Empirical Analysis of Auctioneer Profitability in QuiBids Penny Auctions

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Abstract

Given the string of bankruptcies of penny auction websites over the past two years, we use empirical data to investigate whether QuiBids remains profitable. Although profitable on an auction-by-auction basis, penny auction sites have problems retaining users. In order to alleviate this problem, QuiBids has implemented a Buy-Now system, in which losing bidders can contribute money they already lost in the auction towards the purchase of the item at a slightly inflated price. We find that QuiBids makes only limited profit after accounting for Buy-Now, but is able to remain profitable due voucher bid pack auctions. We also show that a large proportion of QuiBids' revenues come from experienced bidders, suggesting that rules designed to promote consumer retention may be working as intended.

Introduction

A *penny auction* is a form of an ascending auction in which, in addition to the winner paying its bid to acquire the good up for auction, each bidder pays a fixed cost for each bid it places in the auction. Penny auctions are so-called because each bid typically causes the good price to increase by one penny; bids themselves, however, can cost orders of magniture more than that.

Past empirical studies of penny auctions (e.g. (Augenblick 2011), (Hinnosaar 2010), (Wang and Xu 2012)) have established that penny auction bidders drastically overbid in aggregate. This excessive overbidding earned them the title "the evil stepchild of game theory and behavioral economics" in the Washington Post (Gimein 2009). In other words, penny auctions are extremely costly for buyers. As such, they should be extremely profitable for sellers.

Past research estimates that Swoopo (formerly Telebid), a now defunct penny auction site, generated profits of just under $24 million from September 2005 to June 2009, and that each auction generated average revenues of in excess of 150% of the good's value (Augenblick 2011). This means that Swoopo's profit margin was approximately 33%. According to Fortune magazine, the most profitable sector of the retail economy in 2009 was department stores with a 3.2% average profit margin. Needless to say, this profit margin pales in comparison to the order-of-magnitude larger margin speculated to have been captured by Swoopo.

The fact that penny auctions generate huge profits for sellers means that many buyers are taking huge losses; indeed, everyone but the winner is taking at least a small loss. Furthermore, (Wang and Xu 2012) observe that the penny auction model "offers immediate outcome (win or lose) feedback to bidders so that losing bidders can quickly learn to stop participating". Indeed, "the vast majorities of new bidders who join [BigDeal.com] on a given day play in only a few auctions, place a small number of bids, lose some money, and then permanently leave the site within a week or so". Augenblick further supports this observation with empirical data: 75% of bidders leave [Swoopo] forever before placing 50 bids, and 86% stop before placing 100 bids (Augenblick 2011). The majority of Swoopo's profits came from this "revolving door" of inexperienced bidders—a large number of new bidders who would soon leave the website never to return (Wang and Xu 2012). Consequently, if the supply of new, inexperienced bidders were to run out, a major source of income for these sites would evaporate.

To alleviate this problem, penny auction sites took measures to increase customer loyalty (i.e., to retain buyers), such as *win limits*, where the number of auctions a single bidder could win per month is limited to some small amount (e.g., 12 for QuiBids), and *beginner auctions*, in which all participants are bidders who have never before won an auction. These measures were designed to yield more unique winners, each of whom would be more likely than a loser to return to the site and bid in future auctions.

As of early 2009, many sites were still grappling with the issue of buyer retention, despite implementing these features. By late 2009, a new feature, *Buy-Now*, was adopted by numerous sites (Swoopo, BidHere, RockyBid, BigDeal, BidBlink, Bidazzled, PennyLord, Winno, and JungleCents to name a few (Kincaid 2009; Fance 2010)). Buy-Now allows bidders to contribute money spent in a lost auction towards the purchase price of that item, and buy a duplicate of the item post-auction for the amount of their shortfall. The purchase price of an item on a penny auction site is the retail value of that item marked up, usually by about 20%. Despite the inflated price, this feature still provides an extra sense of security to the bidder. The worst outcome for a bidder is now that she buys the item at an inflated price. This limits a bidder's loss to the difference between the site's marked-up purchase price of the item and its retail price. Because bidders could now choose to utilize the Buy-Now option and limit their losses, they were less likely to be discouraged from future participation.

As the Buy-Now feature limits a bidder's loss, it also limits a penny auction site's gain. To compensate for their losses, many penny auction sites started selling *voucher bids*. Voucher bids are packets of bids that can be used to bid in other auctions. But voucher bids are not equivalent to purchased bids, because they do not contribute in full (or sometimes at all) to Buy-Now spending. That is, if a bidder places 200 bids, 100 with purchased bids, and 100 with voucher bids, at a cost of $.60 each for the purchased bids, it may only have contributed $60 towards its potential to Buy-Now. Voucher bids help offset the potential losses to sellers of the Buy-Now feature, since voucher bids are not fully incorporated into Buy-Now spending.

Between late 2009 and early 2011, almost 150 penny auction sites shut down inexplicably or went bankrupt (Lee 2011). This included such penny auction giants as Swoopo and BigDeal. Notably absent from the bankruptcy list is QuiBids, which has become one of the biggest penny auctioneers. In this paper, we set out to analyze QuiBids profits. We do so using empirical data scraped from the auction's web site. We analyze voucher bid auctions and non-voucher bid auctions separately, and we analyze profitability with and without buyers taking advantage of Buy-Now. We also determine the proportion of profits coming from inexperienced versus experienced bidders. These analyses allow us to identify the effects of QuiBids' auction rules on profitability. We find that despite the recent slew of auctioneer bankruptcies, QuiBids appears to be turning profit margins on the order of 30%, which is consistent with the margins achieved by Swoopo at its prime.

The rest of the paper is organized as follows. We first define penny auctions more formally, and outline some QuiBids-specific implementation details. We then describe the attributes of two QuiBids datasets we have collected. Using these datasets, we estimate QuiBids revenues, costs, and profits, first ignoring and then considering Buy-Now effects and voucher bid auctions. Finally, we present results on the makeup of inexperienced versus experienced bidders in QuiBids auctions and how each group contributes toward auctioneer revenues.

QuiBids' Penny Auction Rules

We first define more formally a standard penny auction. Let p be the current highest bid, let w be the identity of the current highest bidder, and let t be the amount of time remaining before the auction ends. The penny auction starts with an initial bid of $p := \underline{p}$, an initial highest bidder $w := \emptyset$, and an initial clock time of $t := \bar{t}$. The time t begins decreasing, and while $t > 0$, any bidder b may place a bid at some fixed incremental amount δ above the current highest bid. For b to place its bid, however, it must pay the auctioneer an immediate bid fee c. After b places its bid, the new highest bid is $p := p + \delta$, the highest bidder is $w := b$, and the remaining time is reset to $t := \max(t, \underline{t})$, which ensures other bidders have at least time $\underline{t}$ to place an additional bid. When the auction ends (i.e., $t = 0$), the current highest bidder w wins the item and pays the current highest bid p (in addition to any bid fees it paid along the way). Note that even the losing bidders have to pay bid fees.

QuiBids acts as the auctioneer for multiple penny auctions that happen both simultaneously and sequentially across the day. For each of its auctions, QuiBids follows with the above model where $\underline{p} = \$0$, $c = \$0.60$, $\delta = \$0.01$, and $\underline{t}$ is a function with range $\{20, 15, 10\}$ seconds whose output decreases as the time elapsed increases. The starting clock time $\bar{t}$ varies depending on the auction, but is on the order of hours. Additionally, QuiBids adds some variants to the standard penny auction, such as *Buy-Now*, *voucher bids*, and *BidOMatic*, and also imposes some winner restrictions. Each of these aspects is discussed below.

The *Buy-Now* feature allows any bidder who has lost an auction to buy a duplicate version of that good at a fixed price $\overline{m}$. As discussed in the Introduction, if a bidder uses Buy-Now, any bid fees the bidder incurred in the auction are subtracted from $\overline{m}$.

Voucher bids are a special type of good that are sold in penny auctions. When a bidder wins a pack of N voucher bids, it is able to place N subsequent bids in future auctions for a bid fee of $\$0$ instead of the usual fee c. Of course, the bidder had to pay to purchase the voucher bids, but the bidder may be able to purchase them at a total cost that is cheaper using standard bids. However, voucher bids do not necessarily contribute to Buy-Now in the same way as standard bids. Unlike standard bids, which each reduce the Buy-Now price by c, each placed voucher bid reduces the Buy-Now price by $c\rho$. For QuiBids, $\rho = 0$; that is, voucher bids do not contribute at all to Buy-Now. If it has won some voucher bids and then bids in a subsequent auction, the bidder can configure at any time whether to use these voucher bids or to use standard bids.

For completeness, we discuss some features of QuiBids auctions that we do not further analyze in this paper but may be of interest to other researchers studying bidder and auctioneer problems in penny auctions. The *BidOMatic* tool allows a bidder to specify a number of bids that will be automatically submitted at a random time between the reset time $\underline{t}$ and zero seconds. The bidder can specify that the BidOMatic place between 3 and 25 bids on the bidder's behalf. Whether or not a bid is placed with a BidOMatic is public information.

Finally, QuiBids imposes the following win limits on each bidder:

- Each bidder may only win 12 items over a 28 day period.
- Each bidder may not win more than one of the same item valued over $285 in a 28 day period.
- Each bidder may only win one item valued over $999.99 in a 28 day period.
- Voucher bid auctions are not subject to any of the above restrictions and are only subject to a maximum of 12 wins per day limit.
- A subset of auctions, known as beginner auctions, only allow bidders who have never previously won an auction

to bid.

Data Collection

Our analysis relies on two datasets scraped from QuiBids during the seven days following November 15th, 2011. We refer to these datasets as the auction end data A^{end} and full auction bid histories A^{hist}.

Auction End Data

The auction end data contains a single row of data for each of 37,233 auctions. For each auction, we recorded the following information:

- Auction ID - a unique auction number
- Item Name - A brief item description
- Auction End Price - The final price of the item
- Date - Day the auction ended (EST)
- Time - Time the auction ended (EST)
- Purchase Price - The marked-up Buy-Now price
- Winner - The bidder ID of the winning bidder
- Bid-O-Winner - Whether or not the auction was won by a BidOMatic
- Distinct Bidders - The number of distinct bidders in the last 10 bids
- Distinct Bid-Os - The number of distinct bidders using BidOMatics in the last 10 bids
- Last Ten Bidders - The bidder IDs of the last ten bidders

Full Auction Bid Histories

Whereas the auction end data contains cursory information about many auctions, the full auction bid history auctions contains much more detailed information about a smaller set of auctions. The full auction bid histories record every bid placed in 50 different auctions. For each bid placed when the auction clock was at or below its reset time we recorded the following data:

- Auction ID - uniquely identifies each auction
- Bidder ID - uniquely identifies each bidder
- Bid Price - The new price of the item after this bid
- BidOMatic? - Whether or not this bid was placed by a BidOMatic or placed manually
- Bidders in Last 5 - The number of bidders in the last five minutes
- Auction Clock - The time on the auction clock when this bid was placed
- AC Reset - The time the auction clock resets to every time a new bid is placed
- Date - The date on which this bid was placed (EST)
- Time - The time at which this bid was placed (EST)

QuiBids Profitability

We now estimate QuiBids' profitability from our datasets. Our interest is in the revenue and costs passing through the auctions, and we thus ignore other unknown operational and marketing costs, and assume that QuiBids receives zero net profit from its shipping fees.

Let A be some set of auctions and B_a be the set of bidders that placed at least one bid in auction $a \in A$. Let p_a be the winning bid for auction a, w_a be the winning bidder for auction a, and $\overline{m}_a$ be the marked up price for which the good sold in auction a can be purchased through Buy-Now. Let n_a^b be the total number of bids placed by bidder b in auction a and $y_a^b \in [0,1]$ be the fraction of those bids that were standard (i.e., not voucher) bids. Let $x_a^b \in \{0,1\}$ indicate whether bidder b used Buy-Now in auction a.

QuiBids revenue r_a for auction a is equal to the winning price p_a paid by the winner plus, for each bidder, either the total price $\overline{m}_a$ the bidder paid to purchase through Buy-Now, or the total amount the bidder spent on bid fees:

$$r_a = p_a + \sum_{b \in B_a} \left[x_a^b \overline{m}_a + (1 - x_a^b) n_a^b y_a^b c \right]. \qquad (1)$$

QuiBids costs ϕ_a for auction a are proportional to the number of goods it must procure to deliver to the auction winner and all bidders who used Buy-Now. We assume that QuiBids must pay a constant per-good price $\underline{m}_a$ for each good it procures for auction a:

$$\phi_a = \underline{m}_a + \sum_{b \in B_a} x_a^b \underline{m}_a. \qquad (2)$$

QuiBids profit π_a for auction a is simply its revenue minus its costs: $\pi_a = r_a - \phi_a$.

There are some terms in Equations 1 and 2 that are private information and thus not available in either of our datasets. First, we do not observe whether any given bid was a standard or voucher bid, so we do not know what fraction y_a^b of bidder b's bids in auction a were standard bids. Second, we do not know the price $\underline{m}_a$ that QuiBids pays to procure each good in auction a. Third, we have no information about whether or not each bidder used Buy-Now (i.e., x_a^b values).

To estimate the fraction y_a^b of bidder b's bids in auction a that are standard bids, we simply assume that the fraction of standard bids is constant across auctions and bidders: $y_a^b = \hat{y}$ $(\forall a \in A, \forall b \in B_a)$. We take $\hat{y}$ to be one minus the ratio of voucher bids sold to total bids placed in the end data. This gives an estimate of $\hat{y} = 0.9296$.

In order to estimate QuiBids procurement cost $\underline{m}_a$ for the good sold in auction a, one approach would be to take some statistic (e.g., mean or minimum) over sampled prices at which that good can be purchased from popular online retailers. While this approach may be a reasonable approximation, it doesn't scale well, since we would need retail pricing data for each good sold by QuiBids. As an alternative, we assume that QuiBids sets Buy-Now prices so that each good's Buy-Now price is a constant fraction h above its underlying purchase price. That is, $\overline{m}_a / \underline{m}_a = h$. To approximate h, we take a subset of auction data $A' \subset A$ containing auctions for distinct goods. For each auction, we record

Symbol	Description
A^{hist}	the set of auctions in the full auction bid histories
A^{end}	the set of auctions in the end auction data
A_n^{end}	the non-voucher auctions in the end auction data
A_v^{end}	the voucher bid pack auctions in the end auction data
B_a	the set of bidders in auction a
a	a generic particular auction
b	a generic particular bidder
c	bid cost
f_{win}	the fraction of bids placed by auction winners
h	average markup of Buy-Now price over the per-good procurement cost
$\overline{m}$	Buy-Now price
$\underline{m}$	per-good procurement cost
n_a^b	the number of bids placed by bidder b in auction a
p_a	the winning price for auction a
r	revenue
$\underline{t}$	clock reset time
w_a	the winning bidder for auction a
x_a^b	whether bidder b used Buy-Now in auction a
y_a^b	the fraction of bids that are not voucher bids
z^r	relative change in revenues under Buy-Now
z^ϕ	relative change in cost under Buy-Now
δ	bid increment, generally \$0.01
ϕ	cost
π	profit

Table 1: Glossary of symbols.

the minimum price s_a for which that corresponding good is available across a set of online retailers . The estimated markup factor $\hat{h}$ is computed as $\hat{h} = \frac{1}{|A'|}\sum_{a\in A'} \overline{m}_a/s_a$. For an auction $a \in A$, the QuiBids per-good procurement costs are then estimated to be $\underline{\hat{m}}_a = \overline{m}_a/\hat{h}$. Estimated costs $\hat{\phi}_a$ are computed by Equation 2 after replacing the privately-known procurement cost $\underline{m}_a$ with the estimated $\underline{\hat{m}}_a$. For our set A' of 25 distinct goods, we find that $\hat{h} = 1.21$. That is, the Buy-Now price is on average 21% larger than the lowest discovered retail price of each good (see Table 2 for details).

Rather than estimate whether each bidder used Buy-Now in each auction (x_a^b), we will compute possible profits under various assumptions of Buy-Now behavior, which are discussed in the following subsections.

Ignoring Buy-Now Effects

We begin by looking at QuiBids' expected revenues, costs, and profits without accounting for additional revenue and costs that arise from bidders using the Buy-Now option. We also partition the set of auctions in the end data A^{end} into the set of voucher bid auctions A_v^{end} (i.e., the set of auctions in which a pack of voucher bids is the good being sold) and the set of non-voucher bid auctions A_n^{end}. For this analysis we will look only at A_n^{end}, but we will return to the analysis of voucher bid auctions later on.

Note that, if no bidders used Buy-Now (i.e., $x_a^b = 0$ ($\forall a \in A_n, \forall b \in B_a$)), QuiBids revenue for auction a simplifies to

$$r_a = p_a + \sum_{b\in B_a} n_a^b y_a^b c \tag{3}$$

and QuiBids costs similarly simplify to $\phi_a = \underline{m}$.

Profit Breakdown Summing across all auctions in A_n^{end}, we compute the total revenue $r(A_n^{end}) = \sum_{a\in A_n^{end}} r_a$, total cost $\phi(A_n^{end}) = \sum_{a\in A_n^{end}} \phi_a$, and total profit $\pi(A_n^{end}) = \sum_{a\in A_n^{end}} \pi_a$. We find that $r(A_n^{end}) =$ \$2.696M, $\phi(A_n^{end}) =$ \$1.428M, and $\pi(A_n^{end}) =$ \$1.268M. These revenues and costs give profit margin $\pi(A_n^{end})/r(A_n^{end}) = 47.0\%$ (see also Table 5, Row 1).

Figure 1 and Table 3 summarize the distribution over profits π_a ($\forall a \in A_n^{end}$). We find that the median profit is negative, meaning QuiBids loses money on more than half its auctions. However, there are also a significant number of auctions where QuiBids profits exceed \$500. When we split profit data on the good's price (Table 4), we see that QuiBids makes a disproportionately large share of its profit on a relatively small number of auctions. The top 0.132% highest-priced auctions generated 11.1% of Quibids' profits, and the top 2.50% highest-priced auctions generated almost 43% of Quibids' profits. In an extreme case, QuiBids made over \$40K in profit on a single auction for a MacBook Pro, in which over 75K bids were submitted.

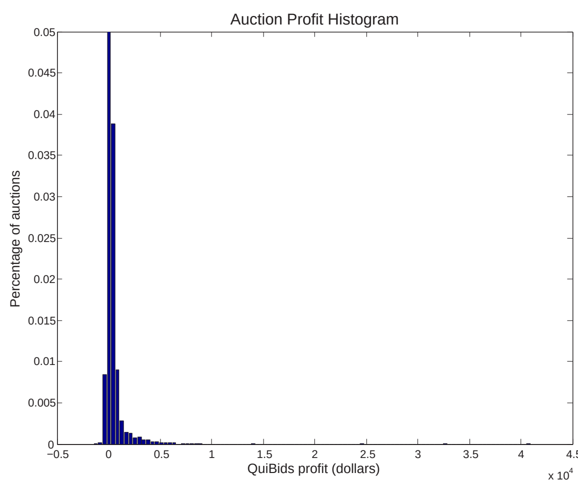

Figure 1: A histogram giving the percentage of QuiBids' auctions in A_n^{end} which yielded various levels of profit.

Mean	\$49.00
Median	−\$9.67
Standard Deviation	\$480.92
Range	\$42.4K
Minimum	−\$1.45K
Maximum	\$40.9K
Sum	\$1,268K
Count	25873

Table 3: Descriptive statistics for the distribution of profits across QuiBids auctions in A_n^{end} for the week of November 15th, 2011.

Item Name	Buy-Now Price	Retail Price	Markup
Samsung-PN51D6500-51-1080P-3D-HDTV	$1,100.00	$952.84	15.44%
The-New-Apple-iPad-16GB-WiFi	$530.00	$499.00	6.21%
Jamo-S426HCS3-51-Home-Theater-system	$430.00	$300.00	43.33%
Palm-Harbor-Outdoor-Wicker-Chair	$220.00	$219.00	0.46%
Nambe-MT0254-Swoop-Bowl	$212.00	$190.00	11.58%
Universal-Remote-MX450-2-LCD	$200.00	$179.00	11.73%
Yamaha-YPT-230-61-Key-Portable-Keyboard	$144.00	$111.64	28.99%
10K-Gold-Onyx-Diamond-Butterfly-Pendant	$137.00	$99.95	37.07%
Garmin-Nuvi-2250LT-GPS	$99.00	$86.50	14.45%
Ogio-METRO-II-Backpack	$82.00	$60.72	35.05%
Adidas-ClimaLite-Navy-and-Gulf-Polos	$74.00	$60.00	23.33%
Burberry-Brit-for-Women-34-oz-Tester	$68.00	$34.00	100.00%
50-Kohls-Gift-Card	$51.00	$50.00	2.00%
50-Department-Store-You-Choose-It	$51.00	$50.00	2.00%
Kalorik-Carnival-Popcorn-Popper	$51.00	$40.00	27.50%
Fox-Racing-Soleed-Digi-Camo-Boardshort	$44.00	$35.00	25.71%
Jensen-JCR-275-Alarm-Clock-Radio	$35.00	$35.00	0.00%
50-Bids-Voucher	$31.00	$30.00	3.33%
WMF-10-in-PP-Flat-Silicone-Ball-Whisk	$30.00	$15.00	100.00%
Kalorik-Jug-Kettle	$27.50	$24.95	10.22%
25-Bass-Pro-Shops-Gift-Card	$26.00	$25.00	4.00%
Slap-Watch-Regular	$20.00	$20.00	0.00%
Axis-GK-310-Multimedia-Keyboard	$16.00	$15.00	6.67%
10-Walmart-Gift-Card	$11.00	$10.00	10.00%
15-Bids-Voucher	$10.00	$9.00	11.11%
		Average Markup:	**21.21%**

Table 2: The 25 items used to estimate the average Buy-Now price markup.

Buy-Now Price Range	$0-$285	$285-$1,000	$1,000+
Count	24,943	881	49
Fraction of Auctions	0.964	0.034	0.002
Total Revenue	$1,539K	$890K	$267K
Total Cost	$1,043K	$320K	$65K
Total Profit	$496K	$570K	$202K
Margin	32.2%	64.0%	75.8%

Table 4: Descriptive statistics for the distribution of profits across QuiBids auctions in A_n^{end} split by Buy-Now price for the week of November 15th, 2011. The bounds for each price range are determined based on QuiBids' win limit rules.

Including Buy-Now Effects

The analysis in the previous section assumed that no bidders had used Buy-Now. At the other extreme, we could compute QuiBids' profit assuming that every losing bidder had used Buy-Now. This would likely lead to a much higher QuiBids revenue than exists in reality, as it would assume that even a bidder who placed a single bid would use Buy-Now, whereas it would actually be cheaper for the bidder to purchase the good at retail without the QuiBids price markup.

In fact, it is not obvious *a priori* whether ignoring Buy-Now effects as done in the previous section artifically raises or lowers the estimate of QuiBids' profits. Whenever a bidder b uses Buy-Now, QuiBids must pay $\underline{m}_a$ to procure the good and receives revenue $\overline{m}_a$ from bidder b for a marginal profit of $\overline{m}_a - \underline{m}_a$. If bidder b had already spent more than $\overline{m}_a - \underline{m}_a$ in the auction through bid fees, QuiBids would achieve greater short-term profit if b did not use Buy-Now. Similarly, if b spent less than $\overline{m}_a - \underline{m}_a$ in the auction through bid fees, QuiBids would achieve greater short-term profit if the bidder used Buy-Now.

Our analysis in this section gives an upper bound on costs, and thus a lower bound on profit, when bidders have a Buy-Now option. To provide this bound, we assume that any eligible bidder that could use Buy-Now to reduce QuiBids overall profits (i.e., any bidder who spent more than $\overline{m}_a - \underline{m}_a$ in bid fees) does use Buy-Now:

$$\hat{x}_a^b = \begin{cases} 1 & \text{if } w_a \neq b \text{ and } n_a^b y_a^b c \geq \overline{m}_a - \underline{m}_a \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

In addition to giving a lower bound on QuiBids profits, this choice of function for $\hat{x}_a^b$ also has an economic interpretation: it assumes that bidders are utility maximizing and that anyone willing to bid in the auction has an underlying value for the good greater than or equal to the good's retail price $\underline{m}_a$. After bidding in the auction and spending bid fees c_a^b, each losing bidder with good value v_a^b faces the option of using Buy-Now for marginal utility $v_a^b - (\overline{m}_a - c_a^b)$, not using Buy-Now and instead buying at retail for marginal utility

$v_a^b - \underline{m}_a$, or not using Buy-Now and not buying at retail for marginal utility 0. The choice of using Buy-Now maximizes the bidder's utility when $c_a^b \geq \overline{m}_a - \underline{m}_a$ (i.e., when the bidder's total bid fees exceed QuiBids' price markup).

Note that determining whether each bidder uses Buy-Now requires knowledge about bid fees the bidder has accumulated in the auction. This information is not available in our dataset of auction end data A^{end}, and so we instead use the dataset with full auction bid histories A^{hist}. From A^{hist}, we estimate the relative change in revenues z^r and costs z^ϕ when bidders use Buy-Now according to $\hat{x}_a^b$ as opposed to never using Buy-Now. More formally, abusing notation to let $r(A|x_a^b = g)$ be the total revenue from auctions in A when each bidder in each auction uses Buy-Now according to g, we compute $z^r = r(A^{hist}|x_a^b = \hat{x}_a^b)/r(A^{hist}|x_a^b = 0)$. Assuming that the auctions in A^{hist} provide a representative sample of the auctions in A^{end}, we apply the same revenue change to the end data in order to account for Buy-Now: $r(A_n^{end}|x_a^b = \hat{x}_a^b) = r(A_n^{end}|x_a^b = 0)z^r$. The term on the left-hand side cannot be directly computed from auction end data, but the terms on the right-hand side are all known. The terms z^ϕ and $\phi(A_n^{end}|x_a^b = \hat{x}_a^b)$ are computed similarly.

Profit Breakdown From the full auction histories A^{hist}, we find $z^r = 1.47$ and $z^\phi = 2.85$. Applying these estimates to A^{end} we find we find $r(A_n^{end}|x_a^b = \hat{x}_a^b) =$ \$3.965M, $\phi(A_n^{end}|x_a^b = \hat{x}_a^b) =$ \$4.068M, and $\pi(A_n^{end}|x_a^b = \hat{x}_a^b) = -\$0.102$M. The corresponding profit margin is $\pi(A_n^{end}|x_a^b = \hat{x}_a^b)/r(A_n^{end}|x_a^b = \hat{x}_a^b) = -2.6\%$ (see also Table 5, Row 2). Although QuiBids appears to making a 47.0% profit margin without Buy-Now, these results suggest that the auctioneer could actually be taking a small loss on non-voucher auctions if all bidders were to use Buy-Now to rationally minimize their loss.

Voucher Bid Auctions

We now seek to analyze the profitability of the voucher bid partition of our dataset, A_v^{end}. An auction a for a voucher bid pack containing n_{bids} bids will have a Buy-Now price of $\overline{m}_a = n_{bids}c$, where the bid cost is $c =$ \$0.60. Since voucher bids cannot be used towards Buy-Now purchases, voucher bid packs are not actually worth $n_{bids}c$. If a bidder places a voucher bid and wins the auction, the voucher bid is worth its full \$0.60 cents. If the bidder loses, however, the voucher bid is worth nothing. We first assume that the reduced value of voucher bid packs is given by the average markup rate h, so that $\underline{m}_a = h\overline{m}_a$. We will refer to this valuation of voucher bid packs as "Valuation 1". Using Valuation 1, we analyze profits of A_v^{end} both ignoring Buy-Now (Table 5, Row 3), and assuming full rational utilization of Buy-Now as described in the previous section (Table 5, Row 4).

We can improve on Valuation 1 using the fraction f_{win} of bids that are spent by winners. The complete bid histories A^{hist} show that only $f_{win} = 4.438\%$ of bids are spent by winners. Assuming that voucher bids are evenly distributed among winners and losers, this implies that we should value voucher bid packs by $\underline{m}_a = f_{win}\overline{m}_a$. We refer this adjusted valuation of voucher bid packs as Valuation 2. Table 5, Row 5 shows profit for A_v using Valuation 2 and accounting for Buy-Now. If QuiBids were to sell a voucher bid pack containing a single voucher bid, its value would be $f_{win}c = 0.04438 \times \$0.60 = \$0.0266$. In other words, voucher bids are nearly valueless, implying that QuiBids' costs in voucher bid auctions are minimal. This allows for the extremely high profit margin of 96.9%. QuiBids thus exploits its users' dramatic overbidding for voucher bids in order to boost its profitability.

Combining Voucher and Non-voucher Auctions

We now investigate QuiBids' overall profitability for the complete set of auctions A by summing revenues, costs, and profits for the two partitions of the dataset. Total revenue is computed as $r(A^{end}) = r(A_n^{end}) + r(A_v^{end})$, with equivalent calculations for cost and profit. As before, we consider three separate scenarios:

- No use of Buy-Now, with Valuation 1 for voucher bid packs (Table 5, Row 6).
- Full rational use of Buy-Now, with Valuation 1 for voucher bid packs (Table 5, Row 7).
- Full rational use of Buy-Now, with Valuation 2 for voucher bid packs (Table 5, Row 8).

Comparing Table 5, Rows 7 and 8, we see that after properly accounting for the value of voucher bids, the profit-limiting effects of Buy-Now are offset. The inclusion of voucher bid auctions boosts QuiBids' profit margin by at least 10%.

Although voucher bids auctions comprise only 30.5% of the total auctions in the end data, they account for the entirety of QuiBids profit—we have seen that in the non-voucher auctions A_n^{end}, QuiBids roughly broke out even or perhaps took a small loss. Voucher bid auctions thus allow QuiBids to be profitable despite Buy-Now.

Bidder Experience

We have already characterized Buy-Now as a strategy designed to limit profitability in the short term in exchange for greater consumer retention, and hence greater profitability in the long term. One proxy for user retention that we can use to evaluate QuiBids' success in this regard is bidder experience. Namely, we investigate what fraction of revenue comes from experienced bidders compared to the fraction from novice bidders.

We define an experienced bidder as any bidder that has placed strictly more than 50 bids, based on Augenblick's assessment that the vast majority of inexperienced bidders (75%) were discouraged before placing 50 bids (Augenblick 2011). New QuiBids users are required to purchase a starter bid pack consisting of 100 bids, so we also investigate the definition of an experienced bidder as a bidder who has placed strictly more than 100 bids. QuiBids has, at the very least, convinced such users to buy a second bid pack. Using the threshold of 50, we find that of the approximately 135,000 bids placed in the complete auction histories, 73.5% are placed by experienced bidders and 26.5% are placed by inexperienced bidders. With a threshold of 100, 57.5% of bids are placed by experienced bidders.

		Count	Revenue	Cost	Profit	Margin	PPA
1	A_n^{end} without Buy-Now	25,873	\$2,696K	\$1,428K	\$1,268K	47.0%	\$49.00
2	A_n^{end} with Buy-Now	25,873	\$3,965K	\$4,068K	$-$\$102K	-2.6%	-\$3.96
3	A_v^{end} without Buy-Now, Valuation 1	11,360	\$698K	\$253K	\$445K	63.8%	\$39.19
4	A_v^{end} with Buy-Now, Valuation 1	11,360	\$1,027K	\$720K	\$307K	29.9%	\$27.01
5	A_v^{end} with Buy-Now, Valuation 2	11,360	\$1,027K	\$32K	\$995K	96.9%	\$87.55
6	A^{end} without Buy-Now, Valuation 1	37,233	\$3,394K	\$1,681K	\$1,713K	50.5%	\$46.00
7	A^{end} with Buy-Now, Valuation 1	37,233	\$4,992K	\$4,788K	\$204K	4.1%	\$5.49
8	A^{end} with Buy-Now, Valuation 2	37,233	\$4,992K	\$4,010K	\$892K	17.9%	\$23.96

Table 5: Profit statistics for non-voucher auctions, voucher auctions, and the combined data. We also include results either ignoring Buy-Now or assuming full rational utilization of Buy-Now, and results for both Valuation 1 and Valuation 2 of voucher bid packs. The final column, labeled “PPA”, gives the profit per auction.

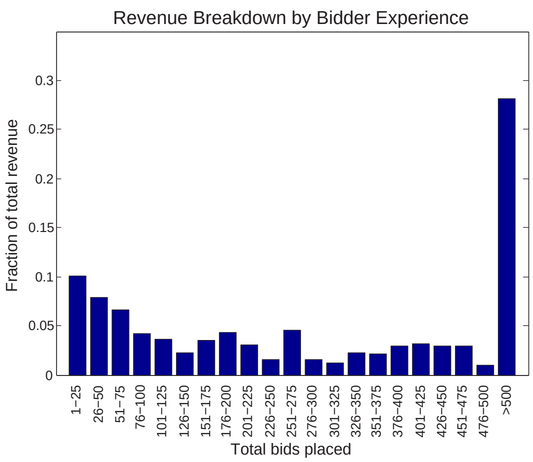

Figure 2: Revenues derived from bidders with various experience. We measure experience using the total number of bids placed over the course of all recorded auctions.

Assuming full rational utilization of Buy-Now and using a threshold of 100, this corresponds to 71.1% percentage of revenues coming from experienced bidders. In other words, nearly three-quarters of QuiBids’ revenue comes from bidders who have purchased at least two bid packs. Figure 2 gives a more detailed breakdown of revenue based on bidder experience. This figure shows that although QuiBids does garner a significant amount of revenue from inexperienced bidders, most of its revenue also comes from experienced bidders. This data is consistent with the notion that QuiBids is effectively utilizing Buy-Now to ensure long-term profitability by combating the “revolving door” effect.

Conclusion

In light of the recent slew of penny auctioneer bankruptcies, we have sought to determine whether QuiBids auctions remain profitable. Our conclusion is a qualified “yes”. Although at first blush QuiBids appears to be achieving large profit margins comparable to Swoopo’s, we find that Buy-Now sharply limits this profitability. In order to remain profitable after the limitations imposed by Buy-Now, QuiBids appears to rely on voucher bid auctions. We find that users overvalue voucher bids, and that by overbidding on essentially valueless voucher bid packs, such users allow QuiBids to make a 96.9% profit margin on voucher bid auctions. QuiBids’ non-voucher auctions may not be profitable under Buy-Now, but voucher bid auctions make up for this deficiency.

We posit that QuiBids purposefully uses Buy-Now to limit short-term profitability in exchange for consumer retention, and hence greater long-term profitability. Voucher bids are a mechanism for enhancing short-term profitability, presumably without having a large negative impact on consumer retention.

Finally, we examine whether rules designed to keep users coming back to the site have been effective. We find that large proportions of QuiBids’ revenues come from experienced bidders. This is a positive signal for QuiBids’ long-term prospects.

References

Augenblick, N. 2011. Consumer and producer behavior in the market for penny auctions: A theoretical and empirical analysis. Unpublished manuscript. Available at http://faculty.haas.berkeley.edu/ned/Penny_Auction.pdf.

Fance, C. 2010. Unique auction site swoopo expands to canada, testing ’buy it now’. http://tomuse.com/penny-auctions-entertainment-shopping-sites-review-compare/#ixzz2Ogx2HoLI.

Gimein, M. 2009. The big money: The pennies add up at swoopo.com. http://www.washingtonpost.com/wp-dyn/content/article/2009/07/11/AR2009071100684.html.

Hinnosaar, T. 2010. Penny auctions are unpredictable. Unpublished manuscript. Available at http://toomas.hinnosaar.net/pennyauctions.pdf.

Kincaid, J. 2009. Unique auction site swoopo expands to canada, testing ’buy it now’. http://techcrunch.com/2009/06/26/unique-auction-site-swoopo-expands-to-canada-testing-buy-it-now/.

Lee, A. 2011. Over 150 closed penny auction sites: Is the model sustainable? http://www.pennyauctionwatch.com/2011/04/over-150-closed-penny-auction-sites-is-the-model-sustainable/.

Wang, Z., and Xu, M. 2012. Learning and strategic sophistication in games: Evidence from penny auctions on the internet.