NEW WAYS TO ORGANIZE THE DIGITAL BUSINESS MODEL "BUY TO PARTICIPATE PRICING"

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Abstract

Pay-per bid ascending auctions are a new type of a digitized auction business model. In the form of entertainment-shopping auctions they are new exciting, fast-paced B-to-C online businesses that are attracting significant interest from consumers and start-ups. It is unique because participants have to pay a fee for each time they increase the auction price. The theoretical model suggests revenue equivalence between different price increments. We will show that only in mixed strategies there is a symmetric subgame perfect equilibrium.

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Introduction

Pay-per bid ascending auctions offered by retailers such as Swoopo.com, Quibids and Dealdash are exciting, fast-paced business-to-consumer online auctions that where recently introduced on the internet are attracting significant interest from consumers and start ups (Cohen 2010; Toennesmann 2014). Unlike other well known auction-sites, such as Ebay, these auctions involve bidding costs for each bid that is placed. In the case of most auctioneers bidding starts at just $0,00 with no reserve price. The price increases by an increment, usually $0,01 or $0,10, and costs the bidder a bidding fee in the range or $0,60 and $0,90 and extends the length of the auction by up to twenty seconds (Reiner 2014). The auction ends when the time is up, and no further bid is going in by any bidder. The winner is the one who made the final bid. Legally, the winner does not have an obligation to purchase the product. Yet, as the product price is usually far below the prices found elsewhere, it does not make sense not to purchase the product.

At first glance, fee-based auctions do not sound very attractive, because the bidder faces the obvious risk of having to pay bidding fees without winning the auction at the end. However, the compelling part of this model is that the bidders who win the auction can save up to 99% of the recommended retail price. Swoopo points out that their winners have an average savings of 77% of the recommended retail price. Weekly journals (Gimein 2009; Lischka 2008; Last 2009), popular magazines, newspapers (King 2012; Zimmermann,A.2011; Choi 2011; McCarthy 2011;Richard,H. 2009) and online blogs are full of emotional debate about this emerging type of online auction. Although some commentators are enthusiastic about the attractive deals and the fun offered in entertainment shopping auctions, others strongly warn consumers against participating in them. Such commentators point to potentially huge losses that might occur because of high bidding costs.

However, all commentators based their conclusions from a fairly limited number of observations; some of them are quite anecdotal.

Inspite of the popularity of pay-per bid auctions, the knowledge about how they work is scarce (Reklaritis 2009; Singla 2012). Although one can find literature about some kinds of auctions (Fay 2004; Jap 2003; Milgrom 2004; Carr 2003) there is only little research on fee-based bidding auctions (Augenblick 2012; Platt et al 2013). Others have compared the effect of the buy-now price feature on bidders behavior (Reiner,J. et al 2014). None of these studies so far have examined the effects of costs per bid, which are likely to vary, because they occur more than once and are similar across bidders. As a consequence, little is known about how auctioneers can profit from these kinds of auctions, and how these auctions affect consumer surplus. In this study we aim to address the need for a theoretical basis for such auctions to more objectively discuss the benefits and perils. Specifically, the goal of this paper is twofold. First, we will outline ascending auctions and develop an analytical model that allows us to determine critical economic differences for auctioneers and consumers. Second, we will formulate predictions that will be tested in an empirical model.

Description of Ascending auctions

Pay-per-bid auctions are implanted as either increasing (ascending) or decreasing (descending) auctions (Kim 2014). They involve bidding costs and are therefore different from well-known auctions sites, such as Ebay. Ascending auctions are related to English auctions as the price incrementally increases bid by bid (Milgrom 1989). In contrast to English auctions bidding is associated with additional tangible costs per bid from the bidder. Each bid increases the price and prolongs the auction time that is ending by a countdown time. If no new bids are placed before the clock runs out, the last and highest bidder is declared the winner of the auction and owns the right to purchase the auction item at the final sales price (Anderson 2012). Using traffic data from Alexa.com outlines some entertainment shopping auctioneers (Tab.1)

Tab.1

Research on online auctions has recently been increasing in popularity (Barrot et al 2010; Dholakia et al 2002; Haruvy; Popkowski Leszczyc 2009; Jap,Naik 2008; Kim 2012). Ever since the internet's broad acceptance, the relatively minor set costs of internet websites permanent new auction formats have emerged, such as name-your-own-price auctions (Amaldoss,Jain 2008; Hinz,Spann 2008; Spann et al 2004) and pay-per-bid auctions.

Economic Analysis of Ascending Auctions Model

In the following we are presenting the theoretical model of ascending pay-per-bid auctions as shown and developed by Platt et al (2014) and Augenblick (2012).

At the beginning we have the formalization of the auction rules. An item being sold has a publicly known recommended value of y, and a finite set N={1,…n} of potential bidders (customers, buyers), who enjoy utility u(ω) from a payoff ω. Each buyer has an evaluation u_i for the product i that is for sale. y_i is independently and identically distributed on the interval [$0,\tilde{y}$] according to the cumulative distribution function F, which is strictly increasing and continuously differentiable with density f and such that $\tilde{y} \geq y_r$. The state of the auction is described by the number of elapsed period q_t and the current winning bidder, I ϵ {1,…,n}. The individual bidding histories are not included in the state, as past bids are sunk. In the summer of 2010 Swoopo introduced a Swoop-it-now option which allowed unsuccessful bidders to purchase the item at retail price minus the bid fees they had already paid. Swoopo does not report when bidders exercise this option, so it is impossible to perform any empirical investigation of it. Every ascending pay-per bid auction begins at a price that the auctioneer sets; it is usually $p_o \geq 0$. Each time someone bids, a new period begins and the price is raised by Δ; thus the price in period q is $p_q = \Delta \cdot q$. During each period, n-1 buyers who are not currently winning simultaneously choose whether to place a bid. If no one places a new bid, the auction closes and the bidder currently winning pays the current price p_q and receives the item. If k>0 customers place a bid, one of them is randomly selected with the probability 1/k; that customer becomes the new current winning bidder, and must immediately pay c dollars/euros as a bid fee. The rules of the game are such that buyers accumulate sunk costs c every time they bid. Therefore, an agent would ideally observe p_t only once, discover a price that he likes (or even lower than that) and would buy the item. Hinnosaar (2010) models ties by charging all k tied players the bid fee, randomly selecting one as the current winner. The equilibrium outcome coincides with ours when Δ =0 or n=2; more generally, its properties stay the same though the analysis is more complicated.

If a customer has initial wealth ω and places the q^{th} bid, he either obtains either $u(\omega - c)$ if someone else places the $q + 1^{th}$ bid, or $u(\omega + y - c - \Delta \cdot q)$ otherwise. Not bidding leaves him with $u(\omega)$. This constitutes a complete-information, extensive-form game. Platt (2014) and Augenblick (2012) show that there is a symmetric subgame perfect equilibrium in mixed strategies for n bidders (Cronshaw, Luenberger 1994). Here, symmetry requires that at period q, all customers who are not currently winning employ the same mixed strategy $\beta_{q+1} \in [0,1]$ of attempting to place the $q + 1^{th}$ bid. Every bidder who is not the current highest bidder places a bid with probability β_q:

$$(1)\ \beta_q = \begin{cases} 1-(1-\mu_0)^{\frac{1}{n}} & if \quad q = 1 \\ 1-\left(1-\frac{c}{\gamma-\Delta}\right)^{\frac{1}{n-1}} & if\ 1 < q \le \frac{\gamma-c}{\Delta} \\ 0 & if \quad q > \frac{\gamma-\Delta}{\Delta} \end{cases}$$

The probability of making a bid β_q is determined such that bidders are indifferent between placing a bid or not. A short glance at the equilibrium strategy makes it clear why the bidders' behavior is stochastic and there is no such thing as a symmetric equilibrium in pure strategies. When we assume that the number of bidders is low, then a bidder could make a good bargain. The price he has to pay is lower than his willingness-to-pay price: $y>q\cdot\Delta+c$. Hence other bidders will usually submit bids as well. In a situation without any bids there can be no equilibrium, i.e. $q < (y - c)/\Delta$. When all bidders bid "like crazy" and submit many bids at the beginning of the auction, it makes sense for a potential buyer to wait until he thinks the auction is almost over. In this situation of "uncontrolled" bids there is no equilibrium either. Only in mixed strategies one can obtain a symmetric equilibrium. The parameter μ_q is the probability that at least one bidder submits a bid If nobody bids, the auction is over; the probability of that is $1-\mu_q$.

Platt et al (2014) showed that if $\mu_1 =1$ one can obtain the same revenue y from the pay-to bid auction, regardless of the bid fee, the bid increment, or the initial price. The variance of revenue, however, depends on these parameters. These lead to the following expected value and variance of the revenue of one auction R_a:

(2) $E(R_a|y) = y$

(3) $Var(R_a|y) = c/c+2\Delta \cdot (y - \Delta)^2$

Equation 3 shows the variance of revenues of a continuous approximation of the distribution of revenues, implied by the bidding strategies in equation 1. Equation (2) and (3) only apply to one auction each, with the recommended retail price y.

In empirical analyses the expected average revenue is calculated by detecting the auction's average revenues during the observation period. The same holds true for determining the variance. Here the variance is estimated by the sample variance of revenues from the auction period. Because the willingness-to-pay price changes over a period the relevant benchmarks are not the conditional moments in equations 2 and 3 but the unconditional expectation and variance given by:

(4) $E(R_a) = E(y)$

(5) $\mathrm{Var}\,(R_a) = \frac{c}{c+\Delta} E(y-\Delta)^2 + Var\,(y)$

From equation 4 and 5 we obtain the following predictions:

Prediction1: An increase in the price increment Δ reduces the variance of auctioneer revenues in ascending pa-per-bid auctions.

Prediction 2: An increase in the price increment Δ leaves the expected revenue in ascending pay-per-bid auctions unaffected.

Conclusion

This paper presents a parsimonious theoretical model of rational bidders in a pay-per-bid auction. In the symmetric subgame perfect equilibrium potential bidders are indifferent about participating and the exact mixed strategy is determined by this indifference condition. Using these mixed strategies we can establish that expected revenue will be near the bidders evaluation of the auctioned item. In sum, pay-per-bid auctions are essentially a form of gambling or entertainment shopping. Thus it is not surprising that participants bear some resemblance to gamblers from other settings. On a broader level, the pay-per-per auction describes an incremental king-of-the-hill contest. The contest is incremental because each replacement of a king reduces the hill´s value to the eventual winner.

Empirical Study of the Model

Based on the economic analyses of ascending auctions, we now aim to empirically test the predictions by comparing the expected revenues derived from the theoretical model with actual revenues. The question is: When and how often are ascending pay-per-bid auctions profitable for the auctioneers as well as when and how many bidders realize savings. We focus on the market leader Swoopo and analyze 42,942 standard and 1,112 penny auctions. Swoopo lists all of their ended auctions on their websites. For each auction, the site provides the final price, the bid fees paid by the winner, the total number of bids placed by the winners and losers and the end time. Also listed are the bid fee and the price increments that occurs with each new bid. Swoopo also provides the usernames of the winner and the last ten bidders of each auction. We do not observe the full history of bids in our data; like for instance the identity of each bidder for each period. This is not relevant, though, since our model predicts bidder indifferences about bidding at any time, and thus has little to say about individual strategies. Swoopo is not the only website to offer pay-per-bid auctions, but it attracted half a million unique visitors per month, which consistently placed it among the top sites. One advantage of studying Swoopo is that, unlike many competitors, it provided information on all past auctions. Also, as the creator of this auction format, their rules were the most transparent. Later entrants began to differentiate themselves with more exotic bid fee pricing and other features that stretch beyond the scope of our theory.

Tab.2

Tab.2 shows the product categories of auctioned products and the number of standard auctions (€0,10 per bid) and penny auctions (€0,01 per bid) in our sample. Additionally data from a second sample were involved. When observing the actual revenue categories and the expected revenues, we calculate the mean revenue across all categories standardized by their recommended retail price. We use equitation (2) to calculate the expected revenues and use a t-test to compare them with actual revenues. To perform the t-test, we apply the variances of standardized expected revenues from equation (3). Tab.2 depicts the standardized means of the actual and expected revenues per auction for both the ten-cent auctions and the penny auctions. Expected revenues are defined as revenue/RRP (RRP = recommended retail price). We assume that the willingness-to-pay price y is equal to the recommended retail price. But when observing the category cash, we find a significant difference between the actual and the expected revenue. In our sample the auctioneer sold €100 for €207. We find a similar situation is for vouchers, but the deviation is not significant for ten-cent auctions. In penny-auctions the generated revenue is four times above their expected value. The explanation for the differences between actual and expected revenues in standard auctions may be, that hedonic products (game, consoles, mp3 players, video games etc) induce more emotions and more bids than utilitarism (practical) products. In penny auctions it is salient that all deviations from the expected revenues are in favor of the auctioneer. Because the data from Swoopo do not contain any information about the product costs, we estimate them as a share of the recommended retail price by using common margins for online retailers.

Profit across categories

When and how often are pay-per-bid auctions profitable for the auctioneer? To answer these questions, we examine the profit that Swoopo made across all identified categories (Tab.3)

Tab. 3

We see that product profit is negative in all categories and bidding profits are always positive. Special cases are jewelries. Here the average final prices are only 3% of the recommended retail prices and the total profit is negative. In total product losses are higher (-123%) than total profit. Compared with the profits from online-retailers Swoopo profits are on average 14% higher (Tab.4), whereas the differences in some categories are respective.

Tab.4

Disregarding the category of jewelry, Swoopo´s profits would be 65% higher than those a comparable online retailer. The result of Tab.4 stresses the importance of assortment management by pay-per bid online auctioneers. In total Swoopo experienced profit losses in 48% off all standard auctions and in 40% off all penny auctions. In Tab.5 we investigate this result in more detail for three categories that have a relatively high number of auctions.

Tab.5

We find that the variance of penny auctions is always significantly greater than that of ten-cent auctions. Thus Prediction 1 from the theoretical model is supported. To compare Prediction 2, we use a two-independent-sample t-test, which additionally accounts for the unequal variance between penny versus ten-cent auctions. Here in contrast to Prediction 2 revenues of penny auctions are in final higher ($p<0,01$) than that of ten-cent auctions. Thus penny auctions are much more profitable for the auctioneer than standard auctions. On the other site they lead to rather unsteady revenues for the auctioneer. According to Prediction 2 their revenues should be unaffected regardless of varying changes in prices. They are also more attractive for winners, because they save 66% of the recommended retail price at standard auction compared to 79% at penny auctions. In contrast to the theoretical model which assumes that the number of bidders has no influence, a linear regression analysis shows, that a high number of competing bidders leads to a greater difference between actual and expected standardized revenues. Auctioneers benefit from a high number of bidders. Byers et al 2010 show: The expected revenue exceeds its equilibrium level, if bidders underestimate the true number of participants; if bidders overestimate the number of participants, the auctioneers revenue will decrease. A large number of bidders in the regression might pick up situations of underestimating the true number of participants (Anderson et al 1998;Gneezy,Smorodinsky 2006). Furthermore, it seems that hedonic (frivolous) and utilitarian (practical) products drive auctioneer revenues (Strahilevitz,Myers 1998). This categories may cause emotional arousal (Hirschman,Holbrook 1982) which results in less rational bidding behavior. More valuable products are sold at greater discounts. Prediction 2 can not be proved.

The winner takes it all

The distribution of the number of won auctions is similar across the categories. This shows that experienced bidders do not favor a particular category. But the results indicate that some bidders are more "skilled" than others, because successes in previous auctions lead to higher savings in future auctions. The risk (of loosing money) that unskilled bidders face seems to be even higher than for the average bidder. Tab.6 shows that the average number of bids are placed by losers (82,8%) compared to those of winners (17,2%); in most categories losers place the majority of bids.

Tab.6

Penny auctions are more attractive for the winners, because the bids that are placed by the final winner of an auction are lower in penny auctions. The average share of winning bids is 20,1% at standard auctions and 16,2% at penny auctions. Furthermore, the share of winning bids is low for those categories that positively drive winner´s profit; there is a significant negative correlation (standard -.272; penny -.325) of these two variables.Tab.7 shows that the average consumer surplus of some categories are respective.

Tab.7

Due to the auction format the surplus at penny auctions are 4.7 times higher compared to standard auctions, which are ranging from 1.7 to 10.1 higher. On the other site, the average loss – the negative surplus – of the losers at penny auctions is almost 9 times higher, ranging from 1.0 to 10.4 higher. On the one hand penny auctions mean high expenses for the losers; on the other hand there are attractive savings for the winners. The standard variation indicates that penny auctions are much more risky than standard auctions for both auctioneers and bidders. Not surprisingly, the high consumer surplus comes at the expense of the losers, which means they have high losses. Thus our economic analysis suggests that an increase in the price increment per bid reduces the variance in auctioneers' revenues in average (Prediction 1). The volatility of achieved revenues is much higher in penny auctions than in ten-cent auctions.

Summary

Pay-per bid ascending auctions that were recently introduced on the internet are an exciting, fast-paced B-to-C business model. They attracted significant interest from consumers and start-ups. Ongoing heated discussions among winners, losers and customer protection agencies, stress the importance of a thorough examination. Hundreds of start-ups (see www.allpennyauctions.com) emerged using this business model, but only a few firms survived. Therefore, the aim of our paper was to empirically analyze the economic effects of alternative ascending auction formats. For this purpose we adapted an existing theoretical model, formulated predictions regarding auctioneers revenues and tested them empirically. The empirical study demonstrates that pay-per bid auctioneers generate a higher profit than online retailers, ceteris paribus. But the profits vary substantially across product categories and between auction increments (penny vs. ten-cent auctions). This stresses the importance of assortment management. Penny auctions are much more profitable for the auctioneer and the winners of auctions than standard auctions. However, the share of bids that winners place at penny auctions is lower on average. And yield revenues per auction are more volatile and consequently more risky than the use of ten-cent auctions. An increase in the price increment reduces the variance of the auctioneer`s revenue. i.e. a higher range in price increments reduces the selling-risk (Prediction 1).

In contrast to Prediction 2 the empirical analyzis provides evidence that an increase in the price increments affects the expected revenue. Despite the fact, that consumers on average are much better off with online retailers that charge the recommended retail price as compared to penny auctions, they still seem to be attractive to consumers. They seem to be more sensitive to the final price and the attractive saving of the winners than to the costs of bidding and the risks they take.

Limitations and future research

Our empirical analysis is based on an impressive number of auctions from Swoopo. However it would be interesting to examine alternative platforms. Furthermore it would be interesting to analyze consumers behavior that is not consistent with the theoretical model, such as non-equilibrium play, the overvaluation of products, risk-loving preferences etc. Also the role of auction fever in the process is not clear. Ascending pay-per bid auctions are a promising field for future research and in-depth analysis of behavior aspects. Additionally, the question would involve determining how long the differences between actual and theoretically expected revenues occur.

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Tables:

Provider	Quibids	Swoopo.com	Dealdash	Madbid
Auction format	ascending	ascending (standard/penny)	ascending	ascending
Starting price	$0,00	€0,00	$0,00	£=0,00
Bidding fee	$0,60	€0,60	$0,60	£0,25-£1,20
Price increment	$0,01-$0,20	€0,01-€0,10	$0,01	£0,01
Market Share	76%	79%	8%	5%

Tab.1: Comparison of the most popular pay-per-bid ascending auctions

Ten–Cent Auctions			Penny Auctions	
Product category	N	Actual Revenue	N	Actual Revenue
Cash	11	2,07		
Voucher	43	0,98	185	4,21
Video Game Console	10,466	1,75		
Fast-Moving Electronic Appliances	1,202	1,34	11	0,73
Software	8,950	1,26		
Computer Hardware	3,025	0,94	510	1,77
DVD	922	0,94		
GPS	1,202	0,91	525	1,58
Toys	1,389	0,90		
Home Appliances	2,243	0,90	13	0,76
Perfume	1,407	0,87		
Small Electronic Goods	2,130	0,86	66	1,31
TV+ Audiovisual	760	0,83	158	1,21
Computer	4,333	0,75		

Accessories				
Housewares	760	0,74		
Others	1,531	0,72		
Jewelry	3,232	0,21		
TOTAL	42,042	1,12	1,557	1,90

Tab.2: Means of Actual Revenues per Auction form Ascending Auctions

Product Category	Number of Items sold	Profit in €	Product Profit in €	Bidding Profit in €	Avg.Profit	Avg.Price (% of RRP)	Avg.RRP	Avg.Product cost
Video Game Console	10,466	2,128,370.34	- 1,544,282.66	3,672,653.00	203,36	70.17(29%)	241.92	217.73
Computer Hardware	3,025	819,639,26	- 721,607.24	1,541,246.50	270,96	45.31(11%)	405.50	283.85
Software	8,950	407,528.06	- 277,780.44	685,308.50	45.53	15.32(23%)	66.23	46.36
GPS	1,103	286,207.35	- 296,880.66	583,088.01	259.48	41.32(9%)	444.99	310.48
TV+Audio Visual	760	129,784.76	- 210,714.24	340,499.00	170.77	48.62(10%)	465.54	325.88
Fast Moving Electronic appliances	1,202	108.326,18	- 176.131.32	284,457.50	90.12	46.92(22%)	214.95	193.46
Home Appliances	2,243	45.769.87	- 162,152.63	207,922.50	20.41	17.76(14%)	128.65	90.05
Small Electronic Goods	2,130	40,269.87	- 126,707.63	166,968.50	18.90	15.12(14%)	106.58	74.61
Perfume	1,407	19,583.38	- 36,911.62	56,495.00	13.92	8.03(14%)	57.11	34.26
Toys	1,389	12,638.26	-	52,415.00	9.10	7.55(15%)	51.69	36.18

			39,776.74					
Computer Accessories	4,333	10,374.00	- 136,620.50	146.994.50	2.39	6.78(12%)	54.74	38.31
DVD	922	5,837.83	- 13,376.67	19,214.50	6.33	4.17(16%)	26.68	18.68
Housewares	407	2,389.73	- 21,468.77	23,858.50	5.87	11.72(13%)	92.10	64.47
Cash	11	1,632.40	- 1,002.10	2,634.50	148.40	47.90(34%)	139.00	139.00
Other	1,531	1,538.45	- 69,810.56	71,349.01	1.00	9.45(12%)	80.34	56.23
Free Bid Vouchers	43	22.20	- 1,268.50	1,268.50	0.52	5.90(17%)	34.88	34.88
Jewelry	3,232	- 315,803.27	- 712,006.77	396,203.50	-97.71	24.51(3%)	816.04	244,81
TOTAL	43,154	3,704,099.66	- 4,548,477.56	8,252,576.52	85.83	25.09(12%)	201.58	129.96

Tab.3: Profit of pay-per-bid ascending auctions across Product Categories

Product Category	Profit of Swoopo	Profit of Online Retailer	Difference absolute	% increase	Share of Profitable standard auction	Share of profitable penny auction	Number of standard auction	Number of penny auction
Video Game Console	2,128,370.34	253,190.89	1,875,179.45	741%	74.36%	100.00%	10,465	1
Computer Hardware	819.639.26	367,995.32	451,643.94	123%	43.07%	65.23%	2,585	440
Software	407,528.06	177,779.80	229,748.26	129%	57.96%	0.00%	8,949	1
GPS	286,207.35	148,365.44	137,841.91	93%	28.20%	61.88%	633	480
TV+Audio Visual	129.784.76	106,008.43	23,776.33	22%	36.45%	45.86%	627	133
Fast Moving	108,326.18	25,837.02	82,489.16	319%	58.74%	18.18%	1,191	11

Electronic Appliances								
Home Appliances	45,769.87	86,555.43	-40,785.56	-47%	45.52%	38.46%	2,230	13
Small Electronic Goods	40,260.87	67,970.90	-27,710.03	-41%	45.31%	53.57%	2,102	28
Perfume	19,583.38	32,158.82	-12,575.44	-39%	55.08%	n.a.	1,407	0
Toys	12,638.26	21,523.71	-8,885.45	-41%	49.60%	n.a.	1,389	0
Computer Accessories	10,374.00	71,150.24	-60,776.24	-85%	43.07%	65.23%	2,585	440
DVD	5,837.83	7,379.81	-1,541.98	-21%	48.59%	n.a.	922	0
Housewares	2,389.73	11,245.91	-8,856.18	-79%	40.29%	n.a.	407	0
Cash	1,632.40	-	-	-	81.82%	n.a.	11	0
Other	1,538.45	36,006.43	-34,467.98	-96%	34.94%	0.00%	1,528	3
Free Bid Vouchers	22.20	-	-	-	41.86%	n.a.	43	0
Jewelry	-315,803.27	1,846,214.29	- 2,162,017.56	-117%	21.97%	0.00%	3,231	1
TOTAL	3,704,099.68	3,259,382.44	444,717.24	14%	52.00%	60.00%	42,042	1,1112

Tab.4: Comparison of Profit of Swoopo with Profit of a Comparable Online Retailer and Share of Profitable Auctions

Penny auction

Article Category	**N**	**Mean Profit**	**Mean Price**	**Mean Number of bids**	**Mean standardized revenue**	**Standard Deviation**
GPS	480	467.19	16.45	1645	1.57	1.48
Computer Hardware	440	1,398.32	43.23	4323	1.83	1.89
TV+Audio	133	534.34	26.02	2602	1.16	1.32
TOTAL	1,112				1.58	1.64

Ten-Cent Auction

Article Category	**N**	**Mean Profit**	**Mean Price**	**Mean Number of bids**	**Mean standardized revenue**	**Standard Deviation**
GPS	623	99.45	60.49	605	0.91	0.77
Computer Hardware	2,585	79.06	45.66	457	0.94	0.80
TV+Audio	627	93.65	53.42	534	0.83	0.75
TOTAL	42,042				1.12	1.02

Mean standardized revenue, defined as revenue/RRP; RRP:recommended retail price

Tab.5: Profit Comparison of Standard versus Penny Auction

Product Category	**Average number of bids**	**Average number of bids from winner**	**Average bidding fees paid by winners in €**	**Average number of bids from losers**	**Average bidding fees paid by losers in €**
GPS	1,057.28	152.26	76.13	905.02	452.51
Computer Hardware	1,019.01	154.54	77.27	864.47	432.24
TV+Audio Visual	896.05	153.88	76.94	752.17	371.09
Video Game Console	701.83	79.38	39.69	622.45	311.23
Cash	479.00	107.55	53.78	371.45	185.73
Fast moving Electronic Aplliances	473.31	73.34	36.67	399.96	199.98
Jewelry	245.18	54.44	27.22	190.73	95.37
Home Appliances	185.40	44.08	22.04	141.31	70.66
Small Electronic Goods	156.78	34.25	17.13	122.53	61.27
Software	153.18	24.60	12.30	128.57	64.29
Housewares	117.24	29.71	14.86	87.53	43.77
Other	95.51	26.07	13.04	69.44	34.72
Perfume	80.31	19.51	9.76	60.79	30.40
Toys	75.47	18.88	9.44	56.60	28.30

Computer Accessories	67.85	17.02	8.51	50.83	25.42
Free Bid Vouchers	59.00	16.00	8.00	43.00	21.50
DVD	41.68	11.85	5.93	29.83	14.92
TOTAL	347.30	59.84	29.92	287,.45	143.73

Tab.6: Average Number of Bid from Winner and Losers across Categories

	Standard auction			**Penny auction**		
	mean	sum	Standard deviation	mean	sum	Standard deviation
Consumer surplus of winners in €	**141.62**	**5,950,668.45**	**239.49**	**659.15**	**731,178.49**	**370.03**
Jewelry	766.29	2,475,870.48	433.36	n.a.	n.a.	n.a.
GPS	259.87	161,899.45	149.11	427.02	204,968.64	125.09
TV+Audio Visual	218.70	137,123.23	290.96	942.43	125,343.64	362.53
Computer Hardware	188.75	487,921.52	173.55	869.60	382,625.54	371.75
Video Game Console	134.93	1,412,086.03	94.20	n.a.	n.a.	n.a.
Fast moving electronic appliances	132.73	158,080.24	127.96	302.51	3,327.60	60.36
Home appliances	88.08	196,418.38	110.36	587.72	7,640.37	290.45
Small electronic goods	74.16	155,920.26	64.99	197.14	5,519.97	201.53
Housewares	66.92	27,236.66	54.45	n.a.	n.a.	n.a.
Other	58.07	86,586.86	55.12	584.24	1,752.73	173.84
Perfume	40.11	56,441.04	19.81	n.a.	n.a.	n.a.
Computer	40.00	173,262.98	33.06	n.a.	n.a.	n.a.

Accessories						
Software	39.73	355,505.79	30.16	n.a.	n.a.	n.a.
Cash	38.51	423.60	55.34	n.a.	n.a.	n.a.
Free Bid Vouchers	38.51	999.30	28.04	n.a.	n.a.	n.a.
Toys	35.30	49,028.63	27.95	n.a.	n.a.	n.a.
DVD	17.21	15,863.98	10.09	n.a.	n.a.	n.a.
Consumer surplus of losers in €	**-137.10**	**-5761,262.50**	**197.24**	**-1,227.31**	**-1.365,893.00**	**1,675.39**
Video Game Console	-314,16	-3,287,700.50	240.15	n.a.	n.a.	n.a.
GPS	-244.48	-152,310.00	248.25	-734.17	-352,400.00	747.81
TV+Audio Visual	-215.12	-134,881.50	390.26	-1,137.05	-151,227.00	1,443.08
Fast moving electronic appliances	-202.92	-241,683.00	212.53	-201.27	-2,214.00	205.80
Cash	-186.91	-2,056.00	122.30	n.a.	n.a.	n.a.
Free Bid Vouchers	-186.91	-1,021.50	43.93	n.a.	n.a.	n.a.
Computer Hardware	-184.29	-476,395.50	251.55	-1,922.26	-845,795.50	2,227.81
Jewelry	-97.33	-314,479.50	101.18	n.a.	n.a.	n.a.
Home appliances	-69.58	-155,153.00	105.06	-623.85	-8,110.00	824.67
Software	-65.42	-585,354.00	78.38	n.a.	n.a.	n.a.
Small electronic goods	-60.75	-127,694.00	78.77	-210.77	-5,901.50	349.52
Housewares	-45.16	-18,380.50	54.47	n.a.	n.a.	n.a.
Other	-35.58	-53,047.00	48.81	-81.67	-245.00	46.65
Perfume	-31.19	-43,884.00	27.09	n.a.	n.a.	n.a.
Toys	-28.89	-40,127.00	31.53	n.a.	n.a.	n.a.

Computer Accessories	-26.03	-112,773.50	36.06	n.a.	n.a.	n.a.
DVD	-15.54	-14,322.00	15.71	n.a.	n.a.	n.a.
Total consumer surplus in €	**4.53**	**189,405.95**	**300.51**	**-568.16**	**-631,792.71**	**1,704.41**

Tab.7: Consumer Surplus of Winner and Loser

Conclusion

This paper presents a parsimonious theoretical model of rational bidders in a pay-per-bid auction. In the symmetric subgame perfect equilibrium potential bidders are indifferent about participating and the exact mixed strategy is determined by this indifference condition. Using these mixed strategies we can establish that expected revenue will be near the bidders evaluation of the auctioned item. In sum, pay-per-bid auctions are essentially a form of gambling or entertainment shopping. Thus it is not surprising that participants bear some resemblance to gamblers from other settings. On a broader level, the pay-per-per auction describes an incremental king-of-the-hill contest. The contest is incremental because each replacement of a king reduces the hill´s value to the eventual winner.

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Abstract

Today online shopping is widely accepted in the developed countries due to various factors like convenience, product comparison, 24x7 availability etc. In the present scenario, the internet is not only a source of communication and entertainment, but increasingly a medium of business transactions for

entrepreneurs as well. This paper is the first to empirically analyze pay-per bid ascending auctions, the new exciting, fast –paced B-to-C online auctions that where recently introduced to the internet, and which are attracting significant interest from consumers and start-ups. The aim of the empirical study is to investigate, when and how often pay-per bid auctions are profitable for auctioneers as well as when and how many bidders realize savings.