

The Behavior of QuiBids and Its Users

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Abstract— This paper analyzes a company called QuiBids. QuiBids runs a business based off the idea of penny auctions, where a bidder must pay a fee for every bid. A penny auction usually ends with a low final price, leaving one bidder with a huge discount and many with loss, as the result of their fruitless efforts. It also often leaves the company with a huge profit. The only challenge with this business model is perhaps maintaining user activity. Through theoretical and empirical analyses, I identify various bidder and company behavior in order to better understand this business.

Keywords- Penny Auctions; QuiBids; Sunk Costs; Marketing; Bots

I. INTRODUCTION

We have all heard of the company called eBay. eBay runs an online business on the conventional idea behind auctions. Users are able to register an account on their website for free. Afterwards, they can either put items they own up for auction or bid on auctions other people put up. Those auctions are usually up for a fixed time, during which bidders can bid any amount they are willing to pay. Once the time is up, the highest bidder wins the auction.

Thanks to the success of eBay, a whole new generation of online auction websites appeared. Among them is a company called QuiBids. Though it runs an auction website, QuiBids differ from eBay in many ways. Whereas in eBay, users provide the auctions, the company itself provides the items up for bid in this business. However, what is most different is the logistics behind bidding.

The auctions on QuiBids are known as penny auctions, which is a relatively new online auction format that is based off the idea of "all-pay auction". All-pay auction refers to an auction in which all bidders must pay regardless of whether they win the auction. For penny auctions, bidders have to pay for each bid. That is the reason why they are sometimes referred to as "pay-to-bid" auctions.

Penny auctions typically operate on the following rule. First, a user is required to purchase a non-refundable bid package. A bid package contains a certain number of bidding credits such that each credit is worth less than one dollar. A bid credit usually increases the price of an auction by a penny and gives winning status to the user. This is why such auctions are known as penny auctions. Second, the winner is the user who bids last, meaning no other user bids after this user. Auctions

initially start at zero dollars with a time period of one day. They are associated with some fixed time such as thirty seconds. As bids come in, if they are made in that last fixed time period, the countdown timer is reset to the fixed time. The winner of an auction pays the final price and receives the product.

Let us take a look at an auction in my data set. On May 26, 2011, an auction entitled 'Apple MacBook Pro 17" 2.2GHz 750GB 4GB' was sold. The winner of the auction was a user named "cuti0308". cuti0308 paid a total of \$2,243.73 for this item that is listed as being worth \$2,499.76. That is from 2,222 bids worth 60 cents each and the final price of \$910.53. This user saved about 10%. However, for QuiBids, this auction bought in revenue of 2,200% the value of the item! With a final price of \$910.53, that means this auction received 91,053 bids. Since each bid cost 60 cents, the total revenue was \$55,542.33 ($91,053 * 0.06 + 910.53$). It is because of auctions like these and that each bid is a bet that no one else will place a bid after you that many people consider penny auctions a form of gambling. As a result, penny auctions are often characterized as scheme that exploits people.

This paper is a study on the dynamics within QuiBids. QuiBids was founded in late 2009 and has since been increasing in popularity. Currently QuiBids is ranked the 453rd most popular website in the United States. At its peak, QuiBids 450,000 hits in one day. On average, it receives about 150,000 hits per day. The amount of traffic QuiBids receives is more than any of its competitors. This is what makes QuiBids the best focus for studying penny auctions.

The evidence for the behavior of QuiBids and its users are from data I collected from QuiBids.com. The dataset consists of about 500,000 auctions with over 94 million bids total representing about 2,500 different products. This data is for auctions occurring between April 21, 2011, and August 5, 2011. Being able to only gather information on the last 10 bids per auction, I only have information on about 4 million bids, which suggest that there exist at least 200,000 users. My data shows that QuiBids runs about 4,500 auctions every day.

I find that QuiBids is very profitable even though it loses money on many auctions. Most users, as expected, lose money. Therefore, many suffer from believing that they have a negative expected value of bidding. Logically, this implies that users should not participate. However, I find that user activity is sometimes based on expected outcomes. I have noticed that

QuiBids has a way of modifying its inventory to retain its users.

I have also found that strategies matter. I have analyzed my limited bidding history to identify a subset of users that are probably cheating. That includes using bots and/or multiple accounts. I consider these users advanced as they tend to profit. Users that I will consider novice are those that manually bid at some random point in the countdown while relying mostly on luck to win. These users make up a majority of the dataset and are the reason for the site's profits.

In the past few years, a few studies have been done to understand penny auctions. They all studied various users bidding behavior and have come to conclusions such as that fact that a good strategy can greatly influence the chance of a user succeeding and that users do learn. These are conclusions I have also come up with. Some believe that penny auctions achieve a level of equilibrium, such that the amount of revenue generated is not dependent of the number of users given that number is at least two. Some also theorized that the bidding behavior is random, and therefore hard to exploit. My study shows that that is true, but I find that there are users that do this successfully. As of the time of writing this, no other paper focuses on QuiBids, but I have found that results mentioned from analyzing other penny auctions generally apply here.

II. BACKGROUND

Penny auction websites are relatively new. One of the earlier companies is Swoopo. Swoopo was founded for Germany in 2005, but was available for the United States in 2008. Since then, hundreds of similar websites have been founded. Swoopo and all the other websites have been highly criticized. The reason simply that the businesses would make huge profits at the cost of its users. Penny auctions are often compared to gambling, which is illegal online in the United States. In essence, both are games. They both utilize skill, luck, and psychology. And they both require strategy to win. As a result, several lawsuits were filed over the years. A recent lawsuit affected the following websites: (1) Swoopo.com, (2) OohiLove.com, (3) BidCactus.com, (4) QuiBids.com, (5) Beezid.com, and (6) BigDeal.com. The lawsuit claimed that these penny auctions websites are violating United States gambling laws: "This action alleges that Defendants operate illegal Internet gambling websites, by permitting persons to play games of chance for money and/or make a wager upon the result of a game or contest." Swoopo, along with OohiLove, shut down their businesses a few days later.

The penny auction industry brands itself as "entertainment shopping". Penny auction websites attract users through display advertising. They often buy out keywords such as "cheap hdtv" and show advertisements that emphasize the final prices of in-demand item such as apple products. Since consumers are attracted to huge discounts, it can be predicted that such advertisements get high interest. Figure 1 is an advertisement QuiBids once ran. After getting users on the website, keeping them there is the real challenge.

 <p>32 GB Apple iPad 3Gs Price: \$649 Bid: \$30.67 SOLD Save: 92%</p>	 <p>Apple iMac 27" 1 TB Price: \$1553 Bid: \$85.78 SOLD Save: 95%</p>
 <p>Apple MacBook Pro 15.4" 250 GB Price: \$1385 Bid: \$65.84 SOLD Save: 75%</p>	 <p>Apple TV Black wi-fi Price: \$99 Bid: \$12.15 SOLD Save: 88%</p>

Department Stores are Ripping you Off
Save up to 90% Off
* simulation of typical auction results

QuiBids
BID NOW

Figure 1. Advertisement that ran on 11/02/2010.

III. QUIBIDS

QuiBids is one of largest penny auction websites. It was founded on July 2009 but launched in October 2009. Since then, it has grown to over 2.6 million unique visitors a month. For comparison, eBay receives about 77 million unique visitors in a month. Nonetheless, a business this large must maintain a decent reputation if it wants to remain popular. As of October 2011, it has a BBB rating of A- and prides itself in being relatively transparent.

The QuiBids website is well organized with an attractive color scheme. At the top, they have a section that: (1) summarizes the bidding procedure, (2) establishes the credibility by linking to third party reports, and (3) shows how much users benefit. Right underneath is a list of current auctions. Attempting to bid without an active account prompts the user for registration or login. The registration link then directs the user to a carefully planned out landing page, which contains things such as positive testimonials.

The way QuiBids auctions work are representative of penny auctions in general. Before a user can bid, he must first credit his account by purchasing a bid pack. Each bid in a bid pack is worth \$0.60. As of December 2011, QuiBids releases auctions with an initial countdown clock that lasts for 15 hours. As mentioned previously, the starting price of any auction is \$0. Each bid, which is nonrefundable, raises the price of an auction by one penny. If a bid is placed about a strategically determined countdown time such as 15 seconds, the countdown clock resets to 15 seconds. A user wins an auction if no other user bids afterwards and the timer goes down to zero. To obtain the product at this point, the user must pay the final price.

Perhaps to maintain good relations with users, QuiBids has something known as "Buy Now". The way this works is that a user can buy the product up for auction at the listed value price minus the value of all the bids the user placed. This provides the user with a sense of security, where the user knows that no matter what, he would never pay more than the retail price of an item. With this feature, a user simply has a loss of the value of all his bids.

The "Buy Now" feature can be seen as QuiBids way of making users more comfortable with bidding. QuiBids also has another feature known as "BID-O-MATIC". Bid-O-Matic is a

bid agent that places bids automatically for the bidder. This tool can be told when to bid and how many times. It claims to be able to always bid at a random time before an auction ends as long as it remains active. This is just another method QuiBids uses to make users comfortable with bidding and prolong the auction duration, which usually translates to greater revenue.

Some other features of QuiBids including limiting the number of wins in any given month to 12 items, showing the location of other bidders in a live map, and giving users the ability to earn "badges", representing certain achievements. QuiBids also has something known as "Beginner Auctions", which are auctions available to new users. A new user can only win one such auction. Those auctions are usually easy to win since they are open to only a small subset of users. They also represent products that are generally now worth much. All these features are there to encourage user activity.

QuiBids auctions several categories of products. They include bid packs, gift cards, electronics, house wares, etc.

IV. DATA

My dataset, collected from QuiBids.com, contains general information and bidding history of all auctions available to a regular user from April 21, 2011, to August 5, 2011. Each auction is associated with a unique auction id. I wrote a script to collect these ids during this time span. Using another script, I gathered more information on the auctions. Figure 2 shows the hierarchy of the data.

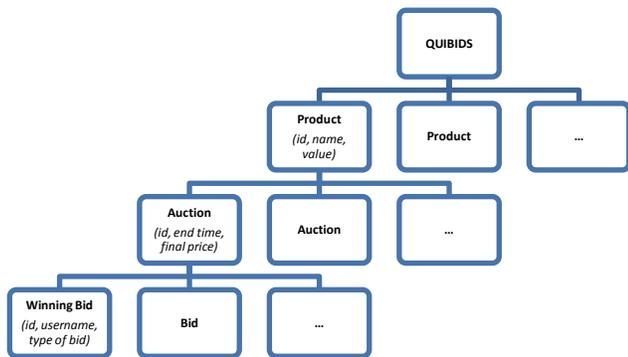


Figure 2. Hierarchy of the QuiBids data.

For each auction, I have information on the product that includes a unique product id, the name of the product, and its retail value. I also have auction level information such as the ending time and final price. In addition, I have the limited bidding history for each auction that includes only the last 10 bids. For each bid, I have the bid id, which represents the number of bids placed at that time, the username of the bidder, and the type of bid (manual or automatic). Note that this dataset lacks any information on users that chose to buy products for auctions at retail value. Figure 3 shows the distribution of auctions over time.

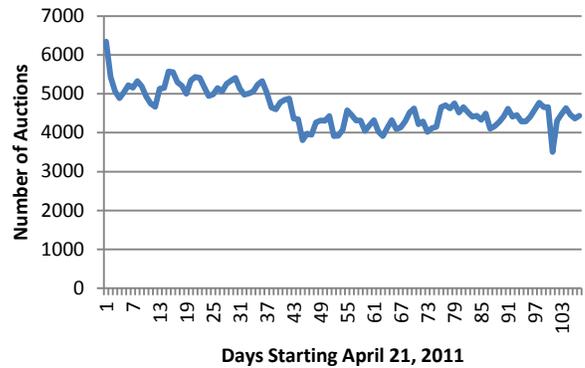


Figure 3. Number of auctions over time.

Information on nearly 500,000 auctions was recorded. In total, there were about 2,500 unique products. The frequencies of those products, however, vary greatly. For example, the product entitled "25 Bids Voucher", which is a bid pack of 25 bids worth \$15, made up about 55,000 auctions, which represents about 10% of all auctions. These auctions represent about 94 million bids. However, only 4 million bids were captured and those represent about 200,000 unique users. An interesting thing to point out is that about 75,000 auctions ended with no bidders!

V. THEORETICAL ANALYSES

A penny auction can be modeled by the following. We can let p represent any auction price of the item. Since items start at \$0, we can let $p = \$0$ initially. Whenever a user bids, he pays a cost c and the auction price increases by i . For QuiBids, $c = \$0.60$ and $i = \$0.01$. We can let $t \in \{0, 1, 2 \dots\}$ represent the current time period. After a user places a bid, the current time period ends and a new one begins. When an auction gets to the point where subsequent bids reset the countdown timer to a set period s , we know that $t_{duration} < s$. Users interested in an auction must decide whether to bid and when to bid in that period. A user wins an auction if no other user bids within s seconds. Let N represent the number of users interested in an auction at any given time. When one user makes a bid in time period t , he is betting c that no other user in N will bid in $t + 1$. Let v be the value of a product up for auction to any user.

For a user that is interested in an auction, we can consider two things that affect his bids. One is the total number of users that are bidding. It is intuitive that the number of people interested in an auction would affect a new user's chance of participating. For example, in the case where there are lots of users interested in an auction, it is unlikely that a new user will join the bidding war. The other is the timing of other bids. It is also intuitive that a user establishes some sort of reputation based on their bidding patterns. An observing user is likely to be affected by what he sees. For example, in the case where a user witnesses other users consistently bidding at the last second, it is likely that an interested user observing the bidding activity would hold off on bidding in order to save bids.

We can assume that no user wants to pay more than what an item is worth to them. Let us say that all users have the same

value for an item. At the time period in which $v = p + c$, the users discontinues further bidding. We can let $T = p / i$ represent some time period in which the auction price is p . At some point, it is the case that $p = v - c$. It follows that $T = (v - c) / i$ at that instance. That represents the time period in which users know that by bidding, they have nothing to gain. A user who bids at $t = T$ ends up paying v . In period $t \leq T$, we can assume that all users play mix strategies. Since $p = ti$, $c = v - ti$. We can let γ_{t+1} represent the probability that no user will bid in time period $t + 1$. Hence we can come up with this expression that represents equilibrium:

$$c = (v - ti)\gamma_{t+1}. \quad (1)$$

It follows that following expression must also be true:

$$(v - ti) / c = (1 - \lambda_{t+1})^{N-1}. \quad (2)$$

In this expression, λ_{t+1} represents the probability a user will bid in the next time period. Since N represents the total number of users, it basically says that the number of users participating in an auction would affect an individual user probability of bidding.

Let us consider the other property that affects bidding behavior: the time in which bids are placed. In order to show that this has an influence in penny auctions, we can look at the dynamics of eBay. In eBay, whenever a user places a bid, only the price goes up. The timer remains the same. We can come up with the following conclusion about bids placed there:

Bids placed closer to the end of a time period are superior to those placed before.

This is based on the idea that the last user that bids wins. If we consider the last 20 seconds, we can say that bids placed in the first 10 seconds are inferior to bids placed in the last 10 seconds simply because bids placed in the last 10 seconds always replace the bids placed in the first 10 seconds.

This situation is similar in the case of penny auctions. For penny auctions, the method of replacing users is slightly different. Let's say that we are in the last 20 seconds. Users that plan on bidding in the first 10 seconds are inferior to those that plan on bidding in the last 10 seconds. Since the timer resets to say, 20 seconds, it may seem like the user who bids in the first 10 seconds have an advantage since he currently holds the winning bid. However, this user is out one bid while the many users waiting saved their bids. The action of the current winner can be modeled by the following:

$$c \leq (v - ti)\gamma_{t+1}. \quad (3)$$

This says that in time period t , what the user expects to gain is greater than or equal to the value of the bet, based on estimating the probability that no other users bid in the next time period. For a user to bid in time period $t + 1$, the following expression must be true.

$$c \leq (v - ti - i)\gamma_{t+2}. \quad (4)$$

The value of an item continues to decrease in subsequent time periods. However, it only decreases by one penny. A user that bids in the previous time period loses c , which is much greater than i . So theoretically, the user that planned on bidding last has the advantage. He would spend the least money for the increase in the probability that no user bids in a future time period. Hence, a user that bids at a certain time should affect other users bidding behavior.

In the equilibrium model proposed by Augenblick, three assumptions were made. It assumes that users bid simultaneously. However, it is usually the case that users bid strategically during the time period. It also assumes that the number of users is fixed. However, it is often the case that this is not visible to users. Lastly, it assumes that all bidders are the same and always bid optimally. This is never the case in penny auctions. To understand the behavior of users, these assumptions must be more accurate in representing users.

A. Strategic Play

In a large penny auction website, it is reasonable to expect that the users make up a variety of strategies. For example, some users are considered aggressive bidders. They would bid immediately after other bidders. Such strategies are probably attempts to intimidate other users. In addition, QuiBids users are limited in the number of auctions they are allowed to win in any given month. This suggests that some users are better than others in knowing when to bid and how to bid.

B. Variable Number of Users

According to the equilibrium model, the revenue generated from auctions does not depend on the number of users. Since it is assumed that each user would adjust his chance of bidding based on the number of users participating in an auction, we can say that even two bidders are enough to achieve expected revenue. However, there are several reasons why this prediction might not hold in penny auction websites such as QuiBids. One is that the true number of bidders is not known. What QuiBids does is tell the user the number of users that had bid on the auction in the past five minutes. It can be assumed that given this short period of time, the number reported is below the auction number of users interested in an auction. Several users could just be waiting for the right moment to take action. By underestimating the number of users, one might overbid. This occurs when the user bidding underestimates the probability that another bid will follow his bid. Another reason why this predication might not hold is that even in the case where the number of users interested in an auction is known, the user bidding might have a tough time adjusting his number of bids. Users are more susceptible to suffer from winner's curse. In economic theory, winner's curse refers to the situation in which the winner in an auction bids too much.

C. Irrational Bidders

It can be said that humans have a knack for learning. Even in the case of penny auctions, learning occurs. When a bidder comes across a penny auction for the first time, he usually doesn't know much about how to play in such as way that his chances of winning the auction is optimal. So for the first bid, it is reasonable to assume that he bids "blindly". However, as a user bids more and more, he gets a better idea of what to do.

After playing an auction, the user has to decide whether to participate in another. If so, he then picks which auction and decides on how to bid. Whether to participate in future auctions is an easy choice to make because it is just a matter of deciding whether he has disposable money. However, deciding on which auction to participate in and what strategy to use is not an easy choice. Making any particular decision for these is done without much accurate feedback on whether the decision is good. This process involves strategic thinking. Some users have the ability to learn to play better while others do not.

As a result, QuiBids can make excessive profits from inexperience users. However, in order to continue making profit, QuiBids has to always attract new users as these inexperienced users tend to give up. It can also be the case that QuiBids makes excessive profits from experienced users. Given the circumstance of penny auctions, it is not predictable when exactly users would stop bidding. The experienced users may have a good strategy, but if they suffer from addiction, they too can lose money given the unpredictable nature of penny auctions.

VI. EMPIRICAL ANALYSES

In order to test the hypotheses in the previous section, I have conducted experiments on QuiBids.com and analyzed data that I have collected.

A. *Bidding Closest to Zero*

If you observe any auction on QuiBids.com, you will notice that the most user bidding activity occurs during the timer reset time period. Unless users are using the bid agent, “Bid-O-Matic”, the bids occur when the timer gets close to zero. The “Bid-O-Matic” bids at a random time during the countdown.

One of my hypotheses states that a user that bids would affect the bidding behavior of other users. I came to the conclusion that the user that bids last will be the user that pays the least for increase in the probability that other users don’t bid in a future time period. As the price goes up, many users would lose interest because the final price and all the cost of bidding would be greater than how much they value the item up for auction. The cost associated by bidding for the user that plans on bidding closest to the timer countdown of zero would usually be least. That means that the final price would have the dominating cost in net gain.

A user that wants to be the person that bids closest to when the countdown timer goes down to zero, would click the bid button when the timer is at 1 second. According to humanbenchmark.com, the average human reaction time is 215 milliseconds. This means that the bid button is clicked when the countdown timer is at about 0.8 seconds. Then a http request is made to QuiBids servers. On a typical broadband connection, that will take about 100 milliseconds. So this user bids with about 0.7 seconds to spare. However, it is usually the case that several users are playing this strategy. This is why after a user bids playing this strategy, another user quickly bids and takes over the role as the current winner. The skilled user who can time just right to delay a bit before reacting would most likely be the one who holds the title of current winner for a subsequent normal time period. Or, ironically, it can be the lucky user who has the greatest reaction time and/or greatest

network latency that is less than 1 second combined. For the sake of argument, we can say that most users with this strategy bid with 0.7 seconds to spare.

To test my hypothesis, I have to make sure I have the greatest probability of being the user that places a bid closest to the zero second mark. At RPI, I measure the time it takes for QuiBids to act on a bid request to be about 60 milliseconds. If I can just make a bid request if necessary right before the last 60 milliseconds, I would be satisfying the condition to test my hypothesis.

There’s no way I can do this manually so I wrote a Google Chrome browser extension. This program watches the countdown timer. Just to be in the safe side, it waits for the last 200 milliseconds in any time period. If some other user bids before this time, the program waits for the last 200 milliseconds of the new time period. Otherwise, it simulates a bid request at a random delay of up to 100 milliseconds. This simulates the “lucky” users, who manage to get a bid request processed with very little time to spare.

I credited my account with 70 bids, worth \$42 dollars. I chose the target to be a product entitled “\$250 American Airlines Gift Card”, worth \$250. According to my data, on average, this item has a final price of about \$10, which represents 1,000 bids. If only one regular user and I were participating in this auction, the final price would be at max \$1.40. One of my goals was to last long in the bidding war. Another goal was to ensure high probability of winning. So I enabled my chrome extension and took a break, believing that this experiment should frustrate other users to the extent that they would all give up (reaching high probability of others no longer bidding).

When I checked on the status several hours later, I arrived a bit too late to win. I ran out of bids. However, my hypothesis was proven to be true. This auction turned out to be an outlier among all the other auctions for this item. It lasted to a final price of about \$40, meaning 4,000 bids. I was the only user that lasted from beginning to end, to when someone won due to my lack of bids. I had the greatest advantage among other early users and hence, greatest probability to save money and win. My data showed that users that participated near the end were new users to this auction. However, due to my strategy and the fact that I had used up all 70 bids, it is reasonable to say that I was the only one to prevent 70 instances in which other users could have won. It could have easily been the case they no one prevented me from winning in a subsequent time period.

B. *Multiple Accounts*

My other hypothesis states the probability that a user bids declines with increasing number of users interested in an auction. Given this, a person can have an advantage by using multiple accounts. He can have his group of accounts actively participate in an auction so that the normal users overestimate the number of users interested in the auction in interest. That is because QuiBids only provides a limited snapshot of the bidding history to users. By overestimating, the number of normal users participating in some auction would decline. At some point, this user that has multiple accounts can disable all but one of them. Since normal users would expect that another

of his account would place a bid, won't see this coming. So the user with multiple accounts would have a very high probability of winning the auction.

In the previous section, I had to actively participate in order to show that users can have an advantage by bidding closest to zero if necessary. That is because my dataset only provides a limited bidding history, containing information on only the last 10 bids. In addition, it lacked the time in which bids were being placed, so I had no way of figuring out whether a bid placed was placed last for an intended time period. However, to show that this hypothesis is true, I can use my dataset this time. I have to first figure out which users belong to some person. Then I can evaluate whether the use of multiple accounts was a success, meaning one of the accounts won an auction.

To analyze my dataset, I created a graph. The nodes are individual users. I determined edges by joining together users that participated in the same auction. Since my dataset is limited to information on the last 10 bids, only users that make up those groups were joined. Recall that QuiBids dataset contains about 200,000 unique users for about 500,000 auctions. Figure 4 shows the number of bids distribution. Intuitively, it seems highly unlikely that users are linked many times given that limitation of last 10 bids in my dataset. In addition, the fact that most auctions get between 30 and 300 bids only reinforces this fact. However, figure 5 shows surprising results. It shows that there were several users that interacted in at least 10 auctions together.

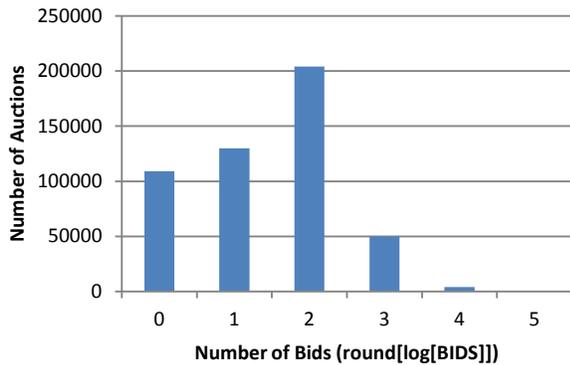


Figure 4. Distribution of the number of bids.

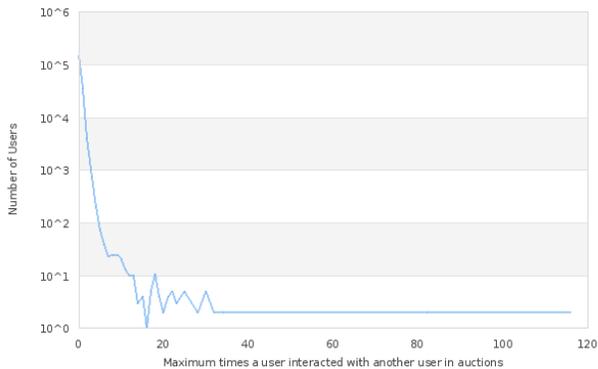


Figure 5. Strength of links distribution.

The more times a user interacted with another user, the more reason I have to believe that those users belong to the same person. A person who is strategic enough to have two accounts most likely knows that the most accounts he has, the greater the probability of winning. I wanted to identify groups of users that belong to some person. In order to do that, we can compute something known as the clustering coefficient.

The clustering coefficient is a measure of to what extent nodes in a graph cluster together. I constructed a new graph based on users that have interacted at least 10 times. After calculating the clustering coefficients, I have found that several users among this subset of suspicious users have high clustering coefficients. This means that many suspicious users have strong links to each other. Table 1 shows two users, AuctionSaver and jgroos. AuctionSaver's cluster has a total of 5 users while jgroos' cluster has a total of 3 users. All the users in each group have a link to each other. This means that they participated in some auction together. Another interesting thing to note is that AuctionSaver interacted with a user in his cluster 169 times. Jgroos interacted with a user 139 times. Earlier I mentioned how unlikely it is that two users interact 10 times. As a result, I have little doubt in believing that these accounts are cheating.

TABLE I.

User	Linked With	Max. Edge Weight	Clustering Coefficient
AuctionSaver	IDONTQUIT123, TARGTGFTCARD, dontryme, and smashcare	169	1
jgroos	oninone, sdroc21	139	1

a. Two groups of users that probably belong to two people.

To see whether this method is a good way to win auctions, let us examine the behavior of the first group. On April 29, 2011, an auction went up for 'Samsung 64" 3D Plasma HDTV' worth \$2,699.99. Table 2 lists the bidding history that has the last 10 bidders. This auction ended at \$4.52, meaning it was a huge loss of money for QuiBids. However, the most interesting thing to note is that all five of the accounts from the first group in Table 1 were part of the last 10 bids! As expected, one of the accounts won.

TABLE II.

BID	BIDDER	TYPE
\$4.52	dontryme	BidOMatic
\$4.51	AuctionSaver	BidOMatic
\$4.50	IDONTQUIT123	BidOMatic
\$4.49	AlecOverton	BidOMatic
\$4.48	smashcare	BidOMatic
\$4.47	dontryme	BidOMatic
\$4.46	AuctionSaver	BidOMatic
\$4.45	grammycoco	Single

BID	BIDDER	TYPE
\$4.44	jrwwolfgang88	Single
\$4.43	Jet800	Single

a. Bidding history of Auction #612423957.

I have shown that having multiple accounts does indeed decrease the probability of other users bidding. For the auction that I have shown the bidding history for in Table 2, several accounts belonging to the same person have bid on the item and using the “Bid-O-Matic”. The normal users that saw the avalanche of automatic bidders chose to save their bids, causing the person behind the cluster of interest to win.

C. Supply Rule

It is inevitable that most users that participate in auctions run by QuiBids will lose money. If they are losing, wouldn't they leave? To answer that question, I took a look at the traffic to QuiBids.com thanks to a service called quancast. Figure 6 shows the traffic to QuiBids.com from April 3, 2011, to September 29, 2011, which covers the time span of my dataset. It seems that up to late June, the number of unique user kept declining sharply. However, it then became steady. Intuition tells me that QuiBids made some change and that is the reason traffic stopped declining. My goal in this analysis is to figure out what they changed and how they changed it.

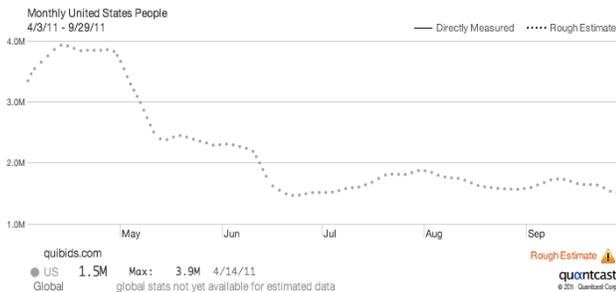


Figure 6. Traffic to QuiBids.com over time span of dataset.

Users would only bid for what they want to have. Perhaps QuiBids made a change to its inventory? The answer to this question is yes. Figure 7 shows the number of unique products over time.

On about the 87th day in my dataset, QuiBids reduced the number of unique products offered. In order to figure out how things have changed for the better, I am reducing my analysis to 20 days before and after day 87. Figure 8 shows the change. By changing the number of unique products, maybe QuiBids also changed the number of auctions per day? Figure 9 shows the number of auctions over the trimmed time span. Based on this, I find that QuiBids did not change the number of auctions it offered in any given day by a significant amount.

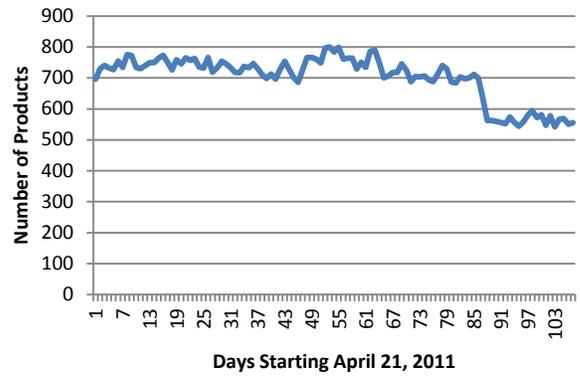


Figure 7. Number of unique products up for auction over time.

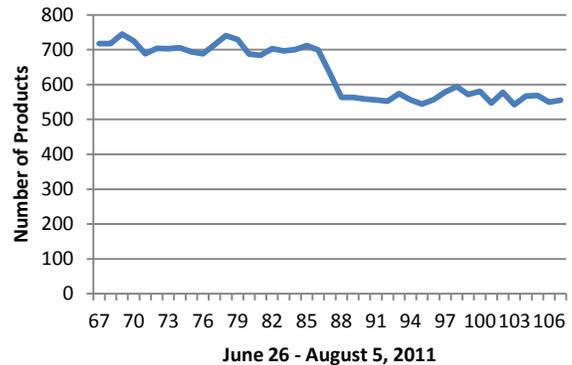


Figure 8. Number of unique products up for auction over time (days).

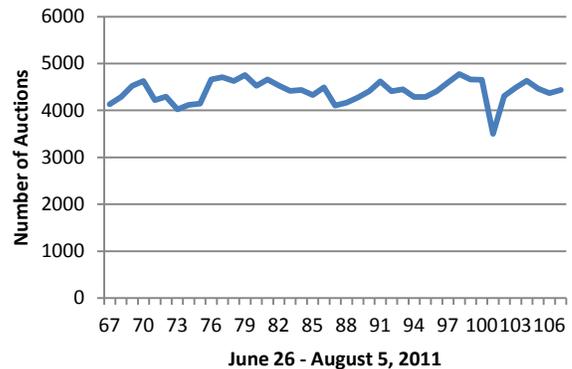


Figure 9. Number of auctions over time (days).

The number of bids placed on QuiBids is equivalent to the revenue. Since traffic was falling sharply, there are fewer users to bid on auctions. However, according to figure 10, fewer users did not lead to a decline in number of bid. For a penny auction business, the revenue equals the number of bids placed. This means that during this time, when traffic was falling, the revenue QuiBids was making didn't change much. It must mean that users do adjust their bidding habits based on the number of users participating, so QuiBids achieves some level of equilibrium. However, QuiBids must have realized that at

some point, the sharp decline in users would affect their business negatively. Its goal must have then been to retain users. It achieved that goal by changing its inventory, as it is shown by the traffic chart (figure 6).

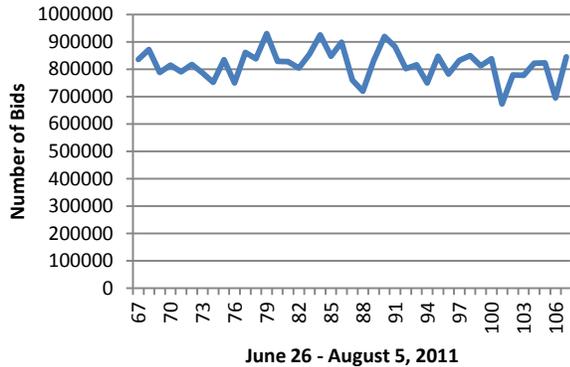


Figure 10. Number of bids over time (days).

The question that remains is how did QuiBids change its inventory? What is its supply rule? To answer this question, I have to analyze the change. I divided the trimmed dataset into two: (1) 20 days before day 87 and (2) 20 days after day 87. That means the before dataset represents the days from June 26 to July 15, 2011. The after dataset represents the days from July 17 to August 5, 2011.

The before dataset has 1,442 unique products and represent a total of 88,516 auctions. The after dataset has 1,058 products and represent 88,194 auctions. In addition, I have captured 51,632 users for the before dataset and 48,486 users for the after dataset.

To analyze the change, I did the following. First I let each product represent a community. Each user is attached to communities based on the amount of interest shown for products as a percentage of all interest by the user. Afterwards, I attempted to join communities. That is based on how similar the users are in any two community. Similarity is based on the percentage of common products the pair of users was interested in. I did this process a couple of time for the two time-period individually. The reason for doing this is see if QuiBids was making changes to its inventory on the basis of category. This process reduced the number of communities a few hundred in both the before and after dataset.

At this point, the communities in each dataset are accurately associated with the total number of bids and the number of auctions. To view the change, I chose to generate two tree maps. The size of the rectangles would represent the amount of auctions QuiBids dedicated to a community as a percentage of all auctions. The shades of rectangles represent the amount of bids as a percentage of all bids. The darker the shade, the more interest users gave to the products represented by a community. Figure 11 shows the tree map for the before dataset and figure 12 shows the tree map for the after dataset.

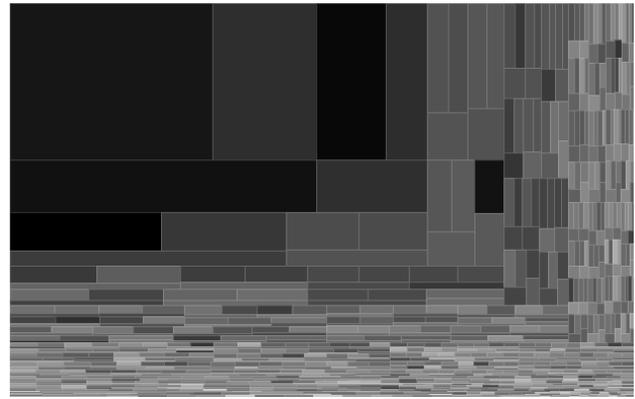


Figure 11. Tree map of communities for the before dataset.

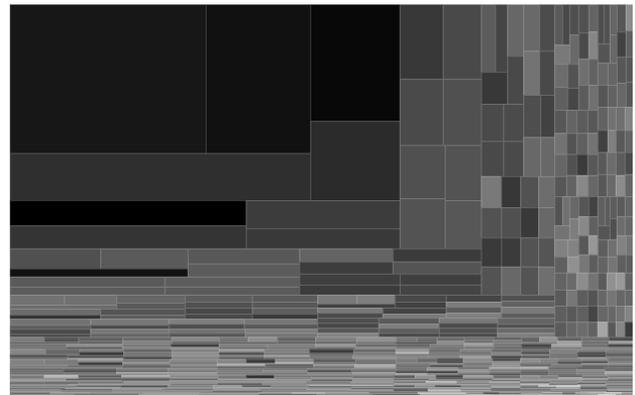


Figure 12. Tree map fo communities for the after dataset.

In any region of the tree map, the closer the shade of one rectangle is to its surrounding rectangles, the more it means that the products in that community is well represented in terms of the number of auctions. From these two tree maps, I can conclude that QuiBids got rid of products that received the least interest. These are rectangles with shades closer to white. QuiBids also increased the number of auctions for products that received high interest.

So what is QuiBids' supply rule? QuiBids seems to want to maintain a certain number of auctions every day. That makes sense because then it's easier to play with other variables. It also wants to appeal to users, and that is by giving them what they want, but to an extent. It also wants to ensure profitability. This is probably the reason why there are rectangles that still do not fit well in the region they are in.

VII. CONCLUSION

After analyzing my dataset in various way, I have come to various conclusions about the way users bid and the way QuiBids structures its inventory to ensure interest. In the theoretical analyses section, I made several hypotheses on things that affect bidding behavior. One is that the total number of users bidding impacts the probability that one user bids. The more users that bid, the less likely it is that some user will bid in a subsequent time period. Another is that the time in which users bid impact others bidding. In the empirical analyses

section, I have conducted an experiment and did some analysis on my data to check the veracity of my hypothesis. I have found that it is much better to be the user bidding when the countdown is closest to zero, only if necessary. This would allow for the user to use his bids only when necessary, meaning the price increase per bid would be greatest for this bidder. As the auction price increases, other users have less of an incentive to bid due to their cost of bidding accumulating over time. To exploit this means you would have a much greater probability of saving money than other users. I have also found that using multiple accounts is a great way to ward off others from bidding, and therefore increasing your chance of winning. Though analyzing link among users, I have found an effective way to detect this method of cheating. By looking at an extreme example, where one person probably represents five users, I have shown that this method of cheat works.

QuiBids manages to maintain interest by providing hope to consumers that they can be the owners to in demand, high priced items. QuiBids alters its inventory so that it keeps up with the demand and still attains profitability. After luring users, the entertainment provided by users cause them to continue bidding. As they bid, they can only hope. Many users choose to maintain this hope by continuously bidding, leading to the understanding of sunk cost. In the experiment that I have done, the user that won the auction actually bid on the gift card for over 240 times. This is the reason why that auction became an outlier. That user knew that he already spent a lot of money so by continuously bidding, he would at least win the auction, even though the savings might be minimal.

The economic factors along with careful actions by QuiBids are what make QuiBids the success it is now. However, with it come many issues. Penny auction have a tendency to upset users and maintain a bad reputation. As a result, several lawsuits have been filed that not only claim deception, but also the fact that penny auction websites are gambling websites in disguise. A benefit that cannot be argued is that penny auctions do provide users with a way to save money. A user of QuiBids would never go in and spend more than the retail value of a product. It is really the bidding habits of users that cause them to have loss and cause QuiBids to make very high profits.

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