Selling a Dollar for More Than a Dollar? Evidence from Online Penny Auctions*

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Abstract

Online penny auctions, emerged recently, are seen as an adaptation of the famous dollar auction and as "the evil stepchild of game theory and behavioral economics." In this paper, we use the complete bid and bidder history at such a website to show that penny auctions cannot sell a dollar for more than a dollar in the long run because of bidder learning across auctions and bidder heterogeneity in strategic sophistication. The website we study profited from a revolving door of new bidders but lost money to experienced bidders as a group because of the existence of experienced and strategically sophisticated bidders who profit from the website.

Keywords: penny auction, behavioral industrial organization, strategic sophistication

JEL Classification: D03, D44, L81

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1 Introduction

Martin Shubik's (1971) famous dollar auction suggests the possibility of selling a dollar for more than a dollar. Can a firm adapt the dollar auction into a selling mechanism that sustains selling a dollar for more than a dollar over time? A new auction format recently emerged on the Internet, called the penny auction, might be seen as such an attempt. Penny auctions were described by Richard Thaler in the *New York Times* as a "diabolically inventive" adaptation of the dollar auction.[1] An article in the *Washington Post* asserts that penny auction is "the evil stepchild of game theory and behavioral economics" because it "fiendishly plays on every irrational impulse buyers have."[2] The primary purpose of this paper is to use the complete bid and bidder history at a major penny auction website to show that penny auctions cannot sell a dollar for more than a dollar in the long run.

Unlike eBay, penny auction websites sell products themselves, using rules similar to the following. First, a bidder must pay a small nonrefundable fee (e.g., \$0.75) to place a bid. A bid is an offer to buy the product at the current auction price. The auction price for any product is initially 0 and is increased by a fixed amount whenever a bid is placed. The increment is typically one penny, thus the name of penny auction. Second, the winner is the *last* bidder, the person whose bid is not followed by any other bid before a timer (e.g., of 30 seconds) expires. The timer is reset whenever a new bid is placed. The auction winner receives the product and pays the auction price. Consider an example in our data set. A bidder won an iPad auction after placing 70 bids, and the auction price was \$64.97. The winner paid a total cost of \$117.47 ($= 70 \times 0.75 + 64.97$) for the iPad, and the website's revenue was \$4,937.72 ($= 6,497 \times 0.75 + 64.97$)! A penny auction thus combines elements of an all-pay auction with a series of lotteries. Penny auctions are not a standard auction, in which the bidder who bids the highest amount wins (Krishna 2002, p. 29). The winner of a penny auction is often not the bidder who places the largest number of bids.

Central to our paper is the idea that no matter how effective an individual penny auction might be in exploiting bidder biases, it offers bidders immediate feedback on winning or losing so that losing bidders can quickly learn to stop participating. Consistent with this simple logic of individual rationality, we find that the website made positive profits, but its profits came from a revolving door of new bidders: the overwhelming majority of new bidders who joined the website on a given day played in only a few auctions, placed a small number of bids, lost some money, and then permanently left the site within a week or so. The website lost money to experienced bidders as a group: a very small percentage of bidders were experienced, but they won most of the auctions and earned substantial profits from the website. These findings suggest that penny auction websites cannot sustain excessive profits without attracting a revolving door of new customers who will lose money.[3]

[1] Richard H. Thaler, "Paying a Price for the Thrill of the Hunt," *New York Times*, November 15, 2009.

[2] Mark Gimein, "The Big Money: The Pennies Add Up at Swoopo.com," *Washington Post*, July 12, 2009.

[3] This feature is shared somewhat by Ponzi schemes. We are not suggesting that penny auctions are Ponzi schemes or necessarily scams.

The secondary purpose of our paper is to document and explain the observation that while experienced bidders as a group earned significant profits from the website, most experienced bidders actually lost money to the website. Our hypothesis is that not all experienced bidders in penny auctions are fully rational; they differ in their degree of strategic sophistication. We propose a measure of strategic sophistication and find evidence that experienced bidders' earnings are correlated with their strategic sophistication.

Our evidence comes from a nearly ideal bid-level data set collected from a major penny auction website (BigDeal.com). The data set covers all of the more than 22 million bids placed by more than 200,000 bidders in more than 100,000 auctions for a period of about 20 months, starting from the website's first day of operation to two days before the site's closure. The data set records the complete bid history of each bidder as well as the precise timing of each bid. We use a product's retail price at Amazon as an estimate of the product's market value. We define the auctioneer's profit as its revenue minus the market value of the products sold. Similarly, we define a bidder's profit or loss as the market value of the products she won minus her cost of bidding. Given these definitions, our conclusion that penny auctions cannot sustain selling a dollar for more than a dollar does not mean that penny auctions cannot sustain normal profits.

Four papers on penny auctions (Augenblick 2011; Platt et al. 2010; Hinnosaar 2010; and Byers et al. 2010) appeared before our paper. All four papers use data from Swoopo, the first penny auction website, and find that Swoopo made excessive profits during the sample periods they study. These papers' explanations for the observed exessive profits are very different from ours. Platt et al. (2010), which has been published as Platt et al. (2013), emphasize bidders' risk-loving preference. Their evidence is based on auction-level data (e.g., the number of bids in an auction), and they do not study bid- or bidder-level data. Byers et al. (2010) propose bidder asymmetry as a potential explanation for excessive profits, but they do not offer empirical evidence. Augenblick (2011) emphasizes the sunk cost fallacy as the explanation for overbidding at Swoopo. He notes that most of the bidders in his sample play in a small number of auctions and place a small number of bids, but he does not study the timing of bidder entry and exit, which is critical for observing whether there is a revolving door of new bidders. It is also unclear whether inexperienced bidders in his sample lost money and whether experienced bidders made money. Hinnosaar (2010) deals largely with a technical issue in modeling penny auctions.

These alternative explanations (risk-loving preferences, bidder asymmetry, and the sunk cost fallacy) imply that penny auctions may sustain exessive profits even in the long run. Our findings, however, suggest that penny auctions may generate excessive profits in the short run but not in the long run. Indeed, Swoopo, BigDeal, and many other penny auction websites have come and gone. We do find that a small number of experienced bidders consistently lose money over time; such bidders may have risk-loving preferences (Platt et al. 2010) or they may derive utility from the mere act of bidding in penny auctions.

Two papers on penny auctions (Caldara 2012; Goodman 2012) appeared after our paper. Caldara (2012) conducts lab experiments to study penny auctions, and his lab findings support our conclusion that penny auction websites profit from a revolving door of new bidders. He concludes (p. 32) that "excessive revenues will only last as long as [penny] auction websites can attract new, inexperienced bidders." Goodman (2012) is similar to Augenblick (2011) but focuses on the role of reputation in penny auctions.

Our paper contributes to the behavioral industrial organization literature that focuses on how profit-maximizing firms exploit consumer biases. See sections of Ellison (2006) and DellaVigna (2009) for reviews of the literature and DellaVigna and Malmendier (2006) for an excellent example. Our findings suggest that market experience can limit overbidding, at least in auctions with clear feedback, and that firms' ability to exploit consumer biases is constrained by consumer learning.[4] Our findings also suggest that when firms exploit inexperienced bidders, they may be exposed to the risk of being exploited by experienced and sophisticated players.

Our paper also relates to the behavioral game theory literature (e.g., Camerer 2003; Crawford et al. 2013), which uses principles of behavior economics to study strategic interactions and finds that subjects in experimental games often have limited and heterogeneous strategic sophistication. An emerging literature uses the behavioral game theory approach to study strategic interactions in field settings (Goldfarb and Yang 2009; Goldfarb and Xiao 2011; Brown et al. 2012). These studies often measure players' strategic sophistication as in level-k/cognitive hierarchy models (e.g., Camerer et al. 2004; Costa-Gomes and Crawford 2006). Because penny auctions are a complicated dynamic game, we cannot measure players' strategic sophistication in the same way. Our measure is specific to penny auctions. Nonetheless, our paper provides evidence that player heterogeneity in strategic sophistication is important for understanding penny auctions, a large-scale game in the field. Other than Caldara (2012), previous studies on penny auctions did not cite the behavior game theory literature.

Our paper relates further to the large literature on online auctions. See Bajari and Hortaçsu (2004) for a review of the literature and Einav et al. (2014) for a recent example. In particular, our paper is related to empirical studies of overbidding in auctions (e.g., Malmendier and Lee 2011). Finally, our paper is related to a few recent studies of nonstandard auction formats. Raviv and Virag (2009) and Houba et al. (2011) study the lowest unique bid auction, and Ostling et al. (2011) study the lowest unique positive integer game.

2 Background, Auction Rules, and Data

2.1 The Penny Auction Industry

The first penny auction firm, Swoopo, was founded in Germany in 2005, and it started its U.S. website in 2008. By November 2010, at least 125 penny auction websites targeting U.S. consumers were being monitored by Compete.com, a web traffic monitoring company. The total number of unique monthly visitors to these penny auction websites reached 25.1% of that to eBay in November 2010 but has since declined sharply. Table 1 lists the 11 websites whose traffic was ranked in the top

[4] See List (2003) for evidence that market experiences may eliminate some forms of market anomalies.

5 of all penny auction sites for any two consecutive months from February 2010 through April 2011. We emphasize that among the 9 sites in Table 1 that were in existence in February 2010, 3 were closed in 2011, 2 barely attracted any visitors in October 2011, 1 was closed in 2012 (Bidrivals), and the other 3 sites experienced a dramatic traffic decline in 2011. Most penny auction websites attract little traffic and do not last for long.

Table 1: Monthly Traffic on the Largest Penny Auction Websites

Website	Unique visitors					Win
	Feb. 2010	Nov. 2010	Apr. 2011	Oct. 2011	BIN	limit
BigDeal.com	480,230	1,324,947	943,327	Closed	Yes	Yes
Bidcactus.com	1,428,316	3,411,705	1,979,846	740,981	Yes	Yes
Beezid.com	1,110,859	755,917	549,908	432,352	Yes	Yes
Bidsauce.com	356,811	690,014	344,514	9,052	Yes	Yes
Swoopo.com	286,142	171,141	Closed	Closed	Yes	Yes
Quibids.com	173,142	4,541,783	4,586,523	2,638,490	Yes	Yes
Bidrivals.com	63,329	419,945	490,751	144,468	Yes	Yes
Wavee.com	26,863	1,696,803	62,214	Closed	Yes	?
Bidhere.com	17,359	542,079	750,175	3,731	Yes	Yes
Zbiddy.com	0	0	945,149	1,772,935	Yes	Yes
Biggerbidder.net	0	0	120,078	664,636	No	No
Total number of sites	47	125	158	116		
All sites	4,710,541	16,866,475	12,524,625	9,234,509		
eBay.com	64,766,668	67,197,011	69,929,590	77,232,991		
% of eBay traffic	7.3%	25.1%	17.9%	12.0%		

Notes: The 11 websites shown in this table include all the penny auction sites whose traffic was ranked in the top 5 of all penny auction sites in any two consecutive months from February 2010 through April 2011. We obtained the traffic data from Compete.com, and the Buy-It-Now (BIN) and win limit information from each individual penny auction website. For websites that still exist, the BIN and win limit information is as of March 2013.

Penny auctions are highly controversial. The Better Business Bureau (BBB) in the United States has received many consumer complaints against penny auction websites.[5] In fact, it named penny auctions one of the top 10 scams of 2011.[6] Three sites in Table 1 (Bidsauce, Swoopo, and Wavee) have an F rating, the worst BBB rating. Lawsuits have been filed against various penny auction websites, alleging penny auctions are a form of gambling. The industry brands itself as an *entertainment shopping* industry. Penny auction websites advertise that auction winners obtain products at deep discounts. It has been reported that penny auction sites "have driven up the price of advertising keywords on *Google* such as 'cheap iPad.' Buying keywords on search sites is the primary way the auction sites advertise products for sale."[7]

Nearly all penny auction websites have two additional salient rules: win limits and a Buy-It-Now (BIN) option. Win limits restrict the number of auctions a bidder can win. An individual

[5] "Online Penny Auctions: Friend or Foe?" http://www.bbb.org/blog/2010/10/online-penny-auctions-friend-or-foe/.

[6] http://www.bbb.org/us/article/bbb-names-top-ten-scams-of-2011-31711.

[7] Brad Stone, "Penny Auction Sites Hurt by Glut of Competitors," *Bloomberg Businessweek*, August 12, 2010.

bidder at BigDeal, for example, was restricted to at most 10 wins during a 30-day period. Once a bidder reached the win limit, she was prohibited from bidding in any auction until the 30-day period expired. Some websites impose much more stringent win limits. For example, bidders at Zbiddy.com, a relatively new entrant, are allowed to win only one product with a retail price of $999 or higher during a 28-day period and to win only one product with a retail price of $499 or higher during a 7-day period.

The BIN option in penny auctions works differently from that found on eBay. A bidder who exercises the BIN option in penny auctions does not stop the auction. Instead, she stops her own bidding and obtains a product that is the same as the one under auction by paying the difference between the posted retail price for the product and the cost of her bids. Penny auction websites post a retail price for any product to be auctioned. For example, the posted retail price for an iPad auction with the BIN option in our data set is $899.99. A losing bidder in this auction placed 1,067 bids, so her cost of bids is $800.25 ($= 1,067 \times 0.75$). This bidder needs to pay only $99.74 ($= 899.99 - 800.25$) more to exercise the BIN option and obtain an iPad that is the same as the one being auctioned. With the BIN option, this bidder pays the posted retail price of $899.99 to buy an iPad. Without the BIN option, this bidder would have paid $800.25 for nothing. The BIN option allows losing bidders who placed a large number of bids to recover some of their costs, which has the effect of reducing the profitability of penny auction websites. On the other hand, by eliminating the risk of losing a large amount of bids, the BIN option may allow a website to attract more bidders, which is perhaps why almost all penny auction websites now offer the BIN option.

2.2 BigDeal

BigDeal was one of the largest penny auction websites and appeared to be a serious business endeavor. It received $4.5 million initial funding from well-known venture capital firms.[8] Perhaps to mitigate potential concerns of shill bidding, BigDeal displayed the bid history of all live and past auctions on its website. Bidders could easily see the bid history of live and recently finished auctions.[9] BigDeal is also unique among penny auction websites in that it posted on its website photos and biographies of its managers and board of directors.

The rules of BigDeal auctions were representative of all penny auctions. Prior to bidding in any auction, bidders had to buy packs of bid tokens. Each bid token cost $0.75.[10] The auction price for any product started at $0, and each bid cost a single nonrefundable token and raised the auction price by a fixed increment. The price increment was $0.01 in most auctions and $0.05 or $0.15 in a large number of auctions in the early part of our sample.

BigDeal typically released an auction with an initial countdown clock that lasted for 36 hours.

[8] Brad Stone, "BigDeal Puts a New Spin on 'Entertainment Shopping,'" *New York Times* Bits Blog, December 19, 2009.

[9] BigDeal created a separate web page for each auction that contained the general information and bid history of the auction. By clicking link buttons on the homepage or the "winner page" of BigDeal, one could have access to such web pages. It required increasingly larger numbers of clicks to access web pages of auctions finished earlier.

[10] BigDeal sold bid-tokens in packs of 30, 50, 100, 200, 300, and 500 tokens. Unused tokens can be sold back to the website at the price of $0.75 per token.

If a bid was placed when more than 30 seconds were left on the initial countdown clock, the clock continued to run down. If a bid was placed when less than 30 seconds was left, however, the timer would always be extended by 30 seconds. A bidder won only if her bid was not followed by any other bid when the 30-second timer expired. It is not surprising that nearly all bids were placed after the 30-second timer started. Once the 30-second timer started, the timer was set to last 30 seconds ex ante, but whenever a bid was placed within this period, this period ended immediately and a new period started. Hence, the length of a time period ex post could range from 0 to 30 seconds.

In addition to her bidding cost, the winner also paid the auction price to attain the product. BigDeal offered losing bidders the BIN option in all auctions except for some bid pack and iPad auctions. BigDeal offered bidders a bid agent (called BidBuddy) that placed bids automatically on their behalf. The bid agent did not bid strategically. A bidder could impose three restrictions on her bid agent: the maximum number of bids, at what auction price to start to bid, and at what auction price to stop. A bidder could also deactivate a bid agent at any time. BigDeal auctioned several categories of products, including packs of bid tokens, video games and consoles, Apple products, and non-Apple electronics (such as computers, TVs, phones, cameras, and GPS, housewares, gift cards, handbags, jewelry, and movies).

2.3 Data

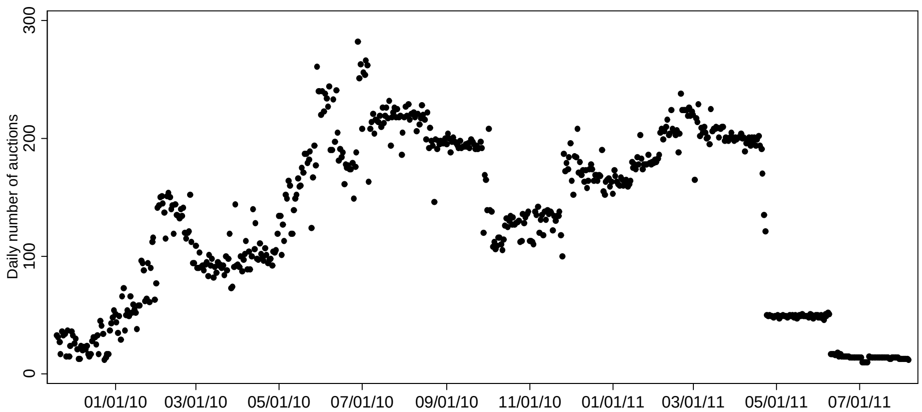
Our data set, downloaded from BigDeal.com, covers the general information and the bidding history of all auctions released by BigDeal from November 19, 2009, the first day of the website's operation, through August 6, 2011, two days before the website was closed. Auction-level information includes the auction price increment, the posted retail price, product name and description, the final auction price, the winner, and whether the BIN option was available. We do not observe which losing bidders exercised the BIN option. The BIN option was not available for bid pack auctions until late November 2010, and it was also not available for iPad auctions for some periods "due to inventory restrictions."

Another auction-level variable is whether an auction was a beginner auction that accepted bids from new members only. Most beginner auctions featured 10-token or 20-token bid packs. Beginner auctions were not offered until November 30, 2010.

The bid history for each auction includes every single bid: the exact second when a bid was placed, the screen name of the bidder, and whether the bid was placed manually or by a bid agent.

Figure 1 shows the number of regular (non-beginner) auctions ended each day for the entire sample period. There was a dramatic decline in the number of auctions per day in late April 2011, which was a sign that BigDeal was preparing to shut down. Because the operation of BigDeal was no longer normal after that, we do not consider the auctions ended on or after May 1, 2011. For the sample period of November 19, 2009, through April 30, 2011, BigDeal offered a total of 110,703 auctions, including 78,634 regular auctions and 32,069 beginner auctions. Among these auctions, 61 regular auctions and 3,423 beginner auctions failed to attract a single bidder. A total of 207,069 bidders placed at least one bid during our sample period, and together they placed a total of 22,598,266 bids.

Figure 1: Daily Number of Regular Auctions



Since the winner of a penny auction is the bidder who bids last, the bidder with the most bids in a penny auction often does not win the auction. The winner's total number of bids is smaller than or equal to that of at least one losing bidder in 53.8% of the 77,944 regular auctions with two bidders or more. In fact, in 154 auctions, the total number of bids placed by the last bidder is less than 1% of that by another bidder. The winners of such auctions often are "jumpers" in that they used the strategy of jumping in: starting to bid in an auction only after a large number of bids had already been placed in the auction.

3 Bidder Dynamics and Sources of Auctioneer Profit

We study bidder dynamics in sections 3.1 and 3.2 and calculate bidder or auctioneer profit in Section 3.3. We consider all 207,069 bidders in this section.

3.1 Conceptual Considerations

In this section, we focus on the implications of bidder learning across auctions. We offer more theoretical discussions of penny auctions in section 4. Recognize that the decision of whether to participate in another auction is a simple binary choice. When making this decision, bidders are given accurate and immediate feedback on their gains or losses in the auctions in which they have played. According to Tversky and Kahneman (1986, p. S274), "accurate and immediate feedback about the relation between the situational conditions and the appropriate response" is conducive to effective learning. We then expect the principle of individual rationality to hold for all bidders with regard to the decision of whether to bid in another auction. That is, a bidder quits the website if her utility gain from playing in one more auction is expected to be negative.

Suppose some bidders behave as gamblers: they either have risk-loving preferences or derive utility from the mere act of bidding.[11] Under this assumption, bidders may continue to play even

[11] Chance plays an important role in determining the outcome of penny auctions. Penny auction bidders, however,

if they keep losing money.

Suppose bidders do not behave as gamblers. Under this assumption, bidders quit the website if they keep losing.

Therefore, excessive profits can only come from (1) inexperienced bidders who lose money but quit quickly or (2) experienced bidders who consistently lose money but continue to play.

3.2 A Revolving Door of New Bidders

In this subsection, we present compelling evidence that BigDeal was characterized by a revolving door of new bidders who never won any regular (i.e., non-beginner) auctions.[12] This finding is critical for understanding the sources of auctioneer profit that we document in the next subsection.

Table 2: Distribution of Three Measures of Bidder Participation Intensity

	Percentiles							
	50%	75%	90%	95%	99%	99.5%	99.75%	99.95%
Number of auctions	3	8	16	25	76	128	201	422
Number of bids	22	55	150	300	1,350	2,622	4,954	16,928
Duration	1	4	29	84	258	320	364	430

Table 2 shows the distribution of three measures of bidder participation: the number of auctions a bidder participated in, the number of bids submitted, and importantly, the duration of a bidder. We define the duration of a bidder as the number of days from the date she placed her first bid through the date she placed her last bid in our sample. All three measures of participation indicate that the vast majority of the bidders at BigDeal were fleeting participants. The 75th percentile of bidders' duration is only 4 days, the 75th percentile of the number of auctions participated is 8, and the 75th percentile of the number of bids is 55. A very small percentage of bidders were persistent participants. Only 10.1% of the bidders lasted 29 days or more, 5.2% of the bidders played in 25 auctions or more, and 5.1% of the bidders placed 300 bids or more.

To directly see the phenomon of a revolving door of new bidders, consider Figures 2(a) to 2(d), which present the dynamics of bidder entry and exit. Figure 2(a) shows the weekly sum of each day's new bidders and permanent quitters. The number of new bidders is close to the number of permanent quitters on a weekly basis. Figure 2(b) shows the weekly average of the daily percentage of new bidders whose duration would be no more than 7, 14, or 28 days. Figure 2(c) shows the weekly average of the daily percentage of new bidders whose total number of auctions would be no

are unlikely to have the Friedman and Savage (1948) utility function that is concave at the current wealth level and convex above it. The maximum return in penny auctions is relatively small; no product auctioned at BigDeal had a retail price higher than $3,000. However, Golec and Tamarkin (1998) present evidence that horse track bettors seek skewness in return, not risk. It is also possible that some bidders may derive intrinsic utility from the mere act of bidding in penny auctions.

[12] A high degree of customer churn itself is not a puzzle. Indeed, customers for a new industry may try and then leave. However, unlike legitimate industries that typically would like to have a large number of repeat customers, penny auctions do not like repeat customers because, as we show in section 3.3.2, they lose money to repeat or experienced customers as a group.

more than 7, 14, or 28. These two figures indicate that most new bidders quit the website quickly. Figure 2(d) shows the weekly average of the daily percentage of bidders who would appear on the website for less than 7, 14, or 28 days. This figure shows that most bidders on a given day were relatively new to the website. Note that the weekly averages here are all weighted by the number of bidders on each weekday. Note also that the sudden drop in the number of new bidders in Figures 2(a) and 2(d) around week 40 of 2010 was related to the sudden drop in the number of non-beginner auctions in Figure 1 around the same time.[13]

Figure 2(a): Weekly Sum of New Bidders and Quitters Each Day

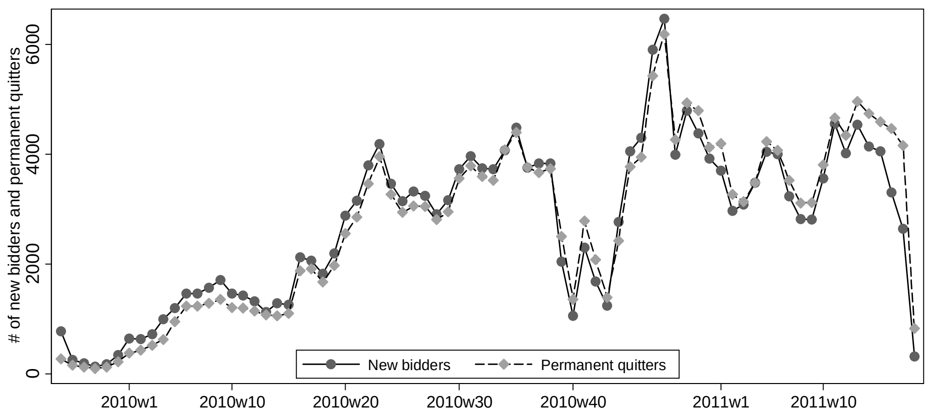
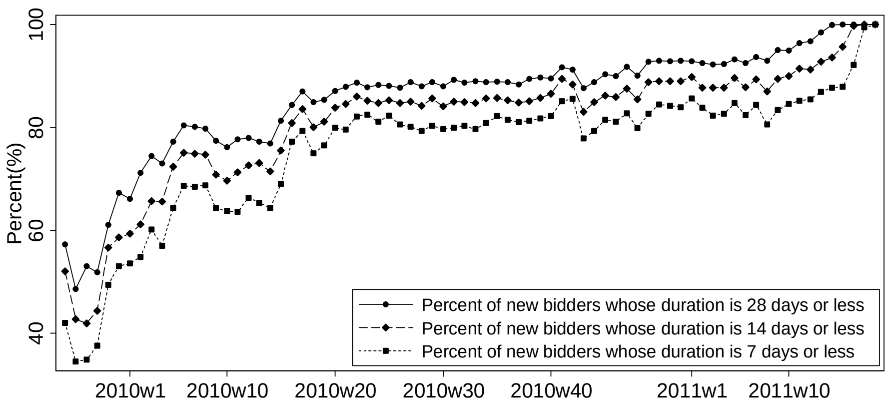


Figure 2(b): Weekly Average of Daily Percentage of New Bidders Whose Duration Is No More Than 7, 14, or 28 Days



[13] From September 25, 2010, to September 29, 2010, the number of new bidders decreased from around 500 per day to less than 100 per day. We do not know why the number of new bidders decreased during this period. As a result, BigDeal's daily profit reached the local minimum of -$1,633 on September 27, 2010. In response, BigDeal started to offer fewer regular auctions the following day. Though the number of new bidders recovered in October, BigDeal retained the low level of supply until the end of November. BigDeal started to offer beginner auctions on November 30, 2010.

Figure 2(c): Weekly Average of Daily Percentage of New Bidders Who Bid in No More Than 7, 14, or 28 Auctions

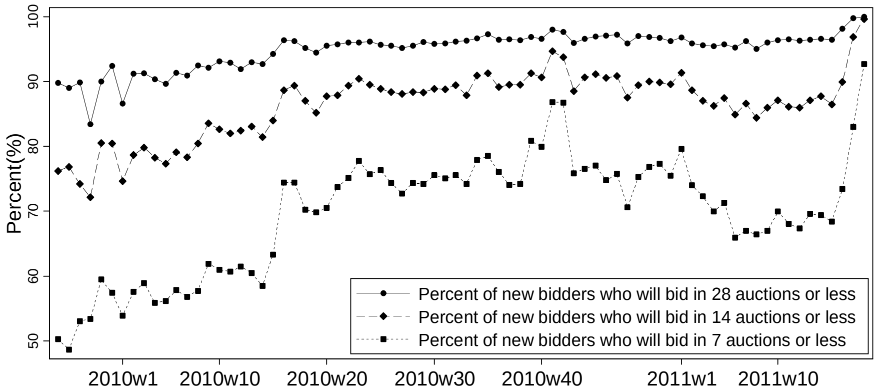
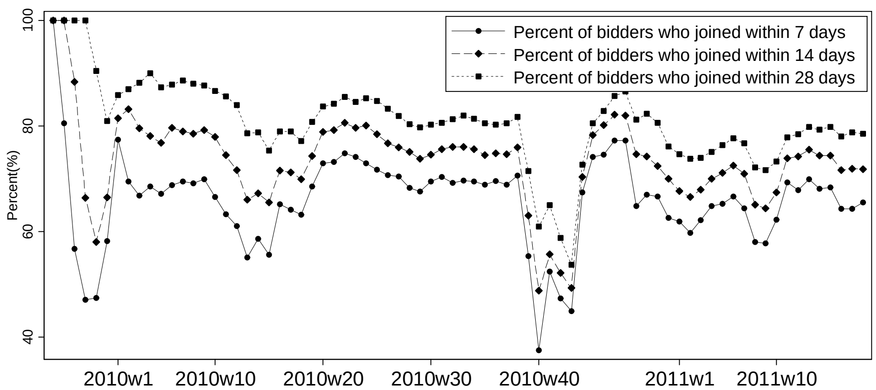


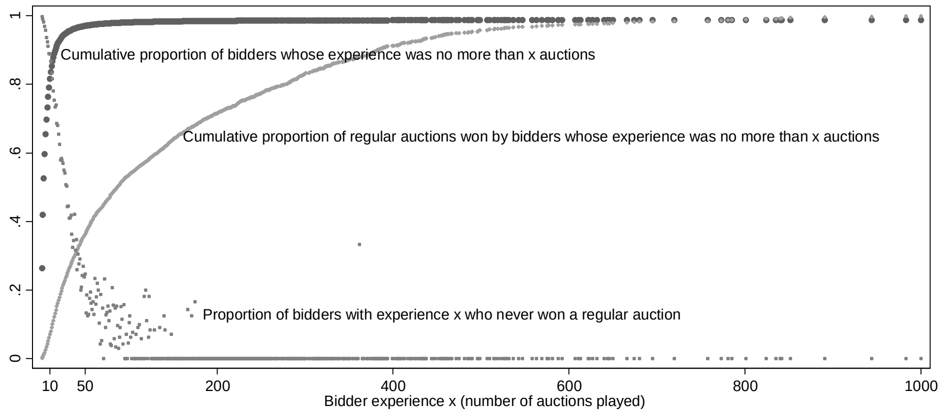
Figure 2(d): Weekly Average of Daily Percentage of Bidders Who Joined the Site No More Than 7, 14, or 28 Days Prior



Inexperienced bidders rarely won regular auctions, and experienced bidders won most of the auctions. This can be seen from Figure 3. In this figure, the x-axis is a bidder's experience x (i.e., the total number of regular auctions in which they played), and the y-axis indicates three different variables. The first variable is the proportion of bidders with experience x who never won a regular auction (the L-shaped curve in the figure). The proportion of bidders who never won a regular auction is extremely high for those bidders who played in only a small number of regular auctions. For example, 95.8 (88.8) percent of the bidders who played in 5 (10) auctions never won a regular auction. In contrast, essentially 0 percent of the bidders who played in 200 or more regular auctions never won a regular auction.

The two increasing curves in Figure 3 indicate, respectively, the cumulative proportion of bidders whose experience was no more than x auctions and the cumulative proportion of regular auctions won by bidders whose experience was no more than x auctions. Unless x is very large, the curve for cumulative proportion of bidders is much higher than the curve for cumulative proportion of regular auction wins, indicating that inexperienced bidders won a very small percentage of the regular auctions. For example, 66% of all bidders played in no more than 5 regular auctions, and the proportion of regular auctions won by these bidders is merely 2.5%.

Figure 3: Distributions of Bidder Participation and Performance



Notes: Excluded are two bidders who played in over 1,000 regular auctions

Why do most new bidders quit quickly without winning any regular auction? Our interpretation is that most bidders, before playing, did not know the difficulty of winning penny auctions or the existence of experienced bidders who win most of the auctions. Though we do not have direct evidence, it appears plausible that many bidders may have been enticed by the advertisements of deep discounts and joined the website in the hope of winning some items easily and cheaply. If so, such bidders quickly realized that their expectations were wrong.

3.3 Bidder or Auctioneer Profit

In this subsection, we estimate the auctioneer's profit and each bidder's profit or loss. Our results indicate that BigDeal made considerable profit from inexperienced bidders but lost money to experienced bidders as a group. This finding suggests that penny auction websites cannot sustain excessive profits without attracting a revolving door of new bidders who will lose money. We also find that experienced bidders differed greatly in their earnings; while most experienced bidders lost money, a small percentage of experienced bidders made significant amounts of profits.

3.3.1 Profit Definition and Computation

We define a bidder's profit as the total value of the products she won or bought minus her total cost. We define the auctioneer's profit as its revenue minus the total value of the products auctioned or sold through the BIN option. These two definitions suit the purpose of studying whether penny auctions generate revenues that are above the values of the products sold, and if so, which types of bidders are the sources of the excessive profit. We are not concerned with the auctioneer's profit over its cost, which we do not observe. Given these definitions, our conclusion that penny auctions cannot sustain excessive profits does not mean that they cannot sustain normal economic profits. Since the auctioneer's revenue equals bidders' total cost, one dollar lost by a bidder is one dollar of additional profit earned by the auctioneer. We describe below how to compute profit from the bidders' perspective.

Following the literature on penny auctions, we approximate the value of a product by the retail price of the same product at Amazon.com in mid-June, 2011.[14] Therefore, our measure of seller profit can reveal how much more money penny auctions can generate than Amazon does from the same products. We find 61.7% of the non-token BigDeal auctions involved products sold at Amazon.[15] For these auctions, the Amazon prices were, on average, 78.0% of the retail prices posted by BigDeal. In 97.6% of these auctions, the Amazon price was less than the BigDeal retail price. We assume that the value of a non-token product that does not have a matched Amazon product was 78% of the retail price posted by BigDeal.[16] We will discuss the value of bid tokens later.

A bidder's profit depends on the number of auctions she won and lost and the dollar amount she made in each of the auctions she played. Consider bidder i who participated in $n = 1, 2, \ldots, N$ auctions. Let π_{in} denote bidder i's profit (or loss) from her nth auction. Her total profit, π_i, is then $\pi_i = \pi_{i1} + \pi_{i2} + \cdots + \pi_{iN}$. It is straightforward to calculate her profit in any auction that she won; calculating her loss in an auction that she did not win is more involved because we need to estimate whether she exercised the BIN option. We use the following simple proposition to estimate whether a bidder exercised the BIN option. Suppose bidder i lost an auction after placing b bids, and the posted retail price for the product is r. To exercise the BIN option, bidder i needs to pay $r - bc$ to purchase the product, where c is the cost per bid.

Proposition 1: *If the BIN option is available, then (a) the inequality $bc \leq r$ must hold; (b) and bidder i exercises the BIN option only if $r - bc \leq v$.*

Part (a) says that bidder i's cost of total bids should not exceed the posted retail price of the product if the BIN option is available. Once a bidder's cost has reached the posted retail price, she can exercise the BIN option and obtain the product for free. Part (b) says that bidder i exercises the BIN option only if her additional cost, $r - bc$, is no more than v, the value of the product.

We show here how to compute a bidder's profit in a non-token product auction. It is slightly more involved to compute bidder profit in a token auction because of a subtlety with the valuation of bid tokens obtained from the BIN option. We explain this subtlety in Appendix A.

[14] We searched Amazon.com in mid-June 2011 and found an exact match for 601 of the 1,687 unique non-token products auctioned by BigDeal. All of the matched products are new, and the vast majority of them were sold by multiple sellers on Amazon, often at different prices. We recorded the price posted by the main or featured seller, which is the manufacturing firm of the product or Amazon itself or a large seller. For iPads, we use Apple's official prices.

[15] Non-token auctions refer to any auctions that do not feature packs of bid tokens.

[16] Our results are robust to departures from this assumption. For example, we considered the following two alternative assumptions that do not use any Amazon prices: (1) the value of any product (including both non-token and token products) is 90% of the retail price posted by BigDeal for this product (so that a rational losing bidder would exercise the BIN option if the cost of bids she already incurred is above 10% of the retail price for this product); (2) the value of any product is 70% of the retail price posted by BigDeal for this product. A key variable in our analysis is individual bidders' total earning from all auctions. The Spearman rank order correlation coefficient is above 0.94 between any pair of the three measures of individual bidders' total earning: the measure based on the 78% assumption and two measures based on the two alternative assumptions. Our regression results from equation (4) and (5) in section 4.2 also remain qualitatively similar if we use the two alternative assumptions.

Suppose the posted retail price for the product in bidder i's first auction is r_1, the value of the product is v_1, the final auction price is p_1, and her number of bids is b_{i1}. Then, if she won, her profit is

$$\pi_{i1} = v_1 - p_1 - 0.75b_{i1}. \tag{1}$$

Note that the opportunity cost of a bid is always \$0.75 because unused bid-tokens can be sold back to the website at the price of \$0.75 per token. The winner of a bid pack auction may obtain tokens at substantial discounts, but when such tokens are used in subsequent auctions, the opportunity cost of such a token should still be the price of a token, \$0.75. The use of such tokens allows a player to avoid buying some tokens at the price of \$0.75 per token.

If bidder i lost, her profit depends on whether the BIN option is available, and if the option is available, whether she exercises it. Suppose the BIN option is not available. Then her profit is simply

$$\pi_{i1} = -0.75b_{i1}. \tag{2}$$

If the BIN option is available, bidder i's profit depends on whether she exercises the BIN option:

$$\pi_{i1} = \begin{cases} -0.75b_{i1} & if \quad r_1 - 0.75b_{i1} > v_1 \\ -(r_1 - v_1) & if \quad r_1 - 0.75b_{i1} \leq v_1 \end{cases}. \tag{3}$$

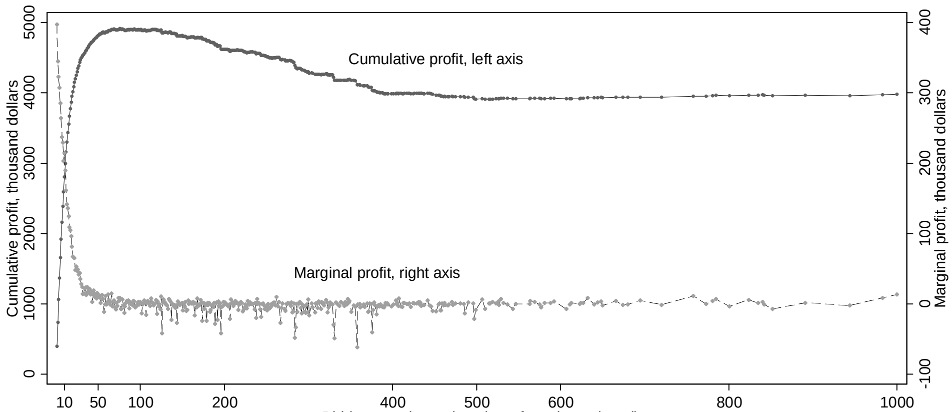
If the cost of exercising the option is bigger than the value of the product, $r_1 - 0.75b_{i1} > v_1$, she does not exercise the option and her loss is simply her bidding costs, $0.75b$. If she exercises the option, she uses r_1 to obtain a product of value v_1, so her loss is $r_1 - v_1$. Equation (3) assumes implicitly that $r_1 > v_1$. In the rare event that $r_1 < v_1$, bidder i exercises the BIN option after losing and obtains a profit.

3.3.2 Sources of Auctioneer Profit

The website profited from a large number of inexperienced bidders but lost money to experienced bidders as a group. This can be seen from Figure 4. In this figure, the x-axis is the total number of auctions in which a bidder participated, x, and the y-axis is either the website's marginal profit from bidders who played in exactly x number of auctions or the website's cumulative profit from bidders who played in x number of auctions or less. The website's marginal profit from bidders with experience x is initially large but diminishes quickly. The marginal profit from bidders who played in only one auction (i.e., $x = 1$) is nearly \$400,000, because a large number of bidders played in a single auction and almost all of them lost money. The marginal profit from bidders who played in exactly 30 auctions (i.e., $x = 30$) is about \$30,000, and the marginal profit from bidders whose experiece is 30 auctions or more is sometimes negative. Correspondingly, the website's cumulative profit from bidders with experience x or less increases quickly when x is small. The cumulative profit reaches its largest value, \$4.91 millions, when experience x is 76 auctions, and it then exhibits a downward trend until reaching the value of slightly over \$3.9 millions when experience x is about

500 auctions. After that point, the website's cumulative profit remains roughly at \$3.9 millions.[17]

Figure 4: Distribution of Auctioneer Profit



The total value of the products auctioned by BigDeal is \$9.9 million, and the total value of the products sold through the BIN option is \$16.6 million. Therefore, the total profit of \$3.9 million generated by BigDeal amounts to about 15% of the total value of the products it auctioned or sold through the BIN option.

The finding that the main source of auctioneer profit is inexperienced bidders holds over time. To see this point, consider Figure 5, which shows the weekly average of the percentage of profit each day generated from three groups of bidders: those who had been on the website for 7 days or less, those between 8 and 28 days, and those 29 days or more. The vast majority of the auctioneer's profit in almost all weeks came from inexperienced bidders (those who had joined the website no more than 7 days ago), and the auctioneer lost money in most weeks to experienced bidders (those who stayed on the website for more than 4 weeks). For example, during week 49 of 2010, the website earned large amount of profits from inexperienced bidders but lost large amount of money to experienced bidders so that the weekly average of daily percentage of profits generated from the experienced bidders was 303.0% and the weekly average of daily percentage of profits generated from the inexperienced bidders was -228.7%.

The website lost money to experienced bidders as a group, but most of the experienced bidders actually lost money to the website. If experienced bidders are defined to be those with at least 50 (40) auctions, 68% (71%) of them lost money and these losing bidders together lost a total amount of \$1.26 millions (\$1.49 millions). In contrast, the winning experienced bidders together won a total amount of \$2.07 millions (\$2.17 millions).

Bidder heterogeneity in earnings can be seen from Figure 6, which plots individual experienced bidders' profit against the number of auctions they participated in. Some of the experienced bidders lost a considerable amount of money while others earned a significant amount. For example, 2 bidders lost more than \$10,000, while 30 earned more than \$10,000; 93 bidders lost at least \$2,000

[17] The upward trend, which is clear if we zoom in, indicates that bidders who played in more than 500 auctions generally lost money to the website.

each, while 247 bidders earned at least $2,000 each. Most bidders with large gains or losses played in a large number of auctions. Why is it that some experienced bidders make large amount of profits while others lose large amount of money? We address this quesiton in the following section.

Figure 5: Weekly Average of Daily Percentage of Profits Generated
from Three Group of Bidders

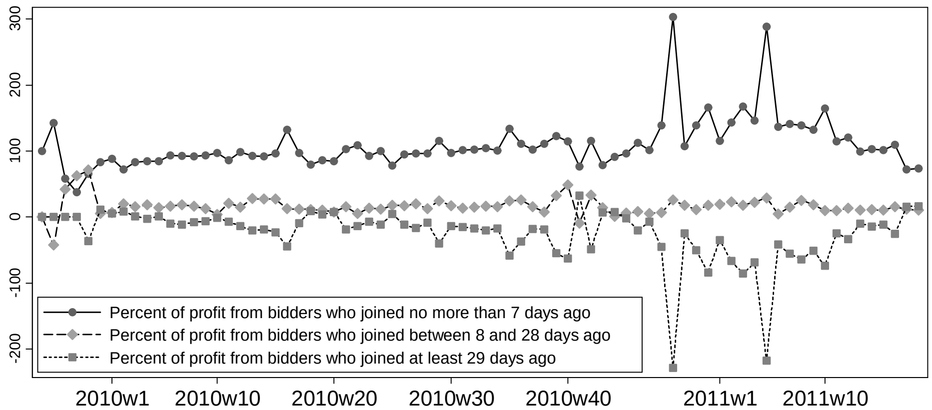
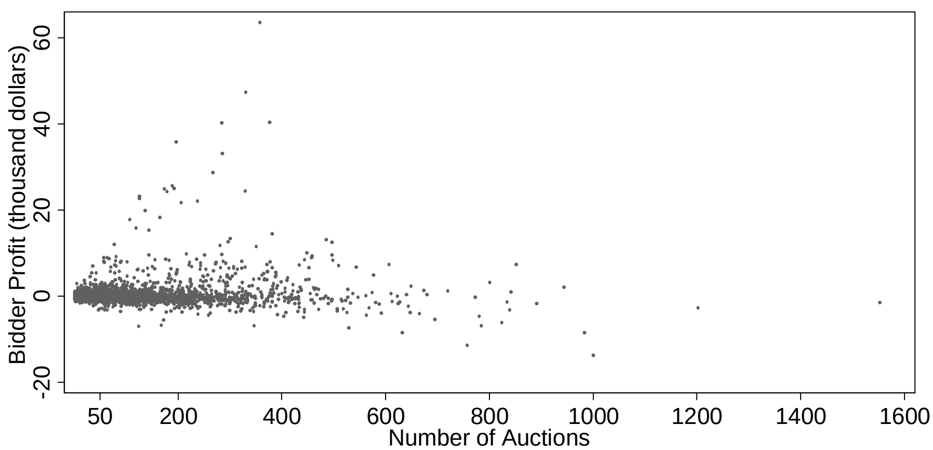


Figure 6: Bidder Profit Versus Bidder Experience



4 Bidder Earnings and Strategic Sophistication

In this section, we provide an explanation for why some experienced bidders earned substantial profits while other experienced bidders lost money. We propose a measure to proxy for players' strategic sophistication and present evidence that experienced bidders' earnings are correlated with our measure of their strategic sophistication. This finding suggests that it is inappropriate to assume all bidders in penny auctions are fully rational. We also find that a small number of experienced but unsophisticated players consistently lost money over time; such bidders may behave as gamblers. The existence of experienced and sophisticated bidders provide an explanation for why penny auction websites impose win limits; win limits constrain sophisticated players' potential earnings.

4.1 Conceptual Considerations

We begin this section by considering how one might characterize the equilibrium of a penny auction if all bidders are fully informed and rational. Let the value of the auctioned item be v dollars. Each time period, $t = 0, 1, ...$, is set to last 30 seconds, but whenever a bid is placed, this period ends and a new period, $t + 1$, starts. Period 1 represents the period after the first bid is placed. A bidder wins if her bid is not followed by another bid within 30 seconds. In each period t, a player has to decide whether to submit a bid, and if so, when to submit that bid during the 30-second timer. The cost of a bid is simply \$0.75. The expected benefit of a bid is the payoff from winning the auction times the probability of winning. For simplicity, assume that the price increment is zero instead of 1 penny. This assumption implies that the payoff from winning the auction in any period t is always v dollars.[18] If all bidders are fully informed and rational and the timing of placing a bid within the 30-second timer can be ignored, one may characterize the equilibrium of this game by a mixed strategy in which all players are indifferent as to whether to place an additional bid (Augenblick 2011; Platt et al. 2013). However, such a mixed-strategy equilibrium implies that the expected profits for all the bidders and the auctioneer are zero, which is contradictory to our findings.

Bidders in penny auctions certainly differ in terms of experience and earnings, and we hypothesize that bidders' earnings are correlated with their strategic sophistication. A major finding of the behavioral game theory literature is that players in experimental games exhibit heterogeneity in strategic sophistication. Crawford et al. (2013, p. 21), for example, write that "subjects' [strategic] thinking is heterogeneous, so no model that imposes homogeneity will do justice to their behavior." Penny auctions are much more complicated than typical experimental games, so we expect the lab finding of bidder heterogeneity in strategic sophistication to extend to the field setting of penny auctions.

Our proxy for strategic sophistication is based on the idea that a more sophisticated bidder should be less likely to make strategic errors. We say that a bidder commits a strategic error if she plays a strategy that has a lower expected payoff than another strategy.

The strategy space for a player in a penny auction is large, but any strategy must specify (1) the player's action (i.e., placing a bid or not) in each period t, (2) if the action is to place a bid in period t, the timing of placing that bid within the 30-second time clock, and (3) the conditions under which to take the actions.

The timing of placing a bid within the 30-second time clock is important. To see why, consider a stylized example. Suppose there are three players in a penny auction. Let player A follow strategy 1: "Starting from period 0, place a bid at the 30th second of the timer if and only if no other bidder places a bid before then and my total number of bids in the game has not exceeded 100." Let players B and C follow strategy 2: "Starting from period 0, place a bid at the 15th second of the timer if and only if no other bidder places a bid before then and my total number of bids in the game has

[18] If the price increment is zero, the auction price is always zero so that the winner of the auction does not need to pay any additional money to obtain the product (other than her sunk bidding fees).

not exceeded 100." The only difference between these two strategies is the timing of placing bids within the time clock. Yet, player A wins the auction by placing a single bid, because players B and C exhaust their budgets before player A places her first bid! The first strategy allows a player to obtain more information about the strategic environment (i.e., whether any bidder places a bid between the 15th and the 30th second) and avoid placing a bid in a period when competitors plan to bid.

Consider now two general strategies, S_1 and S_2, that are identical to each other except for the timing of placing a bid in a single period t. Strategy S_1 requires a player to place the bid at the 30th second of period t if and only if no other player places a bid before then, while strategy S_2 requires a player to place the bid at the 15th second if and only if no other player places a bid before then. The following proposition holds:

Proposition 2: *Bidder i's expected payoff from playing strategy S_1 is higher than that from playing strategy S_2, under the following assumptions:*

A1: *The time cost of playing in penny auctions is zero.*

A2: *Whether bidder i places a bid at the 15th second or at the 30th second of period t, her competitors' strategies remain the same.*

A3: *If one of bidder i's competitors plans to place a bid between the 15th second and the 30th second of period t, then this bidder plans to bid in period $t+1$ if bidder i places a bid at the 15th second of period t.*

Proof: See Appendix B.

Assumption A1 allows us to ignore the time cost of money in our analysis. Assumption A2 rules out the possibility that a bid at the 15th second has some special strategic value so that it induces less competition than a bid at the 30th second does. Different from a bid at the 15th second, bids in the first few seconds may have the strategic value of inducing less competition (i.e., smaller number of competitors and/or smaller number of bids from existing competitors). Many bidders often place a bid immediately after a competing bid and do so repeatedly for some periods. Such aggressive bids may signal a large budget and intimidate some bidders. Assumption A2 essentially says that middle bids, bids in the middle of the time clock, do not have such a strategic value. To understand assumption A3, consider the following question: Suppose bidder i knows that a competitor, say bidder j, plans to place a bid at the 27th second of period t, should bidder i ignore this information and place a bid at the 15th second of period t? Intuition suggests that the information is valuable and that bidder i should not place a bid at the 15th second. If bidder i places a bid at the 15th second, bidder j saves a bid in period t and is thus in a position to place the saved bid in period $t+1$. Assumption A3 is meant to capture the intuition that competitors who plan to bid in period t but do not need to do so because of a 15th-second bid in the period are especially likely to plan to bid in period $t+1$.

The intuition for this proposition is quite simple. By planning to bid at the 30th second instead of the 15th second, a bidder can observe the valuable information of whether any competitor places a bid between the 15th second and the 30th second. In the above specific example where the timing of placing multiple bids differs in this way, the value of last-second bids magnifies: those players (i.e., bidders B and C) who bid at the 15th second do not even know the existence of the competitor who plans to bid at the last second (i.e., bidder A) until they have exhausted their budgets!

Since the expected payoff from a last-second bid is higher than that of a middle bid, placing a middle bid is a strategic error. We can therefore proxy a bidder's lack of strategic sophistication by her proportion of middle bids. A smaller proportion of middle bids reflects a stronger degree of strategic sophistication. This is equivalent to stating that a larger proportion of aggressive and last-second bids together reflects a higher degree of strategic sophistication. In Appendix C, we further clarify what Proposition implies and what it does not imply and present evidence on the relationship between bidder profit and aggressive (or last-second) bids.

A bidder's proportion of middle bids reflects how the bidder plays the game. In the next section, we show that bidders' earnings are correlated with their proportions of middle bids. In addition, we show that a bidder's proportion of middle bids in her first few auctions can predict her earnings in her subsequent auctions. The proposition that placing middle bids is a strategic error applies to other penny auction websites. We note that Caldara (2012) adopts our measure of stratetic sophistication in his lab experiments and finds that subjects' proportions of middle bids are correlated with their earnings as well. We emphasize that we are not claiming that our measure of strategic sophistication is as good as measures based on bidders' exogenous characteristics such as IQ.

4.2 Empirical Results

In this section, our empirical analysis considers only experienced bidders. We define experienced bidders as those who played in at least 50 auctions. There are 3,746 such experienced bidders in our sample. Our results are not sensitive to the cutoff number of auctions. When measuring an experienced bidder's strategic sophistication, we consider only manual bids that were placed in the middle of the 30-second timer. To see our definition of "the middle", consider Figure 7(a), which shows the histogram of the timing of all manual bids (19.3 million) in our sample, which were placed by experienced as well as inexperienced bidders after the 30-second timer started. The vast majority of these manual bids were placed either at the beginning or at the end of a time period; 68.5% were in the first 5 seconds and 14.8% in the last 5 seconds. We consider manual bids only because bidders do not have control over the timing of those bids placed by the bid agent. Figure 7(b) shows the histogram of the timing of all the bids (2.1 million) placed by the bid agent.

We classify a manual bid to be in the middle of the 30-second time period if it was placed from the 9th second through the 22th second (i.e., it was not placed in the first or last 8 seconds). The results are not sensitive to the selected range for middle bids. We show below that the results are very similar even if we broaden the definition of middle bids to be those from the 6th second through the 25th second.

Figure 7: Histogram of the Timing of Manual or Automatic Bids

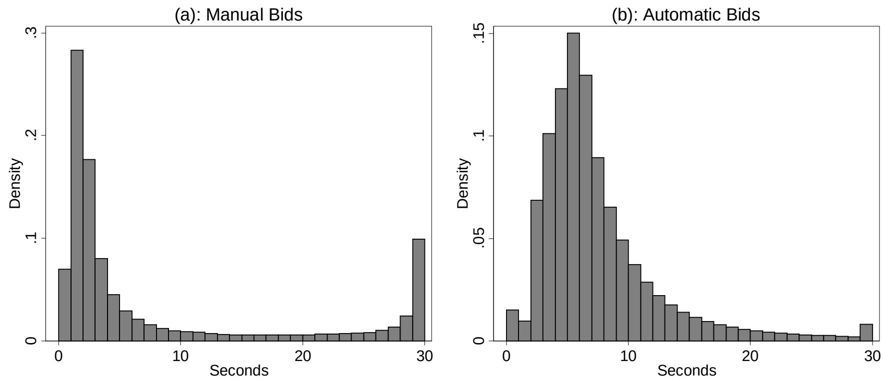
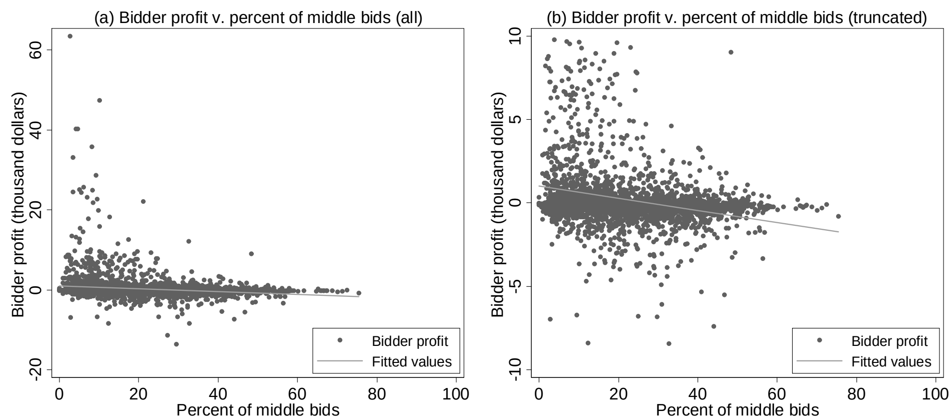


Figure 8: Bidder Profit and Proportion of Middle Bids



Notes: This figure considers only experienced bidders who played in at least 50 auctions. Figure (a) considers all experienced bidders, and figure (b) considers a truncated set of experienced bidders (those whose profits are in the range of [-10,000, 10,000] dollars).

Experienced bidders differ in their degree of strategic sophistication. Figures 8(a) and 8(b) plot bidder profit against percent of middle bids, where both variables are measured over all auctions in which a bidder played. Figure 8(a) considers all experienced bidders, and Figure 8(b) considers a truncated set of experienced bidders, those whose profits are in the range of [10,000, 10,000] dollars. Smaller proportions of middle bids are associated with higher bidder profits. For example, 986 of the 3,746 bidders who played at least 50 auctions placed less than 5% of their bids in the middle, and together they earned a total profit of \$1,149,395. In contrast, 374 of the 3,746 bidders placed more than 20% of their bids in the middle, and together they lost \$120,458.

We use the following model to study how strategic sophistication affects individual bidders' total amount of earnings in subsequent auctions:[19]

$$\pi_i(n > J) = c + \beta_1 Middle_i(n \leq J) + \epsilon_i, \tag{4}$$

where $\pi_i(n > J)$ is bidder i's total earning after her Jth auction, and $Middle_i(n \leq J)$ is bidder i's percentage of middle bids up to her Jth auction. Note that the value of $Middle_i(n \leq J)$ is between 0 and 100, not between 0.01 and 1. Since our focus here is on experienced bidders, we present estimates for those bidders who played in at least 50 auctions. The results are not sensitive to the cutoff number of auctions. We expect coefficient β_1 to be negative.

Table 3 reports the ordinary least square estimates of equation (4). In specifications (1) and (2), the dependent variable is bidder i's earning after her first $J = 10$ auctions, and the independent variable is her percentage of middle bids up to her 10th auction. In specification (1), middle bids are those from the 9th through the 22th second, and in specification (2), middle bids are those from the 6th through the 25th second. The marginal effect of a 1% increase in the percentage of middle bids on bidder earning in subsequent auctions is estimated to be \$-21.96 in specification (1) and \$-14.51 in specification (2). Specifications (3) and (4) repeat specifications (1) and (2), respectively, except that $J = 20$. The estimates remain similar.

Table 3: Impact of Strategic Sophistication on Future Bidder Earning

	Bidder earning after her first 10 auctions		Bidder earning after her first 20 auctions	
	(1)	(2)	(3)	(4)
Percent of middle bids (9-22 seconds) in the first 10 auctions	-21.96***			
	(-6.00)			
Percent of middle bids (6-25 seconds) in the first 10 auctions		-14.51***		
		(-5.49)		
Percent of middle bids (9-22 seconds) in the first 20 auctions			-28.68***	
			(-5.97)	
Percent of middle bids (6-25 seconds) in the first 20 auctions				-19.45***
				(-6.18)
Constant	457.9***	493.8***	541.1***	602.4***
	(6.03)	(5.88)	(6.21)	(6.31)
Number of observations	3,740	3,740	3,746	3,746
R^2	0.008	0.007	0.010	0.011

Notes: The numbers in parentheses are t-statistics based on Huber/White robust standard errors. *** $p < 0.01$.

We use the model below to study how strategic sophistication affects bidder earning per auction over time:

$$\pi_{in} = c + \delta_1 \cdot n_i + \delta_2 \cdot n_i \cdot Middle_i + \varphi_i + \epsilon_{in}, \tag{5}$$

[19] Because individual bidders' total earnings are quite dispersed, we considered the log-modulus transformation of the bidder profit variable. Let x denote the bidder profit variable. Its log-modulus transformation is then $\ln(1+x)$ if $x \geq 0$, and $-\ln(1-x)$ if $x < 0$. The regression results using this transformation remain qualitatively similar (i.e., the percent of middle bids has a negative effect on bidder profit in subsequent auctions).

where the dependent variable π_{in} is bidder i's earning in her nth auction, n_i is bidder i's nth auction (i.e., $n_i = n$ for $i's$ nth auction), $Middle_i$ is bidder i's percentage of middle bids (9-22 seconds) in her first 10 auctions, and φ_i is the bidder fixed effect. The interaction term is meant to capture the idea that a bidder's earning over time depends on her strategic sophistication. We expect the estimated coefficient for δ_2 to be negative.

Table 4 reports the estimated results for equation (5). Specification (1) considers all bidders who played in at least 50 auctions. The estimated marginal earning of playing in one more auction, $0.019 - 0.00054 \cdot Middle_i$, is smaller for bidders whose percentage of middle bids is higher, indicating that bidding earning over time depends on strategic sophistication. Recall that the value of $Middle_i$ is between 0 and 100, not between 0 and 1, so the impact of strategic sophistication on bidder earning over time is economically significant.

One concern with equation (5) is that the estimated effect of playing in one more auction may simply reflect a selection effect. This concern is based on the idea that more sophisticated players self-selected to play in more auctions. Figure 6, however, indicates that bidders with the most profits are not the bidders who played in the largest number of auctions. Nonethess, we consider a few more specifications to show that selection is not driving our results. In specification (2), we restrict the sample to the first 200 auctions of those bidders who played in more than 200 auctions. This specification allows us to estimate those bidders' additional earnings from playing in one more auction in their first 200 auctions, without any selection concerns. The estimates, again, indicate that the marginal earning from an additional auction is smaller for less sophisticated bidders. In specification (3), we consider only sophisticated bidders, those whose percentage of middle bids was no more than 5%. The estimates indicate that these sophisticated bidders earned an average profit of \$2.952 from the beginning and earned more per auction as they played in more auctions. Specification (4) considers only unsophisticated bidders, those whose percentage of middle bids in their first 10 auctions was at least 20%. The results for these unsophisticated bidders are in stark contrast to those for the sophisticated bidders. The estimated marginal effect of playing in one more auction for these unsophisticated bidders is no longer statistically different from 0. The constant term is \$-1.497, implying that these unsophisticated bidders lost money from the beginning and continued to lose money as they played in more auctions.

The small number of experienced bidders who consistently lost money over time may be characterized as gamblers, and to such bidders, penny auctions may be a form of gambling. Such bidders may have risk-loving preferences or they may derive utility from the mere act of playing in penny auctions. On the other hand, the existence of experienced and sophisticated bidders who profit from penny auctions suggest that skills matter in this game, providing a natural explanation for why penny auction websites impose win limits. By setting limits on the number of auctions a bidder can win, a penny auction website makes it easier for less sophisticated players to win so that more bidders may stay on the website for a longer period of time.

How should one interpret the difference in the time trend for bidder earning between sophisticated and unsophisticated bidders? One interpretation is that sophisticated bidders learned to play

Table 4: Effect of Experience and Strategic Sophistication on Bidder Profit per Auction

	All (1)	First 200 Auctions (2)	% of middle bids $\leq$ 5% (3)	% of middle bids $\geq$ 20% (4)
Auction number (n)	0.019***	0.040***	0.018***	0.004
	(3.96)	(3.92)	(2.90)	(1.24)
% of middle bids $\times$ n	-0.00054***	-0.001**		
	(-2.57)	(-2.16)		
Constant	0.337	-0.245	2.952***	-1.497***
	(1.04)	(-0.38)	(4.02)	(-4.29)
Num. of bidders	3,740	520	1,295	699
Num. of obs.	456,397	104,000	165,168	80,453

Notes: Bidder fixed effects are included in all regressions. Specification (2) considers only the first 200 auctions of the bidders who played in more than 200 auctions. The reported constant is the average bidder fixed effect. The numbers in parentheses are t-statistics based on Huber/White robust standard errors. *** $p < 0.01$,** $p < 0.05$

better as they gained more experience, but unsophisticated bidders did not learn to play better over time. Not all players can learn to be a consistent winner of a competitive game. Poker game is a good example. Instead of a learning effect, one may also hypothesize the time trend to be a reputation effect. That is, experienced and sophisticated bidders may gain a positive reputation that helps them win auctions. In this paper, we do not attempt to empirically identify which effect is more important.[20]

5 Conclusion

Our results in this paper suggest that penny auctions cannot sell a dollar for more than a dollar in the long run. We find that BigDeal profited from a revolving door of new bidders but lost money to experienced bidders as a group because of the existence of sophisticated and experienced bidders. There were experienced bidders who lost money, but the number of such bidders was small. Though it is not a puzzle for large customer churn in a new industry, it raises a big concern while a lot of experienced customers earn profits from the seller. Our findings suggest that in auctions with clear feedback, market experience can limit overbidding, implying that market experience can constrain firms' ability to exploit consumer biases. Our findings also suggest that when firms exploit inexperienced players, they may be exposed to the risk of being exploited by some experienced players.

Our findings also suggest that the behavioral game theory concepts of player learning from

[20] We believe the role of reputation is limited in our context. First, BigDeal was characterized by a revolving door of new bidders, and most new bidders are unlikely to know which bidders are experienced and sophisticated. Second, sophisticated bidders presumably are the players who may attempt to learn whether their competitors are sophisticated or not. Since sophisticated bidders can learn their competitors' degree of strategic sophistication from their bidding behavior in the *current* auction, we suspect that few bidders try to recall their competitors' degree of sophistication in the past, especially considering that the number of experienced competitors is large.

experience and player heterogeneity in strategic sophistication are important for understanding penny auctions, a game thought to be a stepchild of game theory and behavioral economics. It is inappropriate to assume all bidders in penny auctions are experienced and fully rational. We expect our main findings to be applicable to other penny auction websites. Caldara (2012) has indeed confirmed that our main findings hold in his lab experiments of penny auctions.

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Appendix A: Computing Bidder Profit from Token Auctions

The computation for bidder profit from a token auction is slightly different from the computation for a non-token auction because of a subtlety with the valuation of a bid token obtained through the BIN option. Consider a token aution. If a bidder wins this auction, her profit can be computed as in equation (1). Since a bid token's price is \$0.75, we presume its value is \$0.75 for any winner of any token auctions. If she loses this auction and the BIN option is not available, then her loss can be computed as in equation (2). If she loses this auction but the BIN option is available, her loss can be computed as in equation (3). However, the value of a bid token is no longer \$0.75 when she is deciding whether to exercise the BIN option, for the following reason. When BigDeal made the BIN option available to token auctions in late November 2010, it imposed a restriction on tokens bought through the BIN option[21]: such tokens have reduced values toward exercising the BIN option in a subsequent auction.[22] The value of a token with this usage restriction should be smaller than \$0.75, but we do not have a way of estimating the reduced value.

Table A1: Distribution of Bidder Profit from All Auctions

	0.05%	0.1%	1%	10%	50%	90%	95%	99%	99.9%	99.99%
Bidder profit (0.9)	-1,798	-1,278	-342	-74	-9.0	-.75	6.25	166	2,499	15,433
Bidder profit (0.8)	-1,860	-1,312	-352	-75	-9.0	-.75	5.96	160	2,471	15,395
Bidder profit (0.7)	-1,974	-1,359	-358	-75	-9.8	-.75	5.59	156	2,448	15,358

Note: The three numbers in parentheses (0.9, 0.8, and 0.7) are the assumed possible discount rates for bid tokens bought through the BIN option.

Fortunately, our overall estimates of bidder profits are not sensitive to how bidders discount tokens bought through the BIN option. This is because the BIN option was available for token auctions for about only 25% of the sample period and the discount rate only affects bidders whose number of bids in a token auction was significant enough to consider exercising the BIN option. Consider three possible reduced values for a BIN-purchased bid token: 0.9×0.75, 0.8×0.75, and 0.7×0.75. Call 0.9, 0.8, and 0.7 the discount rates. Table A1 contains the distribution of bidders' profits from all auctions, with bidders' losses in token auctions computed using these three possible discount rates. The difference between any two of the three 10th percentiles is less than a dollar, and so is the difference between any two of the three 90th percentiles. Only the extreme percentiles noticeably differ; a smaller discount rate, which implies bigger loss upper bounds, leads to a slightly smaller extreme percentile. In addition, the Spearman rank order correlation coefficient is above

[21] Recognize that some usage restrictions have to be imposed on the BIN option for token auctions. Otherwise, since the value of a token purchased through the BIN option is \$0.75, all losing bidders will exercise the BIN option and fully recover the bids they have lost; no bidder ever loses in such auctions. Since the winner of a token auction may obtain a discount, the auctioneer most likely loses money by conducting such token auctions.

[22] Suppose a bidder lost an auction of 100 bid tokens after placing 90 bids. She can exercise the BIN option and obtain 100 bid tokens by paying \$7.50 ($= 75 - 90 \times 0.75$), which is called the BIN price for this bidder. The value of a bid obtained this way toward exercising the BIN option in a subsequent auction is only \$0.075, which equals the bidder's BIN price (\$7.50) divided by the number of bids obtained through the BIN option (100).

0.99 between any pair of the three bidder profits. Since the estimates of bidder profits are not sensitive to the assumed discount rate (0.9, 0.8, or 0.7) for BIN-purchased tokens, we report results assuming 0.8 is the discount rate for such tokens.

Appendix B: Proof of Proposition 2

Proof: Prior to period t, strategies S_1 and S_2, by construction, are identical to each other, so their expected payoffs prior to that period must be the same.

The strategic environment bidder i faces in period t can be either (1) no competitor plans to bid between the 15th second and the 30th second, and (2) at least one competitor plans to bid between the 15th second and the 30th second.

If condition (1) holds, bidder i is indifferent between playing S_1 or S_2. Placing a bid at the 15th second in period t incurs a cost of \$0.75 and moves the game to period $t+1$ in which a new subgame, G_1, starts. Placing a bid at the 30th second in period t also incurs a cost of \$0.75 and moves the game to period $t+1$ in which a new subgame, G_2, starts. These two subgames are strategically equivalent. By assumption A2, bidder i's competitors' strategies in G_1 are the same as their strategies in G_2. By construction, bidder i plays the same strategy in these two subgames. Therefore, bidder i obtains the same expected payoff whether she places the bid at the 15th second or at the 30th second.

If condition (2) holds, bidder i is better off by playing S_1 instead of S_2. If bidder i plays S_1, she does not need to place a bid in period t because one of her competitors, say, bidder j, places a bid before the 30th second. The game then moves to period $t+1$ in which bidder j's competitors, including bidder i, need to respond within 30 seconds. Denote by G_{t+3} the subgame that starts in period $t+1$. Bidder i's payoff from playing S_1 is her expected payoff from playing in subgame G_{t+3}.

If bidder i plays S_2, she forgoes the chance to observe if condition (2) holds and places a bid at the 15th second, assuming no one else places a bid before then. The game then moves to period $t+1$ in which bidder i's competitors need to respond within 30 seconds. By assumption A3, one of bidder i's competitors,[23] say bidder j, submits a bid in period $t+1$. The game then moves to period $t+2$ in which bidder j's competitors, including bidder i, needs to respond within 30 seconds. Denote by G_{t+4} the subgame that starts in period $t+2$. Bidder i's expected payoff from playing S_2 is: - \$0.75 + her expected payoff from playing subgame G_{t+4}.

Subgames G_{t+3} and G_{t+4} are strategically equivalent to each other. By construction, bidder i follows the same strategy when playing in either subgame. By assumption A2, each of bidder i's competitors, when playing G_{t+3}, uses the same strategy as the one she uses when playing G_{t+4}. Then, bidder i's expected payoff from playing G_{t+3} is the same as her expected payoff from playing G_{t+4}. Therefore, bidder i's expected payoff from playing S_1 is \$0.75 higher than her expected payoff from playing S_2.

[23] We are implicitly assuming that the identity of this competitor does not matter.

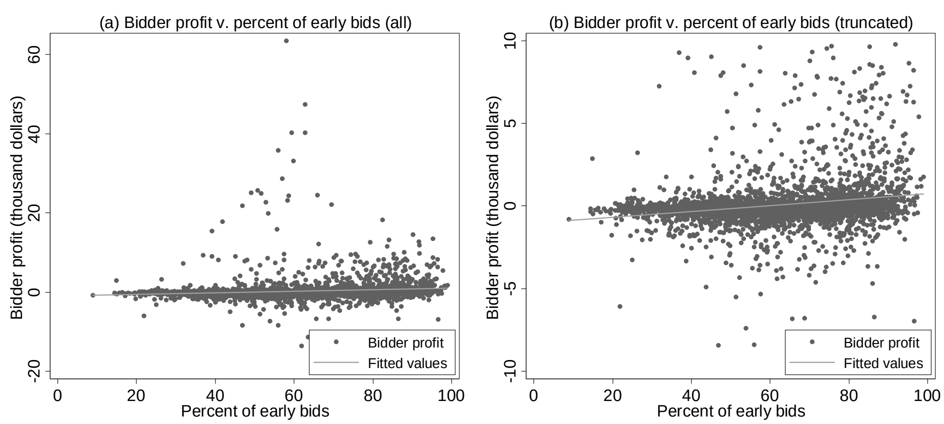
Appendix C: Bidder Profit and Early or Late Bids

Our measure of strategic sophistication is based solely on Proposition 2. In this appendix, we clarify what this proposition implies and what it does not imply. We also present evidence that bidder profit increases with percentage of early bids, which is consistent with our informal argument in the theory section that early bids may have the strategic value of signaling a large budget and intimidating some competitors.

Proposition 2 essentially says that a bidder is more strategically sophisticated if her percentage of middle bids is smaller. Proposition 2 implies that bidder profit increases with the total percentage of late bids and early bids. Proposition 2 does not imply that the simple correlation between late bids and bidder profit should be positive. Larger number of late bids is the same as smaller sum of middle bids and early bids: smaller number of middle bids increases bidder profit, but smaller number of early bids may decrease bidder profit. Proposition 2 does imply that late bids increase bidder profit after controlling for the effect of early bids.

Figures A1(a) and A1(b) plot bidder profit against percentage of early bids, where experienced bidders are those who played in at least 50 auctions and early bids are those placed in the first 5 seconds of the 30-second timer. Figure A1(a) considers all experienced bidders, and Figure A1(b) considers a truncated set of bidders whose profits are in the range of [-10,000, 10,000] dollars.

Figure A1: Bidder Profit and Proportion of Early Bids

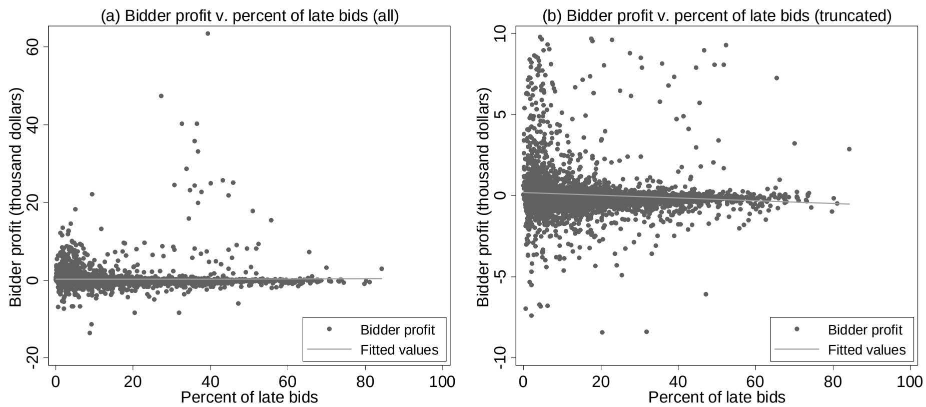


Notes: Here we consider only experienced bidders who played in at least 50 auctions. Figure (a) considers all experienced bidders, and Figure (b) considers a truncated set of experienced bidders, those whose profits are in the range of [-10,000, 10,000] dollars.

Figures A2(a) and A2(b) plot bidder profit against percentage of late bids, where experienced bidders are again those who played in at least 50 auctions and late bids are those placed in the last 5 seconds. Figure A2(a) considers all experienced bidders, and Figure A2(b) considers the truncated set of experienced bidders.

Table A2 presents the OLS estimates of linear regressions in which the dependent variable is

Figure A2: Bidder Profit and Proportion of Late Bids



Notes: Here we consider only experienced bidders who played in at least 50 auctions. Figure (a) considers all experienced bidders, and Figure (b) considers a truncated set of experienced bidders, those whose profits are in the range of [-10,000, 10,000] dollars.

bidder profit and the independent variable is either percentage of early bids or percentage of late bids. Columns (1) and (2) investigate the relationship between early bids and bidder profit, with column (1) considering all experienced bidders and column (2) considering the truncated set of experienced bidders. The estimates indicate that percentage of early bids and bidder profit are positively correlated. This finding is consistent with our informal argument that early bids may have the strategic value of signaling a large budget and intimidating some competitors. Despite this finding, we do not use percentage of early bids as our measure of strategic sophistication for two reasons. First, we do not have a rigorous theory of why early bids tend to increase bidder profit; we only have an informal argument. Second, the most successful bidders at BigDeal did not place the largest percentage of early bids (see Figure A1(a)).

Table A2: Bidder Profit and Percent of Early or Late Bids

	Bidder profit (dollars)				
	(1)	(2)	(3)	(4)	(5)
Percent of early bids (0-5 seconds)	19.14***	18.14***			38.08***
over all auctions	(9.90)	(11.65)			(11.00)
Percent of late bids (26-30 seconds)			2.42	-8.20***	32.29***
over all auctions			(0.67)	(-4.86)	(5.86)
Constant	-933.22***	-1052.55***	173.26***	185.67***	-2658.56***
	(-8.04)	(-12.53)	(3.04)	(4.22)	(-10.16)
Number of observations	3,746	3,714	3,746	3,714	3,746
R-squared	0.0142	0.0470	0.0002	0.0071	0.0305

Notes: Column (1), (3) and (5) consider all experienced bidders who played in at least 50 auctions. Column (2) and (4) consider the truncated set of experienced bidders, those whose profits are in the range of [-10,000, 10,000] dollars. Numbers in parentheses are t-statistics based on robust standard errors, $^{***}p<0.01$.

Columns (3) and (4) investigate the relationship between late bids and bidder profit, with column (3) considering all experienced bidders and column (4) considering the truncated set of experienced bidders. The estimates indicate that bidder profit and percentage of late bids are not correlated when we consider all experienced bidders and are negatively correlated when we consider the truncated sample of experienced bidders. This is consistent with the idea that Proposition 2 does not imply that the simple correlation between late bids and bidder profit should be positive. Column (5) of Table A2 confirms that once the effect of early bids is controlled for, more late bids does tend to increase bidder profit.