is statistically significant for all specifications. Between two identical auctions where we squat in one auction and snipe in the other, our probability of winning increased by 9% in the auction where we sniped. When we look at auctions with different levels of bids by us separately, we find that the impact of sniping is smaller in auctions where our bid was expected to win around 90% of times (and ended up winning 93% of times) than the auctions with lower valuations. This makes sense because, as we won most of these auction with either strategies, the relative benefit of sniping in winning the auction was lower. Nevertheless, the benefits of sniping are significant.

On the other hand, the effect on our expected payment conditional on winning was much weaker. Table 5 shows that our expected payment conditional on winning was lower by around 20 cents in auctions where we sniped if we do not control for any day or movie specific fixed effects. However, the impact is reduced by half and becomes insignificant when movie- and day-specific fixed effects are included.

The weak overall effect on our final surplus is a combination of these two and therefore taken by itself obscures the strong and significant effect from sniping on the probability of winning.

Another bottom-line effect from sniping that is not captured by surplus alone is the

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	0.09	0.10	0.13
	(2.12)	(2.20)	(3.90)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	565	559	552
Mean Dep. Variable	0.50	0.50	0.50
	(0.50)	(0.50)	(0.50)
Adjusted R-squared	0.35	0.40	0.44

Table 4: Marginal effect of sniping on winning probability.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	−0.20	−0.09	−0.10
	(−5.63)	(−1.11)	(−1.59)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	283	283	283
Mean Dep. Variable	12.62	12.62	12.62
	(2.25)	(2.25)	(2.25)
Adjusted R-squared	0.24	0.52	0.51

Table 5: Effect of sniping on price conditional on winning.

effect on sellers' revenues. If the final outcomes were unaffected by the choice of squatting or sniping, then sellers' average revenues would be the same in the two treatments. However, we find that sniping decreases revenue by more than 30 cents controlling for auction characteristics and the coefficients are significant for all specifications, see Table 6.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	−0.40	−0.31	−0.35
	(−54.88)	(−3.29)	(−4.10)
Opening Price	−0.07	−0.09	−0.07
	(−5.23)	(−3.61)	(−3.09)
Shipping cost	0.22	0.27	0.31
	(4.59)	(11.50)	(18.46)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	566	566	566
Mean Dep. Variable	13.61	13.61	13.61
	(2.47)	(2.47)	(2.47)
Adjusted R-squared	0.05	0.41	0.42

Table 6: Impact of Sniping on Revenue.

In an ascending auction such as those held on eBay, any strategy that allows the auction to close at a price below the bidder's value would be dominated. This still allows for a great variety of bidding behavior over the course of the auction. However, one unambiguous implication is that the final price must equal the value of the second-highest bidder independent of whether we snipe or squat. Thus, our results on revenue allow us to reject the hypothesis that all, or nearly all opponents use undominated strategies. Later, we suggest that an alternative naïve bidding strategy better explains our data.

4.2 The Escalation Effect

Our results on the effect of sniping on winning probability and sellers' revenue are indirect evidence of the escalation effect: opponents bid less aggressively when we snipe. We now look for direct evidence of the escalation effect by examining the impact of sniping on

the bidding behavior of opponents. In an eBay auction for private-value goods, only a bidder's final bid in an auction matters for payoffs. To test for the escalation effect, we look at the effect of sniping on each competitor's final bid in the auction.

In all the auctions, 1791 opponents placed 2954 bids. After an auction ends, eBay publishes all bids up to the second highest bid. As a result, some of the opponents' bids in the data set are right-censored. Table 7 presents results from censored normal regressions of the final bids of each of our opponents on characteristic variables for the auction and the bidder's feedback rating. The average of the dependent variable was $11.17. If we sniped, then on average the final bid of an opponent was lower by at least $1.58 cents and the impact is significant.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	−1.58	−1.61	−1.64
	(−8.03)	(−8.47)	(−8.55)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	1781	1781	1781
Mean Dep. Variable	11.71	11.71	11.71
	(3.55)	(3.55)	(3.55)
Pseudo R-squared	0.07	0.08	0.08

Table 7: Censored normal regression of effect of sniping on opponent's final bid.

For a given sequence of arrivals of opponent bidders to an auction, the price in the squatting auction is weakly higher than that in the sniping auction as the price equals the second highest bid. As a player placing a bid implies that her valuation is above the current price, conditional on bidding the expected value of a bidder's valuation is increasing in the current price. However, we cannot directly control for the current price or the numbers of bidders (potentially including us) or opponents who have placed a bid so far in the regressions as they are endogenously determined. The regressions in Table 7 includes only auction characteristic variables the bidder's feedback rating as regressors. Nevertheless, if we include an instrument for the number of potential bidders as suggested

in appendix A.3 or the timing of the bid as regressors to indirectly control for the effect of the current price, the impact of sniping barely changes. Just to look at the effect of the current price, if we ignore endogeneity issues and include the current price when the bidder first placed a bid as a regressor, the coefficients of sniping almost do not change. For example, the coefficient of the sniping dummy in the censored normal regression of last bids of opponent bidders presented in column (1) of Table 7 goes from -1.58 to -1.52 with the inclusion of the price variable. Here we should note that the current price when the bidder first placed her bid has a positive and significant and the fit of the equation improves significantly and the pseudo R-squared goes from 0.07 to 0.16 when we include this endogenous variable as a regressor. This suggests that the negative impact of sniping on opponent bids we find is not only due to our inability to control for a player's expected valuation conditional one her placing a bid.

Overall, opponents bid less aggressively when we snipe, consistent with the escalation effect. To measure the escalation effect in a way that is not affected by the difference in progression of price between the two treatments, we examine the highest among all bids by opponents in an auction. In the benchmark model, the highest-valued opponent places a bid equaling her valuation in both treatments. Running censored regression of the highest of opponent bids in the auctions that received at least one opponent bid, presented in Table 8, we find that the highest opponent bid was lower by more than a dollar in the sniping treatments. The coefficients are significant at 99% confidence level. The impacts of sniping in both tables 7 and 8 are also significant if we look at auctions with different levels of our bids separately.

4.3   The Competition Effect

Indirect Evidence   In Table 1, we related auction outcomes to the number n of opponents submitting bids. For any number $n \geq 1$ sniping increases our conditional expected surplus. Curiously, however, for $n = 0$ the comparison is reversed. At first glance it seems impossible for there to be any difference in expected surplus conditional on zero opponents, since in that case the price paid is just the opening price. But there is a correlation

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	−1.54	−1.13	−1.16
	(−3.83)	(−3.59)	(−3.81)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	527	527	527
Mean Dep. Variable	13.51	13.51	13.51
	(2.60)	(2.60)	(2.60)
Pseudo R-squared	0.07	0.16	0.18

Table 8: Censored normal regression of effect of sniping on highest bid among opponents.

between the opening price and the event $n = 0$ and because of the competition effect, this correlation is stronger when we snipe than when we squat.

To see this, suppose that there are two auctions being held simultaneously, and the experimenter is bidding on object 1. There are two scenarios under which no opponents bid on object 1: no other bidders have values greater than the opening price or exactly one other bidder has a value greater than the opening price and she bids on object 2. The first case is associated with high opening prices, the second with relatively lower opening prices on average. But the relative likelihood of the second case is higher when we squat because in that case the opponent is certain to bid on object 2 in order to avoid competing with us. By contrast, when we snipe, the opponent may still bid on object 1 in the second case as she is not yet aware that we are planning to snipe. This argument is formalized below in Proposition 5.

Thus, the comparison of expected surplus conditional on zero opponents is indirect evidence of the competition effect.

Direct Evidence Table 3 showed that squatting significantly reduces the number of opponents and the size of the impact is large. However, the increase in the number of opponent bidders who place a bid in sniping auction is accentuated by the fact that in a

squatting auction the price will be higher conditioning the number of *opponents*.[14] Instead if we condition for the number of *bidders* (including ourselves), then in the benchmark model the price should rise at similar pace in expectation in both treatments leading to similar number of bidders in expectation.

In a market with many buyers and sellers, similar auctions should receive comparable number of bidders as when the price in one auction is driven up, buyers should move to another auction. This suggests that similar auctions should receive similar number of non-sniping bids.[15] Table 9 presents Poisson regressions of the number of distinct bidders who placed a bid up to the penultimate minute of an auction on auction characteristics. The dependent variable counts the experimenter in squatting treatments but not in sniping treatments, hence in the benchmark model we would expect a negative coefficient on the sniping dummy. In fact, we find that sniping increases the number of bidders placing bids in an auction before the auction has just one minute left by more than 0.3 bidders on average and this increase is significant.[16]

Another way in which the competition effect may manifest itself is that bidders are discouraged from bidding in an auction when they expect the price may be very high. In particular this would mean that when we squat with a high bid and therefore remain the high bidder through most of the auction, potential bidders will be deterred from bidding. Indeed, when we include the interaction term for the size of our bid and a dummy for squatting, we find that its effect on the number of non-sniping bidders is negative and statistically significant. In squatting auctions, the larger our bid is the lower is the number of non-sniping bidders. On the other hand, the impact of the interaction term of the size of our bid and a dummy for sniping is positive and statistically significant. These suggest that large squatting bids by us reduce competition.

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[14]Nevertheless, this effect alone should increase the expected number of opponents bidding in the sniping treatment by less than one.

[15]We do not include sniping bids here as they do not give time to other bidders at the auction site to react to these bids.

[16]This impact persists if we use the numbers of bidders prior to the last three or five minutes of an auction as the dependent variable instead. The impact also does not change when we restrict attention only to auctions that received at least one bid prior to the closing minutes.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	0.11	0.10	0.09
	(19.12)	(21.63)	(9.40)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	566	566	566
Mean Dep. Variable	3.54	3.54	3.54
	(2.14)	(2.14)	(2.14)
Pseudo R-squared	0.17	0.20	0.21

Table 9: Effect of sniping on total number of (non-sniping) bidders.

5   Alternative Models

The literature includes a few alternative models of auctions and bidder behavior that would generate a positive benefit from sniping. Here we assess these models in light of the experimental data.

In the Roth and Ockenfels (2002) model (referred to as RO henceforth), bidders play a carrot-stick equilibrium in which early bidding is punished by bidding wars, and late bidding is rewarded by the small probability that late bids by the opponents will fail to materialize due to an exogenous probability of untransmitted bids. The bidding wars used in the RO strategies can be viewed as largely consistent with the escalation effect we have identified.[17] On the other hand, due to the exogenous probability of untransmitted late bids, in the RO model we would expect to see fewer opponents submit bids when we sniped than when we squatted, in contrast to the competition effect.

However, the clearest evidence against the RO strategies is the effect of our sniping on the sniping behavior of others. In the RO equilibrium, opponents bid early whenever a bidding war has broken out, and snipe when it has not. Thus, the RO model would predict that our own sniping would increase the prevalence of sniping by others.

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[17]Nevertheless, conditional on being able to place a bid, a bidder's final bid will be the same whether she went on to a bidding war or sniped in the RO model .

In our experiments we see no significant effect of our sniping on the timing of opponent's bids. Table 10 presents Poisson regression of the number of opponents placing bids in the last minute of an auction. The effect of sniping is positive but insignificant in all cases. In these regressions, we clustered the error terms of the auctions in the same run and used robust standard errors. When we do not use robust standard errors, we still get insignificant coefficients for sniping. We looked at some other measures of late bidding such as number of bids and number of auctions receiving late bids. We also looked at bids by opponents in the last three or five minutes. In almost all cases, the effect of sniping on late bidding by opponents is insignificant albeit positive. Given this result, we conclude that our sniping does not seem to have induced sniping by opponents.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	0.13	0.12	0.15
	(0.53)	(0.47)	(0.53)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	566	566	566
Mean Dep. Variable	0.24	0.24	0.24
	(0.49	(0.49)	(0.49)
Pseudo R-squared	0.04	0.10	0.14

Table 10: Effect of sniping on number of opponents who snipe.

In the model of Rasmusen (2006), opponents can learn their valuation only at a cost. Opponents who expect to face little competition have no incentive to learn their valuation and instead simply bid low. If we were to squat against such an opponent we would provide that opponent with an incentive to learn her valuation and bid accordingly while she will not invest in value discovery and bid her average value if we snipe.

One empirical implication of the Rasmusen model is that in auctions we lose, the final price will be higher on average when we squat than when we snipe. For example, if our value is v_0, and we snipe, then the opponent will bid her average value $\bar{v}$ and so outbid us only if $\bar{v} > v_0$. On the other hand, if we squat, the opponent will learn her valuation

v and bid $\max\{v, v'\}$ where her initial bid before value discovery is v'. She will outbid us iff $\max\{v, v'\} > v_0$. Thus, the distribution of an uninformed bidder's bid when we squat will stochastically dominate the distribution of her bid when we squat. Hence, in the presence of such uninformed opponents and conditional on highest of their bids being above v_0, the expected final price will be higher when we squat.

In our experiment, we found no statistically significant difference between squatting and sniping in the expected final price conditional on losing. Table 11 shows that seller revenue in auctions we lost was not significantly affected by whether we sniped or squatted for any of the econometric specifications.

	Specification		
	(1)	(2)	(3)
Regressor			
Sniping Dummy	-0.12	-0.25	-0.26
	(-0.50)	(-1.21)	(-1.40)
Fixed Effects			
Movie	No	Yes	Yes
Starting Day	No	No	Yes
Summary			
Observations	283	283	283
Mean Dep. Variable	14.61	14.61	14.61
	(2.29)	(2.29)	(2.29)
Pseudo R-squared	0.16	0.46	0.45

Table 11: Effect of sniping on seller revenue in auctions we lost.

6   Concurrent Auctions Model

The evidence in the previous sections suggest that the experimental outcomes in a given auction are best understood by considering that auction in the context of the larger market. To that end we examine in this section a theoretical model of concurrent auctions.

We suppose that there are two auctions running simultaneously. Each auction is a dynamic second-price auction as modeled in Section 3. Bidders arrive in sequence and can bid in one or both auctions. We first consider a model in which bidders are *sophisticated* who understand and choose optimal bidding strategies. This model will capture some

aspects of the competition effect, but none of the escalation effect. This will finally lead us to consider a model with naïve bidders which can explain all of the qualitative results from the experiment.

6.1 Sophisticated Bidders

There are two auctions for perfectly substitutable goods, labeled 1 and 2. Each bidder demands at most a single unit. There are $N + 2$ periods—periods 0 to $N + 1$. Bidders arrive in sequence so that bidder $i \in \{1, 2, \ldots, N\}$ arrives and bids in period i. At the beginning of each period, the observed price in each auction $k \in \{1, 2\}$, p_{ik} equals the second-highest bid submitted in auction k in periods 0 to $i - 1$. When bidder i arrives, she observes the prices in both auctions and decides whether and how to bid. To motivate our model of bidding, it will help to outline the strategic issues that arise when auctions run concurrently.

When there are two auctions running simultaneously, a bidder i would like to bid in the auction where she would pay the lowest price. However, i only observes the current price in an auction and not the current high bid, and the latter determines the price if i becomes the high bidder. To find the auction with the lowest high bid, i would like to alternate between auctions, submitting small incremental bids until he becomes the high bidder in one of them. For example, suppose the observed price in both auctions is p and the (unobserved) high bids are q_{i1} and q_{i2} in auctions 1 and 2 respectively, with $q_{i1} < q_{i2}$. A sophisticated bidder i would steadily raise the price in each auction until he becomes the high bidder. In this case that would occur when the price reaches q_{i1} at which point i becomes the high bidder in auction 1 and ceases bidding in auction 2. To incorporate this behavior into our model, we will allow bidders to continuously raise the price in both auctions.

Once i has found the auction k with the lowest price, she may want to submit an additional bid to ensure that he remains the high bidder in auction k. Indeed we will show that it is optimal to submit a bid equal to v_i, i's value for the object. To incorporate this into our model, we will allow bidders to submit an additional bid before their bidding

period ends.[18]

Formally, the game is defined as follows. The price and current high bids in both auctions are initialized at m, the minimum opening bid. As in Section 3, bidder i's valuation v_i is independently drawn from the continuously differentiable strictly increasing distribution F on support $[0, 1]$. At the beginning of period i, the current prices p_{ik} and the current high bidders for each auction k are observed by bidder i. The current high bids $q_{i1} \geq p_{i1}$ and $q_{i2} \geq p_{i2}$ are unobserved where $q_{11} = q_{12} = m$. Bidding by i consists of two steps. First, i is given the opportunity to continuously raise prices in both auctions. To do this, i specifies an upper bound $\kappa_i > \min\{p_{i1}, p_{i2}\}$. The price in auction k is then raised to $\tilde{p}_{ik}$ equaling the third highest of $\{q_{i1}, q_{i2}, p_{ik}, \kappa_i\}$. If $\kappa_i \leq \min\{q_{i1}, q_{i2}\}$ then the current high bidders in the two auctions stay unchanged. Otherwise, suppose $q_{ik'} > q_{ik''}$; then bidder i becomes the current high bidder in auction k'' and the high bidder in auction k' stays unchanged. If $q_{ik'} = q_{ik''}$ then i becomes the high bidder in one of the auctions randomly and the high bidder in the other auction stays unchanged. In the second step, i can submit a final bid $b_{ik} \geq \tilde{p}_{ik}$ in each auction k. This concludes i's bidding period. The next period begins with new prices p_{i+1k} equal to the second highest of $\{\tilde{p}_{ik}, q_{ik}, b_{ik}\}$. The new high bid q_{i+1k} will be $\max\{b_{ik}, q_{ik}\}$. For simplicity, we assume that bidders 1 to N know their positions in the bidder arrival sequence. The results in this section will remain valid even without this assumption.

In the sniping treatment, the experimenter randomly selects an auction k bids v_0 in auction k in period $N+1$. In the squatting treatment, the experimenter randomly selects an auction k and bids v_0 in auction k in period 0. This means that the initial high bid in auction k, q_{1k} is equal to v_0. Once again, we will only look at equilibrium in undominated strategies.

Proposition 2 *In the concurrent auction model with sophisticated bidders, the game can be solved by backward induction. Each bidder $i \in \{1, \ldots, N\}$ uses the following bidding strategy*

    1. If (and only if) $v_i > \min\{p_{i1}, p_{i2}\}$, then bidder i submits $\kappa_i = v_i$.

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[18]eBay refers to this as a "proxy" bid.

2. If (and only if) i becomes the high-bidder in auction k, then i submits a final bid
   $b_{ik} = v_i$ *in auction k.*

The experimenter wins with a higher probability and earns a higher expected surplus by squatting rather than sniping.

6.2   Naïve Bidders

The results of the previous section demonstrate that extending the model to allow for concurrent auctions, while generating one aspect of the competition effect, is not by itself enough to capture the experimental outcomes we observe. Our empirical analysis suggests that the presence of naïve opponents is another important consideration. In this subsection we analyze a model of concurrent auctions with naïve opponents who act as if the auction were an English auction rather than a dynamic second-price auction.

In an isolated English auction a bidder with value v_i would optimally remain in the auction actively bidding until the price exceeds v_i. The key contrast with sophisticated bidders is that when a naïve bidder becomes the high-bidder in an auction, he does not submit a proxy bid, but rather remains inactive until another competitor arrives and competes. The ensuing competition raises the price until it rises above the smaller of the two bidders' values at which point that bidder drops out. The other bidder is then the high bidder and becomes inactive until another competitor arrives.

Our model incorporates this behavior into a market with concurrent auctions. Notice that when naïve bidders compete in two auctions, the current high bidders at any stage i will be the bidders with the two highest values among bidders $\{1, \ldots, i\}$. The prices in both auctions will equal the third-highest value as the bidder with the third-highest value will have dropped out at that price. The highest bids will also equal this price as naïve bidders do not use proxy bids. This is the basis for our model. All that remains is to describe the behavior of the experimenter.

We begin with the sniping treatment. After bidder i arrives at the market, the price in both auctions is (mechanically) raised to the third-highest value among $\{v_1, \ldots, v_i\}$, denoted by p_{i+1}. This process continues until period N. Thus, p_{N+1} equals the third

highest of $\{v_1, \ldots, v_N\}$. Then he randomly selects an auction k and submits a bid equal to v_0 in k. The experimenter wins at price p_{N+1} if $v_0 > p_{N+1}$, otherwise he loses.

In the squatting treatment, in period 0, the experimenter randomly selects an auction k and submits a (proxy) bid of v_0 in k. The auction then proceeds as described above with the modification that the price p_i at stage i will now equal the third highest among $\{v_0, v_1, \ldots, v_i\}$ (i.e. v_0 is now included.) The experimenter wins if he remains the high bidder until the end. This occurs iff $v_0 > p_{N+1}$ where p_{N+1} equals the third highest of $\{v_0, v_1, \ldots, v_N\}$. If he wins, the experimenter pays price p_{N+1}.

Proposition 3 *When bidders $i \in \{1, 2, \ldots, N\}$ are naïve then the experimenter's expected surplus and probability of winning is higher in the sniping treatments.*

When bidders are naïve, sniping reduces the seller's expected revenue and also the highest among the bids placed by bidders $i \in \{1, 2, \ldots, N\}$.

The result that, compared to squatting, sniping is strictly less profitable when bidders 1 through N are sophisticated and strictly more profitable when they are naïve does not depend on any assumptions on F and N. If a bidder is sophisticated with probability α and naïve with probability $1 - \alpha$, then either sniping or squatting can be more profitable or both can be equally profitable depending on F, N and α. This holds true even if other bidders strategically decide whether to snipe or squat. We analyze $\alpha \in \{0, 1\}$ to get sharper predictions and to contrast the two extreme cases.

Given that the presence of naïve bidders can theoretically replicate the benefit of sniping while absence of them fails, we provide results parallel to those in Proposition 1 for the concurrent auctions model with naïve bidders. In the mechanical model we presented, naïve bidders do not directly place bids. Hence, we have to incorporate the notion of the number of opponents bidding in the auction in which the experimenter submits his bid into this model. In the squatting treatment, the first bidder (in terms of arrival sequence) with valuation above m bids in the auction in which the experimenter did not bid. All subsequent bidders bid in both auctions iff $v_i > p_i$. Thus, the number of opponents can be calculated by the number of periods such that $p_t > p_{t-1}$. In the sniping treatment, the first opponent to have valuation above m bids in the auction where the experimenter

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will eventually snipe. Suppose this is bidder l. The next bidder to have valuation above m bids in the auction in which bidder l did not bid. All future bidders to place bids (i.e., $v_i > p_i$) bid in bot auctions. Thus, if there are zero periods such that $p_t > p_{t-1}$ then the number of opponents is zero or 1 with equal probability and otherwise, the number of opponents can be calculated by adding one to the number of periods for which $p_t > p_{t-1}$.

Proposition 4 *In the concurrent auction model with naïve bidders,*

1. *The distribution over the number of opponents who submit bids is larger in the sniping treatment than in the squatting treatment, in the sense of first-order stochastic dominance.*

2. *For any n, the probability that the experimenter wins conditional on n opponents bidding in the auction where he bid is larger in the sniping treatment than in the squatting treatment, strictly so iff $n \geq 1$.*

3. *For any n, conditional on the experimenter winning against n opponents bidding in the auction where he bid, the expected price paid is lower in the sniping treatment than in the squatting treatment, strictly so iff $n \geq 1$.*

4. *The overall expected surplus for the experimenter is higher in the sniping treatments.*

With sophisticated bidders, the first statement of the proposition will hold true and the fourth statement will be exactly the opposite as already seen in Proposition 2. Statements 2 and 3 will hold true for $n = 0$. For $n \geq 1$, with sophisticated bidders, statements 2 and 3 of Proposition 4 may hold only for certain F and N.

Proposition 5 below shows that concurrent auctions allow us to capture the competition effect that leads to higher surplus conditional on zero opponents in squatting treatments. In the benchmark model, our expected payoff conditional on zero opponent and the probability of having zero opponent is the same in both sniping and squatting treatments for any given opening price. Therefore, the expected payoff in auctions where no opponent places a bid is independent of the treatment. However, in our data set,

average surplus in sniping auctions was only three-quarters of that in squatting auctions conditional on no opponents.

Proposition 5 *Conditional on facing zero opponents, the expected opening price is lower and the expected surplus is higher in the squatting treatment.*

For any given opening price, the probability of getting zero opponents is lower in the sniping auction in the concurrent auctions model no matter whether bidders 1 to N are sophisticated or naïve. A sniping auction not attracting any opponent implies that the opening price, equaling the payment, is relatively high leading to a lower surplus.

7 Conclusion

We conclude by discussing a possible extension of our research. Rather than attempt to identify the bidding strategy that maximizes surplus, we have simply compared the common practice of sniping to the natural benchmark strategy of squatting. We find that market competition results in the payoff to these two strategies being roughly equalized. On the other hand, it is not hard to see that either of these strategies could be improved upon in a market such as eBay where many auctions for the same item run nearly concurrently. Indeed there is an important search aspect to bidding that our analysis ignores. A bidder who snipes would optimally monitor simultaneously many auctions that are set to close at a similar time. As the closing time approaches, she would attempt to forecast the closing prices based on bidding history and bid on the item which is likely to have the lowest price. Similarly, a bidder who squats would seek an auction with the most favorable opening price. The most favorable price could be the lowest price, or conceivably it could be a higher price in order to signal toughness. In our experiment, we randomly selected the auctions on which to bid at the opening and so we cannot assess whether any additional profit opportunity exists based on combining these search aspects with optimal bidding. Conducting a more elaborate experiment in order to test this should be a goal for future research.

A   Proofs

A.1   Proof of Proposition 1

The proof of Proposition 1 will make use of the following lemma. We defer the proof of the lemma until after the main proof of Proposition 1.

Lemma 1 *Fix $\bar{p} \in [0,1]$, and let $h : [0,1] \to [0,1]$ be any non-decreasing function which is not constant over $[0,\bar{p}]$. Let p^{snipe} and p^{squat} be the random variables corresponding to the highest bid among opponents in the snipe and squat treatments, respectively. Denote by O_n the event that exactly n opponents submit bids, and $\bar{P}$ the event that the highest bid among opponents is no greater than $\bar{p}$. We have*

$$\mathbf{E}\left[h(p^{\mathrm{snipe}}) \mid O_n, \bar{P}\right] \leq \mathbf{E}\left[h(p^{\mathrm{squat}}) \mid O_n, \bar{P}\right]$$

with a strict inequality iff $n \geq 1$.

   Proof of Proposition 1.   We begin with the inequalities in parts 2 and 3 which are immediate consequences of Lemma 1. For part 3 we take h to be the identity function and $\bar{p} = v_0$. Then $\mathbf{E}\left[h(p^{\mathrm{squat}}) \mid O_n, \bar{P}\right]$ and $\mathbf{E}\left[h(p^{\mathrm{snipe}}) \mid O_n, \bar{P}\right]$ give the expected price conditional on winning when n opponents submit bids. For part 3 we take h to be the indicator function

$$h(p) = \begin{cases} 0 & \text{if } p < v_0 \\ 1 & \text{otherwise.} \end{cases}$$

and set $\bar{p} = 1$. Then $\mathbf{E}\left[h(p^{\mathrm{squat}}) \mid O_n, \bar{P}\right]$ and $\mathbf{E}\left[h(p^{\mathrm{snipe}}) \mid O_n, \bar{P}\right]$ give the probability of *losing* conditional on n opponents submitting bids.

   Turning to the last statement, that the expected surplus is the same from squatting and sniping. This follows immediately from the observation that the final price equals the second-highest among all values $\{v_0, v_1, \ldots v_N\}$, regardless of treatment. To see why, note that when bidders bid their values, the price never exceeds the second-highest value, and hence the bidders with the highest and second-highest values always submit bids.

   Finally, we prove the first statement. Consider any valuation profile $(v_1, \ldots, v_N)$ for the opponents such that n of them will place bids in the squatting treatment. Consider

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any stage t at the beginning of which the current price p_t is less than v_0, the bid of the experimenter. In this scenario, p_t is equal to the highest value among all bidders prior to t. Bidder t bids iff $v_t > p_t$. Consider now the identical valuation profile in the sniping treatment. In this case, the current price will be equal to the second-highest value among bidders prior to t, hence no greater than p_t. If t were to bid in the squatting treatment, she will bid in the sniping treatment as well.

By a similar reasoning, we can show that when $p_t \geq v_0$, bidder t will bid in the sniping treatment whenever she will bid in the squatting treatment. It follows that for any valuation profile, the number of bids submitted is at least as high in the sniping treatment as in the squatting treatment. Moreover, the inequality is strict with positive probability. First-order stochastic dominance follows immediately. ∎

Proof of Lemma 1. Consider the event that the auction arrives at stage t, among the opponents the current highest bid is p_t, subsequently exactly j additional opponents submit bids and the highest bid among opponents is no greater than $\bar{p}$. We let $\phi^{\text{snipe}}(t, j, p_t)$ and $\phi^{\text{squat}}(t, j, p_t)$ denote the expected value of $h\left(p^{\text{snipe}}\right)$ and $h\left(p^{\text{squat}}\right)$ conditional on this event in the sniping and squatting treatments respectively. We will prove the following claim by induction on j.

Claim: For every $j = 1, \ldots N$, there exists a strictly increasing function $g_j(\cdot)$ such that if $t \leq N - j + 1$ and $p_t < \bar{p}$, then

1. $\phi^{\text{squat}}(t, j, p_t) \geq g_j(p_t)$ with a strict inequality if $t < N - j + 1$,

2. $\phi^{\text{snipe}}(t, j, p_t) \leq g_j(p_t).$ with a strict inequality if $p_t > m$.

We begin by showing the claim for $j = 1$. We define the function g_1 as follows.

$$g_1(p) = \mathbf{E}\left[h(v) \mid \bar{p} > v > p\right].$$

The assumption that F has full-support and that h is non-decreasing and non-constant over $[0, \bar{p}]$ implies that g_1 is strictly increasing.

In the squat treatment, suppose that at the beginning of stage $t \leq N$, the current price is p_t, and consider the event that $p^{\text{squat}} < \bar{p}$ and exactly 1 additional opponent will

submit a bid. Let t' be the (random) stage at which that last opponent bids. Note that t' can take on any value between t and N, and p^{squat} will be the bid submitted at stage t', i.e. $v_{t'}$. Taking expectations with respect to the value of $v_{t'}$, we can express

$$\phi^{\text{squat}}(t, 1, p_t) = \mathbf{E}\left[h\left(v_{t'}\right) \mid E_1 \cap E_2 \cap E_3\right]$$

where the events E_1, E_2, and E_3 are defined as follows.

1. $E_1 = \left\{v_{\hat{t}} \leq p_t \text{ for all } t \leq \hat{t} < t'\right\}$ (i.e. no bids between t and t')

2. $E_2 = \left\{\bar{p} > v_{t'} > p_t\right\}$ (i.e. bidder t' bids)

3. $E_3 = \left\{v_{\hat{t}} \leq \min\left\{v_{t'}, v_0\right\} \text{ for all } t' < \hat{t} \leq N\right\}$ (i.e. no bids after t').

Note that, given p_t, the event E_1 conveys no additional information about $v_{t'}$. Furthermore, conditioning on the event E_3 increases the conditional expectation of $h\left(v_{t'}\right)$, strictly so when $t' < N$. The latter holds with positive probability when $t < N$, since with positive probability $t' = t$. Thus, using the fact that h is non-decreasing,

$$\phi^{\text{squat}}(t, 1, p_t) = \mathbf{E}\left[h\left(v_{t'}\right) \mid E_2 \cap E_3\right] \geq \mathbf{E}\left[h\left(v_{t'}\right) \mid E_2\right] = g_1\left(p_t\right)$$

with a strict inequality when $t < N$. This establishes the claim for $j = 1$ in the squatting treatment.

In the snipe treatment, suppose date t has been reached and the current high bid among opponents is p_t and the current price is $r_t \leq p_t$. Consider the event that exactly one additional bid is placed and the $p^{\text{snipe}} < \bar{p}$. Suppose t' is the stage at which that last bid is placed.

We can divide the conditioning event into two cases. First, consider $r_t < v_{t'} \leq p_t$. Note that this case has positive probability when $p_t > m$ and in this case $p^{\text{snipe}} = p_t$. The alternative case is $p_t < v_{t'} < \bar{p}$. Here, $p^{\text{snipe}} = v_{t'}$. Hence conditional on this second case, the expectation of $h(p^{\text{snipe}})$ is

$$\mathbf{E}\left[h\left(v_{t'}\right) \mid E_1 \cap E_2 \cap E_3\right]$$

where

1. $E_1 = \{v_{\hat{t}} \le r_t \text{ for all } t \le \hat{t} < t'\}$ (i.e. no bids between t and t')

2. $E_2 = \{p_t < v_{t'} < v_0\}$ (i.e. bidder t' bids)

3. $E_3 = \{v_{\hat{t}} \le p_t \text{ for all } t' < \hat{t} \le N\}$ (i.e. no bids after t').

Notice that given p_t and r_t, the events E_1 and E_3 convey no additional information about $v_{t'}$ so we can simplify to

$$\mathbf{E}\left[h\left(v_{t'}\right) \mid E_1 \cap E_2 \cap E_3\right] = \mathbf{E}\left[h\left(v_{t'}\right) \mid E_2\right] = g_1\left(p_t\right)$$

The definition of g_1 implies that $g_1\left(p_t\right) > h\left(p_t\right)$, i.e. the expectation in the second case exceeds the expectation in the first case. Therefore, the overall conditional expectation no greater than $g_1\left(p_t\right)$, i.e.

$$\phi^{\text{snipe}}\left(t, 1, p_t\right) \le g_1\left(p_t\right)$$

and strictly smaller when the first case has positive conditional probability. The first case, i.e. $r_t < v_{t'} \le p_t$, has positive conditional probability so long as $r_t < p_t$. In the snipe treatment r_t is the second highest bid at time t among the opponents, or m if fewer than two opponents have bid. If $p_t > m$, then at least one opponent has bid, and with probability 1, his bid strictly exceeds the second-highest bid, i.e. $p_t < r_t$. We conclude that the inequality is strict if $p_t > m$ and this establishes the claim for $j = 1$ in the snipe treatment.

Now, for the inductive step, assume the claim holds for $j - 1$ and define

$$g_j\left(p\right) = \mathbf{E}\left[g_{j-1}\left(v\right) \mid p < v < \bar{p}\right]$$

Note that by the induction hypothesis, g_{j-1} is increasing and hence so is g_j and $g_j\left(p\right) > g_{j-1}\left(p\right)$ for any $p < \bar{p}$.

In the squat treatment, suppose that at the beginning of stage $t \le N - j + 1$, the current price is p_t, and consider the event that $p^{\text{squat}} < \bar{p}$ and exactly j additional opponents will submit bids. If t' is the next opponent to bid, then the price becomes $v_{t'}$ after she bids. The conditional expected value of $h\left(p^{\text{squat}}\right)$ is, by the induction hypothesis, at least

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$g_{j-1}(v_{t'})$ with a strict inequality if $t' < N - j + 2$. Note that the latter holds with positive probability when $t < N - j + 1$.

Taking expectations with respect to the value of $v_{t'}$, a lower bound (strict when $t < N - j + 1$) on the conditional expectation of $h(p^{\text{squat}})$ is

$$\phi^{\text{squat}}(t, j, p_t) \geq \mathbf{E}_{v_{t'}}[g_{j-1}(v_{t'}) \mid E]$$

where E is the event that $v_{\hat{t}} \leq p_t$ for all $\hat{t} \in \{t, \dots t' - 1\}$ and $\bar{p} > v_{t'} > p_t$. By independence, the inequality can be written

$$\phi^{\text{squat}}(t, j, p_t) \geq \mathbf{E}[g_{j-1}(v) \mid p_t < v < \bar{p}] = g_j(p_t).$$

This establishes the inductive step in the squatting treatment.

In the snipe treatment, suppose the current high bid among opponents is p_t and the current price is $r_t \leq p_t$. Consider the event that exactly j additional bids are placed and $p^{\text{snipe}} < \bar{p}$. Suppose t' is the next bidder to place a bid.

If $m \leq r_t < v_{t'} \leq p_t$, then the high bid after player t' bids is still p_t and by the induction hypothesis p^{snipe} will be strictly less than $g_{j-1}(p_t)$. If instead $p_t < v_{t'} < \bar{p}$ then $p^{\text{snipe}} \leq g_{j-1}(v_{t'})$. Hence the conditional expectation of $h(p^{\text{snipe}})$ is bounded above by

$$\phi^{\text{snipe}}(t, j, p_t) \leq \mathbf{E}[g_{j-1}(v_{t'}) \mid E_1 \cap E_2]$$

where $E_1 = \{v_{\hat{t}} \leq r_t \text{ for all } \hat{t} \in \{t, \dots t' - 1\}\}$ and $E_2 = \{p_t < v_{t'} < \bar{p}\}$. The bound is strict if the first case, $m \leq r_t < v_{t'} \leq p_t$ holds with positive conditional probability, which is true whenever $p_t > m$. Given p_t and r_t, the event E_1 conveys no additional information about $v_{t'}$ so we can simplify the bound to

$$\phi^{\text{snipe}}(t, j, p_t) \leq \mathbf{E}[g_{j-1}(v) \mid p_t < v < \bar{p}] = g_j(p_t).$$

This concludes the proof of the claim.

We use the claim to prove the lemma. Let n be the total number of opponents submitting bids. Note that

$$\mathbf{E}\left[h\left(p^{\text{snipe}}\right) \mid O_n, \bar{P}\right] = \phi^{\text{snipe}}(1, n, m) \tag{2}$$

$$\mathbf{E}\left[h\left(p^{\text{squat}}\right) \mid O_n, \bar{P}\right] = \phi^{\text{squat}}(1, n, m). \tag{3}$$

The claim implies that (3) exceeds (2) and strictly so if $1 \leq n < N$, using the condition for strict inequality in the first part of the claim. It remains to show treat the case $n = N$, i.e. all opponents bid. In that case, an opponent must submit a bid $v_1 = p_1 > m$ in the first period. Then

$$\mathbf{E}\left[h\left(p^{\text{snipe}}\right) \mid O_n, \bar{P}\right] = \mathbf{E}_{v_1}\left[\phi^{\text{snipe}}\left(2, N-1, v_1\right) \mid v_1 < \bar{p}\right] \tag{4}$$

$$\mathbf{E}\left[h\left(p^{\text{squat}}\right) \mid O_n, \bar{P}\right] = \mathbf{E}_{v_1}\left[\phi^{\text{squat}}\left(2, N-1, v_1\right) \mid v_1 < \bar{p}\right]. \tag{5}$$

The claim implies that $\phi^{\text{snipe}}\left(2, N-1, p_1\right) < \phi^{\text{squat}}\left(2, N-1, p_1\right)$ for all $p_1 < \bar{p}$ since $p_1 > m$, using the condition for strict inequality in the second part of the claim. It follows that (5) strictly exceeds (4). ■

A.2 Proofs for the Concurrent Auctions Model

Proof of Proposition 2. Notice that, in any undominated strategies, $b_{ik} \leq v_i$ for both k and $b_{ik} = v_i$ for at least one k as long as $\widetilde{p}_{ik} < v_i$ for some k for all $i \in \{1, \ldots, N\}$. We will prove the proposition using backward induction. First we analyze the optimal strategy of bidder N. After placing κ_N, if she is the high bidder in auction k then it implies that the highest of bids by all bidders 1 to $N-1$ is (weakly) lower in auction k. Since in which auction bidder 0 bids is randomly decided, bidder N's optimal strategy in undominated strategies is $b_{Nk} = v_N$ and $b_{Nk'} = 0$ for $k' \neq k$. Now suppose she is not the highest bidder in any of the auctions after submitting κ_N implying that the prices in each auction, $\widetilde{p}_{Nk}$, are at least as great as κ_N. The next paragraph shows that, in equilibrium, $\kappa_N = v_N$. Therefore, if bidder N is not the high bidder in either of the auctions after the initial bid, she does not place any more bids. That is, $b_{Nk} = 0$ for $k \in \{1, 2\}$ in that case.

The main function of the initial bid κ_N is to figure out $\min\{q_{N1}, q_{N2}\}$. Since $\widetilde{p}_{Nk}$ does not cross $\min\{q_{N1}, q_{N2}\}$, the optimal κ_N equals v_N as for a smaller κ_N, she may fail to learn which auction has the lower highest bid even when $\min\{q_{N1}, q_{N2}\} < v_N$. In fact, $\kappa_N = v_N$ weakly dominates any other κ_N. For $\kappa_N < v_N$, bidder N's final payoff can be different from that in the $\kappa_N = v_N$ case iff $\kappa_N < \min\{q_{N1}, q_{N2}\} < v_N$. However, in that case, bidder N will be better off with $\kappa_N = v_N$ as she would learn for sure which auction

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has the lower q_{Nk}. For $\kappa_N > v_N$, $\widetilde{p}_{Nk}$ will be different for some k from the $\kappa_N = v_N$ case when $v_N < \min\{q_{N1}, q_{N2}\} < \kappa_N$. However, in that case, bidder N's payment conditional on winning is above v_N. Hence, in any equilibrium in undominated strategies, bidder N chooses $\kappa_N = v_N$ if $v_N > p_{Nk}$ for some k.

Now we assume that bidders $j \in \{i+1, \ldots, N\}$ follows the strategy $\kappa_j = v_j$ and $b_{jk} = v_j$ if and only if she becomes the high bidder in auction k after placing the initial bid κ_j. Then, bidder i's best response is to choose $b_{ik} = v_i$ if she becomes the high bidder in auction k after placing κ_i. She bids nothing in the auction(s) where she is not the high bidder. Moreover, using logic similar to that in the previous paragraph, we can show that $\kappa_i = v_i$. Bidder i's final payoff by choosing $\kappa_i < v_i$ can be different from that in the $\kappa_i = v_i$ case iff $\kappa_i < \min\{q_{i1}, q_{i2}\} < v_i$. In that case, she will be better off with $\kappa_i = v_i$ as she would learn for sure which auction has the lower q_{ik}. If $v_i < \min\{q_{i1}, q_{i2}\} < \kappa_i$, then $\widetilde{p}_{ik}$ will be different for some k from the $\kappa_i = v_i$ case. Then, bidder i pays above v_i if she wins. Therefore, in any equilibrium in undominated strategies, bidder i chooses $\kappa_i = v_i$ if $v_i > p_{ik}$ for some k.

Finally we calculate the experimenter's probability of winning and expected payoff. Suppose A is a set of numbers and the function $\mathbf{L}(A)$ is such that

$$
\mathbf{L}(A) = \begin{cases} m \text{ if } |A| < L \\ \text{the } L^{th} \text{ highest element in } A \text{ if } |A| \geq L. \end{cases}
$$

We denote $\mathbf{L}(\{v_1, \ldots, v_N\})$ by $v_{(L)}$. If the experimenter squats then the two bidders (including the experimenter) with the highest two valuations win and both pay the third highest valuation as the price. He wins and pay $v_{(2)}$ iff $v > v_{(2)}$. The experimenter's expected surplus from the squatting treatment equals

$$
\Pr\left(v_0 > v_{(2)}\right)\left(v_0 - \mathbf{E}\left[v_{(2)} | v_0 > v_{(2)}\right]\right)
$$

and the probability of winning equals $\Pr\left(v_0 > v_{(2)}\right)$. If the experimenter snipes and bids in auction k then, q_{N+1k} equals $v_{(1)}$ or $v_{(2)}$ with equal probability. His probability of winning from sniping is

$$
\frac{1}{2}\Pr\left(v_0 > v_{(1)}\right) + \frac{1}{2}\Pr\left(v_0 > v_{(2)}\right)
$$

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and his expected surplus equals

$$\frac{1}{2}\Pr\left(v_0 > v_{(1)}\right)\left(v_0 - \mathbf{E}\left[v_{(1)}|v_0 > v_{(1)}\right]\right) + \frac{1}{2}\Pr\left(v_0 > v_{(2)}\right)\left(v_0 - \mathbf{E}\left[v_{(2)}|v_0 > v_{(2)}\right]\right).$$

Thus, the expected payoff and probability of winning for the experimenter is higher if he squats when bidders $i \in \{1, 2, \ldots, N\}$ are sophisticated. ■

Proof of Proposition 3. The experimenter's expected surplus from the squatting treatment equals

$$\Pr\left(v_0 > v_{(2)}\right)\left(v_0 - \mathbf{E}\left[v_{(2)}|v_0 > v_{(2)}\right]\right)$$

His expected surplus from the sniping treatment equals

$$\Pr\left(v_0 > v_{(3)}\right)\left(v_0 - \mathbf{E}\left[v_{(3)}|v_0 > v_{(3)}\right]\right)$$

Thus, the expected payoff and probability of winning is higher for the experimenter if he snipes when bidders $i \in \{1, 2, \ldots, N\}$ are naïve. ■

Lemma 2 *Fix $\bar{p} \in [0, 1]$, and let $h : [0, 1] \to [0, 1]$ be any non-decreasing function which is not constant over $[0, \bar{p}]$. In the concurrent auctions model, suppose p^{snipe} and p^{squat} are the random variables corresponding to $v_{(2)}$ in the snipe and squat treatments, respectively. Denote by O_n the event that exactly n opponents submit bids, and $\bar{P}$ the event that $v_{(2)}$ is no greater than $\bar{p}$. We have*

$$\mathbf{E}\left[h\left(p^{\text{squat}}\right) \mid O_n, \bar{P}\right] \geq \mathbf{E}\left[h\left(p^{\text{snipe}}\right) \mid O_n, \bar{P}\right]$$

with a strict inequality iff $n \geq 1$.

Proof of Lemma 2. We can prove this lemma exactly the same way as we proved Lemma 1 incorporating concurrent auctions. Hence, instead of repeating the entire proof, we will just sketch out the differences between the two proofs.

Consider the case where p_t equals $\mathbf{2}\left(\{v_1, \ldots, v_{t-1}\}\right)$, and subsequently exactly j of bidders i to N place a bid and the second highest of the valuation of all opponents, $v_{(2)}$, is no greater than $\bar{p}$. In the snipe treatment, the current price for both auctions equals $\mathbf{3}\left(\{v_1, \ldots, v_{t-1}\}\right)$. On the other hand, the current price for both auctions in the squatting

treatment equals p_t. Let us denote $\mathbf{1}\left(\{v_1,\ldots,v_{t-1}\}\right)$ and $\mathbf{3}\left(\{v_1,\ldots,v_{t-1}\}\right)$ respectively by q_t and r_t where $r_t \le p_t$.

To prove claims 1 and 2 as in Lemma 1, we can follow the same procedure with the difference that we redefine the function g_1 as follows.

$$g_1(p) = \mathbf{E}\left[h\left(\min\{v_a, v_b\}\right) \mid \bar{p} > v_a, v_b \ge p\right].$$

Moreover, E_3 in the squat treatment now equals $\left\{v_{\hat{t}} \le \min\{v_{t'}, v_0, q_t\} \text{ for all } t' < \hat{t} \le N\right\}$. Using this E_3, we can show that since h is non-decreasing then

$$\phi^{\text{squat}}(t, 1, p_t) = \mathbf{E}\left[h\left(\min\{v_{t'}, q_t\}\right) \mid E_2 \cap E_3\right] \ge \mathbf{E}\left[(\min\{v_{t'}, q_t\}) \mid E_2\right] = g_1(p_t)$$

with a strict inequality if $t < N$.

For the snipe treatment, consider the event that exactly one additional bid is placed. Suppose t' is the last opponent to place a bid. First, consider $r_t < v_{t'} \le p_t$. This case has positive probability when $p_t > m$ and in that case $p_{N+1}^{\text{snipe}} = p_t$. The alternative case is $p_t < v_{t'}$ and the current price becomes p_t. Here, the final price p_{N+1} equals p_t and E_1, E_2 and E_3 will be the same as those in Lemma 1. Therefore,

$$\phi^{\text{snipe}}(t, 1, p_t) = \mathbf{E}\left[h\left(\min\{v_{t'}, q_t\}\right) \mid E_1 \cap E_2 \cap E_3\right] = \mathbf{E}\left[h\left(\min\{v_{t'}, q_t\}\right) \mid E_2\right] = g_1(p_t)$$

and this establishes the claim for $j = 1$ in the snipe treatment.

For the inductive step, assume the claim holds for $j - 1$ and define

$$g_j(p) = \mathbf{E}\left[g_{j-1}\left(\min\{v_a, v_b\}\right) \mid p \le v_a, v_b < \bar{p}\right].$$

Note that by the induction hypothesis, g_{j-1} is increasing in p for $p < v_0$ and hence so is g_j. Moreover, $g_j(p) \le g_{j-1}(p)$, strictly so if $p < v_0$. Again, we can prove the inductive step using the same line of argument used in proving the inductive step in Lemma 1. The only difference is that, in the squat treatment, we redefine E as the event that $v_{\hat{t}} \le \min\{p_t, v_{t'}\}$ for all $\hat{t} \in \{t,\ldots t' - 1\}$ and $\bar{p} > v_{t'} \ge p_t$ to incorporate concurrent auctions. Finally, we can use the claims to prove the lemma as done in Lemma 1. ∎

Proof of Proposition 4. First we fix a valuation profile $(v_1,\ldots,v_N)$ for the opponents. Consider player t has just arrived at the auction site and the current price in

auction 1 in the squatting treatment p_t^{squat} is less than v_0, the bid of the experimenter. That is, $p_i^{\text{squat}} = \mathbf{2}\left(\{v_1, \ldots, v_{t-1}\}\right)$. We consider player i to have placed a bid iff $p_{t+1} > p_t$ and, this implies, bidder t bids iff $v_t > p_t^{\text{squat}}$. Consider now the identical valuation profile in the sniping treatment. In this case, p_t^{snipe} equals $\mathbf{3}\left(\{v_1, \ldots, v_{t-1}\}\right)$, hence, is no greater than p_t^{squat} at any t. Therefore, if the bidder were to bid in the squatting treatment, she would bid in the sniping treatment as well.

By a similar reasoning we can show that when $p_t^{\text{squat}} \geq v_0$, a bidder arriving at time t would bid in the sniping treatment whenever she would bid in the squatting treatment. It follows that for any valuation profile, the number of bids submitted is at least as high in the sniping treatment as in the squatting treatment. Moreover, the inequality is strict with positive probability. First-order stochastic dominance follows immediately.

In the naïve bidders model, the second and third statements follow from Lemma 2 and we choose the same hs as in Proposition 1. For part 2 we take h to be the indicator function

$$h(p) = \begin{cases} 0 & \text{if } p < v_0 \\ 1 & \text{otherwise.} \end{cases}$$

and set $\bar{p} = 1$. Then $\mathbf{E}\left[h\left(p^{\text{squat}}\right) \mid O_n, \bar{P}\right]$ gives the probability of *losing* conditional on n opponents submitting bids in auction 1 in the squatting treatment in the concurrent auction model when bidders are naïve.[19] On the other hand, the probability of *losing* conditional on n opponents submitting bids in auction 1 in the sniping treatment is less than or equal to $\mathbf{E}\left[h\left(p^{\text{snipe}}\right) \mid O_n, \bar{P}\right]$ when bidders are naïve. The equality holds only when $n = 0$.[20] For part 3 we take $h(p)$ to be the identity function and set $\bar{p} = v_0$. Then $\mathbf{E}\left[h\left(p^{\text{squat}}\right) \mid O_n, \bar{P}\right]$ gives the expected price conditional on winning when n opponents submit bids in the squatting treatment. On the other hand, the expected price conditional on winning when n opponents submit bids in the sniping treatment is less than or equal to $\mathbf{E}\left[h\left(p^{\text{snipe}}\right) \mid O_n, \bar{P}\right]$ when bidders are naïve, the equality holding only when $n = 0$.

Part 4 of the proposition was proved in Proposition 3. ∎

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[19] This is also the probability of losing in squatting treatment when bidders are sophisticated.

[20] When bidders are sophisticated, the probability of losing in the snipe treatment is $\mathbf{E}\left[f(p^{\text{snipe}}) \mid O_n, \bar{P}\right]$ and $\mathbf{E}\left[f(r^{\text{snipe}}) \mid O_n, \bar{P}\right]$ with equal probability where $r^{\text{snipe}} = \mathbf{1}\left(\{v_1, \ldots, v_N\}\right)$.

Proof of Proposition 5. Suppose $\widehat{N}$ denotes the number of bidders with valuation above m and n is the number of opponents who place a bid in the auction in which the experimenter placed a bid. Conditional on $n = 0$, the experimenter's probability of winning is 1 and his payment is the opening price m. If the experimenter squats, then bidders 1 through N do not bid in auction 1 if and only if at most one bidder has valuation above m; that is, $\widehat{N} = 0$ or 1. If he snipes then the experimenter has no opponent with probability 1 if $\widehat{N} = 0$ and with probability $\frac{1}{2}$ if $\widehat{N} = 1$. That is, the probability of getting zero opponent are

$$F^N(m) + (N-1)F^{N-1}(m)(1 - F(m))$$

and

$$F^N(m) + \frac{N-1}{2}F^{N-1}(m)(1 - F(m))$$

in squatting and sniping treatments respectively. This is true in both sophisticated bidder and naïve bidder concurrent auction models. Given that it is less likely to have no opponents when the experimenter snipes, the expected value of the opening price m is higher when he snipes conditional on having no opponents. Therefore, conditional on none of bidders 1 to N placing a bid, the experimenter obtains higher expected surplus in the squatting treatment as the expected opening price is lower in those auctions. ∎

A.3 Robustness Issues

In this paper, we present only the simplest of the empirical analyses. However, the results are usually robust to all the variations in analysis that we considered.

To control for day specific fixed effects, we controlled for the day in which an auction started. An alternative would be to control for the day we placed a bid. This controls for the day specific fixed effects if a bidder randomly decides on whether to bid now on an auction that is immediately ending or bid now on an auction that is not ending soon. With this fixed effect, the coefficient of interest always have the same sign as the coefficients without any fixed effects or a fixed effect for the day the auction started. However, sometimes the sizes of the coefficients of interest and the t-statistics are quite a bit larger. One caveat is that if the bidder does not randomly choose whether to bid

on an auction ending soon or not, then this is a choice variable. That is why we do not present the results from regression with the bidding day specific fixed effects. If we allow for differing day specific fixed effects for different titles, the qualitative effect of sniping or its significance level on any dependent variable does not change either.

The result that sniping significantly increases our payoffs is robust to analyzing different measurements of surplus and to estimating other functional forms than the one presented in equation 1. The impact of sniping on surplus is positive and statistically significant if we use surplus in percentage terms instead of absolute surplus as the dependent variable. The qualitative impact of sniping also stays unchanged if we look at only at the auctions where we won. The impact of sniping stays positive and significant and almost unchanged if we include higher orders of the opening price as independent variables. When we look at log of absolute surplus and consider all the auctions we participated in, the positive impact of sniping on surplus become statistically significant (at 95% confidence level) even without robust standard errors. Using Durbin-Watson statistics, we can accept the null hypothesis that there was no first order auto-correlation between two consecutive auctions, in terms of starting time, in the data set.

If we look at auctions in the two different runs separately, we once again find positive impact of sniping on surplus. For both runs, the impact of sniping is statistically significant if we cluster the standard errors of auctions with the same valuation level together. If we look at auctions with different valuation levels separately, the impact of sniping becomes positive but statistically insignificant.

The number of opponents who placed a bid in an auction, or the observed number of opponents, depends on the opening price, whether we sniped in the auction, seller characteristics etc. in addition to the true number of opponent bidders present at an auction. As a result, using the observed number of opponents as a regressor leads to endogeneity problems. However, we can use a two-stage method to create an instrument for the true number of opponents present in an auction. For this, first we regress the observed number of bidders on a dummy for sniping treatments, the opening price and shipping cost, seller characteristics and dummies for the time period during which the

auction took place. We can argue that valuations of bidders is not correlated with the days in which an auction took place but is correlated to the true number of bidders at an auction. We also assume that the observed number of opponents is linearly related to the true number of opponents and other exogenous variables. Then, we can us the difference between the predicted number of observed opponents and the actual number of observed opponents as an instrument for the true number of opponents. When we include this instrument as a regressor, there is no significant change in the coefficients of interest in all the regressions we present. For example, the coefficient for the sniping dummy in the regression of our surplus, presented in column (1) of Table 2, goes from 0.182 to 0.187 when we include this instrument as a regressor. Because of the negligible effect of this instrument, we present only regressions without it in all the tables in this paper.

Table 12: Overview of Auctions

Title	# Auctions		Valuation (in USD)			
	Run 1	Run 2	Level 1	Level 2	Level 3	Level 4
The Lord of the Rings - The Return of the King	49		20	16		
The Last Samurai	26	21	18	14	11	9
Shrek	7		18	14		
Along Came Polly	23	13	18	14	11	9
Pirates of the Caribbean	9		18	14		
Master and Commander - The Far Side of the World	26		17	13		
Miracle	16		17	13		
Love Actually	6		17	13		
Mystic River	33	23	17	13	11	9
Harry Potter and the Chamber of Secrets	13		17	13		
50 First Dates	26		17	13		
Big Fish	8		16	12		
Seabiscuit	15		16	12		
Lost in Translation	8		16	12		
X2: X-Men united	4		15	11		
Cold Mountain Â Â Â Â Â Â Â Â Â Â		18			12	10
Hidalgo Â Â Â Â Â Â Â Â Â Â		16			12	10
13 Going on 30 Â		25			13	11
Kill Bill vol 2		60			14	12
The Passion of Christ		121			15	13

Table 13: Summary statistics of some auction characteristics

	Mean / Count	Std. Dev.	Max	Min
Opening price	3.88	3.31	9.99	0.01
Shipping cost	3.79	1.23	9.99	0
Total opening price	7.67	3.42	15.49	0.01
Seller feedback score	1277.22	2861.68	30995	0
Number of novice sellers	12			
Number of sellers with feedback score above 100	433			
Number of sellers based in the US	491			
Number of auctions that started on a weekend	175			

Table 14: Summary statistics of auction outcomes

	Count	We Won	Winning Ratio	Average Final Price
All auctions	566	283	50%	13.61
Auctions in Run 1	269	212	79%	13.40
Auctions in Run 2	297	71	24%	13.81
Auctions where we sniped	272	143	53%	13.41
Auctions where we squatted	294	140	48%	13.80

Table 15: Summary statistics of bids and bidders

	Mean / Count	Max	Min
	(Std. Dev.)		
Number of bids	6.08	24	1
	(4.26)		
Number of bids — snipe	7.08	24	1
	(4.90)		
Number of bids — squat	5.15	23	1
	(3.33)		
Number of bidders	3.96	10	1
	(2.17)		
Number of bidders — snipe	4.49	10	1
	(2.41)		
Number of bidders — squat	3.48	9	1
	(1.79)		
Number of opponents	3.16	10	0
	(2.30)		
Number of opponents — snipe	3.90	10	0
	(2.55)		
Number of opponents — squat	2.48	8	0
	(1.80)		

Table 16: Summary statistics of surpluses for various treatments

	Mean in absolute terms	Mean in percentage terms
	(Std. Dev.)	(Std. Dev.)
surplus	1.32	8.17
	(2.07)	(12.16)
surplus — we won	2.65	16.34
	(2.25)	(12.75)
surplus — we sniped	1.41	8.83
	(2.07)	(12.37)
surplus — we squatted	1.25	7.57
	(2.07)	(11.95)
surplus — we sniped and won	2.68	16.78
	(2.17)	(12.56)
surplus — we squatted and won	2.62	15.89
	(2.34)	(12.96)
surplus — snipe with valuation level 1	4.03	22.99
	(2.21)	(12.84)
surplus — squat with valuation level 1	3.75	21.21
	(2.54)	(14.22)
surplus — snipe with valuation level 2	1.22	8.89
	(0.31)	(9.28)
surplus — squat with valuation level 2	1.02	7.16
	(1.33)	(8.99)
surplus — snipe with valuation level 3	0.37	2.86
	(0.84)	(6.59)
surplus — squat with valuation level 3	0.22	1.67
	(0.53)	(3.86)
surplus — snipe with valuation level 4	0.14	1.37
	(0.50)	(5.38)
surplus — squat with valuation level 4	0.07	0.78
	(0.33)	(3.68)

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Bid History

DVD MOVIE - ALONG CAME POLLY (STILLER ANISTON) *NEW*   Item number: 6315229515

Currently:	US $12.51	**Quantity:**	1
First Bid:	US $1.99	**Started:**	Aug-09-04 19:37:42 PDT
# of bids:	9	**Ends:**	Aug-16-04 19:37:42 PDT
Time left:	Auction has ended.		
Seller:	sathompson1 (2214 ⭐)		

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Bidding history (Highest bids first)

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

Date of Bid	Bid Amount	User ID
Aug-15-04 12:07:40 PDT	US $12.51	rhi_derrick (5)
Aug-11-04 01:00:42 PDT	US $12.01	jtw0493 (56 ⭐) 👤
Aug-15-04 11:53:33 PDT	US $12.00	rhi_derrick (5)
Aug-15-04 11:53:20 PDT	US $11.00	rhi_derrick (5)
Aug-13-04 09:51:44 PDT	US $10.00	rhi_derrick (5)
Aug-13-04 09:49:05 PDT	US $9.00	rhi_derrick (5)
Aug-13-04 09:48:58 PDT	US $7.00	rhi_derrick (5)
Aug-13-04 09:48:49 PDT	US $5.00	rhi_derrick (5)
Aug-13-04 09:48:41 PDT	US $3.00	rhi_derrick (5)

Bidders: You can retract your bid under certain circumstances only.
Sellers: See how to cancel bids if you need to.

Bid retraction and cancellation history

There are no bid retractions or cancellations.

Figure 2: This auction shows a drawback of squatting. The sole opponent was bidding naïvely and eventually raised the price above our value. Presumably, the opponent would have stopped bidding earlier had he/she become the high bidder at a lower price. By sniping we therefore would have won this auction, possibly at a low price.

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Bid History

$.55 DVD New/Sealed ~MASTER and COMMANDER:...~   Item number: 6314967299

Currently:	US $10.00	**Quantity:**	1
First Bid:	US $0.55	**Started:**	Aug-10-04 20:25:00 PDT
# of bids:	9	**Ends:**	Aug-17-04 20:25:00 PDT
Time left:	Auction has ended.		
Seller:	dvdhntss (540 ☆)		

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Bidding history (Highest bids first)

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

Date of Bid	Bid Amount	User ID
Aug-17-04 05:16:32 PDT	US $10.00	cliff20030 (20 ☆)
Aug-12-04 03:37:59 PDT	US $9.50	jtw0493 (56 ☆)
Aug-17-04 05:16:23 PDT	US $9.00	cliff20030 (20 ☆)
Aug-17-04 05:16:10 PDT	US $7.50	cliff20030 (20 ☆)
Aug-17-04 05:16:01 PDT	US $6.00	cliff20030 (20 ☆)
Aug-17-04 05:15:53 PDT	US $5.00	cliff20030 (20 ☆)
Aug-12-04 04:59:37 PDT	US $4.50	shiela* (2115 ☆)
Aug-10-04 20:40:02 PDT	US $2.00	steven02_35th (73 ☆)
Aug-11-04 16:14:32 PDT	US $0.65	falcons*hockey*rulz (122 ☆)

Bidders: You can retract your bid under certain circumstances only.
Sellers: See how to cancel bids if you need to.

Bid retraction and cancellation history

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Figure 3: This auction shows a drawback of squatting. The winner was bidding naïvely and eventually raised the price above our value. Presumably, the opponent would have stopped bidding earlier had he/she become the high bidder at a lower price. By sniping we therefore would have won this auction, possibly at a low price.

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Bid History

The Lord of the Rings: The Return of the King DVD DVDS Item number: 6315700760

Currently:	US $10.00	Quantity: 1
First Bid:	US $0.01	Started: Aug-11-04 19:11:43 PDT
# of bids:	24	Ends: Aug-18-04 19:11:43 PDT
Time left:	Auction has ended.	
Seller:	scottzcamarc (72 ☆) me	

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Bidding history (Highest bids first)

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

Date of Bid	Bid Amount	User ID
Aug-18-04 19:11:38 PDT	US $10.00	jtw0493 (56 ☆)
Aug-18-04 18:19:13 PDT	US $9.50	vanadiscott (4)
Aug-18-04 13:49:27 PDT	US $9.00	5179468 (10 ☆)
Aug-18-04 18:12:06 PDT	US $8.55	tmpeal (2)
Aug-18-04 12:32:09 PDT	US $7.55	vanadiscott (4)
Aug-17-04 14:19:00 PDT	US $7.05	militellum (50 ☆)
Aug-17-04 17:55:41 PDT	US $7.00	stevedonna97 (85 ☆)
Aug-17-04 17:55:23 PDT	US $6.00	stevedonna97 (85 ☆)
Aug-16-04 23:34:48 PDT	US $5.00	hiper_weirdo (0)
Aug-13-04 20:12:37 PDT	US $4.00	stevedonna97 (85 ☆)
Aug-16-04 18:24:44 PDT	US $4.00	ginaswish (123 ☆)
Aug-14-04 18:10:18 PDT	US $2.00	stevexo666 (19 ☆)
Aug-13-04 12:43:24 PDT	US $1.25	vanadiscott (4)
Aug-11-04 20:20:54 PDT	US $1.00	stevedonna97 (85 ☆)
Aug-13-04 12:43:15 PDT	US $1.00	vanadiscott (4)
Aug-13-04 12:43:02 PDT	US $0.90	vanadiscott (4)
Aug-13-04 12:42:53 PDT	US $0.80	vanadiscott (4)
Aug-13-04 12:42:41 PDT	US $0.70	vanadiscott (4)
Aug-13-04 12:41:51 PDT	US $0.60	vanadiscott (4)
Aug-13-04 12:41:38 PDT	US $0.50	vanadiscott (4)
Aug-13-04 12:40:54 PDT	US $0.36	vanadiscott (4)
Aug-12-04 15:10:05 PDT	US $0.26	95fbruzr (10 ☆)
Aug-12-04 15:09:54 PDT	US $0.16	95fbruzr (10 ☆)
Aug-12-04 15:09:40 PDT	US $0.06	95fbruzr (10 ☆)

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Figure 4: This auction illustrates the benefit of sniping. Our competitors reveal that they are bidding naïvely and the highest-bidding opponent stops bidding after just outbidding her rival. By sniping we avoid provoking her into raising her bid further, enabling us to win the auction.

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Bid History

BIG FISH (2004) NEW FS SEALED DVD   Item number: 6314685915

Currently:	US $8.51	**Quantity:**	1
First Bid:	US $1.00	**Started:**	Aug-07-04 11:28:32 PDT
# of bids:	9	**Ends:**	Aug-14-04 11:28:32 PDT
Time left:	Auction has ended.		
Seller:	cdsanddvdsforsale (117 ⭐)		

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Bidding history (Highest bids first)

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

Date of Bid	Bid Amount	User ID
Aug-14-04 11:28:28 PDT	US $8.51	jtw0493 (56 ⭐) 👤
Aug-14-04 11:04:26 PDT	US $8.01	dogfoodfund2 (14 ⭐)
Aug-14-04 05:42:30 PDT	US $7.01	perkuup (5)
Aug-14-04 05:06:25 PDT	US $6.50	dogfoodfund2 (14 ⭐)
Aug-12-04 14:17:11 PDT	US $6.00	perkuup (5)
Aug-11-04 20:35:45 PDT	US $5.39	bassjazzbo (37 ⭐)
Aug-11-04 14:28:09 PDT	US $5.00	perkuup (5)
Aug-10-04 22:08:12 PDT	US $1.26	bassjazzbo (37 ⭐)
Aug-08-04 21:25:21 PDT	US $1.01	xxxbrenda (129 ⭐)

Bidders: You can retract your bid under certain circumstances only.
Sellers: See how to cancel bids if you need to.

Bid retraction and cancellation history

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Figure 5: This auction illustrates the benefit of sniping. Our competitors reveal that they are bidding naïvely and the highest-bidding opponent stops bidding after just outbidding her rival. By sniping we avoid provoking her into raising her bid further, enabling us to win the auction.