

Empirical Evidence on Competition and Revenue in an All-Pay Contest[†]

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Abstract: The total revenue from an all-pay contest is the sum of each individual player's expenditure, so it is important to ask whether it increases with the number of players, our definition of competition. This is the first paper to use field data to empirically study this question. We document strong empirical evidence that the total revenue of penny auctions, a form of all-pay contest that recently emerged on the Internet, increases with the potential or actual number of bidders. Our results contribute to the large literature on all-pay contests and the nascent literature on penny auctions.

Keywords: all-pay contest, penny auction, competition, number of bidders, revenue

JEL Classification: D03, D44, L81

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1. Introduction

Rent-seeking contests, research and development races, and political campaigns are all examples of all-pay contests in which each agent has to incur expenditures to compete for rewards, whether or not that agent wins the rewards. Because the aggregate expenditure in such an all-pay contest, or the total revenue from the auctioneer's perspective, is the sum of each individual player's expenditure, a critical question for understanding such all-pay contests is how the number of participants, our measure of competition, affects the auctioneer's total revenue.

It seems, at first blush, that an increase in the number of players would boost total revenue, but further reflection suggests that a rational player may adjust her expenditure downward if the number of players rises, so total revenue may not increase. Indeed, standard Nash equilibrium analysis of an all-pay auction with a known common value predicts that the expected revenue of an all-pay auction is the value of the prize.¹ However, the vast majority of experimental studies of the Tullock (1980) rent-seeking contest find that subjects' total expenditure substantially exceeds the value of the prize.² See Table 1 of Morgan et al. (2012) for a summary of the literature. Gneezy and Smorodinsky (2006) report that subjects in their all-pay auction experiments overbid substantially and that the degree of overbidding increases with the number of (inexperienced) players in the auctions. Anderson et al. (1998) offer a model of all-pay auction in which bidders are boundedly rational and total revenue increases with the number of such bidders.

¹ Because each player in such auctions has the incentive to outbid her competitors by only a small amount, there is typically no equilibrium in pure strategies. In mixed-strategy Nash equilibria, players are just indifferent as to whether to participate, so the total revenue equals the common value of the prize (Baye et al. 1996; Bulow and Klemperer 1999).

² Hörisch and Kirchkamp (2010) find that players in their experiments overbid in all-pay auctions but underbid in wars of attrition, another type of all-pay contest.

We are not aware of any paper in the literature that has empirically studied the impact of competition on total revenue in an all-pay contest using field data.³ All-pay contests in the field are typically not suitable for empirical testing because of data constraints; researchers may not observe individual players' expenditure, and variations in the potential or actual number of competitors may be limited. We study penny auctions, a new all-pay selling mechanism that recently emerged on the Internet that can generate data sets that can be employed for empirical testing. Similar to the standard Nash equilibrium analysis of all-pay auctions with a known common value, a standard rational model of penny auctions predicts that the total revenue of a penny auction does not depend on the number of participants. However, we find empirical evidence that the total revenue of penny auctions increases with the potential or actual number of participants. Our paper contributes to the literature on all-pay contests by providing the first piece of evidence that competition increases total revenue in an all-pay contest in the marketplace. Our results also contribute to a nascent literature on penny auction by documenting an important empirical regularity for which new theoretical analyses need to account.

The first penny auction website targeting US consumers appeared in 2006, and it has quickly spawned a sizable and controversial industry.⁴ Penny auctions have been described by Richard Thaler (2009) in the *New York Times* as “devilish” and a “diabolically inventive” adaptation of Martin Shubik’s (1971) dollar auction. In this new online auction format, the price

³ Standard all-pay contests include Tullock rent-seeking contests, all-pay auctions, tournaments, and wars of attrition. We are not aware of any studies that use field data to empirically test the Tullock rent-seeking model or wars of attrition. An empirical literature has studied tournaments such as sports games (e.g., Brown 2011) or performance competition within organizations (e.g., Casas-Arce and Martínez-Jerez 2009). The tournament literature is concerned mostly with the efforts or performance of individual players, not the impact of competition on total expenditure. Carpenter et al. (2008) conduct field experiments to study which sealed bid format, including all-pay auction, raises the most money.

⁴ By November 2010, at least 125 penny auction websites targeting US consumers were being monitored by Compete.com, a web traffic monitoring company. According to its data, in November 2010, the total number of unique monthly visitors to these penny auction websites reached 25.1% of that to eBay, but has since declined sharply. Unlike eBay, penny auction websites sell products themselves. See Wang and Xu (2013) for more details.

of the auctioned product is initially zero and increases by a small and fixed increment whenever a new bid is placed. Each bid is an offer to buy the product at the current auction price, and it costs a nonrefundable fee (e.g., \$0.75). The price increment is typically one cent, thus the name “penny auction.” The winner is the last bidder, whose bid is not followed by another bid before a set time interval (e.g., 30 seconds) expires. The timer is reset whenever a new bid is placed. The winner receives the product by paying the auction price (in addition to her already incurred bidding cost). To see why penny auctions have been called devilish, 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, but the website’s revenue was \$4,937.72 ($= 6,497 \times 0.75 + 64.97$)!

Our evidence comes from a major penny auction website (BigDeal.com) that operated between November 2009 and August 2011. Our empirical analysis is focused on the relationship between the number of potential or actual bidders in a penny auction and the net revenue or profit from the auction. We observe the number of actual bidders in any auction, and more importantly, we are able to use observable and exogenous variables to proxy discrete changes in the number of *potential* bidders for a large number of auctions. We define the net revenue or profit of an auction as the difference between its gross revenue and the value of the products sold through the auction. We observe the gross revenue of each auction, and we approximate the market value of a product by the retail price of the same product at Amazon.com. For our purpose, this is a reasonable approximation because our empirical analysis relies mostly on within-product variations to identify the impact of competition on revenue.

A small but growing literature examines penny auctions. Caldara (2012) uses lab experiments to study penny auctions; one of his findings is that the average revenue from

auctions with five players is larger than that from auctions with three players. Caldara's lab finding thus corroborates our empirical results. Five papers (Augenblick 2011; Byers et al. 2010; Hinnsaar 2010; Goodman 2012; Platt et al. 2013) have studied Swoopo, the first penny auction website, but none has studied empirically the relationship between number of bidders and auction revenue. All five papers find that Swoopo made excessive profit. Augenblick (2011) argues that Swoopo's excessive profit is consistent with the idea that bidders suffer from the sunk cost fallacy. Platt et al. (2013) emphasize risk-loving preferences in explaining Swoopo's excessive profit. Hinnsaar (2010) deals largely with a technical modeling issue, and Goodman (2012) focuses on the role of bidder reputation. Byers et al. (2010) theorize that a possible reason for Swoopo's excessive profit is that bidders may underestimate the number of competitors. This theory, based on the idea that bidders may have incorrect beliefs, can explain our findings if bidders underestimate the degree of competition more when the number of bidders is larger, though our findings could also result from other explanations.

Wang and Xu (2013) use data from BigDeal to show that penny auctions cannot sustain excessive profits in the long run. They find that BigDeal profited from a revolving door of new bidders, but lost money to experienced bidders as a group. The phrase "a revolving door of new bidders" refers to their finding (p.2) that "the overwhelming majority 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." Their findings are consistent with the fact that Swoopo has been closed even though it made excessive profits in the short run.

The remainder of the paper proceeds as follows. Section 2 discusses the auction rules at BigDeal and describes our data set. Section 3 reviews the standard Nash equilibrium analysis of

penny auctions and discusses why competition may increase revenue. Section 4 presents our empirical results. Section 5 concludes.

2. Auction Rules and Data

2.1. BigDeal and Auction Rules

BigDeal, which operated from November 19, 2009, to early August 2011, was one of the largest penny auction websites. It appeared to be a serious business endeavor because it received \$4.5 million in initial funding from well-known venture capital firms (Stone 2009).

The rules of BigDeal auctions are representative of all penny auctions. Prior to bidding in any auction, each bidder had to buy a pack of bid tokens. Each token cost \$0.75. BigDeal always set the initial auction price for any product at \$0.00. A bidder had to give up a single nonrefundable token to place a bid, and each bid raised the auction price by a small increment, which was \$0.01 in most auctions and \$0.05 or \$0.15 in some auctions in the early months of our sample. BigDeal typically released an auction with an initial countdown clock that would last for 36 hours. The initial countdown clock continued to run down if a bid was placed when more than 30 seconds were still left on the clock. However, the countdown clock would always be reset to 30 seconds if a bid was placed when less than 30 seconds were still left. A bidder won if her bid was not followed by any other bid when the timer expired. In addition to her bidding cost, the winner also paid the auction price to obtain the product.

BigDeal offered losing bidders a buy-it-now (BIN) option for all auctions except for a number of iPad and bid token auctions. In contrast to eBay's BIN option, a bidder in penny auctions who exercises the BIN option does not stop the auction. Instead, she stops her own bidding and obtains a product identical to the one being auctioned by paying the difference between the posted retail price of the product and her total bidding cost. BigDeal always posted a

retail price for any product to be auctioned. For example, the posted retail price for an iPad auction with the BIN option in our data set was \$899.99. A losing bidder in this auction placed 1,067 bids, so her cost of bids was \$800.25 ($=1,067 \times 0.75$). This bidder needed to pay only an additional \$99.74 ($=899.99 - 800.25$) to exercise the BIN option and obtain an iPad identical to the one being auctioned. With the BIN option, this bidder paid the posted retail price of \$899.99 to buy an iPad. Without the BIN option, this bidder would have paid \$800.25 for nothing. The BIN option allows losing bidders who have placed a large number of bids to recover some of their costs; this has the effect of reducing the profitability of a penny auction, if the number of potential bidders in the auction is fixed. On the other hand, by eliminating the risk of losing many bids, the BIN option allows a website to attract more bidders, which is perhaps why almost all penny auction websites now offer the BIN option.

2.2. Data

Using self-written scripts we downloaded from BigDeal.com 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. BigDeal displayed the bidding history of all live and past auctions on its website, perhaps to mitigate potential concerns of shill bidding.

In our sample period, BigDeal successfully conducted a total of 115,379 auctions, including 81,345 regular auctions and 34,034 beginner auctions. Whereas regular auctions were open to all bidders, beginner auctions accepted bids only from new members of the website. Most beginner auctions featured 10-token or 20-token bid packs. A total of 218,387 bidders placed at least 1 bid; together, they placed a total of 23,819,374 bids. We observe which bidder placed each of these bids and in which auction.

Following the previous literature on penny auctions, we approximate the market value of a product by the retail price of the same product at Amazon.com in June, 2011. This is a reasonable approximation because we rely mostly on within-product variations to study the impact of competition. In our data set, 61.7% of the nontoken auction products are available at Amazon. The Amazon prices for these products are, on average, 78% of the retail prices posted by BigDeal. Thus, we assume that the value of a nontoken product without an Amazon price is 78% of the posted retail price by BigDeal. Since the cost of a token is \$0.75, we presume its value is \$0.75.⁵

2.3 Revenue Definition and Computation

We define the auctioneer's net revenue from an auction as its total revenue from the auction minus the total value of the products sold by the auction. The products sold by an auction include the products sold through the BIN option. We focus on net revenue instead of absolute revenue for three reasons. First, the absolute revenue of an auction varies with the market value of the product being auctioned. By focusing on net revenue, we can better aggregate results across a variety of products. Second, by focusing directly on net revenue we can easily observe whether auction revenue exceeds the value of the prize, a major focus of the literature on all-pay auctions. Third, the absolute revenue, but not the net revenue, of an auction increases linearly with the number of products sold through the BIN option.

Following the literature on penny auctions, we refer to the net revenue from an auction as the profit from the auction. To see how we compute auction profit,⁶ consider an auction in which the value of the product is v , the final auction price is p , the price increment is k , and the number

⁵ There is one exception. The value of bid tokens bought through the BIN option in token auctions is smaller than \$0.75 because of a usage restriction imposed on such bid tokens. We assume that the value of a token bought through the BIN option is $0.8 \times \$0.75$. See Wang and Xu (2013) for more details.

⁶ An individual bidder's profit or loss can be similarly computed. See Wang and Xu (2013) for details.

of bidders is M . We observe the number of bids placed by each of the M bidders, $\{b_1, b_2, \dots, b_M\}$.

If the BIN option is not available, then the profit, π , of the auction is simply

$$\pi = p + (p/k) \times c - v. \quad (1)$$

If the BIN option is available, the calculation is more involved because we have to estimate which losing bidders may exercise the BIN option. Suppose bidder i has placed b_i bids, so she needs to pay additional cost $r - b_i \times c$, the difference between the posted retail price and her bidding cost, to exercise the BIN option. If the additional cost needed is smaller than the value of the product, v , she should exercise the BIN option. Therefore, the number of losing bidders who exercise the BIN option in this auction is $\sum_{i \neq j}^M I(r - b_i \times c \leq v)$, where j denotes the winner of the auction, and $I(\cdot)$ is an indicator function. Hence, the auctioneer's profit from this auction is

$$\begin{aligned} \pi = & p + b_j c - v \\ & + \sum_{i \neq j}^M [b_i c \times (1 - I(r - b_i \times c \leq v)) + (r - v) \\ & \times I(r - b_i \times c \leq v)]. \end{aligned} \quad (2)$$

Table 1 reports auction profits or losses by product categories. The total profit of all regular auctions at BigDeal amounted to \$4.55 million, so in the aggregate, overbidding occurred. However, overbidding did not occur in auctions for all categories of products. The ‘‘Total profit’’ column of Table 1 indicates that bid token and Apple products (with or without the BIN option), gift cards, and non-Apple electronics were profitable, but product categories such as toys, housewares, and movies were not profitable. The rightmost column shows a similar pattern in auction profit per dollar of product value, 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. Why were some product categories profitable, whereas others were not? One possible explanation, for which we present evidence in section 4, is that, for products of similar value, the

profitable product categories attracted considerably more bidders per auction than did the unprofitable categories. Table 1 is also indicative of the effect of the BIN option on auction profit. The BIN option significantly reduced the profit per dollar of product value for bid token and Apple product auctions. Given that the BIN option was available, however, the frequency with which the BIN option was exercised, as reported in the “BIN frequency per auction” column, was positively correlated with auction profit.

Table 1. Auction Profit from Regular Auctions by Product Categories

Product categories	No. of auctions	Total profit	Total value of products sold	BIN frequency per auction	Profit per dollar of product value
iPads (BIN not available)	958	1,507,701	635,980		2.37
Bid tokens (BIN not available)	11,524	1,099,530	727,830		1.51
Gift cards	2,728	72,597	258,570	1.91	0.28
Bid tokens	8,430	577,986	2,141,130	4.16	0.27
Apple products	3,893	1,297,667	6,108,139	3.17	0.21
Video games and consoles	10,596	216,059	2,194,415	1.00	0.10
Non-Apple electronics	20,990	666,621	8,422,053	1.31	0.08
TVs	1,546	80,255	3,429,954	1.58	0.02
Toys	102	-630	6,268	0.64	-0.10
Housewares	11,519	-233,843	1,488,959	1.04	-0.16
Movies	2,555	-26,393	99,351	0.18	-0.27
Health, beauty, sunglasses, watches	956	-73,387	215,872	0.42	-0.34
Jewelry	2,528	-361,353	726,181	0.17	-0.50
Handbags	3,020	-270,458	519,829	0.16	-0.52
Total	81,345	4,552,351	26,974,532	1.32	0.17

Note: The BIN option was available in all auctions except for some auctions of iPads and bid tokens. Non-Apple electronics refer to computers, cameras, phones, GPS devices, and related electronics

The BIN frequency column of Table 1 indicates that the BIN option was not frequently exercised. This is because the vast majority of bidders at BigDeal placed a small number of bids in any auction, and it is not optimal for them to exercise the BIN option. The vast majority of BigDeal bidders participated in only a few auctions, placed a small number of bids, and then permanently quit the site within a week or so. Of the BigDeal bidders, 75% placed no more than 55 bids in total, and 95% placed no more than 300 bids.

3. Theoretical Considerations

Penny auctions are a complicated dynamic game, and the existing theoretical analyses of this game are all highly stylized, so we first consider the implications of general economic principles in the context of this game. We then review the basic equilibrium model of penny auctions proposed by Augenblick (2011) and Platt et al. (2013), which predicts that auction revenue is independent of the number of potential or actual bidders. We then discuss possible mechanisms through which auction revenue may increase with the number of potential bidders.

Following the existing analyses of penny auctions, suppose that all players have the same valuation of the auctioned product. Players have the choice of not participating in this game, so the principle of individual rationality implies that any model with fully rational, informed, and risk-neutral players should predict that the expected revenue of a penny auction cannot exceed the value of the product being auctioned. Otherwise, some players would have a negative expected surplus from playing the game. Firms have the option of not running penny auctions, so the expected revenue cannot be less than the value of the product either. Therefore, rational models of penny auctions, regardless of how well they capture the specific features of penny auctions, cannot offer the prediction that auction revenue increases with the number of potential competitors. The basic equilibrium model reviewed below is such a rational model.

Suppose an item being auctioned is of value v to all potential bidders, and the number of potential bidders in the auction, M , is fixed and common knowledge. The initial auction price of the item is $p = 0$. Whenever a bidder places a bid, she pays a cost c , and the auction price is increased by k . Each time period t is set to last a fixed number of seconds ex ante, but whenever a bid is placed within this period, the period ends and a new period $t + 1$ starts. A bidder wins if her bid is not followed by another bid when the period ends. For simplicity, 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.⁷ Assume that the BIN option is not available.

A bidder who places 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 after T because the auction price plus a bid cost exceeds the value of the product. In period T , a bidder is indifferent between bidding and not bidding because, if she bids, she pays $v - c + c$ to win a product of value v . In any period $t < T$, all bidders are assumed to play mixed strategies, and the indifference condition that characterizes the subgame perfect equilibrium is given by

$$(v - tk)\mu_{t+1} = c, \quad (3)$$

where μ_{t+1} is the probability that no one else will bid in period $t + 1$. In equilibrium, a bidder's expected payoff of placing a bid equals the cost of a bid. For equation (3) to hold in period t , each of the other $M - 1$ symmetric bidders must bid in period $t + 1$ with probability τ_{t+1} , such that the following equation holds:

$$(1 - \tau_{t+1})^{M-1} = \mu_{t+1}^* = c/(v - tk). \quad (4)$$

That is, bidders adjust their probabilities of placing a bid by solving equation (4). Hence, the number of potential 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 because each bidder's expected gain is zero in equilibrium. The actual number of bidders who submit at least one bid may differ from M , but the expected revenue remains the same no matter how many bidders actually submit bids.

⁷ Hinnosaar (2010) makes the alternative assumption that simultaneous bidders all incur a bid cost. In practice, tying does not occur as time is continuous.

This model makes several critical assumptions, including the assumptions that (a) players' belief about the number of bidders is correct and (b) all bidders are homogeneous and fully rational such that they all bid optimally. If either of these two assumptions is relaxed, auction revenue may increase with the number of potential bidders. Recall that Nash equilibrium is based on two fundamental assumptions: players act optimally given their beliefs about other players' behavior and their beliefs are correct. Byers et al. (2010) modify the basic equilibrium model of the penny auction to incorporate the possibility that bidders may have incorrect beliefs; specifically, that they underestimate the number of potential bidders. Given their (incorrect) beliefs, bidders still act optimally. The number of potential bidders in a penny auction is, in reality, unknown to individual bidders, and the actual number of bidders is not revealed until the end of the auction, so the idea that bidders may underestimate competition is quite plausible. In their model, auction revenue increases with the degree of underestimation, which is the difference between the true number of competitors and bidders' expected number of competitors. If the degree of underestimation is larger when the number of potential bidders is greater, the theory of Byers et al. (2010) would predict that total revenue increases with competition.

Another possible mechanism by which competition could increase total revenue is that players have the correct belief about competitors but do not always act optimally given their correct belief. Anderson et al.'s (1998) logit equilibrium model of all-pay auctions takes this approach. In their model, actions are chosen by a logit probabilistic rule in which choices with higher expected payoffs are chosen more often, but not always. If players' bidding behavior is not always optimal,⁸ they tend to overbid, so revenue would increase with the number of such boundedly rational bidders.

⁸ Bidders may suffer from various behavior biases (e.g., sunk cost fallacy) that lead them to overbid.

A third possible explanation is that products sold by penny auctions may have a private value component. In all-pay auctions with independent private values, total revenue may increase with the number of competitors. The best way to see why this is the case is through the revenue equivalence theorem. It is well known that the expected revenue of a standard first-price auction with independent private values is the valuation of the second highest bidder, which increases with the number of competitors. This result applies to all-pay auctions with independent private values, if revenue equivalence holds.

Our paper takes the first step of establishing that penny auction revenue increases with the number of potential bidders. We suspect that all three mechanisms mentioned above may be relevant for explaining our empirical findings, but it is beyond the scope of this paper to identify which mechanism is more relevant.

4. Empirical Analysis

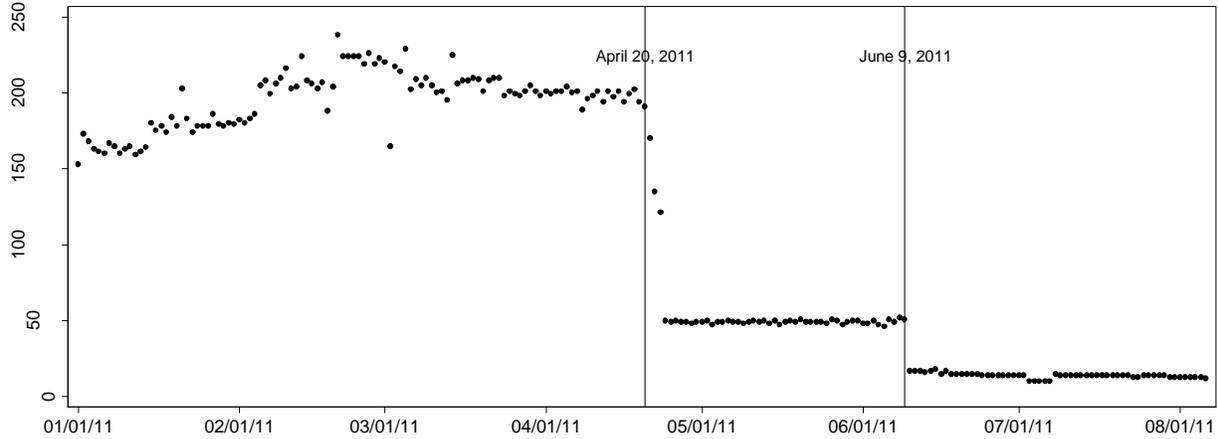
In this section, we present four pieces of evidence to show that profit (or net revenue) increases with the number of bidders in penny auctions. The first three pieces of evidence are all based on the idea of using observable and exogenous variables to proxy a change in the number of potential bidders. Our proxies are dummy variables, so we cannot estimate the marginal effect of one more additional potential bidder. The fourth piece of evidence is the finding that product categories that are more profitable attract more bidders per auction, controlling for product value.

4.1. A Proxy Based on a Sharp Decline in the Number of Auctions

Our first proxy is based on a 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 at around 200 (see Figure 1). The daily number of auctions then started to decrease dramatically during the next four days, and it was

about 50 per day from April 24 through early June, 2011. This change was not announced by BigDeal, so individual bidders would not have noticed it without logging onto the website. We hypothesize that this sudden decrease in auction frequency temporarily hiked the number of potential bidders in each auction, thus increasing auction profit.

Figure 1. Daily Number of Regular Auctions (January 1, 2011, to August 6, 2011)



Our first proxy is a date dummy, defined as 1 for the last 7 days of April 2011 (i.e., April 24–30) and 0 for the 11 days immediately before the decline (i.e., April 10–20). The results are not sensitive to the length of the prior period or to the length of the post period; we obtain essentially the same results even if we triple the length of the prior period and/or triple the length of the post period.

Table 2. Effects of the Sharp Decline in the Daily Number of Auctions

	Dependent variables		
	No. of actual bidders (1)	Total profit (2)	Profit per dollar of product value (3)
Date dummy	8.67*** (5.08)	40.39*** (3.65)	0.20*** (5.37)
Constant	23.45*** (33.83)	48.39*** (10.76)	-0.03** (-2.18)
No. of obs.	854	854	854

Notes: Product fixed effects are included in all regressions. Reported constants are average product fixed effects. Numbers in parentheses are *t*-statistics. ***: $p < 0.01$; **: $p < 0.05$.

In Table 2, we regress three auction outcome variables (two measures of profitability and the actual number of bidders) on the date dummy and product fixed effects. Because 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 attention to seven products that were each featured in at least 10 auctions during the last seven days of April.⁹ These products were all auctioned more often during the previous 11 days. The results indicate that the average number of actual bidders per auction jumped by about 37%, the average profit per auction hiked by about 83%, and the average profit per dollar of product value increased from \$-0.03 to \$0.17.

4.1.1 What Led to the Drastic Decrease in the Number of Auctions?

One concern with the above identification strategy is that the sudden break in auction frequency took place only slightly over three months before the website was closed. In this subsection, we explain what led to the break in late April, 2011 and why the timing of the break, to the individual bidders, is random.

When BigDeal decided to decrease its daily number of auctions in late April, its operation was normal in that it did not experience a declining trend in its daily number of unique bidders (i.e., the daily number of bidders who placed at least one bid, see Figure 2) or in its daily profit level (see Figure 3). Note that both the daily number of unique bidders and the daily amount of auction profit are highly volatile. There are no noticeable changes in the products being auctioned before the break either. Figure 2 shows that after the break, the daily number of unique bidders declined gradually, not drastically, and this is why the number of bidders per auction after the break increased for some periods. Figure 3 shows that the daily amounts of auction profits in the first month after the break remained very similar to those before the break.

⁹ The seven products include an iPod, three bid tokens, two non-Apple electronic products, and a housewares product.

Figure 2: Daily Number of Unique Bidders and Daily Proportion of Bidders Who Joined the Website On and After April 24, 2011

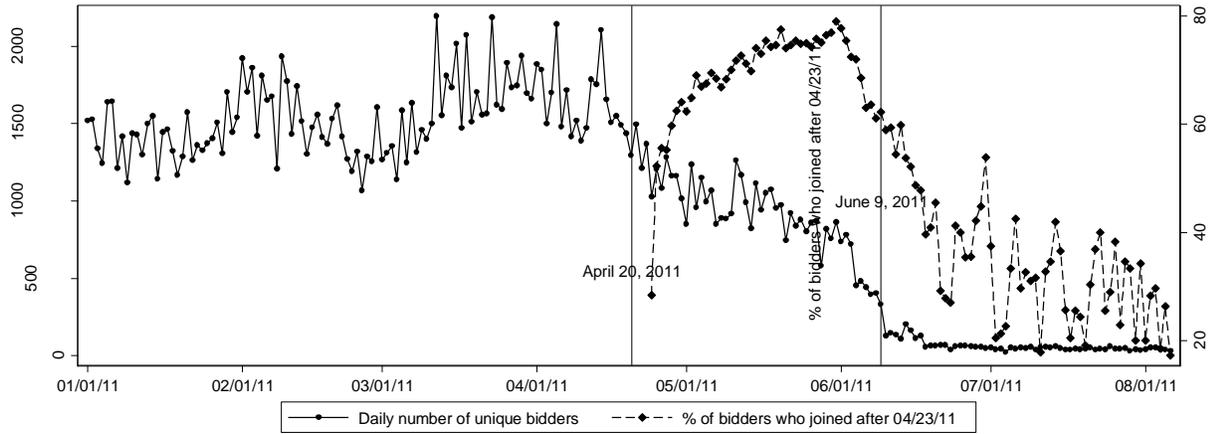


Figure 3: Daily Amount of Auction Profit

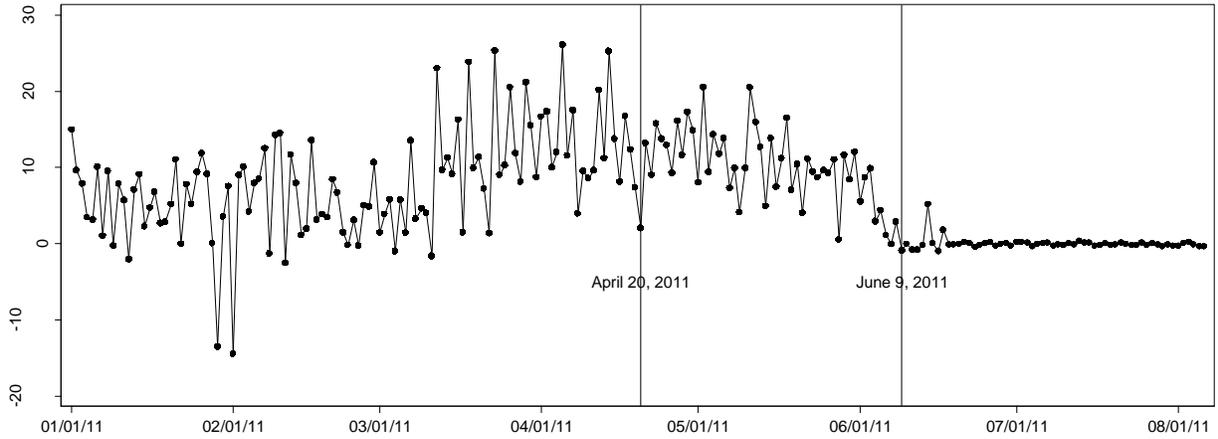
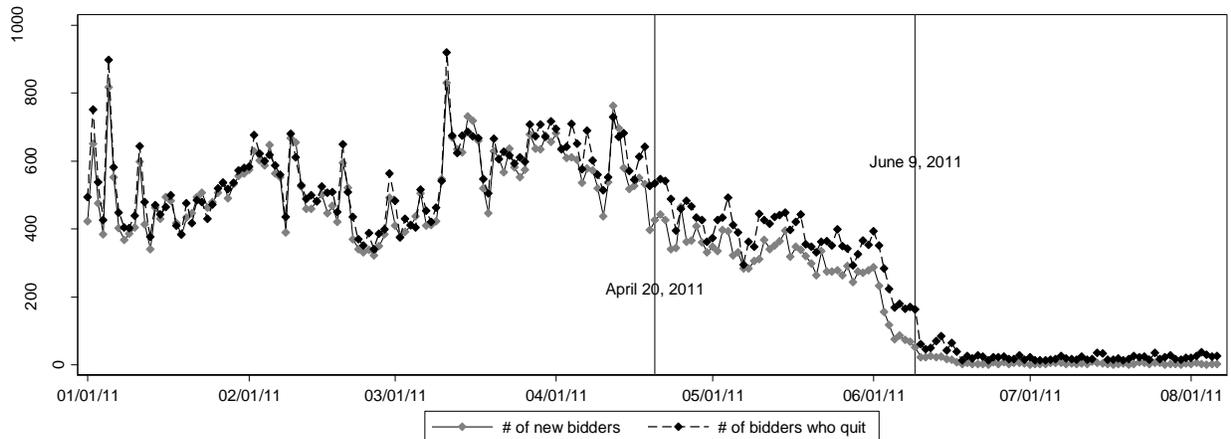


Figure 4: Daily Number of New Bidders and Daily Number of Bidders Who Permanently Quit



If BigDeal's business operation before the break was as usual, what then led to the break? The most plausible explanation is that BigDeal realized that its business model is not sustainable in the long run because it only profited from a revolving door of new bidders and it lost money to experienced bidders as a group. Figure 4 suffices to show the phenomenon of a revolving door of new bidders: the daily number of new bidders before the break in late April is between 400 and 800 on most days, and the daily number of bidders who permanently quit the website is roughly the same. These are extraordinarily high rates of entry and exit, given that the daily number of unique bidders at BigDeal was mostly between 1,000 and 2,000. See Wang and Xu (2013) for more details on the observation of a revolving door of new bidders and for evidence that bidders who chose to stay for long, on average, earned positive profits from the website. This business model is not sustainable because the website, to sustain profits, needs to continuously attract new bidders who shall lose money, a feature shared somewhat by Ponzi schemes.

The decision to drastically decrease auction frequency is an endogenous result (of the unsustainability of the business model in the long run), but the timing of the break is random in the sense that the break could have taken place a few weeks earlier or a few weeks later. Given that BigDeal's operation before the break was business as usual, the abrupt break, to the individual bidders, is unexpected and random. These features of the break in late April are important for our identification strategy. To see this point, consider a second case of dramatic decrease in the number of auctions (which is also shown in Figure 1). On June 10, 2011, the daily number of auctions decreased to 17, from about 50 before that date. However, this second break was a response to the fact that the daily number of unique bidders and the daily profit level were both quickly declining before the break. Therefore, the timing of the second break is not random, and the number of bidders per auction and auction profitability may not increase. Table

3 presents the results of fixed effect regressions based on the second break. In this case, the date dummy equals 0 from June 1 through June 9, and 1 from June 10 through June 30, 2011. Three products were each featured in at least 10 auctions both before and after the second break. The regression results indicate that the second break, in sharp contrast with the first break, did not increase the number of bidders per auction or auction profitability.

Table 3. Effects of the Decline in the Number of Auctions in Early June, 2011

	Dependent variable		
	# of actual bidders	Total profit	Profit per dollar of product value
	(1)	(2)	(3)
Date dummy	0.08 (0.33)	1.92 (1.90)	0.09 (1.56)
Constant	3.95*** (20.46)	-8.62*** (-11.12)	-0.56*** (-12.72)
# of Observations	197	197	197

Notes: Product fixed effects are included in all regressions. Reported constants are average product fixed effects. Numbers in parentheses are *t*-statistics. ***: $p < 0.01$.

Table 4. Product Categories Before and After the First Break

Product categories	03/21/11-04/20/11		04/24/11-05/24/11		% of auctions remaining after the first break
	# of auctions	Profit per dollar of product value	# of auctions	Profit per dollar of product value	
iPads (w/o BIN)	145	3.17	122	3.15	84.1
Apple products (w/ BIN)	146	0.37	129	0.36	88.4
Gift cards	378	0.26			0.0
Bid tokens	2,019	0.23	527	0.34	26.1
TV	107	0.18	73	0.10	68.2
Video games and consoles	409	0.15	121	0.18	29.6
Non-Apple electronics	1079	0.05	438	0.32	40.6
Housewares	957	-0.16	112	0.07	11.7
Movies	20	-0.19			0.0
Health, beauty, sunglasses, & watches	187	-0.28			0.0
Jewelry	235	-0.36			0.0
Handbags	510	-0.53			0.0

BigDeal did not eliminate auctions randomly, though. Table 4 shows the number of auctions, by product categories, for 31 days before and 31 days after the first break. BigDeal eliminated one profitable and four unprofitable categories of products and reduced the number of products in the other categories by various degrees. The reduction in the number of auctions for Apple products is the smallest as they are most profitable. The smaller number of products auctioned after the break may match bidders' preference better, raising the concern that our results may be due to bidders' higher valuations of the auctioned products instead of stronger competition. In the subsection immediately below, we address concerns with bidder selection.

4.1.2 Evidence that Bidder Selection Cannot Explain the Increase in Auction Profitability

Since bidders have the discretion to react to the first break, it is natural to wonder whether bidder selection can explain our results. Other than the possibility that post-break bidders may have higher valuations of the auctioned products, another possibility is that bidders who chose to continue to play after the break are less sophisticated (or more naïve) than those who quitted the website because of the break. In this subsection, we present evidence that is inconsistent with these two alternative hypotheses.

Bidders who are active on and after April 24, 2011, can be separated into three groups: (1) legacy bidders who joined the website before the decrease in the number of auctions started on April 21, 2011, (2) new entrants who joined the website on and after April 24, 2011 when the daily number of auctions declined to be around 50, and (3) bidders who joined during the 3-day transition period (April 21-23).

A good comparison group of bidders for the legacy bidders are those who also joined the website on and before April 20 but quickly quitted between April 21 and April 23, 2011. The evidence indicates that the legacy bidders are more experienced and performed better than the

comparison group of bidders. We measure these two groups of bidders' performance by their net earnings on and before April 20 and their experience by the number of auctions they played on and before April 20, 2011. Table 5 presents both groups' experience distribution. The legacy bidders, on average, are far more experienced than those bidders who quickly quit, and the difference is most pronounced in the upper tail of the distribution. Table 6 presents both groups' performance distribution. The legacy bidders, on average, earned far more than those who quickly quit. The difference is most pronounced, again, in the upper tail of the distribution. These findings are consistent with the general pattern of bidder entry and exit dynamics at BigDeal: most bidders lose money and quickly quit and those who stay for long tend to earn positive profits.

Table 5. Experience Distribution: Legacy Bidders versus Those Who Quickly Quitted

	Percentile					Mean
	10%	25%	50%	75%	90%	
Legacy bidders (4,349)	2	4	11	29	108	40.7
Bidders who quickly quit (658)	2	4	10	21	52	23.6

Notes: Both groups of bidders joined the website on and before April 20, 2011. Legacy bidders refer to those who continued to play on and after April 24, 2011. Comparison bidders are those who quit between April 21 and 23, 2011. A bidder's experience is defined as the number of auctions he or she played on and before April 20, 2011.

Do new bidders, those who joined the website on and after April 24, 2011, have higher willingness to pay than those bidders before the first break? If so, the increase in auction profitability in the last seven days of April may be due to new bidders' higher willingness to pay instead of stronger competition. We address this concern by exploring the idea that if the new bidders have higher willingness to pay, then a larger number of new bidders should imply higher auction profit. As a result of the phenomenon of a revolving door of new bidders, the number of new bidders in an auction continued to increase in early- and mid-May, 2011, which can be inferred from Figure 2. However, we find that auction profit did not continue to increase.

Table 6. Performance Distribution: Legacy Bidders versus Those Who Quickly Quitted

	Percentile					Mean
	10%	25%	50%	75%	90%	
Legacy bidders (4,349)	-176.9	-50	-11.4	-0.75	111.3	120.9
Bidders who quickly quitted (658)	-132.8	-51	-15	-0.75	32.3	6.1

Notes: Both groups of bidders joined the website on and before April 20, 2011. Legacy bidders refer to those who continued to play on and after April 24, 2011. Comparison bidders are those who quitted between April 21 and 23, 2011. A bidder's performance is defined as the net profit (\$) he or she earned on and before April 20, 2011.

We use fixed effect regressions similar to those in Table 2 to show that the number of new bidders in an auction is not correlated with auction profit. Specifically, we compare the outcome of the auctions conducted in May, 2011, with the outcome of the auctions conducted during the last seven days of April. To do so, define four week dummies: the first week dummy equals 1 for the seven days from May 1 through May 7 and 0 otherwise; the second dummy equals 1 for the next seven days and 0 otherwise, and so on. The base period is the last seven days of April.

In Table 7, we regress auction outcome variables on the four week dummies and product fixed effects. We again restrict attention to the seven products that were each featured in at least 10 auctions during the last seven days of April, and it turns out that each of these seven products was each featured at least 10 times in each of the four subsequent 7-day periods. Specification (1) in Table 7 shows that relative to the last seven days of April, the number of new bidders in an auction increased significantly in each of the first three weeks in May, but not in the fourth week. Specifications (3) and (4) in Table 7 show that auction profitability exhibits a complete opposite pattern: relative to the last seven days of April, auction profit did not change in any of the first three weeks, but did change in the fourth week. Moreover, note that this pattern in auction profitability is the same as the pattern in the total number of bidders in an auction (see specification 2 of Table 7). Auction profit changes when the total number of bidders changes, not

when the number of new bidders changes. These results suggest that the total number of bidders in an auction, but not the number of new bidders, affects auction profitability.

Table 7. Effects of Number of Bidders Who Joined on and after 04/24/11

	Dependent Variables			
	# of new bidders (1)	# of actual bidders (2)	Total profit of an auction (3)	Profit per dollar of product value (4)
First week in May, 2011	3.95*** (2.77)	0.53 (0.26)	5.94 (0.36)	-0.02 (-0.53)
Second week in May, 2011	5.06*** (3.54)	1.48 (0.74)	8.38 (0.50)	-0.01 (-0.25)
Third week in May, 2011	5.18*** (3.64)	-0.27 (-0.13)	1.39 (0.08)	-0.02 (-0.52)
Fourth week in May, 2011	1.45 (1.02)	-5.21*** (-2.60)	-24.03 (-1.44)	-0.10*** (-2.63)
Constant	16.64*** (16.55)	28.65*** (20.18)	84.27*** (7.17)	0.08*** (2.81)
# of observations	766	770	770	770

Notes: Product fixed effects are included in all regressions. Reported constants are average product fixed effects. Numbers in parentheses are *t*-statistics. The base period for these regressions is the last seven days of April, 2011. ***: $p < 0.01$.

4.2. A Proxy Based on the Bidder Restriction for Beginner Auctions

Because of the exogenous restriction that beginner auctions are only open to new bidders, we expect the number of potential bidders to be smaller in a beginner auction than in a regular auction for the same product. Hence, beginner auctions are expected to be much less profitable than regular auctions. Bidders in beginner auctions are, of course, much less experienced, but bidders' lack of experience in all-pay auctions, presumably, favors the auctioneer, holding the number of bidders constant. Experimental studies of all-pay auctions (e.g., Davis and Reilly 1998, Gneezy and Smorodinsky 2006, and Lugovskyy et al. 2010) find that the auctioneer's total revenue decreases as players become more experienced. Note that 94% of the (49,885) unique bidders in beginner auctions played in at least one regular auction.

Our second proxy for a discrete change in competition is then a dummy that equals 1 for beginner auctions and 0 for regular auctions. Ten nontoken products were each featured in more than 10 beginner auctions with at least two bidders.¹⁰ These 10 products were all auctioned more often in regular auctions.

Table 8. Effects of the Beginner Auction Restriction

	Dependent variables		
	No. of actual bidders in an auction	Total profit of an auction	Profit per dollar of product value in an auction
Beginner dummy	-4.68*** (-33.58)	-17.37*** (-28.28)	-0.52*** (-35.03)
Constant	7.03*** (103.67)	1.92*** (6.41)	-0.23*** (-32.24)
No. of obs.	3,964	3,964	3,964

Notes: Product fixed effects are included in all regressions. Reported constants are average product fixed effects. Numbers in parentheses are *t*-statistics. ***: $p < 0.01$.

In Table 8, we regress the three auction outcome variables on the beginner dummy and product fixed effects. The number of actual bidders in beginner auctions was less than that of regular auctions by an average of about 5, and the profit is lower by about \$17. These are huge differences considering that a regular auction for the 10 products considered here had an average of 7.03 bidders and resulted in an average profit of \$1.92. The profit per dollar of product value for the beginner auctions was less than that of the regular auctions for the same product by \$0.52.

4.3. A Proxy Based on the Idea that Fewer Bidders Are Active Late at Night

Our third piece of evidence is based on the fact that BigDeal scheduled fewer auctions to start the 30-second timer during late night hours when, presumably, fewer potential bidders were active. Recall that BigDeal typically released an auction with an initial countdown clock that would last for 36 hours and the 30-second timer does not start until only 30 seconds were left on

¹⁰ More than 90% of beginner auctions were 10-token or 20-token auctions, whereas essentially no regular auctions sold these two types of bid packs.

the initial countdown clock. Since nearly all bids at BigDeal were placed after the 30-second timer has started, what affects auction outcome is the time when the 30-second timer starts, not the time when the initial 36-hours countdown clock starts. In what follows, when we say that an auction starts, we mean the 30-second timer starts.

Figure 5(a). Number of Regular Auctions Scheduled To Start the 30-Second Timer at Each Hour (Nov. 19, 2009, to Oct. 4, 2010)

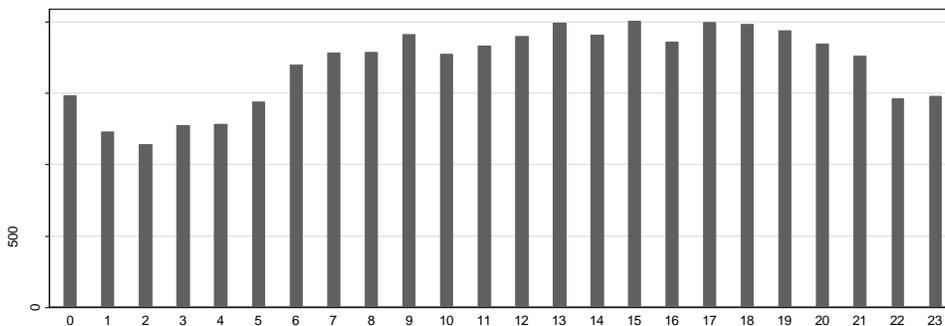
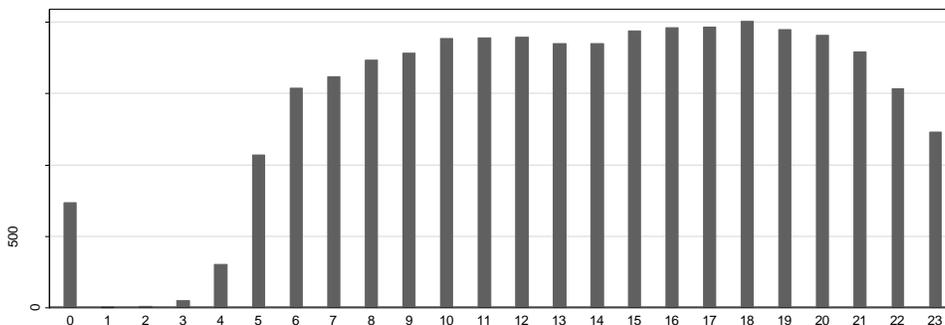


Figure 5(b). Number of Regular Auctions Scheduled To Start the 30-Second Timer at Each Hour (Oct. 5, 2010, to Aug. 6, 2011)



If the number of potential bidders available at each hour did not differ much, and the number of potential bidders had no impact on auction outcomes, we would expect that the number of auctions scheduled to start would be roughly the same at all hours of the day. Figure 5(a) shows the number of regular auctions scheduled to start at each hour from the beginning of our sample to October 4, 2010. The number of auctions scheduled to start between 6 a.m. and 9

p.m. (Standard Pacific Time) was indeed roughly the same, with an average of 1,899 per hour. However, the number of auctions scheduled to start between 10 p.m. and 5 a.m. was considerably less, with an average of only 1,355 per hour. Figure 5(b) shows the same information for the period from October 5, 2010, through the end of our sample period. On October 5, 2010, the number of auctions scheduled to start during the late night hours (from 1 a.m. through 4 a.m.) was dramatically reduced; after that day, few auctions were scheduled to start during the late night hours.

Why did BigDeal essentially stop scheduling auctions to start during the four late night hours? We show that the auctions that started during those hours attracted fewer bidders and generated smaller revenues. Our third proxy for a change in the number of potential bidders is thus a night dummy that equals 1 for the late night hours from 1 a.m. through 4 a.m., and 0 for the hours from 6 a.m. through 9 p.m. We focus on the period on and before October 4, 2010. During this period, the price increment was \$0.01 for most auctions but \$0.15 for a significant number of auctions. We consider these two types of auctions separately as the size of price increment may affect auction outcomes. A total of 33 (38) products were featured in at least 10 regular auctions during the four late-night hours in which the price increment was \$0.01 (\$0.15).

Table 9. Effects of the Late-Night Hours Starting Time

	No. of actual bidders		Total profit of an auction		Profit per dollar of product value	
	$k=\$0.01$	$k=\$0.15$	$k=\$0.01$	$k=\$0.15$	$k=\$0.01$	$k=\$0.15$
Late-night hours	-8.81*** (-12.80)	-1.41*** (-5.24)	-70.90*** (-6.12)	-15.49*** (-3.12)	-0.21*** (-10.77)	-0.13*** (-4.54)
Constant	24.98*** (88.82)	12.77*** (109.32)	71.17*** (15.02)	25.69*** (11.91)	0.04*** (4.92)	0.04*** (3.37)
No. of obs.	4,939	3,268	4,939	3,268	4,939	3,268

Notes: Product fixed effects are included in all regressions. Reported constants are average product fixed effects. Numbers in parentheses are t -statistics. ***: $p < 0.01$.

In Table 9, we regress the three outcome variables on the night dummy and product fixed effects. For auctions with a one-cent increment, the number of actual bidders was, on average, 25 during the daytime hours and 16 during the four late-night hours. Profit per auction decreased by 99.6%, from \$71.2 per auction during the daytime to \$0.27 per auction during the four night hours, and profit per dollar of product value decreased from \$0.04 to \$-0.17. For auctions with a \$0.15 increment, the number of actual bidders per auction, profit per auction, and profit per dollar of product value were all significantly smaller during the four late night hours.

An alternative explanation for the above finding is differences in players' characteristics or behavior between day and night. Other than that BigDeal bidders all have a mailing address in the United States,¹¹ we know little about BigDeal bidders' characteristics. We know that 86% of the (14,171) late-night bidders played in at least one daytime auction,¹² but we also know that 86% of the (73,978) daytime bidders never placed a bid during the late night hours. Hence, the pool of night bidders is not the same as the pool of daytime bidders. Even for the same bidder, his or her behavior may differ between night and day. Bidders' cost of bidding may be higher at late night hours, perhaps due to physical fatigue, so their private value of winning a product may be smaller than that of winning the same product during the daytime.

We cannot rule out these alternative hypotheses. However, the evidence does suggest that day-night differences in bidders' characteristics or behavior cannot be the only reason for the observed difference in auction profit. The correlation between actual number of bidders and auction profit barely decreases if we restrict our sample to late-night auctions only or to daytime

¹¹ BigDeal needs to ship products to auction winners, and its shipping policy is that each product has a single shipping fee that applies to all auction winners.

¹² As before, day time is defined as 6 a.m. through 9 p.m., Standard Pacific Time. In fact, 86% of the late-night bidders also submitted at least one bid in an auction during the day time, 81% of the late-night bidders played in more daytime auctions than in late-night auctions, and 72% of the late-night bidders placed more bids in daytime auctions than in late-night auctions.

auctions only. This can be seen from Table 10 in which we regress profit per dollar of product value on the number of actual bidders per auction and product fixed effects. (The reported R-squared does not reflect the effect of the product fixed effects). We recognize that number of actual bidders is an endogenous variable, and we interpret the results in Table 10 as evidence of correlations instead of causality.

Table 10: Correlations between Auction Profit and Actual Number of Bidders

	Night & Day auctions	Night auctions only	Daytime auctions only
Number of actual bidders	0.01*** (40.86)	0.02*** (15.69)	0.01*** (36.30)
Constant	-0.34*** (-31.92)	-0.48*** (-21.22)	-0.31*** (-25.46)
R-squared	0.25	0.24	0.24
Number of auctions	4,939	835	4,104

Notes: Price increment is 1 cent. The dependent variable is profit per dollar of product value. Product fixed effects are included in all regressions, but the report R-squared does not account for the effect of the product fixed effects. Reported constants are average product fixed effects. Numbers in parentheses are t-statistics. ***: $p < 0.01$.

4.4. Auction Profitability and Product Category

In this subsection, we show that product categories that are more profitable attract more bidders per auction, controlling for product value. This finding is consistent with our hypothesis that auction profit increases with number of bidders.

We compare the number of actual bidders per auction across value-matched products to control the effect of item value because more valuable items, on average, attract more bidders. We focus on the sample period before the first break (i.e., on and before April 20, 2011) to eliminate the effect of the sudden break on auction profit. We use the following procedure to match products across different categories. We separate the products in the unprofitable categories into 15 mutually exclusive groups, such that the first group contains products with a value up to \$30, the second group contains products with a value between \$30 and \$60, and so

on. We ignore a few products in the unprofitable categories that have a value above \$450 as those products were rarely auctioned. (The 15th group contains products with a value between \$420 and \$450.) 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 be conservative, we would like to ensure that the value of any product in the unprofitable categories is at least as large as the value of any of the matched products in the profitable categories. For this purpose, 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 have a total of 14 groups of matched products across different product categories.

Table 11. Intercategory Comparison of Value-Matched Products

	Total profit generated by an auction	Profit per dollar of product value	# of actual bidders in an auction	Market value of the auctioned product
	(1)	(2)	(3)	(4)
Handbags	-106.66*** (-16.27)	-0.42*** (-28.85)	-9.82*** (-16.30)	29.60*** (157.24)
Jewelry	-152.61*** (-24.87)	-0.45*** (-32.79)	-12.31*** (-21.83)	28.92*** (164.15)
Health, beauty, watches, and sunglasses	-128.98*** (-11.13)	-0.36*** (-13.97)	-11.93*** (-11.20)	30.64*** (92.08)
Housewares	-37.76*** (-7.85)	-0.12*** (-10.72)	-0.30 (-0.67)	26.82*** (194.20)
Gift cards	23.87*** (4.83)	0.34*** (31.06)	5.92*** (13.05)	-0.53*** (-3.72)
Bid tokens	57.27*** (16.51)	0.30*** (38.61)	16.84*** (52.83)	-3.59*** (-36.03)
Apple products	54.94*** (9.44)	0.07*** (5.12)	13.64*** (25.50)	-1.89*** (-11.31)
Constant	26.22*** (13.72)	-0.22*** (-51.16)	16.34*** (93.03)	93.69*** (1,706.63)
Observations	33,501	33,501	33,501	33,501

Notes: The constant term is the average group fixed effect for two categories of electronics (the category of video games and consoles and the category of non-Apple electronics (e.g., computers, cameras, phones, GPS devices, and related electronics)). The numbers in parentheses are *t*-statistics. ***: $p < 0.01$.

In Table 11, we regress four dependent variables on seven product category dummies and the group fixed effects. We ignore three small product categories (movies, toys, and TVs) because of their small numbers of auctions or lack of matched products. The constant term is the average group fixed effect of two categories of electronics (the category of video games and consoles and the category of non-Apple electronics). The first two specifications confirm that three categories of products (handbags, jewelry, and the category encompassing health, beauty, sunglasses, and watches) were much less profitable than the two categories of electronics, but three other categories (gift cards, bid tokens, and Apple products) were more profitable. Specification (3) shows that the number of bidders per auction in each of the three least profitable categories was 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 was much larger than that in the two categories of electronics. Specification (4) confirms that the average value of the products in the unprofitable categories was larger than that of the products in the profitable categories by about \$30.

5. Conclusion

How does competition affect total revenue in all-pay contests? This paper takes the first step toward documenting empirical evidence on this relationship from the field. We study penny auctions, a rare form of all-pay contest that generates enough data to make it possible for empirically studying this question. Our evidence suggests that increased competition increases the total revenue of penny auctions. Our findings are inconsistent with models of penny auctions that presume all bidders are fully informed and rational. Our findings could result from bidders' incorrect beliefs about the number of potential bidders or from their inability to always act optimally or from bidders' private valuations of the products sold. It would be interesting for

future research to build and test more general models of penny auctions that can explain our findings.

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