Learning and Strategic Sophistication in Games:

The Case of Penny Auctions on the Internet*

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Abstract

The behavioral game theory literature finds subjects' behavior in experimental games often deviates from equilibrium because of limited strategic sophistication or lack of prior experience. This paper highlights the importance of learning and strategic sophistication in a game in the marketplace. We study penny auctions, a new online selling mechanism. We use the complete bid history at a penny auction website to show that bidders' behavior is better understood through the behavioral game theory approach than through equilibrium analyses that presume all players are experienced and fully rational. Our evidence suggests that penny auction is not a sustainable selling mechanism.

Keywords: behavioral game theory, behavioral industrial organization, auction, learning, strategic sophistication

JEL Classification: D03, D44, L81

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1 Introduction

Most studies of strategic interaction focus on Nash equilibrium or its refinements. Players' behavior in many settings, however, may not have converged to equilibrium (Fudenberg and Levine 1998). Indeed, the behavioral game theory literature finds that subjects' behavior in experimental games often deviates from equilibrium because of limited strategic sophistication or lack of prior experience/learning (Camerer 2003; Crawford, Costa-Gomes, and Iriberri 2010). This paper highlights the importance of learning and strategic sophistication in a game in the marketplace. We study *penny* auctions, a new online selling mechanism that combines elements of an all-pay auction with a series of lotteries. We use the complete bid history at a major penny auction website to show that bidders' behavior is better understood through the lens of learning and strategic sophistication than through equilibrium analyses that presume all players are experienced and fully rational. Our evidence suggests that penny auction, though seen as a bias-exploiting scheme, is not a sustainable selling mechanism as the survival of a penny auction website requires continuously attracting new customers who shall lose money, a feature shared by Ponzi schemes and some other disreputable business models.[1]

Penny auctions emerged recently on the Internet, but have quickly developed into a sizable and highly controversial industry. Penny auction has been described by Richard Thaler in the *New York Times* as "devilish" and a "diabolically inventive" adaptation of Martin Shubik's (1971) dollar auction,[2] and by an article in the *Washington Post* as "the evil stepchild of game theory and behavioral economics."[3] The Better Business Bureau (BBB) named penny auctions one of the top 10 scams of 2011.[4] Unlike eBay, penny auction websites sell products themselves, using auction rules similar to the following. First, a bidder must pay a small non-refundable fee (e.g., $0.75) to place a bid.

[1]We are not claiming that penny auctions are a Ponzi scheme or necessarily a scam.

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

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

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

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 by the time 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 ($= 6,497 \times 0.75 + 64.97$)! Examples like this one have led many to characterize penny auctions as a scheme that exploits consumer follies.

How do bidders play this new auction game?[5] Is penny auction a profitable and sustainable selling mechanism? One approach to answering these questions is to build equilibrium models that presume all bidders are experienced and fully rational. The behavioral game theory approach, on the other hand, would emphasize that players in a new game may be inexperienced and may have limited strategic sophistication. Our empirical findings in this paper strongly support the behavioral game theory approach.

Our evidence comes from a nearly ideal bid-level data set collected from a major penny auction website (BigDeal.com). The dataset covers all of the over 22 million bids placed by over 200,000 bidders in over 100,000 auctions for a period of over 20 months, starting from the website's first day of operation to two days before the site's closure. The dataset 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 so that we may estimate any bidder's earning/loss and the auctioneer's profit,

[5] Penny auction is not a standard auction in which the bidder who bids the most wins (Krishna 2002, p. 29). The winner of a penny auction is often not the bidder who places the most bids. Penny auction is clearly very different from eBay auctions. See Bajari and Hortaçsu (2004) for a review of the online auction literature, and Einav et al. (2011) for a recent example. Another nonstandard auction format is the lowest unique bid auction (e.g., Raviv and Virag 2009; Houba et al. 2011) or the lowest unique positive integer game (e.g., Ostling et al. 2011).

which is defined as revenue minus market value.

We find that the auctioneer profits from a revolving door of new bidders but loses money to experienced bidders as a group. The vast majorities of new bidders who join the website 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. This finding reflects the simple logic of individual rationality: no matter how effective penny auction might be in exploiting bidder biases, it offers immediate outcome (win or lose) feedback so that losing bidders can quickly learn to stop participating. A very small percentage of bidders are experienced and strategically sophisticated, but they win most of the auctions and earn substantial profits. Thus, penny auction websites cannot survive without continuously attracting new bidders who shall lose money.

Experienced bidders differ in their degree of strategic sophistication. We measure an experienced bidder's lack of strategic sophistication by the frequency with which she places a bid in the middle of the timer. Bids in the middle of the timer, we shall argue, indicate that a bidder is not mindful of her competition. Proportion of middle bids is predictive of experienced bidders' overall winnings or losses. We also find that whether a bidder learns to play better depends on her strategic sophistication; only sophisticated bidders learn to earn more money per auction as they play in more auctions.

The behavioral game theory literature is based largely on experimental games. See Camerer (2003) for a review of the large literature. Our results provide field evidence that strategic sophistication "is heterogeneous, ..., so that no model that imposes homogeneity, ..., will do full justice to [players'] behavior." Crawford et al. (2010, p. 28). Our findings yield the new insights that two types of learning, learning to play better and learning to quit, may occur in the same game and that whether a player learns to play better may depend on her strategic sophistication. Our paper adds to an emerging literature that uses the behavioral game theory approach to study strategic interactions in field settings. Brown et al. (2012) study the implications of consumers' limited strategic thinking in the movie industry. Goldfarb and Yang (2009) and Goldfarb and Xiao (2011) find managers' strategic sophistication affects firms' performance; both papers measure managers' strategic sophistication by the number of iterations of best response they perform in selecting an action in a static game, as in level-k/cognitive hierarchy models (e.g., Camerer, Ho, and Chong 2004; Costa-Gomes and Crawford, 2006). Since we study a dynamic game, we cannot measure strategic sophistication in the same way. Another price we pay for studying penny auctions is that we cannot identify players' specific models of learning since players' strategy space is large and individual strategies can be highly complicated.

This paper also relates to the emerging 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) and Malmendier and Lee (2011) for empirical applications. Our finding that most new bidders learn to quit quickly suggests that firms' ability to exploit consumer biases is limited by consumer learning. Indeed, refusing to be a repeat customer of bad services is a simple yet fundamental way by which consumer rationality constrains market outcome. See List (2003) for evidence that market experiences may eliminate some forms of market anomalies.

Previous Studies of Penny Auctions Three working papers (Augenblick 2009, Platt et al. 2010, and Hinnossar 2010) and one published paper (Byers et al. 2010) have recently studied penny auctions. None of the studies take a behavioral game theory approach. Most of the studies focus on the subgame perfect Nash equilibria of a dynamic model that presumes all bidders are experienced and fully rational. In the baseline equilibrium, bidders earn zero expected profit if two bidders or more are competing in an auction. The intuition is that if bidders are fully informed and rational, they will not participate if their expected profit is negative. Our findings are highly inconsistent with the zero-profit prediction or the assumptions that all bidders are experienced and fully rational. Our results are also inconsistent with the implication that the number of bidders does not affect auction profit. We find that a larger number of (potential) bidders increases auction profit.

The previous studies recognize that the zero-profit prediction is inconsistent with the fact that *Swoopo*, the pioneer of penny auctions, made excessive profits. To reconcile, Augenblick (2009) invokes the sunk cost fallacy and extremely slow learning. Augenblick does not consider the concept of strategic sophistication or estimate individual bidders' winnings or losses. His bid-level data set from Swoopo, which covers a period of about 4 months, does not allow for identifying precisely when a bidder joins or exits Swoopo. Platt et al. (2010) attribute auctioneer profits to bidders' risk-loving preference. They analyze auction-level data and do not observe individual players' bidding behavior. Byers et al. (2010) focus on proposing alternative explanations for why Swoopo made exessive profits. A key idea in their paper is that if some bidders underestimate the number of competitors in an auction, they will overbid, and as a result, the auctioneer can obtain excessive profits. Byers et al. use bid-level data to motivate their analyses, but they do not conduct any empirical testing. We find BigDeal also made a positive profit, but the main source of its profit is a revolving door of new bidders. Only a very small percentage of bidders may be characterized as gamblers in that they continue to play after losing many auctions. Sunk cost fallacy and risk-loving preference imply that penny auctions are a sustainable selling mechanism, yet Swoopo, BigDeal, and many other penny auction websites were closed already.Our results are consistent with the idea that many new bidders may have underestimated the difficulty of winning penny auctions.

Section 2 of the paper describes the penny auction industry, the website, and the data. Section 3 reviews the equilibrium model of penny auctions and discusses the implications of learning, strategic sophistication, and number of bidders. Section 4 presents our results. Section 5 concludes.

2 Background, Auction Rules, and Data

2.1 The Penny Auction Industry

Penny auctions, also known as *pay-to-bid* or *bidding fee* auctions, are a new selling mechanism. Swoopo, founded in Germany in 2005, 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 have since declined sharply. Table 1 lists the 11 websites whose traffic was ranked in the top 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, and the other 4 sites also experienced dramatic traffic decline in 2011. Most penny auction websites attract little traffic and do not last for long.

Table 1: Monthly Traffic on Largest Penny Auction Websites

Website	Number of unique visitors					BBB
	Feb 2010	Nov 2010	Apr 2011	Oct 2011	BIN	Rating
BigDeal.com	480,230	1,324,947	943,327	Closed	Yes	A-
Bidcactus.com	1,428,316	3,411,705	1,979,846	740,981	No	A-
Beezid.com	1,110,859	755,917	549,908	432,352	No	N/A
Bidsauce.com	356,811	690,014	344,514	9,052	No	F
Swoopo.com	286,142	171,141	Closed	Closed	Yes	F
Quibids.com	173,142	4,541,783	4,586,523	2,638,490	Yes	A-
Bidrivals	63,329	419,945	490,751	144,468	Yes	C-
Wavee.com	26,863	1,696,803	62,214	Closed	Yes	F
Bidhere.com	17,359	542,079	750,175	3,731	Yes	N/A
Zbiddy.com	0	0	945,149	1,772,935	No	C-
Biggerbidder.net	0	0	120,078	664,636	No	N/A
Total # 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: We obtained the traffic data from compete.com, the Buy-It-Now information from each individual penny auction website, and the BBB rating from BBB's website. The BBB rating is as of September 11, 2011. Swoopo did not have a Buy-It-Now option until mid 2009. 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.

Penny auctions are highly controversial. The Better Business Bureau

(BBB) has received many consumer complaints against penny auction websites.[6] As mentioned in the introduction, BBB named penny auctions one of the top 10 scams of 2011 even though BBB stated that not all penny auction websites are scams. Three sites in Table 1 have an F rating, the worst BBB rating. Lawsuits have been filed against various penny auction websites, claiming penny auctions as 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 key words on search sites is the primary way the auction sites advertise products for sale."[7]

2.2 BigDeal and Auction Rules

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] It posted on its website photos and biographies of its management team and board members. BigDeal has a BBB rating of A-. Perhaps to mitigate potential concerns of shill bidding, BigDeal displayed the bid history of all live and past auctions on its website. Bidders can easily see the bid history of live and recently finished auctions, but it is time consuming to see the bid history of auctions finished more than a few days ago.[9]

The rules of BigDeal auctions are the same as those described in the introduction. Prior to bidding in any auction, bidders must buy packs of bid-tokens. Each token costs $0.75, and each bid costs a single non-refundable

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

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

[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 contains the general information and bid history of the auction. By clicking link buttons on the homepage or the "winner page" of BigDeal, one can have access to such web pages. It requires increasingly larger number of clicks to access web pages of auctions finished earlier.

token. BigDeal typically releases an auction with an initial countdown clock that lasts for 36 hours. If a bid was placed after less than 30 seconds were left on the initial countdown clock, the clock would be reset to be, without exception, 30 seconds. The price increment is 1 cent in most auctions, but is \$0.05 or \$0.15 in a considerable number of auctions in the early part of our sample. A bidder wins if her bid is not followed by another bid when the 30-second timer expires. In addition to her bidding cost, the winner also pays the auction price to attain the product.

BigDeal always posts a retail price for a product to be auctioned. Like most other penny auction websites, BigDeal offers losing bidders a *Buy-It-Now (BIN)* option in auctions for all products except for bid packs and iPads. This BIN option works differently from the Buy-It-Now option 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 exactly 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. That is, a losing bidder can obtain a product after spending an amount of money that is exactly equal to the posted retail price for the product. For example, the posted retail price for an iPad auction with the BIN option in our dataset 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 only needs to pay \$99.74 $(= 899.99 - 800.25)$ more to exercise the BIN option and obtain an iPad. With the BIN option, this bidder pays the posted retail price of \$899.99 for an iPad. Without the BIN option, this bidder would have paid \$800.25 for nothing.

An individual bidder at BigDeal is restricted to at most 10 wins during a 30-day period. Once a bidder reaches the win limit, she is prohibited from bidding in any auction until the 30-day period expires. Nine of the 11 penny auction websites in Table 1 impose win limits.

BigDeal offered bidders a bid agent (called BidBuddy) that places bids automatically on their behalf. The bid agent does not bid strategically. A bidder can 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 can also deactivate a bid agent at any time.

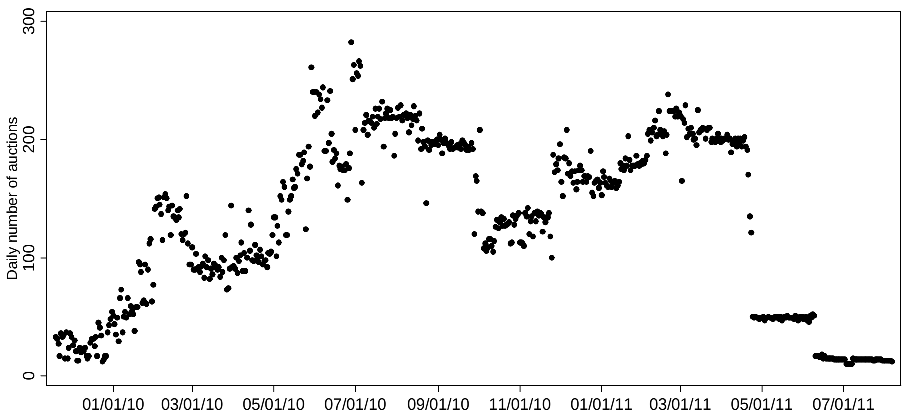
BigDeal auctioned several categories of products, including packs of bid tokens, video games and consoles, apple products, non-apple electronics such as computer, TV, phone, camera, and GPS, house wares, gift cards, handbags, jewelry, and movies.

2.3 Data

Our dataset, 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 is available. We do not observe which losing bidder(s) exercised the BIN option. The BIN option was not available for bid pack auctions until late November 2010, and it was not available for iPad auctions for some periods "due to inventory restrictions." Another auction-level variable is whether an auction is a beginner auction that only accepts bids from new members. Most beginner auctions feature 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. The daily number of auctions declined dramatically in late April 2011, signaling that BigDeal was preparing to shut itself down. Since the operation of BigDeal was no longer normal since then, we do not consider the auctions ended on or after May 1, 2011. For the sample period that we consider, BigDeal offered a total of 110,642 auctions. Among these auctions, 78,573 are regular auctions, all of which attracted at least one bidder. Among the 32,069 beginner auctions, 3,423 failed without attracting a single bidder. A total of 207,085 bidders placed at least one bid during our

Figure1: Daily Number of Non-beginner Auctions



sample period, and together they placed a total of 22,598,266 bids.

2.4 Bidder with Most Bids Often Does Not Win

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 strictly smaller than that of at least one losing bidder in 40.9% of the 77,944 regular auctions with two bidders or more, and is equal to the maximum number of bids by any losing bidder in 12.9% of the auctions. Hence, the winner has the (strictly) largest number of bids in less than half of the regular auctions. In fact, in 3,302 auctions, the total number of bids placed by the last bidder is less than 10% of that by another bidder. 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 have already been placed in the auction.

3 Theoretical Considerations

This section reviews the basic equilibrium model of penny auctions and discusses the implications of strategic sophistication, learning, and number of bidders.

A penny auction can be characterized as follows. Suppose an item being auctioned is of value v to all potential bidders. The initial auction price of the item is $p = 0$. Whenever a player places a bid, she pays a cost of c immediately, and the auction price is increased by k. Each time period t is set to last s seconds ex ante, but whenever a bid is placed within this period, this period ends immediately and a new period $t+1$ starts. Hence, the length of a time period ex post could range from 0 to s. A bidder needs to decide whether to bid in a period and, if so, when to place her bid. A bidder wins if her bid is not followed by another bid within s seconds.

The basic equilibrium model of penny auctions makes three critical assumptions (e.g., Augenblick 2009 and Platt et al. 2010). First, it assumes all bidders are homogeneous and fully rational so that they all bid optimally. Second, the model ignores the timing of placing a bid within a time period. It assumes all potential bids within a period are placed simultaneously and if two players or more decide to bid in a period, one player's bid is randomly accepted and only this bidder incurs a bid cost.[10] Third, it assumes that the number of players in an auction, M, is fixed and known to all. After presenting the subgame perfect equilibrium, we argue that these three assumptions need to be relaxed to understand bidders' behavior.

A bidder who makes a bid in period t is betting c that no player will bid in period $t+1$. Assume $T = (v-c)/k$ is an integer so that the auction price in period T is $v - c$. The game can then be solved by backward induction. No player bids in any period $t > T$ since the auction price plus bid cost exceed the value of the product. In period T, a bidder is indifferent between bidding and not bidding. If she bids, she pays $v - c + c$ to win a product of value v. In periods $t \leq T$, all bidders are assumed to play mixed strategies, and the indifference condition that characterizes the subgame perfect equilibrium is given by

$$(v - tk)\mu_{t+1} = c, \tag{1}$$

[10] Hinnosaar (2010) makes the alternative assumption that simultaneous bidders all incur a bid cost.

where μ_{t+1} is the probability that no one will bid in period $t+1$. In equilibrium, a bidder's expected value of placing a bid equals the cost of a bid. In order for equation (1) to hold in period t, each of the other $M-1$ symmetric players must bid in period $t+1$ with probability τ_{t+1} such that the following equation holds:

$$(1-\tau_{t+1})^{M-1} = \mu^*_{t+1} = (v-tk)/c. \quad (2)$$

That is, bidders adjust their probabilities of placing a bid by solving equation (2). Hence, the number of players in an auction affects an individual player's probability of bidding, τ_{t+1}, yet has no impact on μ^*_{t+1}, which characterizes the equilibrium. If there are at least two bids, the expected revenue for the auctioneer is v since all bidders' expected gain is zero in equilibrium.

Strategic Sophistication. A major finding of the behavioral game theory literature is that subjects in experimental games exhibit heterogeneity in strategic sophistication. We expect this lab finding to extend to the field setting of penny auctions, a competitive game that admits a variety of dynamic strategies. The fact that most penny auction websites impose win limits suggests that some bidders play better than others. Indeed, we find that some BigDeal bidders win many auctions and earn tens of thousands of dollars while others lose thousands of dollars. In this paper, we attempt to link (experienced) bidders' winnings/losses with their strategic sophistication. We measure a bidder's lack of strategic sophistication by the frequency she plays an inferior action: placing a bid in the middle of the time clock. This measure is based on the following observation.

Under reasonable assumptions, placing a bid in the middle of a time period is inferior to placing the bid at the end of the same period.

To emphasize, this observation compares middle of the clock bids (simply middle bids) with last-second bids. This observation does not refer to bids placed at the beginning of a time period. Many bidders often place a bid immediately after a competing bid and do so repeatedly for some periods. However, aggressive bids, by themselves, do not indicate whether a player is sophisticated or not. The effectiveness of aggressive bids depends critically on the competitive environment in which they are used. Imagine a set of time periods during an auction when a large number of sophisticated bidders are actively competing with bidder A, and a second set of time periods during the same auction when only a small number of unsophisticated bidders are competing with bidder A. Aggressive bids by bidder A are, presumably, less likely to be effective during the first set of time periods than during the second set of periods. In any case, our evidence suggests that the frequency with which a player bids aggressively is not positively related to her performance (in terms of profit or loss).

We offer two justifications for why middle bids are inferior to last second bids.[11] To understand our justifications, it is useful to first consider the concept of strategic sophistication. According to Crawford (1997, p. 209), "Strategic sophistication refers to the extent to which a player's beliefs and behavior reflect his analysis of the environment as a game rather than a decision problem, taking other players' incentives and the structure into account. ... it is a multi-dimensional concept, which must be adapted to specific settings ..." To bid strategically in penny auctions, a bidder must analyze the bidding environment and take into account competitors' bidding behavior. The number of potential competitors in a penny auction is unknown, and bidders may employ a variety of strategies. A sophisticated bidder should not simply bid randomly with a fixed probability. Instead, she must constantly learn who are competing with her and what strategies her competitors are using so that she may respond optimally. Last-second bids allow a bidder to gain maximum information about her competitors. Let the ex ante length of a time period be 30 seconds and assume network connection is perfect. If a player bids at the $15th$ second of period t, she loses the chance to observe if any bidder may place a bid between the $15th$ second and the $30th$ second and if multiple players may bid simultaneously at the $30th$ second of the same period. Suppose, on the

[11] We are not claiming that a middle bid is worse than a last-second bid no matter what strategies competitors might use. For example, a middle bid is justified if her competitors use the following strategy: "bid forever if someone places a last-second bid, but never bid again if someone places a middle bid." Sophisticated players recognize that few, if any, players follow such strategies and act accordingly.

other hand, she waits for the last second to bid in period t. If someone else bids before then, she can always plan to bid at the last second of period $t+1$. If someone bids before the end of the new period, she can plan to bid at the end of period $t+2$, and so on. By bidding this way, she saves bids, keeps the auction alive, and obtains more information about who are competing with her and what strategies her competitors are using. (We are not claiming that a sophisticated bidder should always bid this way. It may be optimal for a bidder to bid aggressively (i.e., place a bid immediately after a competing bid) for some periods when she thinks that she is competing with a small number of bidders who are not sophisticated.) A large number of middle bids thus suggest that a player is not mindful of her competition, indicating a lack of strategic sophistication.

To see our second justification, suppose some players are more sophisticated than others and the sophisticated ones realize this is the case. Sophisticated bidders then presumably know that they are more likely to win an auction that they chose to participate and that their value of participating in the auction is positive. Then, these sophisticated bidders' option value of keeping the auction alive is positive for at least some periods.[12] If so, a sophisticated bidder has the incentive to bid at the last second: she wants to keep the auction alive, but she does not want to be the one to place a bid. A large number of middle bids, again, indicate a lack of strategic sophistication.

Learning. After playing in at least one auction, a bidder needs to make three decisions. First, she needs to decide whether to participate in another auction. If yes, she needs to decide which auction to participate and how to bid in the chosen auction. It is much easier to learn to make a rational choice with regard to the first decision than the latter two. According to Tversky and Kahneman (1986, p. S274), effective learning "requires accurate and immediate feedback about the relation between the situational conditions and the appropriate response." The first decision is simple; it is a binary choice and bidders are given accurate and immediate feedback on their gains or losses in the auctions in which they have played. The latter two decisions are much

[12] In the equilibrium model, the option value of keeping an auction alive is always zero.

more complicated in that they involve strategic thinking, and bidders are not given any direct feedback on how to play better. Some bidders may learn to play better, but others may lack the strategic ability to do so. Not everyone can learn to play chess or poker at a high level. The principle of individual rationality is then expected to hold for all bidders with regard to the first decision, but not necessarily with regard to the latter two decisions.

Suppose bidders are risk-neutral or risk-averse. Under this assumption, bidders leave the website permanently if they consistently lose. Sustained excessive profits can only come from inexperienced bidders who have not learned the consequences of playing in penny auctions. That is, for an auctioneer to sustain excessive profits for an extended period of time there must be new and inexperienced bidders who are joining the website while the old bidders are leaving. Suppose some bidders' preferences are similar to those of lottery players (Platt et al. 2010).[13] Under this assumption, an auctioneer can obtain excessive profits from experienced bidders who continue to play even if they have a negative expected gain. Chance plays an important role in determining the outcome of penny auctions. It is also possible that some bidders may derive intrinsic utility from the mere act of bidding in penny auctions.

Number of Bidders. The equilibrium model predicts that two bidders are enough to ensure that the expected revenue of a penny auction is the value of the product. Each bidder is assumed to perfectly adjust her probability of placing a bid according to the number of bidders. This prediction may not hold for two possible reasons. First, penny auctions permit continuous entry, so the true number of bidders in an auction is unknown. Bidders may underestimate the true number of bidders, which leads to overbidding (Byers et al. 2010). Second, when the number of potential bidders is large, it may be more difficult for bidders to adjust their number of bids downward even if they know the true number of competitors. The experimental literature on auctions finds

[13] Penny auction bidders 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 has a retail price over $3,000. However, Golec and Tamarkin (1998) present evidence that horse track bettors seek skewness in return, not risk.

that experienced subjects in experiments of first-price or second-price common value auctions suffer from the winner's curse when the number of bidders is large, but not when it is small (e.g., Kagel and Levin 1986, Kagel, Levin, and Harstad 1995). The literature also finds inexperienced subjects overbid more in experiments of all-pay auctions when the number of bidders is larger (e.g., Gneezy and Smorodinsky 2006). This inability to adjust bids downward may be exacerbated if the true number of bidders is unknown, as in penny auctions.

Buy-It-Now Option. The BIN option complicates any attempt to build equilibrium models of penny auctions that presume all bidders are fully informed and rational.[14] However, the BIN option does not affect our arguments on strategic sophistication and learning. Here we present two useful observations about 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.

If the BIN option is available, then (a) The inequality, $bc \leq r$, must hold; (b) Bidder i exercises the option if and only if $bc \geq r - v$.

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. Subsection 4.6 presents evidence to support this observation. Part (b) of this observation says that bidder i exercises the BIN option if and only if her cost of bids, bc, is no less than $r - v$, the difference between the posted retail price and bidder $i's$ valuation of the product. We invoke part (b) to estimate which bidders exercise the BIN option.

[14] We introduce the BIN option into the basic equilibrium model in an online appendix (available at http://www.economics.neu.edu/zwang/). The main insights from this equilibrium analysis are that the game with the BIN option differs greatly between the case of 2 players and the case of 3 players. The latter case is much more complicated.

4 Results

4.1 A Revolving Door of New Bidders

In this subsection, we present compelling evidence that BigDeal is characterized by a revolving door of new bidders. The vast majorities of new bidders who join BigDeal on a given day play in only a few auctions, place a small number of bids, and then permanently leave the site within a week or so without winning any regular or non-beginner auctions. (Recall that beginner auctions are only open to new members.) A very small percent of bidders are persistent participants, but they win most of the regular auctions.

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	319	364	430

Table 2 shows the distribution of three measures of bidder participation: the number of auctions a bidder participated, the number of bids submitted, and the duration of a bidder. We define the duration of a bidder by 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 are fleeting participants. The $75th$ percentile of the number of auctions participated is 8, the $75th$ percentile of the number of bids is 55, and the $75th$ percentile of bidders' duration is only 4 days. A small percent of bidders are persistent participants. Only 5.2% of the bidders played in 25 auctions or more, 5.1% of the bidders placed 300 bids or more, and 10.1% of the bidders lasted 29 days or more.

It is illuminating to consider the dynamics of bidder participation over time. Figure 2(a) shows the weekly sum of each day's new bidders at BigDeal. Figure 2(b) shows the weekly average of the daily percent of new bidders whose duration will be no more than 7, 14, or 28 days. Figure 2(c) shows the weekly average of the daily percent of new bidders whose total number of auctions will be no more than 7, 14, or 28. The finding that most bidders are fleeting participants holds true for essentially all weeks. Note that bidders who joined BigDeal toward the end of our sample naturally have lower participation intensity. Figure 2(d) shows the weekly average of the daily percent of bidders who have appeared on the website for less than 7, 14 or 28 days. Most bidders on a given day are relatively new to the website. Note that the weekly averages here are all weighted by the number of bidders in each week day.

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

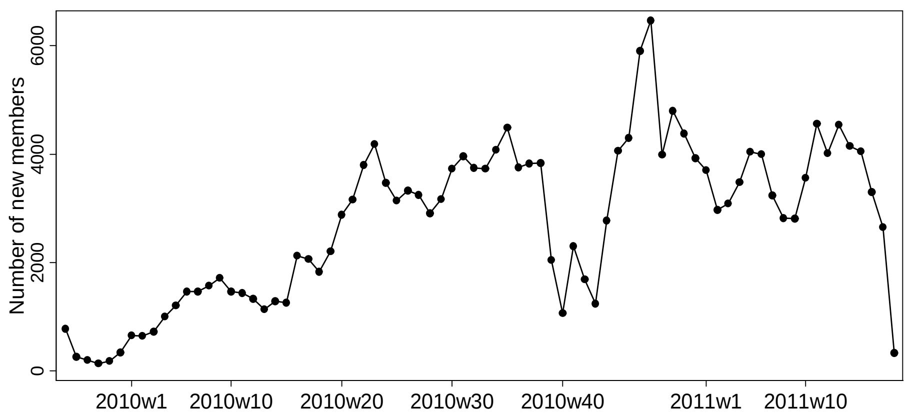


Figure 2(b): Weekly Average of Daily Percent of New Bidders Whose Duration is No More Than 7, 14, or 28 Days

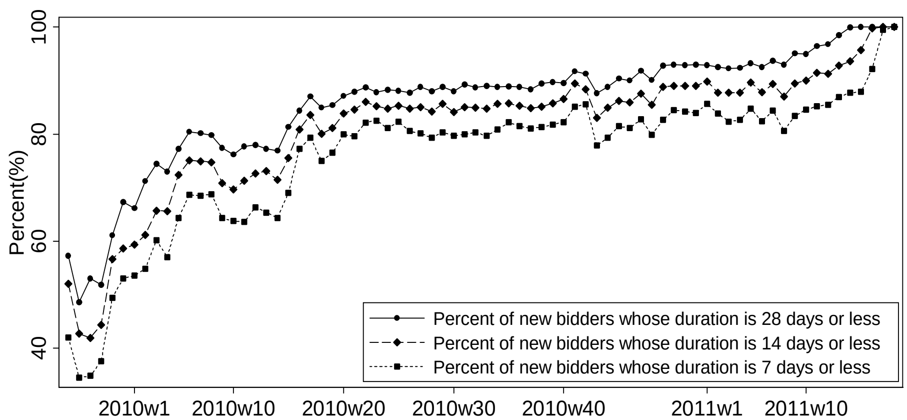


Figure 2(c): Weekly Average of Daily Percent of New Bidders Who Bids in No More Than 7, 14, or 28 Auctions

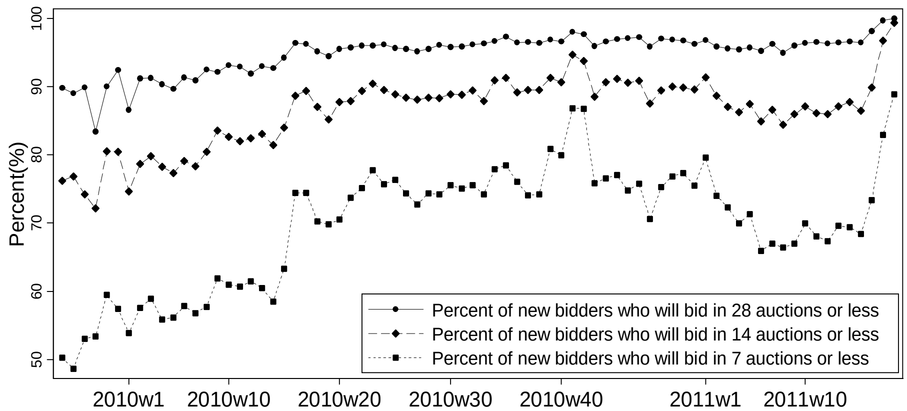
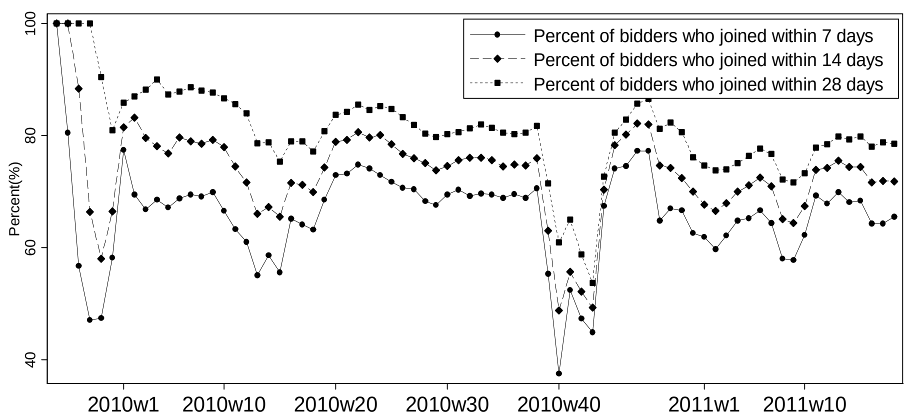


Figure 2(d): Weekly Average of Daily Percent of Bidders Who Joined the Site No More Than 7, 14, or 28 Days Ago



To facilitate exposition, we classify bidders into three mutually exclusive groups: persistent, fleeting, or moderate bidders. Whether a bidder is fleeting or persistent is inherently a matter of degree. We shall use the following working definition. A bidder is persistent if her total number of auctions is at least 50. A bidder is fleeting if her total number of auctions is at most 15. Moderate bidders are those in between, neither persistent nor fleeting. Panel A of Table 3 presents summary statistics of the three groups of bidders.

By our definition, 89.2% of the bidders are fleeting, and only 1.8% persistent. However, the persistent bidders won 64.4% of the regular or non-beginner auctions. Note that 96% of the fleeting bidders and 61% of the moderate bidders never won a regular auction, and only 10.2% of the persistent bidders never won a regular auction. Subsection 4.2 shows that 94% of the fleeting bidders lost money (after considering the effect of beginner auctions).

Table 3: Descriptive Statistics of Three Groups of Bidders

	Fleeting	Moderate	Persistent	All bidders
Panel A:				
Number of bidders	184,702	18,637	3,746	207,085
(% of all bidders)	(89.2)	(9.0)	(1.8)	(100)
Number of bids	7,132,452	4,903,658	10,562,156	22,598,266
(% of all bids)	(31.6)	(21.7)	(46.7)	(100)
Number of regular auction wins	9,173	18,791	50,609	78,573
(% of all regular auction wins)	(11.7)	(23.9)	(64.4)	(100)
% of bidders who never won a regular auction	96.1	60.8	10.2	91.3
Panel B:				
Bidder profit in token auctions (0.9)	-473,993	-378,946	-384,452	-1,237,391
Bidder profit in token auctions (0.8)	-540,168	-445,903	-494,364	-1,480,435
Bidder profit in token auctions (0.7)	-575,063	-485,712	-570,833	-1,631,608
Bidder profit in all auctions (0.9)	-3,495,909	-1,175,018	924,342	-3,746,585
Bidder profit in all auctions (0.8)	-3,562,085	-1,241,976	814,430	-3,989,631
Bidder profit in all auctions (0.7)	-3,596,980	-1,281,784	737,961	-4,140,803
% of bidders who lost money (0.9)	94.3	86.1	66.7	93.0
% of bidders who lost money (0.8)	94.4	86.6	67.9	93.3
% of bidders who lost money (0.7)	94.5	86.9	68.8	93.4

Notes: Regular auctions refer to non-beginner auctions. 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. See subsection 4.2 for explanations.

Why do most new bidders lose money and quit quickly? Our interpretation is that these bidders did not know the consequence of playing in penny auctions before playing. 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 items easily and cheaply. If so, such bidders quickly realized that it is actually difficult to win penny auctions.

4.2 Bidder or Auctioneer Profit

In this subsection, we estimate the auctioneer's profit and each bidder's profit or loss. Our results show that BigDeal made considerable profit from the fleeting and moderate bidders, but lost money to the persistent bidders. The persistent bidders differ greatly in their performance; while most persistent bidders lost money, a small percent of persistent bidders made significant amount of positive profits. These findings indicate that the main source of auctioneer profit is inexperienced bidders and that the experienced bidders are not homogenous.

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 if 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 revenue. We are not concerned with the auctioneer's profit over its cost, which we do not observe. 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 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.[15] We find

[15] 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. The vast majorities of these matched products were sold by multiple sellers on Amazon, often at different prices. We

61.7% of the non-token BigDeal auctions involve products sold at Amazon.[16] For these auctions, the Amazon prices are, on average, 78.0% of the retail prices posted by BigDeal. In 97.6% of these auctions, the Amazon price is smaller than the BigDeal retail price. We assume the value of a non-token product that does not have a matched Amazon product is 78% of the retail price posted by BigDeal. We will discuss the value of bid tokens below.

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. It is a bit involved to calculate her loss in an auction that she did not win because of the need to estimate if she exercised the BIN option. We demonstrate here how to compute her profit in her first three auctions. Assume her first two auctions are for non-token products and the third auction is for bid tokens. Her profits for the other $N - 3$ auctions can be similarly computed.

Suppose she won her first auction. Suppose the posted retail price for the product in her 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, bidder $i's$ profit from winning her first auction is

$$\pi_{i1} = v_1 - p_1 - 0.75 b_{i1}. \tag{3}$$

Note that the cost of a bid is always \$0.75. 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.

Suppose bidder i lost her second auction after placing b_{i2} bids, the posted retail price for the product in this auction is r_2, and the value of this product is

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.

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

v_2. Bidder $i's$ loss from her second auction 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

$$\pi_{i2} = -0.75 b_{i2}. \tag{4}$$

If the BIN option is available, bidder i exercises the option if her cost of bids exceeds $r_2 - v_2$, the difference between the posted retail price and the valuation of the product. In this case, bidder $i's$ profit in her second auction is

$$\pi_{i2} = \begin{cases} -0.75 b_{i2} & if \quad 0.75 b_{i2} \leq r_2 - v_2 \\ -(r_2 - v_2) & if \quad 0.75 b_{i2} > r_2 - v_2 \end{cases}. \tag{5}$$

If bidder $i's$ cost of bids is smaller than $r_2 - v_2$, she does not exercise the BIN option so her loss is simply the cost of her bids. If her cost of bids exceeds $r_2 - v_2$, she exercises the BIN option so her loss is $r_2 - v_2$. In other words, she pays the posted retail price $r_2 = 0.75 b_{i2} + (r_2 - 0.75 b_{i2})$ for a product of value v_2. Equation (5) assumes implicitly that $r_2 > v_2$. In the rare event that $r_2 < v_2$, bidder i exercises the BIN option after losing and obtains a positive profit, $\pi_{i2} = v_2 - r_2 > 0$.

Consider bidder $i's$ third auction, which features bid tokens. If she wins this auction, her profit can be computed as in equation (3). 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 (4). If she loses this auction but the BIN option is available, her loss can be computed as in equation (5). 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 upon tokens bought through the BIN option:[17] such tokens have reduced values toward

[17] 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

exercising the BIN option in a subsequent auction.[18] 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.

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 only available for token auctions during 25% of the sample period and the discount rate only affects bidders whose number of bids in a token auction is 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 4 contains the distribution of bidder profits from all auctions, with bidders' losses in token auctions computed using the three possible discount rates. The difference between any two of the three $10th$ percentiles is less than a dollar, 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 0.99 between any pair of the three bidder profits.

Table 4: 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.

We use the relationship between bidder profit and bidder group to further illustrate that our results are not sensitive to the assumed discount rate

discount, the auctioneer most likely loses money by conducting such token auctions.

[18] 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 \$7.5 ($= 75 - 90 \times 0.75$), 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 (\$7.5) divided by the number of bids obtained through the BIN option (100).

for tokens purchased through the BIN option. Consider panel B of Table 3, which contains, by bidder group, bidder profits from token auctions only, bidder profits from all auctions, and proportion of bidders who lost money when considering all auctions. These three statistics are not sensitive to the assumed discount rate for BIN-purchased tokens. Hence, we shall report results assuming 0.8 is the discount rate for such tokens.

The fleeting bidders together lost \$3.56 million in all auctions, the moderate bidders lost \$1.24 million, but the persistent bidders as a group earned \$0.81 million in all auctions. The proportion of bidders who lost money is 94.4%, 86.6%, and 67.9% for the fleeting, the moderate, and the persistent bidders, respectively. BigDeal generated a total profit of \$3.99 million, 15.1% of the total value of the products it auctioned or sold through the BIN option. The total value of the auctioned products (\$9.9 million) is smaller than the total value of the products sold through the BIN option (\$16.6 million).

Figure 3(a) shows the auctioneer's weekly profit. The profit is small in the first few weeks since the number of auctions is small. Figure 3(b) shows the weekly average of the percent of profit each day generated from three groups of bidders: those who have appeared on the website for 7 days or less, those between 7 and 28 days, and those 29 days or more. The vast majority of the auctioneer's profit in almost all weeks comes from those who joined the website less than 7 days ago, and the auctioneer lost money in most weeks to those bidders who have stayed on the website for over 4 weeks.

We note that some of the persistent bidders lost considerable amount of money while others earned considerable amount; 90 lost over \$2,000 while 225 earned over \$2,000; 2 lost over \$10,000 while 30 bidders earned over \$10,000. What causes the significant difference in bidders' performance? We turn to this question in the following subsection.

4.3 Strategic Sophistication and Bidder Profit

In this subsection, we present evidence that (1) persistent bidders differ in their proportion of middle bids, our measure of strategic sophistication; and

Figure 3(a): The Auctioneer's Weekly Profit

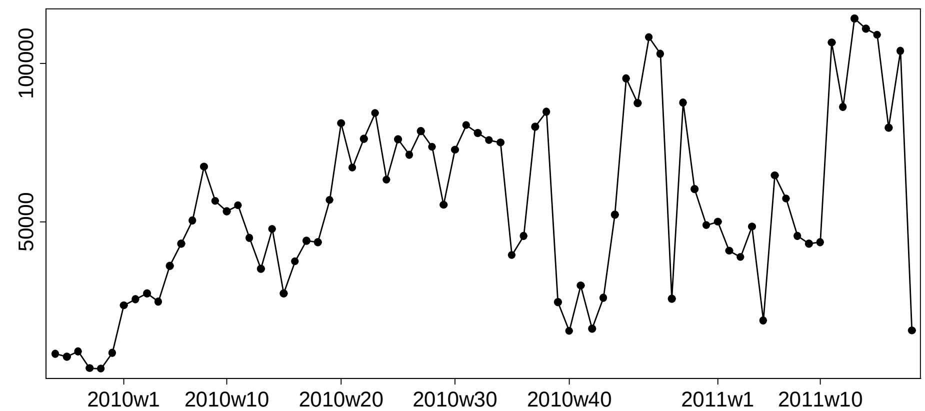
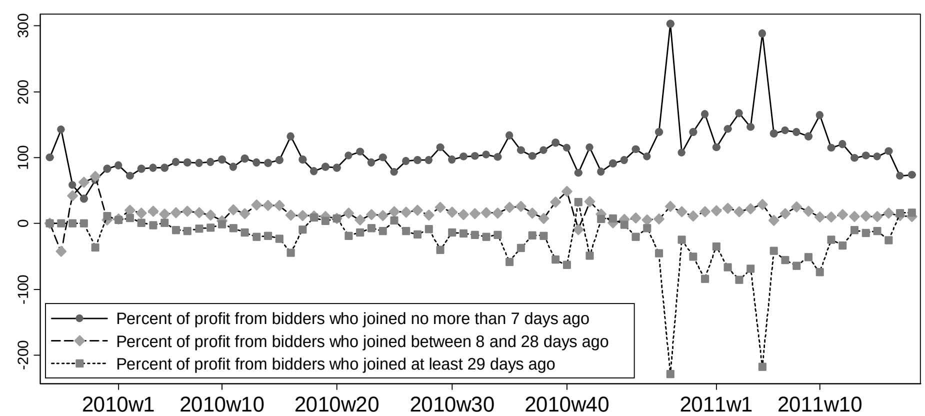


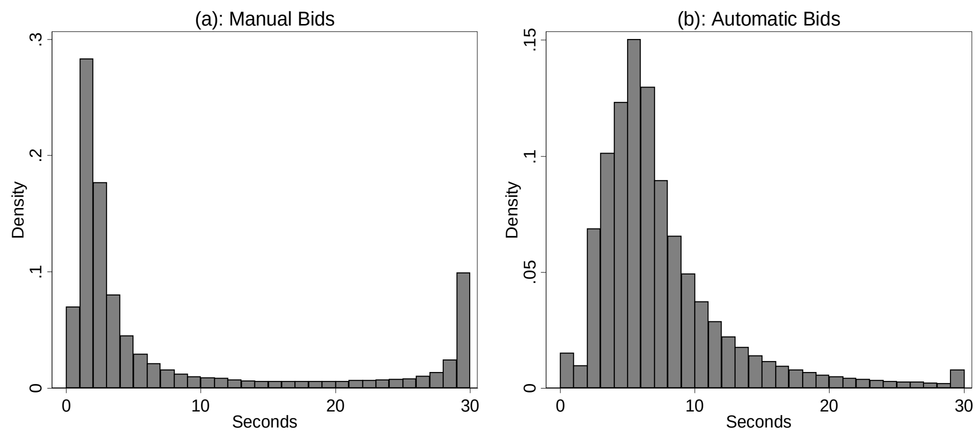
Figure 3(b): Weekly Average of Daily Percent of Profit Generated from Three Group of Bidders



(2) our measure of strategic sophistication is predictive of performance. The results for moderate bidders, not presented here, are qualitatively similar, but our measure of strategic sophistication is not applicable to fleeting bidders.

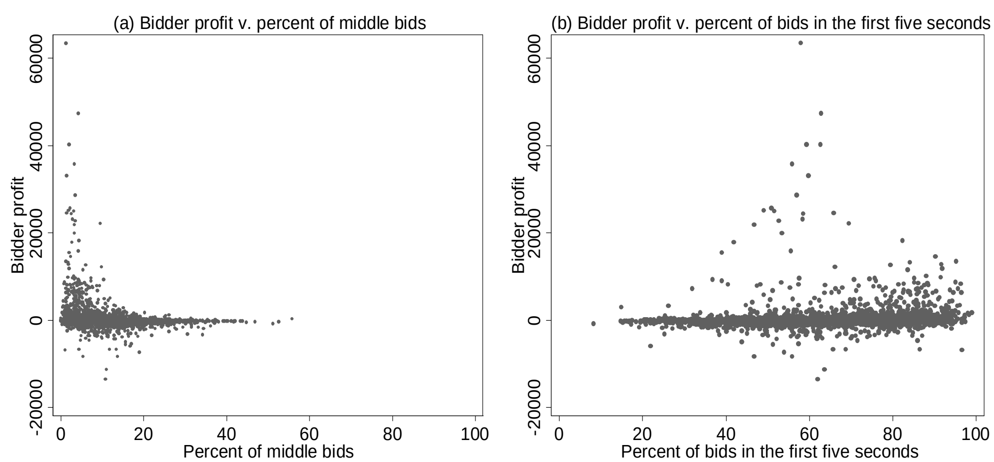
When measuring a bidder's strategic sophistication, we only consider manual bids that were placed in the middle of the 30-second timer. To see our definition of "the middle," consider Figure 4(a), which shows the histogram of the timing of all manual bids (21.5 million) that were placed after the 30-second 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

Figure 4: Histogram of the Timing of Manual or Automatic Bids



five seconds and 13.7% in the last four seconds. We consider manual bids only because bidders do not have control the timing of those bids placed by the bid agent. Figure 4(b) shows the histogram of the timing of all the bids (2.1 million) placed by the bid agent. To be conservative, we classify a manual bid to be in the middle of the 30-second time period if it was placed from the $10th$ second through the $22th$ second.

Figure 5: Bidder Profit and Percent of Middle or Aggressive Bids



Persistent bidders differ in their degree of strategic sophistication. While

984 of the 3,746 persistent bidders placed less than 5% of their bids in the middle, 375 placed 20% or more of their bids in the middle. Figure 5(a) shows the relationship between strategic sophistication and bidder profit. Smaller proportions of middle bids are associated with higher bidder profits. Figure 5(b) shows the relationship between persistent bidders' profits and their proportions of bids placed in the first five seconds. For the 14 most successful bidders, the percent of bids in the first five seconds is between 47% and 66% and the percent of bids in the last four seconds is between 27% and 45%. Hence, the most successful bidders place their bids at both the beginning and the end of the 30-second timer period. For the rest of the persistent bidders, however, there is no clear relationship between aggressive bidding and profit. This is consistent with our idea that aggressive bids, by themselves, do not reflect a bidder's strategic sophistication.

We use the model below to estimate the effect of strategic sophistication on bidders' profit:

$$\pi_i = c + \beta_1 Middle_i + \beta_2 N_i + \beta_3 Middle_i \cdot N_i + \epsilon_i, \tag{6}$$

where π_i is bidder $i's$ total profit or loss, $Middle_i$ is bidder $i's$ proportion of middle bids, and N_i is bidder $i's$ total number of auctions. The interaction term $Middle_i \cdot N_i$ is meant to capture the idea that the impact of strategic sophistication on a bidder's profit depends on the number of auctions in which she played. The impact of strategic sophistication is expected to be bigger for bidders who participated in a larger number of auctions.

Table 5 reports the ordinary least square (OLS) estimates for equation (6). In specification (1), the proportion of middle bids is the only explanatory variable, and its coefficient, as expected, is significantly negative. The marginal effect of a 1% increase in proportion of middle bids is estimated to be \$-67.4. In specification (2), we add in the number of auctions and the interaction term. The estimated marginal effect of proportion of middle bids is $36.2 - 0.92N_i$, which is negative (since $N_i \geq 50$) and is increasingly negative for bigger N_i. The estimated marginal effect of N_i is $11.9 - 0.92Middle_i$, which is negative

Table 5: The Effect of Strategic Sophistication on Bidder Profit

	Dependent variable:			
	Bidder profit in all auctions		Bidder profit after the first 30 auctions	
	(1)	(2)	(3)	(4)
Proportion of middle bids in all auctions	-67.4*** (-11.00)	36.2*** (3.90)		
Proportion of middle bids in a bidder's first 30 auctions			-37.00*** (-7.01)	-7.49 (-1.10)
Number of auctions		11.9*** (15.51)		
Number of auctions - 30				5.44*** (9.17)
Proportion of middle bids×Number of auctions		-0.92*** (-14.44)		
Proportion of middle bids in the first 30 auctions×(Number of auctions - 30)				-0.30*** (-6.64)
Constant	918.2*** (11.81)	-462.2*** (-3.95)	591.03*** (8.72)	65.83 (0.75)
Number of observations	3,746	3,746	3,746	3,746
Adjusted R^2	0.03	0.09	0.01	0.03

Note: In parentheses are t-statistics. *** $p < 0.01$.

for unsophisticated bidders and positive for sophisticated bidders. We note that N_i is endogenous, so we caution that the estimated marginal effect of N_i is only suggestive. We offer more discussions on the relationship between a bidder's profit and her number of auctions in the next subsection.

A concern with equation (6) is that a bidder's proportion of middle bids and her total profit are endogenous. One way to address this concern is to see if our measure of strategic sophistication predicts bidders' *future* performance. That is, we can define $Middle_i$ as bidder $i's$ proportion of middle bids in her, say, first 30 auctions and π_i as her total profit after her first 30 auctions. In this case, N_i should be defined as bidder $i's$ total number of auctions minus 30. Specifications (3) and (4) in Table 5 report the estimated results for equation (6) using the new measures of the dependent and independent variables. The results remain similar. When the proportion of middle bids in a bidder's first 30 auctions is the only independent variable, its coefficient is again significantly negative. When the interaction terms are added, the estimated marginal effect is again negative and increasingly negative for bigger N, and the estimated marginal effect of N is again negative for unsophisticated bidders and positive for sophisticated bidders.

4.4 Strategic Sophistication and Learning

The fleeting bidders learn to quit. Do the persistent bidders learn to play better? In this subsection, we present evidence that whether a persistent bidder learns to play better depends critically on her level of strategic sophistication.

Before proceeding, we emphasize what our measure of strategic sophistication is and is not. We make two points here. First, it turns out that persistent bidders, on average, do not decrease their proportion of middle bids as they gain more experience. This finding suggests that a bidder's proportion of middle bids reflects a relatively stable attribute of a bidder. This attribute, in our opinion, is the degree to which a bidder is mindful of her competition. Second, we emphasize that a bidder's proportion of middle bids captures only a basic aspect of her bidding behavior and does not fully characterize her strategic ability. Two bidders with the same proportion of middle bids may not play penny auctions the same way; they may differ in making such decisions as which auction to participate and when to bid aggressively in an auction. Since a high proportion of middle bids is indicative that a bidder is not mindful of her competition, we hypothesize that such bidders are unlikely to learn to play better in more complicated aspects of the game that are not captured by our measure of strategic sophistication. On the other hand, a bidder with a low proportion of middle bids may learn to play better in more complicated aspects of the game. An analogy might be useful. Proportion of middle bids as an imperfect measure of strategic sophistication is similar to GRE quantitative score as a measure of research ability in economics. GRE quantitative score is not a comprehensive measure of research ability, but a student with a poor GRE quantitative score is unlikely to do well in economic research.

To see that experienced bidders, on average, did not learn to decrease their proportions of middle bids, consider a simple fixed-effect regression model in which the dependent variable is bidders' proportion of middle bids. A bidder's proportion of middle bids in an auction in which she placed only one or two bids is not a reliable measure of a bidder's strategic sophistication. Since many bidders do submit only one or two bids in some auctions and a bid may be placed before the 30-second countdown clock started, we group consecutive auctions into groups and consider bidders' proportion of middle bids in such groups of auctions. Consider the following fixed-effect model:

$$Middle_{ig} = c + \alpha Exp_{ig} + \theta_i + \epsilon_{ig}, \tag{7}$$

where $Middle_{ig}$ is bidder $i's$ proportion of middle bids in auction group g, Exp_{ig} is bidder $i's$ experience when playing in group g, and θ_i is the bidder fixed effect. To see how we measure $Middle_{ig}$ and Exp_{ig}, consider an example. Suppose bidder i played in a total number of 58 auctions. Order these 58 auctions by time and let every five consecutive auctions constitute an auction group; the first five auctions is the first group, auctions 6 through 10 the second group, and so on. The experience variable, Exp_{ig}, takes the value of 1 for the first group of auctions, 2 for the second group, and so on. In this example, bidder $i's$ last group includes three auctions only. The results are not sensitive to the number of auctions included in a group.

Table 6 reports the estimates for equation (7). Specification (1) considers all persistent bidders, and the estimated coefficient for the experience measure is 0.000096 and is not statistically significant at the 5% level. Specification (2) considers persistent bidders who made a positive profit, and the estimated coefficient for the experience measure is -0.000074 but is statistically insignificant. (We obtain similar results even if we restrict the sample to the highly successful bidders only.) Specification (3) considers persistent bidders with a negative profit, and the estimated coefficient for the experience measure is 0.00023, with a p-value of 0.001. These results suggest that persistent bidders, on average, did not learn to place a smaller percent of bids in the middle of the 30-second timer.

Table 6: The Effect of Experience on Strategic Sophistication

	All persistent bidders (1)	Persistent bidders with a positive profit (2)	Persistent bidders with a negative profit (3)
Experience	0.000096	-.000074	0.00023***
	(1.88)	(-1.07)	(3.23)
Constant	0.10***	0.085***	0.11***
	(90.11)	(50.2)	(76.95)
# of bidders	3,738	1,199	2,539
# of observations	77,556	30,691	46,865

Note: Dependent variable is a bidder's proportion of middle bids in a group of 5 auctions. Bidder fixed effects are included in all regressions. The reported constant is the average bidder fixed effect. In parentheses are t-statistics based on Huber/White robust standard errors.*** $p < 0.01$.

We use the model below to study if persistent bidders learn to play better (in other aspects of the game that affect outcome) as they gain more experience:

$$\pi_{in} = c + \delta_1 Exp_{in} + \delta_2 Exp_{in} \cdot Middle_i + \delta_3 Exp_{in}^2 + \varphi_i + \epsilon_{in}, \tag{8}$$

where the dependent variable π_{in} is bidder $i's$ profit or loss in her nth auction, Exp_{in} is bidder $i's$ experience when she plays her nth auction, $Middle_i$ is bidder $i's$ proportion of middle bids in all of her auctions, and φ_i is the bidder fixed effect. The interaction term is meant to capture the idea that experience improves a bidder's performance only if she is strategically sophisticated enough. In other words, a bidder with too low a strategic ability may not be able to learn to play better at all. Here, $Exp_{in} = n$. The square of experience is added in equation (8) to capture the idea that the marginal effect of experience may diminish as experience increases. The marginal effect of experience is $\delta_1 + \delta_2 Middle_i + 2\delta_3 Exp_{in}$. We expect that the estimated coefficients for both δ_2 and δ_3 to be negative. After presenting the estimated results, we discuss two concerns with the interpretation of equation (8).

Table 7 reports the estimated results for equation (8). Specification (1) considers all persistent bidders. The estimated marginal effect of experience from this specification is $0.048 - 0.0023 \cdot Middle_i - 0.000035 \cdot n$, confirming that the marginl effect of experience diminishes as proportion of middle bids increases or as experience increases. For a bidder whose proportion of middle bids is, say, 5%, the estimated marginal effect of experience remains positive for any reasonable number of auctions (967 out of the 984 bidders whose proportion of middle bids is 5% or below participated in less than 400 auctions). However, for bidders whose proportion of middle bids is, say, 20%, the estimated marginal effect of experience becomes negative when the number of auctions is large. Specification (2) considers only persistent bidders whose proportion of middle bids is smaller than 5%. The estimates in this specification indicate that bidders whose proportion of middle bids is below 5% earn, on average, a small positive profit in their first auctions and about \$15 in their $100th$ auctions. Specification (3) considers only persistent bidders whose proportion of middle bids is more than 20%. The results for these unsophisticated bidders are in stark contrast to those for the sophisticated bidders. Bidders whose proportion of middle bids is over 20%, on average, lose \$2.6 in their first auctions and \$2.8 in their $100th$ auctions. These results indicate that sophisticated bidders learn to play better but unsophisticated bidders do not. The unsophisticated but persistent bidders may be characterized as gamblers in that they continued to play despite consistently losing money.

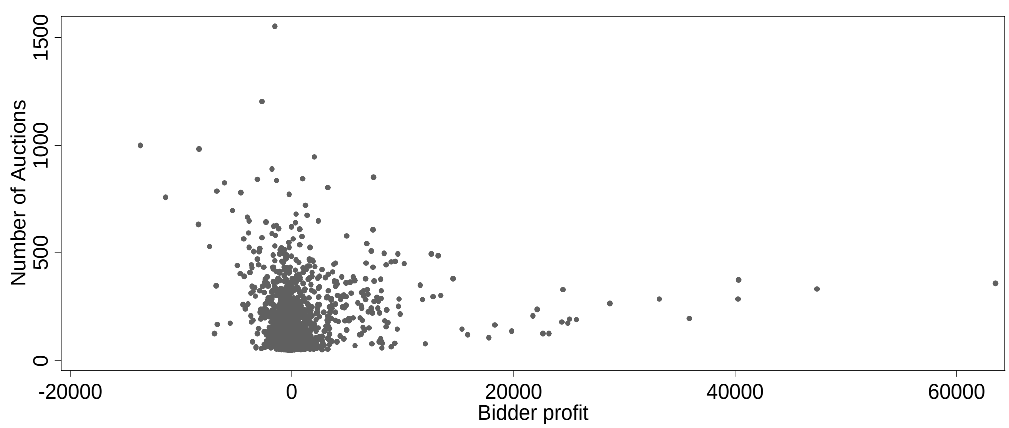
One concern with equation (8) is that the estimated learning effect may simply be a selection effect. This alternative interpretation is based on the idea that more sophisticated players self select to play in more auctions. While noting that selection may play a role, we make two observations here. First, in specification (4), we restrict the sample to be the first 200 auctions of the 521 bidders who played in more than 200 auctions. This specification answers the question of whether the bidders who played in over 200 auctions learned to play better in their first 200 auctions. The estimates, again, indicate a positive learning effect for those bidders with a small proportion of middle bids, but

Table 7: The Effect of Experience and Strategic Sophistication on Bidder Profit per Auction

	All persistent bidders	Pers. bidders % of middle bids < 5%	Pers. bidders % of middle bids > 20%	Bidders with # of auctions > 200
	(1)	(2)	(3)	(4)
Experience	0.048^{***}	0.15^{***}	0.010	0.087^{***}
	(4.88)	(2.74)	(0.83)	(4.40)
% of middle bids	-0.0023^{***}	-0.012	0.000057	-0.0044^{***}
×experience	(-3.96)	(-0.89)	(0.12)	(-4.28)
Experience squared	-0.000018^{***}	-0.00013^{***}	-0.000023^{**}	-0.000069
	(-3.60)	(-4.66)	(2.55)	(-0.82)
Constant	-0.45	1.69	-2.59^{***}	-0.70
	(-1.08)	(1.02)	(-7.87)	(-0.96)
# of bidders	3,746	984	375	521
First 200 auctions	N.A.	N.A.	N.A.	Yes
# of observations	457,016	114,812	40,275	104,200

Note: Bidder fixed effects are included in all regressions. Specification (4) considers only the first 200 auctions of the bidders whose number of auctions is bigger than 200. The reported constant is the average bidder fixed effect. In parentheses are t-statistics based on Huber/White robust standard errors. $^{***}\ p < 0.01, ^{**}\ p < 0.05$

Figure 6: Number of Auctions Versus Bidder Profit (Persistent Bidders)



not for those with a large proportion of middle bids. Second, more successful bidders may not choose to play in more auctions than losing bidders do. In fact, as shown in Figure 6, the relationship between a bidder's total number of auctions and her total profit is not clear cut.

Another concern is that the estimated learning effect may be a reputation effect. This alternative interpretation is based on the idea that experienced and sophisticated bidders may have a reputation that may help them win auctions. However, to be consistent with our results, the reputation argument would require experienced but unsophisticated bidders not to have a positive reputation. While acknowledging that the estimated learning effect may partly reflect a reputation effect, we believe the role of reputation is small in our context. First, BigDeal is characterized by a revolving door of new bidders, and most new bidders are unlikely to know which bidders are experienced and sophisticated. It is time consuming to check the bidding history of previous auctions. 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 memorize and recall their competitors' degree of sophistication in the past, especially considering that the number of experienced competitors is large.

4.5 Number of Bidders and Auction Profit

In this subsection, we highlight the importance of the number of potential or actual bidders in penny auctions. We present five pieces of evidence to show that auction profit increases with the number of bidders in an auction.

Our first three pieces of evidence are based on the idea of using observable and exogenous variables to proxy a change in the number of potential bidders. Our first proxy is based on the sharp decline in the number of regular auctions released at the end of April 2011. For a period of about three months on and before April 20, 2011, the number of regular auctions released each day stayed around 200. The number of released auctions then started to decrease dramatically; the number of auctions ended each day was between 48 and 50 during the last seven days of April 2011. Note that all regular auctions in our sample attracted bids, thus ended successfully. We expect that this sharp decline in the number of auctions hiked temporarily the number of potential bidders and the profitability of the auctions during the last seven days of April 2011. Our first proxy is then a date dummy that is 1 for the last seven days of April 2011, and 0 for the eleven days (April 10 through April 20) immediately before the decline. The results are not sensitive to the chosen length of the prior period.

In Table 8, we regress three auction outcome variables on the date dummy and product fixed effects. Since the outcome of penny auctions is highly volatile and we rely on within-product variations to identify the impact of the number of potential bidders, we restrict our attention to the seven products that were featured in at least 10 auctions during the last seven days of April. These seven products were all auctioned more often during the 11-day prior period. The results indicate that the average number of actual bidders per auction jumped by about 37%, and the average profit per auction hiked by about 83%. In the last column, the dependent variable is an auction's profit per dollar worth of product, which is defined as the total profit generated by an auction divided by the total value of the products this auction sold directly or through the BIN option. The average profit per dollar worth of product increased significantly as well, from $-0.03 to $0.20.

Our second piece of evidence is based on the fact BigDeal scheduled a smaller number of auctions to start the 30-second timer during the night time when, presumably, a smaller number of potential bidders are active. If the number of potential bidders at each hour does not differ much or the number of potential bidders has no impact on auction outcome, we would expect the number of auctions scheduled to start the 30-second timer at any hour of the day is roughly the same. Figure 7(a) shows the number of regular auctions scheduled to start the 30-second timer at each hour of the day from the beginning of our sample to October 4, 2010. The number of auctions scheduled to

Table 8: Impact of a Change in the Number of Potential Bidders due to the Sharp Decline of the Number of Released Auctions at the End of April 2011

	Dependent variables		
	Num. of actual bidders in an auction	Total profit generated by an auction	Profit per dollar worth of product in an auction
	(1)	(2)	(3)
Date dummy	8.67***	40.39***	0.20***
	(5.08)	(3.65)	(5.37)
Constant	23.45***	48.39***	-0.03**
	(33.83)	(10.76)	(-2.18)
Number of observations	854	854	854

Note: Product fixed effects are included in all regressions. The reported constant is the average product fixed effect. In parentheses are t-statistics. *** $p < 0.01$, **$p < 0.05$.

start during the hours 6am through 9pm (Standard Pacific Time) are indeed roughly the same; the average is 1,899 per hour. However, the number of auctions scheduled to start during the hours 10pm through 5am are considerably smaller; the average is only 1,355. Figure 7(b) shows the same information for the period from October 5, 2010 through the end of our sample period. On October 5, the number of auctions scheduled to start during the late night hours were dramatically reduced; since that day, few auctions were scheduled to start during the late night hours from 1am through 4am.

Why did BigDeal stop scheduling auctions to start at the four late night hours? We show that the auctions that started the 30-second timer during those hours attracted fewer bidders and generated smaller revenues. Our second proxy for a change in the number of potential bidders is thus a night dummy that equals 1 for the late night hours from 1am through 4am, and 0 for the hours from 6am through 9pm. We focus on the period on and before October 4, 2010. During this period, the price increment for most auctions is 1 penny, but price increment is $0.15 for a significant number of auctions. We consider these two types of auctions separately as the size of price increment may affect the number of bidders. A total of 38 (42) products were featured

Figure 7(a): Number of Regular Auctions Scheduled to Start the 30-Second Timer at Each Hour of the Day from November 19, 2009 to October 4, 2010

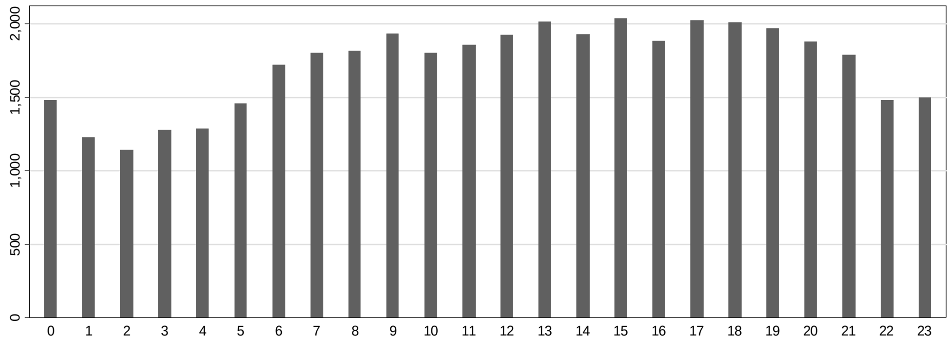
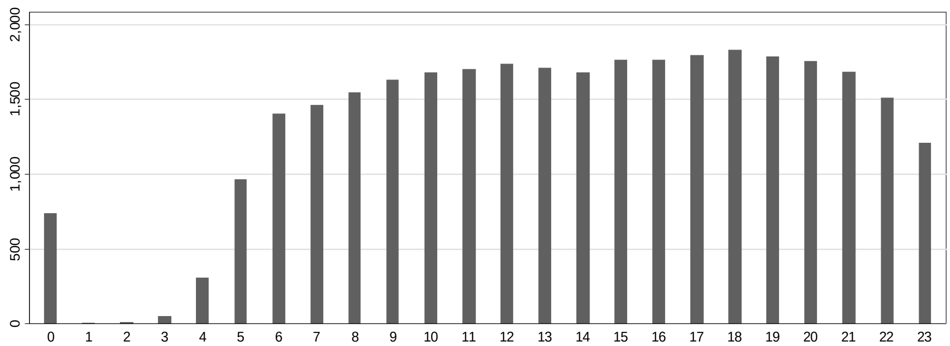


Figure 7(b): Number of Regular Auctions Scheduled to Start the 30-Second Timer at Each Hour of the Day from October 5, 2010 to April 30, 2011



in at least 10 regular auctions during the four late night hours in which the price increment is \$0.01 (\$0.15).[19]

In Table 9, we regress the three outcome variables on the night dummy and product fixed effects. For auctions with 1 penny as increment, the number of actual bidders is, on average, 30 during the day hours and 22 during the four late night hours. Both profit per auction and profit per dollar worth of product are smaller during the four night hours than during the day hours. For auctions with \$0.15 as price increment, the number of actual bidders per auction is, on average, 12.8 during the day time and 11.4 during the late night hours. Therefore, auctions with \$0.15 as price increment, during the day or

[19] The BIN option is always available for these products. We do not consider bid token auctions here because of the BIN option was not available yet.

Table 9: Impact of a Change in the Number of Potential Bidders due to the Late Night Hours Starting Time

	Num. of actual bidders in an auction		Total profit generated by an auction		Profit per dollar worth of product in an auction	
	k=\$0.01	k=\$0.15	k=\$0.01	k=\$0.15	k=\$0.01	k=\$0.15
Late night hours	-7.57***	-1.41***	-54.14***	-15.49***	-0.16***	-0.13***
	(-8.76)	(-5.24)	(-6.06)	(-3.12)	(-4.54)	(-10.57)
Constant	30.03***	12.77***	84.03***	25.69***	0.05***	0.04***
	(122.20)	(109.32)	(33.08)	(11.91)	(3.37)	(10.36)
# of observations	12,582	3,268	12,582	3,268	12,582	3,268

Note: Product fixed effects are included in all regressions. The reproted constant is the average product fixed effect. In parentheses are t-statistics based on robust standard errors (adjusted for clusters). *** $p < 0.01$.

night, have a smaller number of actual bidders per auction. Again, both profit per auction and profit per dollar worth of product are smaller during the four night hours than during the day hours.

Our third proxy for a discrete change in the number of potential bidders is a dummy that equals 1 for beginner auctions and 0 for regular auctions. We expect the number of potential bidders is smaller in a beginner auction than in a regular auction for the same product. Hence, we expect beginner auctions to be much less profitable than regular auctions. Bidders in beginner auctions are, of course, much less experienced, but bidders' lack of experience in beginner auctions presumably favors the auctioneer, holding the number of bidders constant. There are 10 non-token products that were featured in over 10 beginner auctions in which there were at least 2 bidders, and these 10 products were all auctioned more often in regular auctions. (Over 90% of the beginner auctions are 10-token or 20-token auctions, and there are essentially no regular auctions that sell these two types of bid packs.) In Table 10, we regress the three auction outcome variables on the beginner dummy and product fixed effects. The number of actual bidders of the beginner auctions is smaller than that of the regular auction by an average of 5, and the profit is smaller by \$19. These are huge differences considering that a regular auction

Table 10: Impact of a Change in the Number of Potential Bidders due to the Beginner Auction Restriction

	Dependent variables		
	Num. of actual bidders in an auction	Total profit generated by an auction	Profit per dollar worth of product in an auction
	(1)	(2)	(3)
Beginner dummy	-5.18***	-19.40***	-0.57***
	(-33.95)	(-28.75)	(-36.44)
Constant	7.49***	3.70	-0.19***
	(98.24)	(10.95)	(-24.20)
# of observations	3,570	3,570	3,570

Note: Product fixed effects are included in all regressions. The reported constant is the average product fixed effect. In parentheses are t-statistics. *** $p < 0.01$.

for the 10 products considered here has an average of 7.5 bidders and obtains an average profit of \$3.7. Profit per dollar worth of product for the beginner auctions is smaller than that of the regular auctions for the same product by \$0.57.

Our proxies are dummy variables, so we cannot estimate the marginal effect of one more potential bidder. The number of actual bidders in an auction is likely to be correlated with the number of potential bidders, but, unfortunately, it is an endogenous variable. Nonetheless, note that the number of actual bidders in an auction is highly correlated with the profitability of the auction. We computed the correlation coefficient between the number of actual bidders in an auction and the profit of the auction for each of the 160 products that were featured in at least 100 regular auctions. The average correlation coefficient is 0.71, with the $5th$ percentile being 0.45, and the $90th$ percentile being 0.88.

Our last piece of evidence is based on the fact that auction profit differs greatly among the various categories of products. Table 11 reports auction profits or losses by product categories. Bid pack and Apple product auctions without the BIN option are by far the most profitable, a fact to which we return in subsection 4.6. Bid pack and Apple products with the BIN option,

Table 11: Auctioneer Profit from Regular Auctions by Product Categories

Product categories	Num. of auctions	Total Profit	Total value of products sold	Profit per dollar worth of product
iPads (BIN not available)	818	1,278,428	555,890	2.30
Bid packs (BIN not available)	11,524	1,099,530	727,830	1.51
Gift Cards	2,728	72,597	258,570	0.28
Bid packs (BIN available)	7,750	524,301	1,970,070	0.27
Apple products (BIN available)	3,759	1,239,483	5,937,661	0.21
Video games and consoles	10,306	210,152	2,100,307	0.10
Computer, camera, phone, GPS, and related electronics	19,896	631,463	8,248,458	0.08
TVs	1,455	73,127	3,294,010	0.02
Toys	102	-630	6,268	-0.10
House wares	11,176	-233,260	1,425,518	-0.16
Movies	2,555	-26,393	99,351	-0.27
Health, beauty, sunglasses, watches	956	-73,387	215,872	-0.34
Jewelries	2,528	-361,353	726,181	-0.50
Handbags	3,020	-270,458	519,829	-0.52
Total	78,573	4,163,598	26,085,815	0.16

Note: The BIN option is available in all auctions except for some auctions that feature iPads and bid tokens.

Gift cards, video games and consoles, non-Apple electronics such as computer, camera, phone, and GPS are profitable, but handbags, jewelries, health and beauty products, sunglasses, watches, house wares, movies and toys are not profitable. Why is it that some product categories are profitable while others are not? We present evidence that the profitable product categories attract considerably more bidders per auction than unprofitable categories do for value-matched products. We compare the number of actual bidders per auction across value-matched products in order to control the effect of item value. More valuable items, on average, attract more bidders.

We use the following procedure to match products across different categories. We separate the products in the unprofitable categories into 15 mutually exclusive groups; the first group contains products with a value up to $30, the second group contains products with a value between $30 and $60, and the

$15th$ group contains products with a value between \$420 and \$450. We ignore the few products in the unprofitable categories that have a value bigger than \$450 as those products were rarely auctioned. We separate the products in the profitable categories in the same way, and we ignore the auctions in which the BIN option is not available. To ensure that the value of any product in the unprofitable categories is larger than the value of any of the matched products in the profitable categories, we match the second group in the unprofitable categories with the first group in the profitable categories, the third group in the unprofitable categories with the second group in the profitable categories, and so on. We obtain a total of 14 groups of matched products.

In Table 12, we regress four dependent variables on 7 product category dummies and the group fixed effects. We ignore three small product categories (movies, toys, and TVs) because of their small number of auctions or lack of matched products. The constant term is the average group fixed effect of two categories of electronics (video games and consoles, and computer, camera, phone, GPS and related electronics). The first two specifications confirm that three categories of products (handbags, jewelries, and health, beauty, sunglasses and watches) are much less profitable than the two categories of electronics, but another three categories (gift cards, bid packs, and Apple products) are more profitable. Specification (3) shows that the number of bidders per auction in each of the three least profitable categories is smaller than that in the two categories of electronics by at least 60%, and that the number of bidders per auction in each of the three more profitable categories is much larger than that in the two categories of electronics. Specification (4) confirms that the average value of the products in the unprofitable categories is larger than that of the products in the profitable categories by \$30 or so.

Table 12: Inter-Category Comparison of Value-Matched Products

	Total profit generated by an auction (1)	Profit per dollar worth of product in an auction (2)	Num. of actual bidders in an auction (3)	Market value of the auctioned product (4)
Handbags	-107.13***	-0.42***	-9.86***	29.65***
	(-16.51)	(-29.13)	(-16.52)	(158.75)
Jewelries	-152.87***	-0.45***	-12.34**	29.95***
	(-25.07)	(-32.98)	(-22.00)	(165.02)
Health, beauty, sunglasses, and watches	-129.87***	-0.36***	-12.04***	30.71***
	(-11.30)	(-14.16)	(-11.39)	(92.91)
House wares	-37.52***	-0.11***	-0.25	26.90***
	(-7.91)	(-10.61)	(-0.57)	(197.12)
Gifts	23.87***	0.34***	5.91***	-0.47**
	(4.88)	(31.28)	(13.13)	(-3.35)
Tokens	57.04***	0.30***	16.78***	-3.49***
	(16.77)	(39.64)	(53.64)	(-35.63)
Apple products	53.53***	0.07***	13.58***	-1.79***
	(9.29)	(5.20)	(25.62)	(-10.82)
Constant	26.44***	-0.22***	16.32***	93.24***
	(13.98)	(-51.70)	(93.82)	(1713.55)
Number of observations	34,174	34,174	34,174	34,174

Notes: Constant is the average group fixed effect for two categories of electronics (video games and consoles, and computer, camera, phone, GPS and related electronics.) In parentheses are t-statistics. $^{***}p < 0.001$, ** $p < 0.01$.

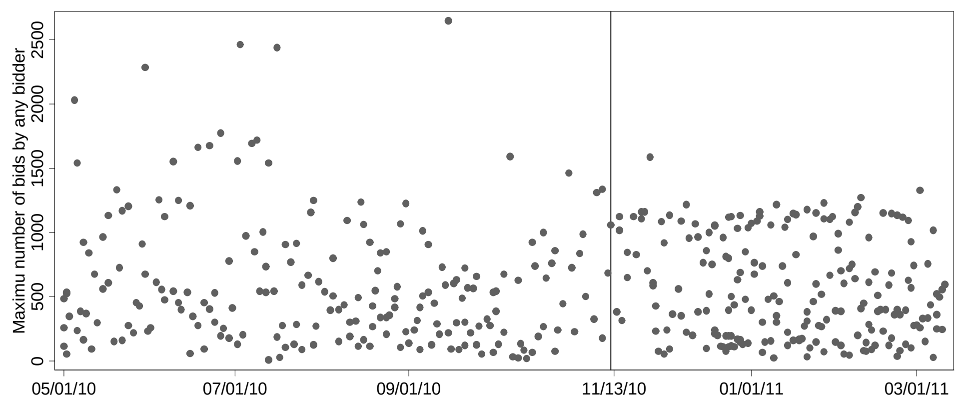
4.6 Impact of the BIN Option on Auction Outcome

We stated in the theory section that a bidder's cost of bids[20] in an auction should not exceed the posted retail price of the product if the BIN option is available. To see this is true, consider Figure 8, which shows the maximum number of bids by any bidder for all the auctions featuring the product of iPad 64GB 3G. This product was auctioned at BigDeal from May 1, 2010

[20] The opportunity cost of a bid is always \$0.75, but those bidders who have won token auctions may not consider the cost of a bid to be \$0.75 in a subsequent auction due to mental accounting.

to March 11, 2011, and the BIN option was not available until November 13, 2010. Before the BIN option became available, the maximum number of bids by any bidder exceeded 1,500 in a considerable number of auctions and exceeded 2,000 in five auctions. After the BIN option became available, the maximum number of bids by any bidder exceeded 1,201 in only 6 of the 204 auctions. This is consistent with the fact that the posted retail price for iPad 64GB 3G is $899.99, a price that only requires 1,200 bids to reach.

Figure 8: The Maximum Number of Bids by Any Bidder for iPad 64GB 3G Auctions



The BIN option allows losing bidders who placed a large number of bids to recover some of their bids, and this has the effect of reducing the profitability of penny auctions. On the other hand, by eliminating the risk of losing a large amount, the BIN option may allow an auction to attract some bidders who otherwise would not have participated in the auction. In Table 13, we use within-product variations to estimate the impact of the BIN option on auction outcome. The fixed effect estimates indicate that the BIN option reduces the profit margin for both bid pack and iPad auctions (which can also be seen from Table 11), and it reduces the absolute amount of profit for bid pack auctions but not for iPad auctions. The absolute amount of profit for iPad auctions is not significantly reduced because iPad auctions with the BIN option attracted a much larger number of bidders and bids.

Table 13: The Impact of BIN on Auction Outcome

	Total profit generated by an auction	Profit per dollar worth of product in an auction	Num of actual bidders in an auction	Num. of bids in an auction
Panel A: Bid Packs				
BIN	-40.89***	-179.33***	4.77***	25.37***
	(-12.85)	(-48.63)	(14.50)	(4.71)
Constant	98.60***	183.71***	23.60***	210.72***
	(47.57)	(76.50)	(110.12)	(60.03)
Number of observations	17,726	17,726	17,726	17,726
Panel B: iPads				
BIN	-168.81	-215.56***	51.74***	1168.62***
	(-0.91)	(-11.73)	(4.38)	(3.71)
Constant	1743.27***	222.38***	163.11***	3323.49***
	(14.00)	(18.08)	(20.64)	(15.76)
Number of observations	695	695	695	695

Notes: Constant is the average product fixed effects. In parentheses are t-statistics. The price increment is \$0.01 for all auctions considered in this table. $^{***}p < 0.01$.

5 Conclusion

What do players actually do in games? A large literature attempts to answer this important question by studying subjects' behavior in experimental games. A central theme of this behavioral game theory literature is that learning and strategic sophistication are important for understanding subjects' behavior. This naturally raises the question of whether learning and strategic sophistication are important for understanding players' behavior in the field. In this paper, we have studied players' behavior in penny auctions, a game in the marketplace. Our empirical evidence indicates strongly that bidders' behavior in penny auctions is better understood through the lens of learning and strategic sophistication than through an equilibrium model that presumes all bidders are experienced and fully rational. Most bidders are inexperienced, and they learn to quit quickly after losing some money. Experienced bidders differ in their degree of strategic sophistication, and a bidder's strategic sophistication is predictive of her overall winning or loss and whether she learns to play better. Our findings thus provide evidence that the concepts of learning and strategic sophistication are important for understanding players' behavior in a large-scale field game.

Is penny auction a sustainable selling mechanism? Our evidence suggests it is not. A central finding of this paper is that BigDeal profits from a revolving door of new bidders, but loses significant amount of money to experienced bidders as a group. This finding suggests that a penny auction website, to survive, must continuously attract new bidders who shall lose money. Our overall findings suggest that the key to understanding penny auctions as a selling mechanism is to focus on bidder learning and strategic sophistication instead of possible bidder biases within an auction. Experienced and strategically sophisticated bidders exploit penny auctions. Inexperienced bidders might suffer from various biases when playing, but they receive immediate and clear outcome feedback so that they may learn to quit quickly. Our results thus highlight that behavioral biases are unlikely to persist in markets in which consumers can obtain quick and unambiguous feedback, and that firms' ability to exploit consumer biases is limited by consumer learning.

References

[1] Augenblick, Ned. 2009. "Consumer and Producer Behavior in the Market for Penny Auctions: A Theoretical and Empirical Analysis." Working paper.

[2] Bajari, Patrick, and Ali Hortaçsu. 2004. "Economic Insights from Internet Auctions." *Journal of Economic Literature*, 42(2): 457–486.

[3] Brown, Alexander L., Collin F. Camerer, and Dan Lovallo. 2012. "To Review or Not to Review? Limited Strategic Thinking at the Movie Box Office." *American Economic Journal: Microeconomics*, 4(2): 1-28.

[4] Byers, John W., Michael Mitzenmacher, and Georgios Zervas. 2010. "Information Asymmetries in Pay-Per-Bid Auctions." *Proceedings of the 11th ACM conference on Electronic commerce*, 1-11.

[5] Camerer, Colin F. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction.* Princeton University Press: Princeton, NJ.

[6] Camerer, Colin F., Teck-Hua Ho, and Juin-Kuan Chong. 2004. "A Cognitive Hierarchy Model of Games." *Quarterly Journal of Economics*, 119(3): 861-898.

[7] Costa-Gomes, Miguel, and Vincent Crawford. 2006. "Cognition and Behavior in Two-Person Guessing Games: An Experimental Study." *American Economic Review*, 96(5): 1737-1768.

[8] Crawford, Vincent P. 1997. "Theory and Experiment in the Analysis of Strategic Interaction" in Kreps David M and Kenneth F. Wallis (eds.), *Advances in Economics and Econometrics: Theory and Applications*, 206-242, Seventh World Congress, Cambridge University Press.

[9] Crawford, Vincent P., Miguel A. Costa-Gomes, and Nagore Iriberri. 2010. "Strategic Thinking." Working paper.

[10] DellaVigna, Stefano. 2009. “Psychology and Economics: Evidence from the Field.” *Journal of Economic Literature*, 47(2): 315-372.

[11] DellaVigna, Stefano and Ulrike Malmendier. 2006. “Paying Not to Go to the Gym.” *American Economic Review*, 96(3): 694-719.

[12] Einav, Liran, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan. 2011. "Learning from Seller Experiments in Online Markets." Working paper.

[13] Ellison, Glenn. 2006. “Bounded Rationality in Industrial Organization.” In *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress Volume 2.* Econometric Society Monographs, No. 42, ed. Richard Blundell, Whitney K. Newey, and Torsten Persson, 142–74. New York: Cambridge University Press.

[14] Friedman, Milton, and L. J. Savage. 1948. “The Utility Analysis of Choices Involving Risk." *Journal of Political Economy,* 56(4), 279-304.

[15] Fudenberg, Drew, and David Levine. 1998. *The Theory of Learning in Games.* The MIT Press: Cambrdige, MA.

[16] Gneezy, Uri. and Ran Smorodinsky. 2006. “All-pay Auctions—an Experimental Study.” *Journal of Economic Behavior and Organization*, 61, 255–275.

[17] Golec, Joseph, and Maurry Tamarkin. 1998. “Bettors Love Skewness, Not Risk, at the Horse Track." *Journal of Political Economy,* 106, 205-225.

[18] Goldfarb, Avi, and Botao Yang. 2009. “Are All Managers Created Equal?” *Journal of Marketing Research,* 46(5): 612-622.

[19] Goldfard, Avi, and Mo Xiao. 2011. “Who Thinks about the Competition? Managerial Ability and Strategic Entry in US Local Telephone Markets.” *American Economic Review*, 101 (7): 3130-3161.

[20] Hinnosaar, Toomas. 2010. “Penny auctions”. Working paper.

[21] Houba, Harold, Dinard van der Laan, and Dirk Veldhuizen. 2011. “Endogenous Entry in Lowest-Unique Sealed-bid Auctions.” *Theory and Decision*, 71: 269-295.

[22] Kagel, John H., and Dan Levin. 1986. “The Winner’s Curse and Public Information in Common Value Auctions.” *American Economic Review*, 76(5): 894–920.

[23] Kagel, John H, Dan Levin, and Ronald M. Harstad. 1995. “Comparative Static Effects of Number of Bidders and Public Information on Behavior in Second-Price Common Value Auctions.” *International Journal of Game Theory,* 24: 293-319.

[24] Krishna, Vijay. 2002. *Auction Theory*. Academic Press: San Diego, CA.

[25] List, John A. 2003. “Does Market Experience Eliminate Market Anomalies?” Quarterly Journal of Economics, 118(1): 41-71.

[26] Malmendier, Ulrike, and Young Han Lee. 2011. "The Bidder’s Curse." *American Economic Review*, 101(2): 749–87.

[27] Ostling, Robert, Joseph Tao-yi Wang, Eileen Y. Chou, and Colin F. Camerer. 2011. “Testing Game Theory in the Field: Swedish LUPI Lottery Games.” *American Economic Journal: Microeconomics*, 3(3): 1-33.

[28] Platt, Brennan C. Joseph Price, and Henry Tappen. 2010. “Pay-to-Bid Auctions.” Working paper.

[29] Raviv, Yaron, and Gabor Virag. 2009. “Auctions by Gambling.” *International Journal of Industrial Organization*, 27: 369-378.

[30] Tversky, Amos, and Daniel Kahneman. 1986. “Rational Choice and the Framing of Decisions.” *Journal of Business*, 59(4), part 2, S251-S275.