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# Sniping and Squatting in Auction Markets†

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*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 small. The two bidding strategies resulted in a variety of other qualitative differences in the outcomes of auctions. We show that a model of multiple concurrent auctions, in which our opponents are naïve or incremental bidders as identified in the lab, explain the results well. Our findings illustrate how the overall impact of naïveté, and the benefit from sniping observed in the lab, may be substantially attenuated in real-world market settings.* (*JEL* D44)

Online auction markets provide economists with access to an almost textbook marketplace that 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 some of 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] This phenomenon is common for most product categories on eBay including those with low resale probability and minimal uncertainty in quality. The prevalence of sniping in second-price auctions in a private-value setting is surprising as auction theory suggests that sniping would be,

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[1] See, for example, Alvin E. Roth and Axel Ockenfels (2002), Patrick Bajari and Ali Hortaçsu (2003), and Tanjim Hossain (2008) for evidence of sniping in online auctions of a wide array of goods.

at best, no more profitable than bidding early if rival bidders follow undominated strategies.

While the practice of sniping has been documented, and rationales have been 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 would require inferring a bidder's valuation from her bidding behavior. This is complicated for two reasons. First, this entails imposing some assumptions about the bidder's rationality (i.e., bidding her value). Yet, sniping in private-value auctions is typically explained as a response to some departure from rational behavior among participants in online auctions. 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, laboratory experiments do not provide us with the endogenously determined market composition of auction markets such as eBay.

A field experiment, however, 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 bid on auctions of brand new movie DVDs. For 20 popular, recently released movies, using a survey of recently concluded auctions, we *induced* or chose bids at four different levels that were expected to win 90 percent, 60 percent, 40 percent, and 20 percent of the auctions, respectively. We used these induced values as our valuations in the auctions in which we participated to measure the benefit from sniping. We randomly divided the set of auctions of the same movie into two groups. In the first group, we bid on the first day of the auction (squatting). In the second group, we sniped using an online bidding service that submitted our bid five seconds before the closing of an auction. In either treatment, we placed only one bid, and that bid was equal to our induced valuation. Our payoff from an auction equaled the difference between our valuation and the final price, including any shipping costs, if we won, and equaled zero if we lost.

We find that sniping does lead to a small, perhaps economically negligible, increase in our payoff. Controlling for auction characteristics, we find that sniping increases our payoffs by \$0.17, slightly more than 1 percent of our average valuation in these auctions. By more carefully analyzing individual bid data, we suggest that 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 as a proxy bid, 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 two illustrative hypothetical auctions that exemplify naïve bidding behavior and its effects. See Tables A4 and A5.

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.

We find that these two effects roughly cancel each other out, leading to a small net impact of sniping. In retrospect, it should not be surprising that the effects should be so neatly balanced for a product category with many auctions that are close substitutes. Free-entry into competing bidding strategies such as sniping and squatting should equate the net payoffs to those strategies, especially in the absence of information asymmetry among bidders.[2] Indeed, our conclusion is that explaining the experimental results requires a theoretical model in which multiple auctions are held concurrently and some bidders are naïve. At the end of this paper, we present a model with concurrent auctions and only naïve bidders, to illustrate how squatting may cause less competition while sniping causes less escalation of opponent bids.

The remainder of this paper is organized as follows. In Section I, we relate our work to the existing experimental and theoretical literature on sniping and bounded rationality in online auctions. In Section II, we describe our experimental design. Our empirical findings are detailed in Section III. Section IV presents a theoretical model based on our experimental design and results. Finally, Section V concludes. All of the proofs are in the Appendix.

## I. 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. Ockenfels and Roth (2006) present a model of eBay auctions in which sniping arises as part of a tacitly collusive equilibrium. Eric B. Rasmusen (2006) has a model with two bidders, one of which does not know her private valuation and can learn it 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. Hossain (2008) proposes a dynamic second-price auction with uninformed bidders who get more information about their valuations from the price during the auction. In equilibrium, uninformed bidders place many bids to learn about their valuations, and informed bidders may snipe to reduce uninformed bidders' learning by bidding. Unlike the concurrent auction market model proposed in this paper, bidders participate in a single auction in those papers.[3]

In laboratory experiments, Dan Ariely, Ockenfels, and Roth (2005) run dynamic second-price auctions with 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

[2] Of course, the advantage of squatting from the competition effect may not be strong enough to balance the advantage to sniping from the escalation effect for goods without close substitutes.

[3] Another potential rationale for sniping, suggested to us by Andy Postlewaite, is based on the observation that many near-perfect substitutes sold in consecutive auctions. The value of an opposing bidder conveys information about the price in subsequent auctions if that bidder is likely to remain in the market. If the opposing bidder's value is high, this should make others more aggressive today. The opposing bidder may then have an incentive to snipe in order to conceal his high value and keep bidding low. This theory would be consistent with the escalation effect, but not the competition effect that we identify.

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]

Roth and Ockenfels (2002) were the first to suggest that sniping may arise as an optimal response to naïve bidding.[5] Using experimental data, Ariely, Ockenfels, and Roth (2005) present evidence of naïve bidding leading to a significant increase in a sniper's surplus. Bidding behavior of the naïve bidders can be observationally similar to those of uninformed bidders suggested in Hossain (2008). 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.[6] We confirm that our bid level data is consistent with incremental or naïve bidding, but the overall effect of naïveté is diminished because of the large free-access market eBay provides. This provides a nice example in which a laboratory experiment uncovers a behavioral bias and then a field experiment completes the picture by demonstrating the impact of such behavioral biases in a large real-world market.[7]

A paper that tests the impact of sniping using field experiments is Sean Gray and David H. 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 dataset. Our experimental design allows us to compare the probability of winning or analyze benefit of sniping for different levels of valuations. Moreover, a large dataset of products from the same category enables us to get statistically significant results.

## II. 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 two strategies: squatting and sniping. In one auction, we place a bid equaling our chosen valuation on the opening day. In the next auction, we place a bid in the last five seconds 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 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

[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.

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

[6] Ariely, Ockenfels, and Roth (2005) caution that the conclusions from their laboratory setting should not be presumed to generalize to the natural market environment.

[7] See John A. List (2006) and Stephen D. Levitt and List (2007) for discussions on some similar studies.

little uncertainty about the quality of the product in terms of both the content and the condition for new DVDs of popular movies. Identical copies of these DVDs are also available at traditional brick-and-mortar stores, albeit usually at a higher price. Many large sellers on eBay are small businesses run from home that purchase new DVDs at a wholesale price, but do not have their own retail stores. Usually the prices on eBay are somewhat lower than the maximum retail price. Average auction prices for these movies fall by 15 to 20 percent one month after the DVD is released. Considering the depreciation and shipping charges, it would not be very profitable to buy from eBay for resale and purchasing for the purpose of eventual resale is not very common. Overall, we can argue that DVDs approximate a private-value good reasonably well. 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. We chose a product where many auctions of identical products are available so that we can observe how much benefit sniping has in a large market with close substitutes.

Using 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 A1 in the Appendix. 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 equaling 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.com charges a fixed fee for unlimited use of the service within a given time frame. Our bid was placed five seconds before the end of the auction.[8]

On eBay, the total price a bidder pays equals the sum of the final price from the auction and the shipping and handling cost. We wanted our total bid to equal $v_k$. Therefore, if, in auction $k$, our induced valuation was $v_k$, and the shipping cost was $s_k$, then we submitted a nominal bid of $b_k = v_k - s_k$. We always report the sum of the price reached in the auction and the shipping cost as the final or total price from an auction. 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 seven-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, above our valuation. In all of our auctions, the sellers

[8] Out of 272 auctions in which we intended to snipe, in only two auctions did our bids not go through even though the bid value was above the current price level.

Table 1—Details of the Different Treatments

| | Run 1 | | Run 2 | |
|---|---|---|---|---|
| | Valuation level 1 | Valuation level 2 | Valuation level 3 | Valuation level 4 |
| Expected winning probability | 90% | 60% | 40% | 20% |
| Distinct movies | 15 | 15 | 8 | 8 |
| Sniping auctions | 68 | 60 | 72 | 72 |
| Squatting auctions | 73 | 68 | 79 | 74 |

*Notes:* Auctions in Run 1 started between August 12, 2004 and August 18, 2004. Auctions in Run 2 started between September 9, 2004 and September 23, 2004.

specified the shipping costs in the auction descriptions and accepted payments via "Paypal."

For the first run of the experiment, we chose the level of bids that were likely to win approximately 90 percent or 60 percent of the time and placed bids on 15 different movies. In the second run, we placed bids that were likely to win 40 percent or 20 percent of the time on 8 titles. Of them, three were included in the first run of the experiment and the other five were released after the first run of the experiment hadstarted. In each run, for each title, we assigned an auction to a treatment chronologically in terms of their starting times. In the first and second auctions, we placed squatting and sniping bids, respectively, with the relatively high valuation (for that run). In the third and fourth auctions, we placed squatting and sniping bids, respectively, with the relatively low valuation (for that run). The exact number of auctions in each treatment are presented in Table 1. As we ended the experiments on a chosen day, without balancing the number of auctions in each treatment, there are more squatting auctions and more auctions at valuation levels one and three. In total, we participated in 566 auctions. Table A2 in the Appendix presents some summary statistics about these auctions. We used the same eBay ID for all the auctions in which we participated. As a result, our feedback number was not constant during the auction. For private-value goods, such as 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.

## III. Results

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 50 percent, of the auctions. Our winning percentages were 47.6 percent and 52.6 percent for squatting and sniping, respectively. We made a total payment of $3,571.26 in the auctions we won.[9] First, we compare our surplus and auction outcomes from sniping and squatting strategies. Next, we attempt to explain these comparison results using escalation and competition effects as defined at the beginning of this paper.

[9] Table A3 in the Appendix summarizes some statistics on auction outcomes.

Table 2—Mean Surplus and Other Outcome Variables across Treatments

| | Snipe | Squat |
|---|---|---|
| Average surplus | 1.410 | 1.245 |
| | (2.069) | (2.074) |
| Average surplus at valuation level 1 | 4.030 | 3.751 |
| | (2.207) | (2.541) |
| Average surplus at valuation level 2 | 1.220 | 1.022 |
| | (1.311) | (1.331) |
| Average surplus at valuation level 3 | 0.369 | 0.221 |
| | (0.839) | (0.527) |
| Average surplus at valuation level 4 | 0.135 | 0.071 |
| | (0.502) | (0.332) |
| Average final price | 13.411 | 13.800 |
| | (2.510) | (2.436) |
| Average final price conditional on winning | 12.436 | 12.806 |
| | (2.270) | (2.221) |
| Percentage of win | 52.5 | 47.6 |
| | (0.500) | (0.500) |
| Average number of opponents | 3.9 | 2.48 |
| | (2.550) | (1.798) |

## A. *Overview of Results*

As we assign auctions to treatments randomly, there should not be any systematic differences in determinants of prices among auctions other than our actions of sniping or squatting. Thus, we can compare means across treatments to get a clear idea about the impact of sniping on auction outcomes. Table 2 presents means of several outcome variables of our auctions across treatments.[10]

Suppose our total bid, equaling our valuation, is $v_k$, and the final price including shipping fees is $p_k$ in auction $k$. If we lose the auction, then our surplus is zero, and if we win, our surplus is $(v_k - p_k)$. Our average surpluses were \$1.25 and \$1.41 in squatting and sniping treatments, respectively, and \$1.32 averaged over all auctions. Our winning probability was 5 percent higher, and the sellers received \$0.39 lower revenue when we sniped. Surprisingly, however, the number of opponents bidding in the sniping treatment was higher by almost one-and-a-half bidders. None of the variables, other than the number of opponents, were significantly different between the two treatments at the 5 percent level. The difference in the final price (including shipping charges), or the revenue, was significant only at the 10 percent level. We find significant differences in the impact of sniping when we control for auction characteristics and use robust standard errors, however.

Now, we look closely to the auctions in which we placed bids with valuation level 1. These bids were expected to win 90 percent of the auctions. Table 3 presents a summary of outcome variables for these 141 auctions. The differences in surplus, final price, winning percentage, and number of opponents between the two treatments follow the same pattern as in Table 2. Table 4 presents the frequency of the

[10] We always report the total price including the shipping fee as the final price.

Table 3—Outcome Variables for Sniping and Squatting Treatments for Valuation Level 1

| Surplus | | Win percent | | Final price | | Opponents | | Count | |
|---|---|---|---|---|---|---|---|---|---|
| Snipe | Squat | Snipe | Squat | Snipe | Squat | Snipe | Squat | Snipe | Squat |
| 4.030 | 3.752 | 95.6 | 90.4 | 13.653 | 13.926 | 3 | 1.562 | 68 | 73 |
| (2.207) | (2.541) | (0.207) | (0.296) | (2.658) | (2.718) | (2.510) | (1.443) | | |

Table 4—Frequency of Final Prices as a Percentage of Our Bid: Valuation Level 1

| Final price/our bid (percent) | Snipe (percent) | Squat (percent) |
|---|---|---|
| 40–50 | 1.5 | 1.4 |
| 50–60 | 2.9 | 6.8 |
| 60–70 | 26.5 | 16.4 |
| 70–80 | 30.9 | 30.1 |
| 80–90 | 19.1 | 17.8 |
| 90–100 | 14.7 | 17.8 |
| > 100 | 4.4 | 9.6 |

final price (including shipping charges) as a percentage of our total bid. There are more auctions with a somewhat lower final price (between 40–60 percent) and a very high price (above 90 percent) in the squatting treatment. As the number of auctions in the two treatments was not the same, we present the percentage of auctions in any specific range. This table suggests that squatting induced more extreme behavior from bidders. This is reinforced by the lower variance of the final price in sniping treatment. Coupled with the fact that sniping treatments actually attracted more bidders, we surmise that some bidders who placed a bid in a sniping auction ended up bidding less aggressively than they would have if they were to place a bid in a squatting treatment.

Of course, from an econometric point of view, we need to control for auction characteristics to provide more efficient estimates. Next, we discuss the impact of sniping on auction outcomes in more detail as we present regression results for our surplus, the seller's revenue, and such.

*Final Outcomes.*—In the regressions, 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:

$$Y_k = \beta_0 + \beta_1\, snipe_k + \beta_2\, op_k + \beta_3\, s_k + \beta \mathbf{X}. \tag{1}$$

Here, $Y_k$ stands for some outcome variable related to auction $k$. The dummy variable *snipe* equals one when we sniped. The opening price and the shipping fee, which are chosen by the seller, are denoted by *op* and *s*, respectively. Variables characterizing the auctions, such as the closing time of the auction, the seller's location and reputation level and fixed effects pertaining to the size of our bid, movie specific

Table 5—Effect of Sniping on Auction Outcomes

| | Surplus | We won | Final price when we won | Final price |
|---|---|---|---|---|
| *Regressor* | | | | |
| Sniping dummy | 0.174** | 0.127*** | −0.082 | −0.348*** |
| | (0.081) | (0.023) | (0.068) | (0.085) |
| Opening price | 0.038 | 0.023*** | −0.037 | −0.071*** |
| | (0.045) | (0.006) | (0.028) | (0.023) |
| Shipping cost | −0.200** | −0.061*** | 0.249*** | 0.311*** |
| | (−0.087) | (0.021) | (0.015) | (0.016) |
| *Summary* | | | | |
| Observations | 566 | 552 | 283 | 566 |
| Mean | 1.325 | 0.500 | 12.619 | 13.613 |
| (standard deviation) | (2.071) | (0.500) | (2.249) | (2.477) |
| Pseudo $R^2$ | 0.595 | 0.425 | 0.498 | 0.415 |

*Note:* Final price includes shipping charges.
***Significant at the 1 percent level.
**Significant at the 5 percent level.

variations, and day specific variations are included as control variables in **X**. The right-hand-side variables are exogenous for all of our opponent bidders. One important unobservable is the number of *potential* bidders including those who visited the auction but did not place a bid. Unfortunately, this cannot be observed directly, and we cannot use the number of *actual* bidders as that is endogenously affected by the treatment and the opening price. By including fixed effects for the day that the auction started, we control, to some extent, for any unmeasured difference in eBay traffic through the course of an auction. We can also use a two-stage method to create an instrument for the true number of opponents present in an auction. However, we do not present regressions with those instruments as that does not change our estimate significantly. In this paper, we present only the simplest of the empirical analyses. The results are usually robust to variations in the functional form of the estimated equation and other specifications.

Table 5 presents regression results concerning the impact of sniping on our surplus, our probability of winning, the final price conditional on us winning the auction, and unconditional final price (the revenue). Robust standard errors are presented in parentheses.[11] We are not independently interested in the coefficients of most regressors other than the sniping dummy. They are used to reduce the nuances in auction specifics, thus increasing the efficiency of the estimates. We suppress the coefficients of most of the regressors in Table 5 and Table 7.

The first column of Table 5 shows that the impact of sniping on surplus is significant at the 5 percent significance level. The surplus is higher by around $0.17 if we snipe. The coefficients for sniping stay significant when we, instead, look at surplus in percentage terms. Sniping increased our surplus by about 1.36 percent

[11] To control for correlation in the error terms from auctions in the same run, we use the Huber-White sandwich estimator of variance in calculating standard errors by clustering these observations.

of our induced valuation. The impact of sniping is qualitatively the same, and statistically significant, if we choose our surplus (our valuation minus the final price including shipping charges) as a fraction of our valuation as the dependent variable. If we subdivide the dataset according to the four different valuation levels, then for each valuation level, the impact of sniping stays positive but becomes statistically insignificant. The overall 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 treatment. When we look at auctions in which our bid was drawn from valuation levels 1–3 (bids that were expected to win at least 40 percent of times), the benefit to sniping increases to \$0.26 and stays significant. While the opening price negatively affects our surplus, the shipping charges had a positive impact on it. Both the opening price and the shipping cost are components of the effective reserve price. Thus, this result is consistent with the finding by Hossain and John Morgan (2006) that a seller can increase her revenue by transferring some of the reserve price from the opening price to the shipping fee. This result is reinforced in the last column of the table.

The second column of Table 5 presents marginal effects coefficients for probit analysis of a dummy showing whether we won an auction. We find that sniping increases the probability of winning, and the increase is statistically significant whether or not we use robust standard errors. Between two identical auctions where we squat in one auction and snipe in the other, our probability of winning increased by 12.7 percent in the auctions where we sniped. When we look at auctions with different levels of bids by us separately, we find that the benefit of sniping is smaller, but still significant, in auctions where our bids were expected to win about 90 percent of the time than the auctions with lower valuations. This makes sense because, as we won most of these auctions with either strategy, the relative benefit of sniping in winning the auction was low.

On the other hand, the effect on our expected payment, conditional on winning, was much weaker. The third column shows that our expected payment, conditional on winning, was lower by about \$0.08 in auctions where we sniped, but the impact is statistically insignificant at any reasonable confidence level. The weak overall effect on our final surplus is a combination of these two effects, and therefore, taken by itself, it 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 effect on sellers' revenues. If the final outcomes were unaffected by the choice of squatting or sniping, then average revenues would be the same in the two treatments. The final column of Table 5 shows that sniping decreases the final price (including the shipping charge) by almost \$0.35, controlling for auction characteristics.

Although the impact of sniping on surplus is relatively small and significant only under a number of econometric specifications, the positive impact of sniping on our probability of winning and negative impact on seller's revenue is relatively large and unambiguously statistically significant. Even if we ignore the increase in surplus due to sniping as economically insignificant, the overall results allow us to reject the hypothesis that sniping and squatting virtually lead to the same outcome. In Section IIIB, we further analyze our data to show that two countervailing effects on surplus

Table 6—Breakdown of Auction Characterisitics According to the Number of Opponents

| | Surplus | | Win percent | | Final price | | Count | |
|---|---|---|---|---|---|---|---|---|
| Opponents | Snipe | Squat | Snipe | Squat | Snipe | Squat | Snipe | Squat |
| 0 | 2.714 | 3.634 | 100 | 100 | 11.841 | 11.930 | 27 | 39 |
| | (2.183) | (2.605) | | | (1.011) | (1.447) | | |
| 1 | 3.284 | 1.530 | 78.8 | 60.9 | 12.415 | 13.437 | 33 | 64 |
| | (2.754) | (2.162) | (0.415) | (0.492) | (2.224) | (2.378) | | |
| 2 | 1.220 | 0.831 | 50.0 | 47.0 | 12.294 | 13.502 | 34 | 58 |
| | (1.928) | (1.599) | (0.508) | (0.503) | (2.286) | (2.278) | | |
| 3 | 1.447 | 0.999 | 62.5 | 44.9 | 12.912 | 13.740 | 32 | 49 |
| | (1.868) | (1.855) | (0.492) | (0.503) | (2.728) | (2.328) | | |
| 4 | 1.046 | 0.444 | 50.0 | 20.5 | 13.512 | 14.973 | 32 | 44 |
| | (1.633) | (1.147) | (0.508) | (0.508) | (2.998) | (2.077) | | |
| 5 | 0.902 | 0.108 | 29.0 | 9.1 | 14.057 | 15.058 | 31 | 22 |
| | (1.815) | (0.359) | (0.461) | (0.294) | (2.612) | (2.194) | | |
| 6 | 0.633 | 0.455 | 28.9 | 9.1 | 14.544 | 15.685 | 38 | 11 |
| | (1.473) | (1.508) | (0.460) | (0.302) | (2.166) | (3.243) | | |
| 7 or more | 0.639 | 0.341 | 37.8 | 14.3 | 14.809 | 16.134 | 45 | 7 |
| | (1.308) | (0.903) | (0.490) | (0.377) | (1.921) | (2.354) | | |

come into play in our experiments, leading to a relatively small difference in surplus between the two treatments.

## B. *Competition and Escalation Effects*

It is clear from Section IIIA that our sniping and squatting led to significantly different outcomes in eBay auctions. Specifically, our sniping increased our surplus slightly and reduced revenue for sellers. However, auctions in the sniping treatment attracted almost one-and-a-half more opponent bidders compared to auctions in the squatting treatment. These seemingly inconsistent results lead us to the striking results presented in Table 6. The table shows two effects of sniping versus 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. Second, 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. These two effects point to a theory where some opponents are naïve and many auctions concurrently take place.

Our hypothesis is that sniping pays because *opponents* are not provoked into bidding aggressively, thereby avoiding what we term the *escalation effect*, and that this benefit is offset and, perhaps, nullified by the *competition effect* which tends to favor squatting. The escalation effect arises from the hypothesis that some online bidders bid naïvely. Rather than treating an eBay auction as a dynamic second-price auction, the bidder acts as though she is involved in an English auction and continuously

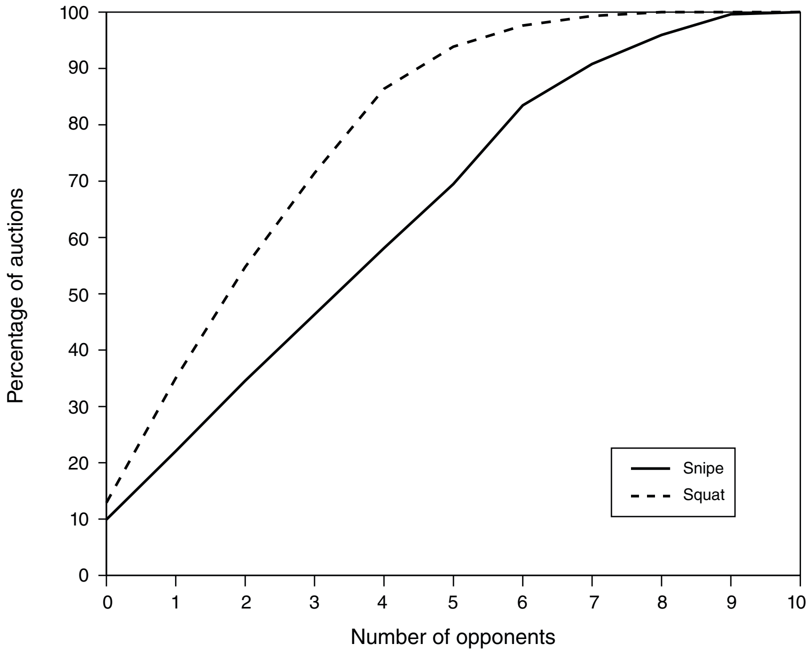


Figure 1. The Competition Effect of Squatting

raises her bid whenever outbid until reaching some drop-out price, but never bidding her value unless the price reaches that point. On the other hand, the competition effect arises from the fact that each individual auction is embedded within the broader eBay market with many auctions of substitutable goods. 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. An opponent in an auction refers to any bidder, other than us, who submitted at least one bid. Table 6 shows that conditional on $n \geq 1$ opponents submitting bids, the surplus was higher for auctions in which we sniped. Indeed, the average surplus from auctions in which we sniped and faced $n + 1$ opponents was higher than those from the auctions in which we squatted and had $n$ opponents, for most values of $n$.

Perhaps the clearest evidence of the competition effect is the following curious result. In auctions where no other bidders placed a bid, our surplus was nearly $1 higher when we squatted than when we sniped. This result cannot be supported by the standard models: when no opponents bid, the winning bidder pays the opening price which is, by design, uncorrelated with our bidding strategy. To see how this arises naturally from the competition effect, consider the following example. 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

Table 7— Impact of Sniping on Number of Opponents and Oppponent Bids

| | Dependent variable | | |
|---|---|---|---|
| | Opponents | Nonsniping bidders | Opponent's final bids |
| *Regressor* | | | |
| Sniping dummy | 1.377*** | 0.389*** | −1.472*** |
| | (0.010) | (0.048) | (0.185) |
| *Summary* | | | |
| Observations | 566 | 566 | 1,781 |
| Mean | 3.163 | 3.542 | 11.179 |
| (standard deviation) | (2.303) | (2.141) | (3.552) |
| Pseudo $R^2$ | 0.655 | 0.612 | 0.079 |

*** Significant at the 1 percent level.
** Significant at the 5 percent level.

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 later in Proposition 1.

Using regressions, the first column of Table 7 shows we can say that squatting decreases the number of opponents by at least 1.35 bidders with 95 percent confidence. The increase in the number of opponents in sniping auctions is accentuated by the fact that the current price rises faster when we squat, reducing the number of visitors with valuation above the current price.[12]

Now, we look at the auctions from a large market point of view. In a market with many buyers and sellers, similar auctions should receive a comparable number of bidders, as when the price in one auction is driven up, buyers should move to another auction. As our bid, on average, won the auctions 50 percent of the time, this suggests that similar auctions should receive similar numbers of *nonsniping bidders*, including ourselves, independent of the treatment.[13] The second column of Table 7 presents regression results using the number of distinct bidders who placed a bid up to the penultimate minute of an auction as the dependent variable. The dependent variable counts the experimenter in squatting treatments but not in sniping treatments. Hence, one may 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 almost 0.4 bidders on average.[14]

[12] Nevertheless, this effect alone should increase the expected number of opponents bidding in the sniping treatment by less than one if we look at a stand-alone IPV auction model.

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

[14] 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. The impact also does not change when we restrict attention only to auctions that received at least one bid prior to the closing minutes.

Our results on the effect of sniping on winning probability and sellers' revenue is 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, 1,791 opponents placed 2,954 bids. eBay makes only the second highest and lower bids available to the public. As a result, the winning bids by opponents are right-censored. The third column of 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 \$1.47.

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. Nevertheless, if we include an instrument for the number of potential bidders or the timing of the bid as regressors to indirectly control for the effect of the current price, the impact of sniping barely changes. Moreover, although sniping and squatting have different impacts on the price progressions, if bidders are equally *aggressive* in bidding under both treatments, the highest opponent bids will be the same under both treatments leading to comparable revenues for the seller. The fact that revenues are significantly lower when we snipe also shows the impact of the escalation effect in a way that is not affected by the difference in progression of price between the two treatments.

## IV. A Concurrent Auctions Model

Empirical evidence in the previous section, and the availability of many identical auctions of our chosen products on eBay, suggests that the experimental outcomes should be theoretically analyzed by considering the auctions in the context of the larger market. To that end, we examine a theoretical model of concurrent auctions. The design of this theoretical model is solely motivated by our experimental design and results.

There are two auctions for perfectly substitutable goods, labeled 1 and 2. Each bidder demands, at most, one unit. We suppose that $N$ potential opponents have values drawn independently from the same differentiable distribution function $F$ on support $[0, 1]$ where $N$ is greater than 2. Let $v_i$ denote the (private) value of bidder $i \in \{1, 2, \ldots, N\}$. This valuation is for the first unit of the good and the marginal value for any additional unit is zero. In addition, we model the experimenter as an additional bidder whose private value is $v_0$. Unlike the models in Eric Budish (2008), the auctions in this model occur simultaneously, and a bidder can participate in both auctions at the same time. This captures the feature of the eBay market for popular products, such as movies, that a bidder can participate in any number of concurrently occurring auctions of virtually the same product. For the main results to go through, we do not need both auctions to go on simultaneously. Rather, overlap of the two auctions for a substantial amount of time will suffice.

When there are two auctions running simultaneously, a bidder $i$ prefers to win the auction in which she would pay the lower price. However, $i$ only observes the current price in an auction and not the current high bid, and the latter determines the price if $i$ were to become the high bidder. To find the auction with the lower high bid, $i$ would like to alternate between auctions, submitting small incremental bids until she 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 she becomes the high bidder. Here, 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. Thus, she figures out that auction 1 has the lower highest bid at that point in time. On eBay, a bidder can place bids any time during the auction and can also submit a proxy bid such that the price in the auction reaches the proxy bid only if someone else places a bid above that bid. We want to incorporate the ability to bid any time a bidder wants to during the auction, and to submit proxy bids into our model while restricting her to bid at only one stage to make some of the theoretical predictions sharper. To that end, we allow a bidder to submit an interim bid and a proxy bid.

Formally, the game is defined as follows. There are $N + 2$ periods; periods 0 to $N + 1$. The experimenter randomly selects an auction $l$, and bids $v_0$ in that auction. Here, $v_0$ is greater than $m$, the opening bid. In the sniping treatment, he bids in period $N + 1$; and in the squatting treatment, he bids in period 0. That is, $b_{0l} = v_0$ and $b_{N+1l} = v_0$ in squatting and sniping treatments, respectively. He does not bid in the other auction $l'$. Bidders arrive in sequence, so that bidder $i \in \{1, 2, \ldots, N\}$ arrives in period $i$. Upon arrival, bidder $i$ observes the prices in both auctions and decides whether, and how, to bid. 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 $p_{11} = p_{12} = m$, $q_{1l} = v_0$ and $q_{1l'} = m$ in the squatting treatment, and $q_{11} = q_{12} = m$ in the sniping treatment. Bidding by bidder $i$ consists of two steps. First, $i$ is given the opportunity to continuously raise prices in both auctions. To do this, $i$ specifies an interim bid $\kappa_i > \min\{p_{i1}, p_{i2}\}$. The interim price in auction $k$ is then raised to $\tilde{p}_{ik}$, equaling the third highest of $\{q_{i1}, q_{i2}, \kappa_1, \ldots, \kappa_i\}$. If $\kappa_i$ is not greater than the second highest of $\{q_{i1}, q_{i2}, \kappa_1, \ldots, \kappa_{i-1}\}$, 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. The interim bid models a bidder who places a bid above the current price whenever she is not the high bidder, up to the price $\kappa_i$. In the second step, $i$ can submit a final bid $b_{ik} \geq \tilde{p}_{ik}$ in each auction $k$. This proxy bid models the fact that the final price in an eBay auction equals the second highest bid received in that auction. This concludes bidder $i$'s bidding period. The next period begins with the new high bids $q_{i+1k} = \max\{b_{ik}, q_{ik}\}$, and new prices $p_{i+1k}$ equaling the second highest of $\{\tilde{p}_{ik}, b_{ik}, q_{ik}\}$. If $b_{ik} > q_{ik}$, then bidder $i$ becomes the highest bidder of auction $k$. The winner of auction $k$ is the bidder who placed the bid $q_{N+2k} = \max\{b_{N+1k}, q_{N+1k}\}$, and she pays the second highest of $\{p_{N+1k}, b_{N+1k}, q_{N+1k}\}$ as the price.

We restrict attention to equilibrium in undominated strategies. In Proposition 1, we show that concurrent auctions allow us to capture the competition effect that leads to higher surplus, conditional on zero opponents in squatting treatments as evidenced in Table 6. In a standard second-price auction model, the probability of having zero opponents is the same in both sniping and squatting treatments for any given opening price. Therefore, the expected payoff conditional on zero opponent is independent of the treatment. However, in our dataset, average surplus in sniping auctions was only three-quarters of that in squatting auctions conditional on no opponent.

PROPOSITION 1: *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 no opponent is lower in the sniping auction in our 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. In the following analyses, we look at cases where bidders 1 to $N$ are all sophisticated or are all naïve separately.

### A. *Sophisticated Bidders*

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 that can explain all of the qualitative results from the experiment.

A sophisticated bidder $i$ uses the interim bid $\kappa_i$ to find the auction $k$ with the lowest price. After that, she may want to submit a final bid $b_{ik}$ to ensure that she remains the high bidder in auction $k$. It is easy to show that a sophisticated bidder will choose $\kappa_1 = v_i$ and $b_{ik} = v_i$. Interestingly, when all the opponents are sophisticated, the experimenter is better off squatting.

PROPOSITION 2: *In the concurrent auction model with sophisticated bidders, the game can be solved by backward induction. Each bidder i uses the following bidding strategy:*

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

When the experimenter squats and bids in auction $k$, the first bidder bids in the other auction. After that, all the sophisticated bidders find out the auction that has the lower highest bid so far using the interim bid. Then she bids her value using the proxy bid if her value is above the interim price in that auction. This way, the bidders (including the experimenter) with the highest two valuations win, and both pay the third highest valuation. If the experimenter wins, he pays the second highest value among $v_1$ to $v_N$. When the experimenter snipes, he bids in one of the auctions randomly without learning which one has the lower high bid. As a result, she competes against the highest value among $v_1$ to $v_N$ with probability half. Hence, squatting is beneficial for the experimenter opposite of what we find in our experiments. This also suggests that a sophisticated bidder would not snipe, even if we allowed her to snipe, when all other bidders are sophisticated.

## B. *Naïve Bidders*

The results of the previous section demonstrate that while concurrent auctions generate the competition effect, they do not completely capture the experimental outcomes we observe. Our empirical analysis suggests that the benefit of sniping comes from the fact that sniping reduces the escalation of bids by opponents. In this subsection, we analyze the concurrent auctions model with naïve opponents. A naïve bidder acts as if the amount she pays, conditional on winning, equals her bid. As mentioned at the beginning of the paper, naïve bidding behavior is similar to the incremental bidding behavior documented by Ariely, Ockenfels, and Roth (2005).

The key contrast with sophisticated bidders is that when a naïve bidder becomes the high bidder in an auction, she 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. Thus, in our formal bidding model, a naïve bidder $i$ always submits $\kappa_i = v_i$ as her interim bid but never submits a final bid $b_{ik}$ in either of the auctions.

To provide an intuition behind the results that follow, we begin with the sniping treatment. As bidder $i$ chooses $\kappa_i = v_i$ and $b_{ik} = 0$, the current high bidders at any stage $i$ are the bidders with the two highest values among bidders $\{1, \ldots, i\}$. The prices in both auctions equal the third highest value. Hence, $p_{N+1}$ equals the third highest of $\{v_1, \ldots, v_N\}$, and the experimenter wins if $v_0$ is greater than the third highest of $\{v_1, \ldots, v_N\}$. However, in the squatting treatment, the price $p_i$ at stage $i$ will equal the third highest among $\{v_0, v_1, \ldots, v_i\}$ (i.e., $v_0$ is now included). Hence, $p_{N+1}$ equals the third highest of $\{v_0, v_1, \ldots, v_N\}$ unlike in the sniping case.

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 $i \in \{1, 2, \ldots, N\}$. We analyze the case where either all bidders are sophisticated or all are naïve to get the stark result that, compared to squatting, sniping is less profitable with sophisticated bidders and is more profitable with naïve bidders. When the opponents consist of $s$ sophisticated and $N - s$ naïve bidders, we can get that sniping is more beneficial, equally beneficial, or less beneficial than squatting depending on $s$, $F$, $N$, and the arrival sequence of the bidders. In that case, some of the sophisticated bidders may snipe while the others squat. As the main objective of this model is to provide a simple theoretical model that explains the results from our experiments well, and not necessarily to provide a comprehensive model of bidding in eBay, we present only the two extreme cases.

Finally, Proposition 4 shows that predictions from this model of concurrent auctions with naïve bidders are consistent with our findings that sniping attracts more bidders but by fixing the number of opponents, the expected payoff, is higher in the sniping treatment when the number of opponents is at least one.

PROPOSITION 4: *In the concurrent auction model with naïve bidders,*

(i) *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.*
(ii) *For any n, the probability that the experimenter wins conditional on n opponents bidding in the auction where he bids is larger in the sniping treatment than in the squatting treatment, strictly so if and only if* $n \geq 1$.
(iii) *For any n, conditional on the experimenter winning against n opponents bidding in the auction where he bids, the expected price paid is lower in the sniping treatment than in the squatting treatment, strictly so if and only if* $n \geq 1$.

At any given period $t \geq 1$, the current prices in the auctions are at least as high in the squatting treatment as in the sniping treatment, as the experimenter's bid is included among the bids in the squatting treatment but not in the sniping treatment where the experimenter bids in period $T + 1$. This leads to the stochastic dominance of the number of opponent bidders in the sniping treatment. This also implies that conditional on the number of opponents, the current price is lower in the sniping treatment. This leads to statements 2 and 3. However, the proof of these two statements is somewhat more involved. When bidders are sophisticated, the first statement of the proposition will hold true. However, statements 2 and 3 will hold true for $n = 0$, but may hold only for certain $F$ and $N$ if $n$ equals 1 or above. Proposition 1 and Proposition 4 thus help us to explain the results found in Table 6.

A point to note is that the auctions will efficiently allocate the goods to the bidders (including the experimenter) with the highest two valuations in the squatting treatment whether bidders are sophisticated or naïve (as long as none of the opponents snipe). However, the sniping treatment will be inefficient with positive probability. With sophisticated bidders, this may occur when the experimenter bids in the auction where the highest valued opponent placed her final bid. With naïve bidders, the high bidders do not bid up to their valuations as they never use proxy bids. This raises the possibility of inefficient allocation.

## V. Conclusion

In this paper, we designed a field experiment using eBay auctions of new movie DVDs to estimate the benefit of late bidding over early bidding. We earned slightly higher payoffs in the auctions in which we sniped. While the probability of winning was higher in the sniping treatment, our expected payment was not significantly different. In our experiment, sniping reduced the final bids by other bidders and the expected revenue, but did not affect the probability of sniping by other bidders. We show that all of these results are consistent with an auction market model, when some bidders are naïve, in the sense that they act as if eBay auctions are English auctions instead of dynamic second-price auctions. Such naïve or incremental bidding is also evidenced in laboratory experiments. Even though bidder naïveté, along with the fixed closing time on eBay, leads to a surprisingly high level of sniping, the easy access market setup and the availability of closely substitutable auctions on eBay seems to reduce the overall benefit of sniping. In some sense, this paper is less about the benefits of a particularly surprising strategy used in eBay. Rather, it is more of a direct analysis of the presence of a particular behavioral bias and its overall impact in a large competitive auction market.

We conclude by discussing a possible extension of our research. Rather than attempting 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.

## Appendix: Proofs

PROOF OF PROPOSITION 1:

Suppose $\hat{N}$ 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 one 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, $\hat{N} = 0$ or 1. If he snipes, then the experimenter has no opponent with

Table A1—Overview of Auctions

| | Auctions | | Valuation (in USD) | | | |
|---|---|---|---|---|---|---|
| Title | 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 | | 18 | | | 12 | 10 |
| Hidalgo | | 16 | | | 12 | 10 |
| 13 Going on 30 | | 25 | | | 13 | 11 |
| Kill Bill: Vol 2 | | 60 | | | 14 | 12 |
| The Passion of the Christ | | 121 | | | 15 | 13 |

Table A2—Summary Statistics of Some Auction Characteristics

| | Mean/count | SD | 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 | 1,277.22 | 2,861.68 | 30,995 | 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 | | | |

probability 1 if $\hat{N} = 0$ and with probability 0.5 if $\hat{N} = 1$. The probability of getting zero opponents, whether the bidders are sophisticated or naïve, 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. 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 the bidders 1 through $N$ placing a bid, the experimenter obtains higher expected surplus in the squatting treatment, as the expected opening price is lower in those auctions.

Table A3—Summary Statistics of Auction Outcomes

| | Count | We won | Winning ratio | Average final price |
|---|---|---|---|---|
| All auctions | 566 | 283 | 50 percent | 13.61 |
| Auctions in run 1 | 269 | 212 | 79 percent | 13.40 |
| Auctions in run 2 | 297 | 71 | 24 percent | 13.81 |
| Auctions where we sniped | 272 | 143 | 53 percent | 13.41 |
| Auctions where we squatted | 294 | 140 | 48 percent | 13.80 |

Table A4—Presence of Escalating Effect under Squatting

| Bidder | Time | Bid |
|---|---|---|
| Final price | | 13.50 |
| Bidder 4 | Day 7 Hour 8 Min 51 Sec 32 | 13.50+ |
| Experimenter's squatting bid | Day 1 Hour 0 Min 0 Sec 1 | 13.00 |
| Bidder 4 | Day 7 Hour 8 Min 51 Sec 23 | 12.50 |
| Bidder 4 | Day 7 Hour 8 Min 51 Sec 10 | 11.00 |
| Bidder 4 | Day 7 Hour 8 Min 51 Sec 1 | 9.50 |
| Bidder 4 | Day 7 Hour 8 Min 50 Sec 53 | 8.50 |
| Bidder 3 | Day 2 Hour 8 Min 34 Sec 37 | 8.00 |
| Bidder 1 | Day 1 Hour 0 Min 15 Sec 2 | 5.50 |
| Bidder 2 | Day 1 Hour 19 Min 49 Sec 32 | 4.15 |
| Opening price | | 4.05 |

*Notes:* A bid of $b+$ indicates that the bid was the winning bid and was equal to or larger than $b$; eBay does not report the exact value of the highest bid.

Table A5—Absence of Escalation Effect under Sniping

| Bid | Time | Bid |
|---|---|---|
| Final price | | 10.35 |
| Experimenter's sniping bid | Day 7 Hour 23 Min 59 Sec 56 | 16.00 |
| Bidder 4 | Day 7 Hour 23 Min 35 Sec 54 | 9.85 |
| Bidder 3 | Day 7 Hour 18 Min 13 Sec 58 | 8.85 |
| Bidder 4 | Day 7 Hour 17 Min 37 Sec 53 | 8.34 |
| Bidder 3 | Day 6 Hour 2 Min 48 Sec 39 | 7.84 |
| Bidder 2 | Day 5 Hour 9 Min 7 Sec 13 | 7.23 |
| Bidder 3 | Day 4 Hour 23 Min 59 Sec 57 | 6.84 |
| Bidder 2 | Day 4 Hour 7 Min 39 Sec 40 | 3.10 |
| Bidder 1 | Day 2 Hour 6 Min 52 Sec 49 | 2.85 |
| Opening price | | 2.84 |

PROOF OF PROPOSITION 2:

Notice that, in any undominated strategy, $b_{ik} \leq v_i$ for both $k$ and $b_{ik} = v_i$ for at least one $k$ as long as $\tilde{p}_{ik} < v_i$ for some $k$ for any $i \in \{1, \ldots, N\}$. We will prove the proposition using backward induction. First, we analyze the optimal strategy of bidder $N$. After placing $\kappa_N$, 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 the auction in which 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 $\kappa_N$, implying that the prices in each auction, $\tilde{p}_{Nk}$, are at least as great as $\kappa_N$. 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 $\kappa_N$ is to figure out $\min\{q_{N1}, q_{N2}\}$. Since $\tilde{p}_{Nk}$ does not cross $\min\{q_{N1}, q_{N2}\}$, the optimal $\kappa_N$ equals $v_N$ because, for a smaller $\kappa_N$, 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 $\kappa_N$. For $\kappa_N < v_N$, bidder $N$'s final payoff can be different from that in the $\kappa_N = v_N$ case if and only if $\kappa_N < \min\{q_{N1}, q_{N2}\} < v_N$. However, in that case, bidder $N$ will be better off with $\kappa_N = v_N$ as she would learn for sure which auction has the lower $q_{Nk}$. For $\kappa_N > v_N$, $\tilde{p}_{Nk}$ 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 $\kappa_j$. Then, bidder $i$'s best response is to choose $b_{ik} = v_i$ if she becomes the high bidder in auction $k$ after placing $\kappa_i$. 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 if and only if $\kappa_i < \min\{q_{i1}, q_{i2}\} < v_i$. 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 $\tilde{p}_{ik}$ 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 $L(A)$ is such that

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

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

$$\Pr(v_0 > v_{(2)})\,(v_0 - E[v_{(2)} \mid v_0 > v_{(2)}])$$

and the probability of winning equals $\Pr(v_0 > v_{(2)})$. 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

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

and his expected surplus equals

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

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 $\Pr(v_0 > v_{(2)})\,(v_0 - E[v_{(2)}\,|\,v_0 > v_{(2)}])$ as the price conditional on the experimenter winning is $v_{(2)}$ in that case. On the other hand, the two opponents with the highest valuations bid only up to $v_{(3)}$ at the end of period $N$ in the sniping treatment. Then the experimenter's expected surplus is $\Pr(v_0 > v_{(3)})\,(v_0 - E[v_{(3)}\,|\,v_0 > v_{(3)}])$. Thus, his expected payoff and probability of winning is higher in the sniping treatment when bidders $i \in \{1, 2, \ldots, N\}$ are naïve.

The proof of Proposition 4 will make use of the following lemma. We defer the proof of the lemma until after the main proof of Proposition 4.

LEMMA 1: *Fix* $\overline{p} \in [0, 1]$, *and let* $h : [0, 1] \to [0, 1]$ *be any non-decreasing function which is not constant over* $[0, \overline{p}]$. *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* $\overline{P}$ *the event that* $v_{(2)}$ *is no greater than* $\overline{p}$. *We have*

$$E[h(p^{squat})\,|\,O_n, \overline{P}\,] \geq E[h(p^{snipe})\,|\,O_n, \overline{P}\,]$$

*with a strict inequality if and only if* $n \geq 1$.

PROOF OF PROPOSITION 4:

First we fix a valuation profile $(v_1, \ldots, v_N)$ for the opponents and assume, without loss of generalization, that the experimenter bids in auction 1. 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, $p_t^{squat} = 2(\{v_1, \ldots, v_{t-1}\})$. We consider player $i$ to have placed a bid if and only if $p_{t+1} > p_t$ and, this implies, bidder $t$ bids if and only if $v_t > p_t^{squat}$. Consider now the identical valuation profile in the sniping treatment. In this case, $p_t^{snipe}$ equals $3(\{v_1, \ldots, v_{t-1}\})$, 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 $p_t^{squat} \geq v_0$, 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.

The second and third statements follow from Lemma 1 when we choose $h$ appropriately. 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 $\overline{p} = 1$. Then $E[h(p^{squat}) \,|\, O_n, \overline{P}]$ 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.[15] 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 $E[h(p^{snipe}) \,|\, O_n, \overline{P}]$ when bidders are naïve. The equality holds only when $n = 0$.[16] For part 3 we take $h(p)$ to be the identity function and set $\overline{p} = v_0$. Then $E[h(p^{squat}) \,|\, O_n, \overline{P}]$ 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 $E[h(p^{snipe}) \,|\, O_n, \overline{P}]$ when bidders are naïve, the equality holding only when $n = 0$.

PROOF OF LEMMA 1:

Consider the situation in which the auctions have just reached stage $t$, subsequently, exactly $j$ of bidders $t$ to $N$ place a bid in either auction by using the intermediate bid $\kappa$ and the second highest of the valuation of all opponents, $v_{(2)}$, is no greater than $\overline{p}$. Let $p_t$ denote $2(\{v_1, \ldots, v_{t-1}\})$. In the snipe treatment, the current price for both auctions equals $3(\{v_1, \ldots, v_{t-1}\})$. On the other hand, the current price for both auctions in the squatting treatment equals $p_t$. Let us denote $1(\{v_1, \ldots, v_{t-1}\})$ and $3(\{v_1, \ldots, v_{t-1}\})$ respectively by $q_t$ and $r_t$ where $r_t \leq p_t$. In the sniping and squatting treatments, the prices in both auctions equal $r_t$ and $p_t$ respectively. We let $\varphi^{snipe}(t, j, p_t)$ and $\varphi^{squat}(t, j, p_t)$ denote the expected value of $h(p^{snipe})$ and $h(p^{squat})$ 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 $p_t < \overline{p}$, then

1. $\varphi^{squat}(t, j, p_t) \geq g_j(p_t)$ with a strict inequality if $t < N - j + 1$,
2. $\varphi^{snipe}(t, j, p_t) \leq g_j(p_t)$ 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:

$$g_1(p) = E[h(\min\{v_a, v_b\}) \,|\, \overline{p} > v_a, v_b \geq p].$$

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

[16] When bidders are sophisticated, the probability of losing in the snipe treatment is $E[f(p^{snipe}) \,|\, O_n, \overline{P}]$ and $E[f(r^{snipe}) \,|\, O_n, \overline{P}]$ with equal probability where $r^{snipe} = 1(\{v_1, \ldots, v_N\})$.

The assumption that $F$ has full-support and that $h$ is non-decreasing and non-constant over $[0,\overline{p}]$ 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 $p^{squat} < \overline{p}$ 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 $\kappa_{t'}$ equaling $v_{t'}$. Taking expectations with respect to the value of $v_{t'}$, we can express

$$\varphi^{squat}(t, 1, p_t) = E[h(v_{t'}) \,|\, E_1 \cap E_2 \cap E_3],$$

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

1. $E_1 = \{v_{\hat{t}} \leq p_t \text{ for all } t \leq \hat{t} < t'\}$ (i.e., no bids between $t$ and $t'$),
2. $E_2 = \{\overline{p} > v_{t'} > p_t\}$ (i.e., bidder $t'$ bids),
3. $E_3 = \{v_{\hat{t}} \leq \min\{v_{t'}, v_0, q_t\} \text{ for all } t' < \hat{t} \leq N\}$ (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 $h(v_{t'})$, 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 nondecreasing,

$$\varphi^{squat}(t,1,p_t) = E[h(\min\{v_{t'}, q_t\}) \,|\, E_2 \cap E_3] \geq E[(\min\{v_{t'}, q_t\})\, E_2] = g_1(p_t)$$

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

For the snipe treatment, consider the event that exactly one additional bid is placed. Suppose $t'$ is the last opponent to place a bid. We can divide the conditioning event into two cases. First, consider $r_t < v_{t'} \leq p_t$. This case has positive probability when $p_t > m$ and in that case $p^{snipe} = v_{t'}$ and $\varphi^{snipe}(t,j,p_t)$ is clearly less than $g_1(p_t)$. The alternative case is $p_t < v_{t'}$ and the current price becomes $p_t$. Here, the final price $p^{snipe} = p_t$. Hence conditional on this second case, the expectation of $h(p^{snipe})$ is

$$E[h(p_t) \,|\, E_1 \cap E_2 \cap E_3]$$

where

1. $E_1 = \{v_{\hat{t}} \leq r_t \text{ for all } t \leq \hat{t} < t'\}$ (i.e., no bids between $t$ and $t'$)
2. $E_2 = \{r_t < v_{t'} < v_0\}$ (i.e., bidder $t'$ bids)
3. $E_3 = \{v_{\hat{t}} \leq p_t \text{ for all } t' < \hat{t} \leq N\}$ (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

$$E[h(p_{t'}) \,|\, E_1 \cap E_2 \cap E_3] = E[h(p_{t'}) \,|\, E_2] \leq g_1(p_t).$$

Therefore, the overall conditional expectation is no greater than $g_1(p_t)$, i.e.,

$$\varphi^{snipe}(t, 1, p_t) \leq g_1(p_t)$$

and strictly smaller when the first case has positive conditional probability. The first case, i.e., $r_t < v_{t'} \leq p_t$, has positive conditional probability so long as $m < p_t$. We conclude that the above 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

$$g_j(p) = E[g_{j-1}(\min\{v_a, v_b\}) \,|\, p \leq v_a, v_b < \overline{p}].$$

Note that by the induction hypothesis, $g_{j-1}$ is increasing in $p$ for $p < v_0$ and, hence, so is $g_j$. Moreover, $g_j(p) \leq g_{j-1}(p)$, strictly so if $p < v_0$.

In the squat treatment, suppose that at the beginning of stage $t \leq N - j + 1$, the current price in auction 1 is $p_t$, and consider the event that $p^{squat} < \overline{p}$ 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 $h(p^{squat})$ is, by the induction hypothesis, at least $g_{j-1}(v_{t'})$ 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 $h(p^{squat})$ is

$$\varphi^{squat}(t, j, p_t) \geq E_{v_{t'}}[g_{j-1}(v_{t'}) \,|\, E],$$

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

$$\varphi^{squat}(t, j, p_t) \geq E[g_{j-1}(v) \,|\, p_t < v < \overline{p}] = g_j(p_t).$$

This establishes the inductive step in the squatting treatment.

In the snipe treatment, suppose the current high bid among opponents in auction 1 is $p_t$ and the current price is $r_t \leq p_t$. Consider the event that exactly $j$ additional bids are placed and $p^{snipe} < \overline{p}$. Suppose $t'$ is the next bidder to place a bid.

If $m \leq r_t < v_{t'} \leq p_t$, then the high bid and the price after player $t'$ bids is $v_{t'} < p_t$ and by the induction hypothesis $p^{snipe}$ will be strictly less than $g_{j-1}(p_t)$. If instead $p_t < v_{t'} < \overline{p}$ then $p^{snipe} \leq g_{j-1}(p_t)$. Hence the conditional expectation of $h(p^{snipe})$ is bounded above by $\varphi^{snipe}(t, j, p_t) \leq E[g_{j-1}(\min\{p_t, v_{t'}\}) \,|\, E_1 \cap E_2]$ where $E_1 = \{v_{\hat{t}} \leq r_t$ for all $\hat{t} \in \{t, \dots t' - 1\}\}$ and $E_2 = \{r_t < v_{t'} < \overline{p}\}$. 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 $\varphi^{snipe}(t, j, p_t) \leq E[g_{j-1}(v) \,|\, p_t < v < \overline{p}] = g_j(p_t)$. 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

$$E[h(p^{snipe}) \,|\, O_n, \overline{P}\,] = \varphi^{snipe}(1, n, m) \tag{2}$$

$$E[h(p^{squat}) \,|\, O_n, \overline{P}\,] = \varphi^{squat}(1, n, m). \tag{3}$$

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 that the lemma holds when $n = N$, i.e., all opponents bid. Then,

$$E[h(p^{snipe}) \,|\, O_n, \overline{P}\,] = E_{p_3}[\varphi^{snipe}(3, N-2, p_3) \,|\, p_3 < \overline{p}\,] \tag{4}$$

$$E[h(p^{squat}) \,|\, O_n, \overline{P}\,] = E_{p_3}[\varphi^{squat}(3, N-2, p_3) \,|\, p_3 < \overline{p}\,]. \tag{5}$$

The claim implies that $\varphi^{snipe}(3, N-2, p_3) < \varphi^{squat}(3, N-2, p_3)$ for all $p_3 < \overline{p}$ since $p_3 = \min\{v_1, v_2\} > m$, using the condition for strict inequality in the second part of the claim. It follows that (5) strictly exceeds (4).

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