Summer 6-30-2018

A Study on Consumers' Learning Effect in the Price Reduction Auction: a case study of Gongtianxia

Yanan Xu
Information Institute, RENMIN UNIVERSITY of CHINA, Beijing 100872, China

Bo Yang
Information Institute, RENMIN UNIVERSITY of CHINA, Beijing 100872, China

Rong Zhang
Information Institute, RENMIN UNIVERSITY of CHINA, Beijing 100872, China

Pengfei Xie
Information Institute, RENMIN UNIVERSITY of CHINA, Beijing 100872, China

A Study on Consumers' Learning Effect in the Price Reduction Auction: a case study of Gongtianxia

*Yanan Xu, Bo Yang *, Rong Zhang, Pengfei Xie*
Information Institute, RENMIN UNIVERSITY of CHINA, Beijing 100872, China

Abstract：GongTianXia's "7 days shot" and "15 minutes shot" is a very typical online price reduction auction. By studying the learning effect of consumers in this online price reduction auction, this paper hopes to provide some suggestions for the formulation of marketing strategy of GongTianXia. Through the research of related literature and the deep analysis of consumer purchasing decision theory, the research problem is divided into two aspects. First, with the increase in the number of participants, whether the proceeds of the auction goods are gradually increasing. Second, with the increase in the number of participants, whether the grasp of the timing is more and more accurate. Through the statistical analysis of the auction data of GongTianXia, this paper verified the existence of consumer learning effect in the price reduction auction.

Keywords：Price reduction auction; Learning effect; Consumer purchase decision theory

1. INRODUCTION

From the beginning of 2014, Gongtianxia.com carried out agricultural and sideline products price-reduction auctions, which were mainly divided into "7-day auction" and "15-minute auction" two types[1]. 7-day auction gets new goods on shelf at 10 pm on the first day, and sets this time as 1st day of the auction of this goods with the initial auction price. Then the auction price will be reduced to a certain price by the platform at 10 pm in the next 6 days, which happened only once at 10 o'clock. It is possible for consumers to bid the good at that certain price during this auction period until 10 pm of the next day. When auction comes to 10 pm of the seventh day, auction price will drop to 1 yuan for all goods. There is a special rule that the total amount of an auction good is limited, which means auction can be stopped in advance if all the auction goods are sold out. The rule of 15-minute auction is similar to 7-day auction. It differs from 7-day auction's rule in the price-dropping interval, and the price will drop to 1 yuan at the last auction period. Both "7-day auction" and "15-minute auction" are [1]an efficient marketing method to stimulate the consumers' purchasing behavior[1].

The definition of *Learning Effect* is staffs can accumulate experience about product production, technical design or management during long-term production process in order to enhance their productivity and reduce average production cost[3]. Through rough observation of our collected data of Gongtianxia.com, we found one user of platform took a gradually higher bid and stayed stable on a particular price tier during his auction experience[5]. There still remains necessity to test whether a single user's auction purchase behavior is significantly influenced by learning effect. We hope our research can analyze and explain the learning effect in this novel marketing mode, thus provide some suggestions on making marketing strategies for auction E-commerce platform.

2. RESERCH CONTENT

This paper aimed at research on the learning effect present by individual consumers in the price-reduction auction process of agricultural and sideline products, mainly expanded by the following two problems.

The first problem is with the increase of the participating number of auctions, whether the auction gain is gradually increasing or not, which is represent by the difference between initial auction price (1st price) and the

* Corresponding author. Email: yangbo_ruc@126.com (YANG Bo)

final bidding price[3]. In other words, consumer can decrease their final bidding price payment by choosing a higher auction tier, to get a larger auction gain. This issue aims at proving that there exists a learning effect in the auction of the agricultural and sideline products for consumers essentially. In order to show whether there is a learning effect, we have established a multiple linear regression model. For the linear regression model, we have added the appropriate control variables to make the results more reliable according to the relevant literature and theoretical research. And then the data and then detailed statistics and analysis to prove that in the agricultural and sideline products price reduction in the consumer whether there is a corresponding learning effect.

The second one refers to the grasp accuracy of the bidding timing with the increasing participating times. We can also divide this problem into two issues. One is the estimation accuracy of the last auction tier (because auction will be stopped before 7th tier if goods are sold out). The other is about the time length used for finalizing their bidding on a particular price tier[3]. Due to the limited amount of remaining goods, the faster a consumer bids for the good, the more possible he can finalize their bidding for this auction.

3. LITERATURE REVIEW

The price-reduction auction, also known as the Dutch auction and originated in the Dutch flower market, is a typical auction type for flower sales[1]. As for sales promotion, Ding and Guo (2005) attached importance to analysis on Dutch auction from economic perspective, and took advantage of empirical research[1]. Jennifer Neujahr and Qiao (2006) discussed the problems existed in the auction[9]. Zhang (2007) analyzed the existing situation and some unique characteristics of Chinese domestic flower auction market in detail, and summarized the shortcomings of it[9]. Qin (2012) systematically and comprehensively studied the law of possible price fluctuation in Chinese domestic agricultural auction market and the related great influencing factors[13].

Learning Effect dated back to 1930s. Wright (1936) found that the unit time of the production aircraft would be reduced by 20% when the aircraft production was doubled in the study of aircraft production costs[8]. For a relatively long period of time, studies of learning effects have been mostly concentrated in the production of manufacturing enterprises. Nowadays, the study of learning effect has been extended to many industry fields. In recent years, there has been some articles about the research on consumer behavior in online auctions affected by learning effect. PB Goes，GG Karuga，AK Tripathi (2012) set research object as consumer behavior in online auctions and explained the decision process by an experience model[10]. Their research found that consumers' decision was influenced by auction desires, previous related experience and a few parameter design in auctions. H Zheng, KY Goh, KW Huang (2011) analyzed consumer behaviors under "1-cent auction" mode, and achieved optimization by adjusting limit conditions[14]. Ma (2014) constructed a mathematical model based on influence of learning effect made on enterprises' promotion activities[14]. However, most related researches focused on learning effect on enterprise level instead of individual behaviors.

4. CHANGES OF CONSUMERS' BIDDING GAIN WITH THE INCREASE OF AUCTION PARTICIPATING TIMES

Consumers generate learning effects in order to obtain a more favorable price advantage in the auction[8]. In the initial auction, due to restrictions on auction total amount and inadequate understanding of the auction, so consumers are willing to give up part of price advantage to grab inexpensive goods, that is, consumers might bid on a relatively low price tier (high price) from their beginning use of the auction E-commerce platform. With the increase in the number of auctions consumer had participated, consumers had a better understanding of the auction process, then he will try to adjust his own auction prices to increase their biding gain. We recognized this adjustment as an expression of auction learning effect. We built a multiple linear regression model in order to verify our basic hypothesis quantifiably and intuitively.

4.1 Variable selection

Firstly, we decided on the selection of dependent and independent variables. Based on literature review, we knew learning effect made great effect on consumer’s auction behavior, so it could be verified if the auction behavior were influenced largely by previous bidding. As for consumer's auction behavior, the final bidding price is an important measure of consumer auction behavior. However, different goods have different prices, so it was not feasible to set the price directly as a variable. Considering the bidding rules of both 7-day auction and 15-minute auction, we found standard seven price tiers could represent the auction prices of various goods, which simplified the standardized process. But as a typical categorical variable, it should not be applied to linear regression. As a result, we introduced price reduction extent, which seen as a bidding gain for consumer from another prospective. In summary, we set bidding gain (price reduction extent for purchased good in this time) in current auction as dependent variable, and bidding gain in previous auction.

Secondly, suitable control variables contributed much to the accuracy of regression model, which is related to consumers’ bidding psychology. Consumer purchase decision-making theory refers to the evaluation and final selection of the properties of goods during the purchase process of a specific type of goods[15]. The whole process includes the determination of consumer needs, the emergence of the purchase motive, the analysis and selection of a variety of commodity purchase options, and following series of practical test after the purchase. The information available from the data collected on Gongtianxia E-commerce platform is primarily relevant to the marketing activities of the price-reduction auction. For the sake of the bidding gain obtained in each auction, all historical, current and future price were still the first consideration of consumers to determine their purchase[17]. As a result, we decided to add seven price-reduction extent to our model as control variables, which were processed in advantage of seven price tiers. 1st price-reduction extent was equal to 0 constantly, so there were six price-reduction extents in total actually. In addition, total remaining amount is limited in one price-reduction auction, stimulating and reminding consumers to bid as soon as possible, so our research considered remaining number of goods as a control variable. Finally, according to the habits of consumers to buy goods through online E-commerce, whether set free for delivery or not, should be included into the linear regression as a control variable.

4.2 Linear multiple regression model of consumer’s bidding gain

We constructed following linear multiple regression model to test whether current consumer’s bidding gain is connected with the previous one on the basis of explanation in 4.1.

$$\begin{aligned} BG(i,j,t) = {} & \beta_0 + \beta_1 * BG(i,j,t-1) + \alpha_1 * PR_2(i,j,t) + \alpha_2 * PR_3(i,j,t) + \alpha_3 * PR_4(i,j,t) + \alpha_4 * PR_5(i,j,t) \\ & + \alpha_5 * PR_6(i,j,t) + \alpha_6 * PR_7(i,j,t) + \alpha_7 * AMT(i,j,t) + \alpha_8 * DEL(i,j) + \varepsilon(i,j,t) \end{aligned} \quad (1)$$

Among them, BG(i,j,t) means the bidding gain obtained by the consumer$_i$ bids for jth kind of goods for the tth time, while PR$_n$(i,j,t) means the nth price reduction extent when the consumer$_i$ bids for jth kind of goods for the tth time. AMT(i,j,t) and DEL(i,j) means the remaining amount of the goods and whether it was free for delivery when consumer$_i$ bids for jth kind of goods for the tth time. ε(i,j,t) is the random error.

4.3 Regression result

4.3.1 7-day auction mode

Table 1. Abstract of regression models

Model	R	R^2	Adjusted R^2	Standard estimation error	Change statistics				
					Change of R^2	Change of F	Degree of freedom 1	Degree of freedom 2	Change of Sig. F
1	.709[a]	0.502	0.502	0.1065168	0.502	4672.713	1	4628	0.000
2	.765[b]	0.586	0.586	0.0971946	0.083	931.342	1	4627	0.000
3	.774[c]	0.599	0.598	0.0956798	0.013	148.670	1	4626	0.000
4	.776[d]	0.603	0.602	0.0952095	0.004	46.818	1	4625	0.000
5	.777[e]	0.604	0.604	0.0950419	0.001	17.327	1	4624	0.000
6	.778[f]	0.606	0.605	0.0948867	0.001	16.137	1	4623	0.000

a. Estimation variable: (Constant), BG(t-1)

b. Estimation variable: (Constant), BG(t-1), PR6

c. Estimation variable: (Constant), BG(t-1), PR6, AMT

d. Estimation variable: (Constant), BG(t-1), PR6, AMT,DEL

e. Estimation variable: (Constant), BG(t-1), PR7, AMT,DEL,PR5

f. Estimation variable: (Constant), BG(t-1), PR7, AMT,DEL,PR5, PR7

Table 2. ANOVA analysis result

Model		Sum of squares	Degree of freedom	Mean square	F	Sig.
1	Regression	53.016	1	53.016	4672.713	.000[b]
	Residual	52.509	4628	0.011		
	Sum	105.524	4629			
2	Regression	61.814	2	30.907	3271.693	.000[c]
	Residual	43.710	4627	0.009		
	Sum	105.524	4629			
3	Regression	63.175	3	21.058	2300.296	.000[d]
	Residual	42.349	4626	0.009		
	Sum	105.524	4629			
4	Regression	63.599	4	15.900	1754.014	.000[e]
	Residual	41.925	4625	0.009		
	Sum	105.524	4629			
5	Regression	63.756	5	12.751	1411.630	.000[f]
	Residual	41.768	4624	0.009		
	Sum	105.524	4629			
6	Regression	63.901	6	10.650	1182.898	.000[g]
	Residual	41.623	4623	0.009		
	Sum	105.524	4629			

a. Dependent variable: BG(t)

b. Estimation variable: (Constant), BG(t-1)

c. Estimation variable: (Constant), BG(t-1), PR6

d. Estimation variable: (Constant), BG(t-1), PR6, AMT

e. Estimation variable: (Constant), BG(t-1), PR6, AMT,DEL

f. Estimation variable: (Constant), BG(t-1), PR7, AMT,DEL,PR5

g. Estimation variable: (Constant), BG(t-1), PR7, AMT,DEL,PR5, PR7

As shown in Table 1, we adopted a stepwise regression method, and the last bidding gain (BG(t-1)) was the first independent variable to enter the regression equation, earlier than several price reduction extents, remaining amount and free delivery or not[17]. And the contribution of last bidding gain made to the change of R^2 is relatively largest among all variables, which indicated the last bidding gain (BG(t-1)) had the most important influence on current bidding gain earned at this time in 7-day auction mode. R^2 increased gradually with the entrance of other control variables, and reached largest at the 6th regression model. Through the ANOVA result shown in Table 2, the whole regression model is significant.

Table 3. Coefficient results

Model		Non-standardized coefficient		Standardized coefficient	t	Sig.
		B	Standard error	Beta		
1	(Constant)	0.258	0.006		40.686	0.000
	BR(t-1)	0.650	0.010	0.709	68.357	0.000
2	(Constant)	0.077	0.008		9.354	0.000
	BR(t-1)	0.444	0.011	0.485	40.492	0.000
	PR6	0.455	0.015	0.365	30.518	0.000
3	(Constant)	0.042	0.009		4.829	0.000
	BR(t-1)	0.428	0.011	0.467	39.291	0.000
	PR6	0.551	0.017	0.442	33.087	0.000
	AMT	0.000	0.000	-0.132	-12.193	0.000
4	(Constant)	0.053	0.009		6.003	0.000
	BR(t-1)	0.416	0.011	0.453	37.844	0.000
	PR6	0.564	0.017	0.453	33.827	0.000
	AMT	-9.7E-05	0.000	-0.108	-9.509	0.000
	DEL	-0.023	0.003	-0.070	-6.842	0.000
5	(Constant)	0.056	0.009		6.355	0.000
	BR(t-1)	0.417	0.011	0.455	38.016	0.000
	PR6	0.759	0.050	0.610	15.262	0.000
	AMT	0.000	0.000	-0.112	-9.871	0.000
	DEL	-0.028	0.004	-0.085	-7.855	0.000
	PR5	-0.227	0.055	-0.158	-4.163	0.000
6	(Constant)	-0.335	0.098		-3.431	0.001
	BR(t-1)	0.412	0.011	0.449	37.314	0.000
	PR6	0.806	0.051	0.648	15.801	0.000
	AMT	0.000	0.000	-0.122	-10.492	0.000
	DEL	-0.037	0.004	-0.112	-8.802	0.000
	PR5	-0.278	0.056	-0.193	-4.967	0.000
	PR7	0.412	0.103	0.047	4.017	0.000

In addition, Table 3 summarized the coefficients of both independent and control variables on dependent variable. The relevance of the consumers' current bidding gain with last bidding gain for the same kind of goods is 0.449 with very great significance. The 2nd, 3rd and 4th price reduction extent was excluded from the regression model at last, which might be connected with the habit that consumers mostly showed much more concern with higher price tier (lower bidding price). Previous four price tiers did not present so much attraction for consumers.

Through Table 3, we got the linear regression model of 7-day auction mode (1).

$$BG(i,j,t)=\beta_0+0.449*BG(i,j,t-1)-0.197*PR_5(i,j,t)+0.648*PR_6(i,j,t)+0.047*PR_7(i,j,t) \\ -0.122*AMT(i,j,t)-0.112*DEL(i,j)+\varepsilon(i,j,t) \quad (2)$$

We found that the last bidding gain had a positive effect on current bidding gain, which indicated that consumers could adjust current auction behavior positively by learning from last auction. The larger the last bidding gain was, the greater current bidding gain was.

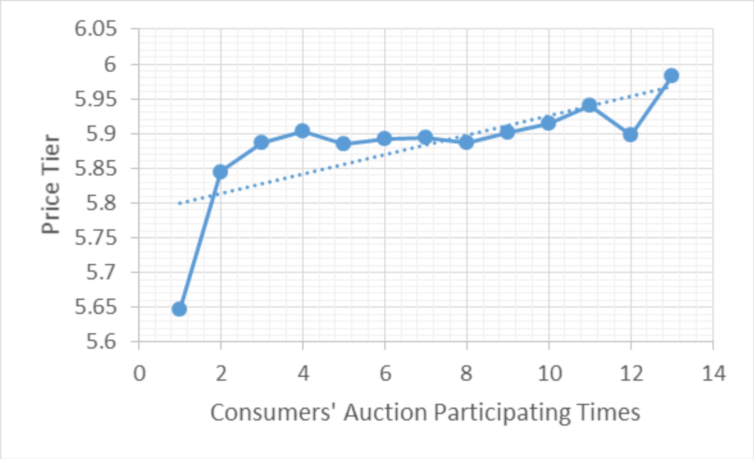

Figure 1. Change of price tier with the increase of auction participating times (7-day)

Next, we needed to focus on the changing trend of bidding price tier with the increase of consumers' auction participating times. Considering the crossover learning impact between different types of goods and the limited amount of auction data, we would not categorize the type of auction goods in the research process of descriptive statistics. Finally we could describe the relationship between bidding price tier and auction participating times shown in Figure 1. In 7-day auction, consumers tended to bid on a gradually higher price tier to obtain lower bargain price at the beginning. When they took part in the auction for more than 4 times, average price tier started to become steady. Fluctuation would occur when times reached more than 10, which might be relevant to exposure of remaining amount and other external pressure. As a whole, bidding price tier presented a upward trend with the increase of consumers' auction participating times in the 7-day auction.

4.3.2 15-minute auction mode

Table 4. Abstract of regression models

Model	R	R^2	Adjusted R^2	Standard estimation error	Change statistics				
					Change of R^2	Change of F	Degree of freedom 1	Degree of freedom 2	Change of Sig. F
1	.816[a]	0.666	0.666	0.1160903	0.666	12822.825	1	6419	0.000
2	.873[b]	0.761	0.761	0.0982156	0.095	2550.067	1	6418	0.000
3	.876[c]	0.767	0.767	0.0970944	0.005	150.069	1	6417	0.000
4	.878[d]	0.770	0.770	0.0963346	0.004	102.621	1	6416	0.000
5	.879[e]	0.772	0.772	0.0960342	0.001	41.212	1	6415	0.000
6	.879[f]	0.772	0.772	0.0959877	0.000	7.209	1	6414	0.007

a. Estimation variable: (Constant), BG(t-1)
b. Estimation variable: (Constant), BG(t-1), PR6
c. Estimation variable: (Constant), BG(t-1), PR6, PR3
d. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL
e. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL, PR7
f. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL, PR7, PR2

Table 5. ANOVA analysis result

Model		Sum of squares	Degree of freedom	Mean square	F	Sig.
	Regression	172.813	1	172.813	12822.825	.000[b]
1	Residual	86.509	6419	0.013		
	Sum	259.321	6420			
	Regression	197.411	2	98.706	10232.500	.000[c]
2	Residual	61.910	6418	0.010		
	Sum	259.321	6420			
	Regression	198.826	3	66.275	7030.134	.000[d]
3	Residual	60.495	6417	0.009		
	Sum	259.321	6420			
	Regression	199.779	4	49.945	5381.754	.000[e]
4	Residual	59.543	6416	0.009		
	Sum	259.321	6420			
	Regression	200.159	5	40.032	4340.629	.000[f]
5	Residual	59.163	6415	0.009		
	Sum	259.321	6420			
	Regression	200.225	6	33.371	3621.894	.000[g]
6	Residual	59.096	6414	0.009		
	Sum	259.321	6420			

a. Dependent variable: BG(t)

b. Estimation variable: (Constant), BG(t-1)

c. Estimation variable: (Constant), BG(t-1), PR6

d. Estimation variable: (Constant), BG(t-1), PR6, PR3

e. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL

f. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL, PR7

g. Estimation variable: (Constant), BG(t-1), PR6, PR3, DEL, PR7, PR2

As shown in Table 4 and 5, last bidding gain is still the first variable entering the regression equation, earlier than price reduction extents, remaining amount and delivery condition, indicating the last bidding gain was the greatest influencing factor in 15-minute auction mode similarly. The goodness of fit of this linear regression model can reach 0.772, a little higher than that of 7-day auction mode, and the regression result is strongly significant.

Table 6. Coefficient results

Model		Non-standardized coefficient		Standardized coefficient	t	Sig.
		B	Standard error	Beta		
1	(Constant)	0.145	0.005		29.428	0.000
	BR(t-1)	0.812	0.007	0.816	113.238	0.000
2	(Constant)	-0.005	0.005		-0.986	0.324
	BR(t-1)	0.514	0.008	0.517	60.721	0.000
	PR6	0.520	0.010	0.430	50.498	0.000
3	(Constant)	-0.049	0.006		-7.926	0.000
	BR(t-1)	0.503	0.008	0.506	59.744	0.000

Model		Non-standardized coefficient		Standardized coefficient	t	Sig.
		B	Standard error	Beta		
	PR6	0.705	0.018	0.583	38.650	0.000
	PR3	-0.192	0.016	-0.164	-12.250	0.000
4	(Constant)	-0.018	0.007		-2.604	0.009
	BR(t-1)	0.489	0.008	0.491	57.741	0.000
	PR6	0.676	0.018	0.558	36.811	0.000
	PR3	-0.164	0.016	-0.140	-10.388	0.000
	DEL	-0.026	0.003	-0.064	-10.130	0.000
5	(Constant)	0.387	0.063		6.097	0.000
	BR(t-1)	0.475	0.009	0.478	54.540	0.000
	PR6	0.622	0.020	0.514	30.934	0.000
	PR3	-0.115	0.018	-0.098	-6.569	0.000
	DEL	-0.028	0.003	-0.070	-11.038	0.000
	PR7	-0.392	0.061	-0.047	-6.420	0.000
6	(Constant)	0.373	0.064		5.863	0.000
	BR(t-1)	0.476	0.009	0.479	54.632	0.000
	PR6	0.658	0.024	0.544	27.256	0.000
	PR3	-0.253	0.054	-0.215	-4.661	0.000
	DEL	-0.030	0.003	-0.074	-11.362	0.000
	PR7	-0.374	0.061	-0.045	-6.103	0.000
	PR2	0.102	0.038	0.093	2.685	0.007

We can conclude that last bidding gain significantly affect current bidding gain positively in consumers' auction participating process since it passed both T-test and F-test. At the same time, 4^{th} and 5^{th} price reduction extent did not pass the test, which might related to the auction scenario where consumers paid more attention to the starting and ending stage of the auction due to the high-valued property of goods in 15-minute auction. The linear regression equation is:

$$\begin{aligned} BG(i,j,t) &= \beta_0 + 0.479 * BG(i,j,t-1) + 0.093 * PR_2(i,j,t) - 0.215 * PR_3(i,j,t) + 0.544 * PR_6(i,j,t) \\ &- 0.045 * PR_7(i,j,t) - 0.074 * DEL(i,j) + \varepsilon(i,j,t) \end{aligned} \tag{3}$$

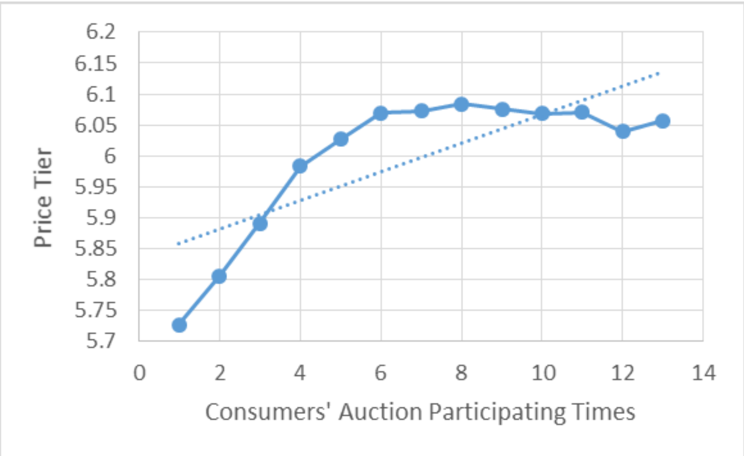

Figure 2. Change of price tier with the increase of auction participating times (15-minute)

Comparing Figure 1 and Figure 2, we found the very similar trend of bidding price tier with the increase of consumers' auction participating times in the 15-minute auction, which went upward firstly and then kept steady. However, the steady pattern appeared after 6 times, later than that in 7-day, 4 times.

5. DESCRIPTIVE ANALYSIS OF CONSUMERS' GRASP ACCURACY OF THE BIDDING TIMING

After the linear regression model, we also wanted to study the trend of consumers' grasp accuracy of the bidding timing as the number of auction participating times increase. Because the linear regression model can only prove that the consumer's last auction behavior significantly affect the current auction behavior, thus proving the existence of consumer learning effect, but it cannot clearly describe the consumer's chosen bidding price tier with the increasing number of auction times. Descriptive statistic method is primarily used for statistical analysis for a situation or data as a whole or a potential connection between them. Therefore, our research also needs to take advantage of this method in order to see whether consumers can grasp the bidding timing more and more accurately when times of participating auctions increase.

Descriptive analysis is divided into two parts: First, we studied the consumer's grasp accuracy of the final price tier (the price tier when all auction goods have been sold out) for the auction. Second, we did some descriptive research on the bidding time from the beginning of the auction at the final price tier.

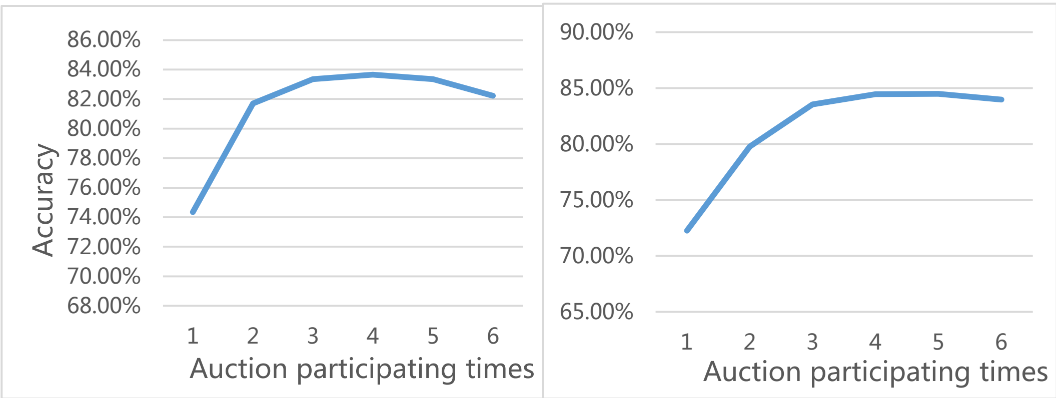

Figure 3. Consumer's grasp accuracy of the final price tier (7-day / 15-minute)

We can see that in both 2 auction modes, with the increase of the number of consumers' participating auctions, consumers' forecast or grasp for the final price tier in the auction was more and more accurate until it arrived at a relatively stable certain level. The curve also complied with the typical learning curve mentioned in the previous introduction. The above figure illustrates the existence of the consumers' learning effect in the price reduction auction of agricultural and sideline products from the view of the consumer's grasp accuracy of the final auction price tier.

Secondly, we were going to verify that with the increase in the number of auction participating times, consumers' bidding reaction time would be shortened or not. The question is raised because the number of goods which sold at a gradually reduced price is limited. This limit probably led to a large number of consumers to bid at the same price tier when auction went to a tipping point, and only the consumers with shorter reaction time was likely to bid the goods successfully.

After extracting the starting time and the consumers' bidding time at the final price tier, we calculated the time span between these two time points, which called as "auction reaction time span". We got the following results eventually.

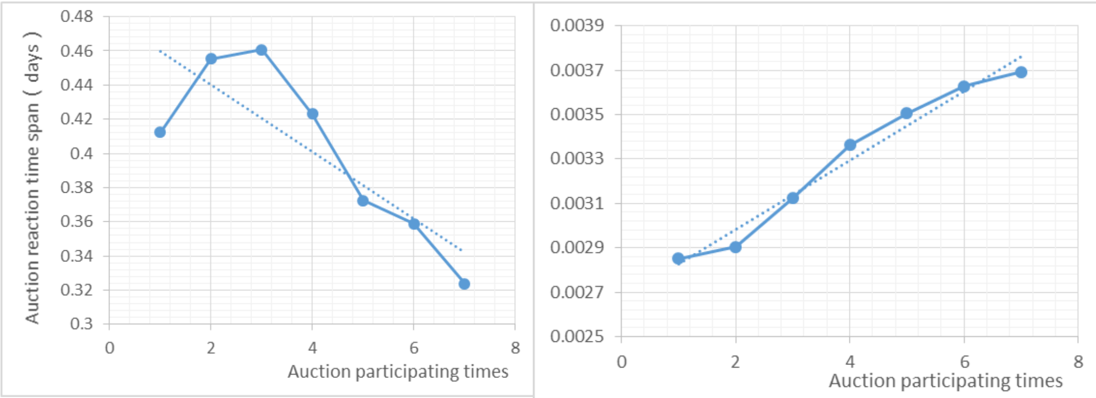

Figure 4. Consumer's auction reaction time span in the final price tier (7-day / 15-minute)

In the 7-day auction, with the increase in the number of auction participating times, the consumers' average auction reaction time span was indeed going down, that is, consumers grasped the bidding timing increasingly accurately. Although there's an increase from the first to the third participating time, the existence of such a fluctuation is mainly because of a certain degree of randomness in the first two times. The overall trend is declining, improving the learning effect on consumers' grasp of bidding time.

However, in the 15-minute auction, the consumer's auction reaction time span increases as the number of auction participating times increased. This result was somehow inconsistent with our guess and 7-day auction result. We attributed the possible reason to the much shorter auction interval compared with 7–day mode and consumer's personal bidding features. For example, auction reaction time spans of consumer A were 9,8 and 7 minutes and so on, and those of consumer B were 5,4 and 3 minutes. If A participated more than 3 auctions, and B did not, then the results will show the 4^{th} average auction time is high. So we adopted an enhanced data processing method, which was to standardize reaction time span according to that of the first auction participating experience for each single consumer, as shown in formula (4) as below. $RTS_{i,t}$ means the reaction time span in the t^{th} participating experience of the i^{th} consumer. And we could draw Figure 4 to describe the relationship between processed reaction time span and auction participating times for 15-minute auction mode.

$$\sum_{i=1}^{N}\frac{RTS_{i,t}-RTS_{i,1}}{RTS_{i,1}}, t=1,2,...,n \qquad (4)$$

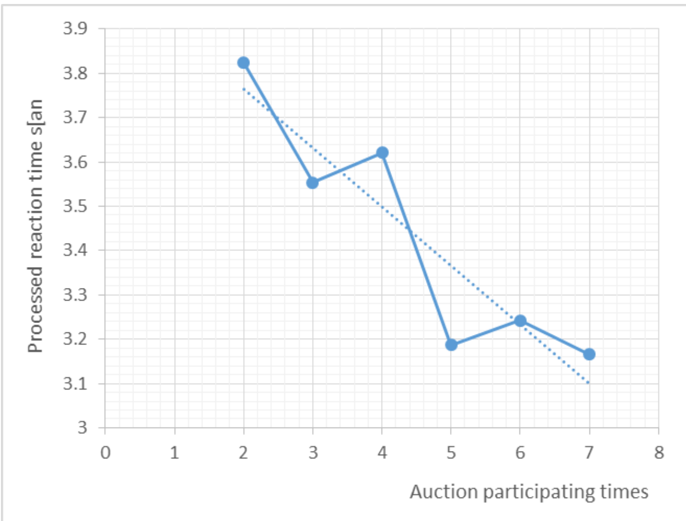

Figure 5. Processed consumer's auction reaction time span in the final price tier (15-minute)

From the above Figure 5, we can see that the consumer's auction time span decreases with the increase in the number of auction participating times, proving the existence of consumers’ learning effect for grasping final bidding timing to some extent[19].

6. Conclusion and Prospects

6.1 Research conclusions

This paper analyzed and summarized the collected data, and gives the relevant verification results for the two questions raised at the beginning of the study. Now, we summarize them as follows.

(1) We validated the presence of consumers’ learning effects in both 7-day and 15-minute auction by linear regression model, which showed last bidding gain had significantly positive impact on current bidding gain with consideration of other control variable factors.

(2) We verified the consumer's auction timing grasp accuracy would be improved with the increase in the number of auction participating times. This conclusion can be reflect in more accurate grasp of the final price tier and shorter reaction time span when consumers take part in more auctions.

6.2 Research contributions

The contribution of this paper is divided into two parts. The first part is the theoretical contribution. This article introduced the learning effect to the online price reduction auction of agricultural and sideline products in the E-commerce platform, which fills the blank of relevant research field.

The second part is about practical contribution. This paper confirms the existence of consumer learning effect in the price reduction auction of agricultural and sideline products from two prospective, which especially reflected in the promoted bidding gain of consumers. This finding can potentially provide referential suggestions for price-reduction auction E-commerce platform to concern more about this learning effect in pricing strategy and auction scheme design.

6.3 Research prospects

(1) To improve the data information required for the study

Because the data information we collected is limited in consumers’ personal information details, we hope to follow up and collect more complete data information for further study.

(2) To promote the experimental results of this study

Because this article is mainly carried out on the platform provided by Gongtianxia.com, so it is still necessary to find out whether our experimental results in this article is also applicable to other price-reduction auction.

ACKNOWLEDGEMENT

This research was supported by the Fundamental Research Funds for the Central Universities, and the Research Funds of Renmin University of China 18XN0002. New media enterprise organization and service change driven by technology: Based on the perspective of the communication theory, innovation theory and big data.

REFERENCE

[1] Li Qingqing. Analysis of the price-reduction auctions of agricultural products in China[J]. Modern Business, 2007, (17): 169-170. (in Chinese)

[2] Xu Yongguo. An overview of the economic theory of auction[J]. Economic Research Journal, 2002, (09): 84-91，95.

(in Chinese)

[3] Zhu Miaohui, Qin Kaida. Price Anomaly and Winner’s Strategic Behavior: Evidence from Rose Auctions[J]. Kunming University of Science and Technology, 2016, (02): 119-126. (in Chinese)

[4] Zhao Guoshun. Research on stock price trend prediction based on time series analysis[D]. Xiamen University, 2009. (in Chinese)

[5] Ye Chunming. Study on a new model of scheduling problems for manufacturing companies based on learning effect[J]. Enterprise Economy, 2015, (04): 5-10. (in Chinese)

[6] Hu Tianshi. Research on electronic commerce model of agricultural products in China[D]. Chinese Academy of Agricultural Sciences, 2005: 134. (in Chinese)

[7] Xing Hao. Research on the design of multi-item online auction mechanism based on Agent[D]. Beijing University of Chemical Technology, 2015. (in Chinese)

[8] Zhang Xuefei. The game scheduling problems with learning effect[D]. Qufu Normal University, 2015: 29. (in Chinese)

[9] Ding Meisheng, Guo Suwen. Economic analysis of price reduction auction[J]. Commercial Times, 2005, (18): 87-89，32. (in Chinese)

[10] Goes P B, Karuga G G, Tripathi A K. Bidding behavior evolution in sequential auctions: characterization and analysis[J]. Mis Quarterly, 2012, 36(4):1021-1042.

[11] Jennifer N, Qiao Wei. How can the auction industry in Holland develope sustainably[J]. China Flowers & Horticulture, 2006. (in Chinese)

[12] Zhang Hailiang. Analysis and research on the operation of Chinese flower auction market[D]. Kunming University of Science and Technology, 2007. (in Chinese)

[13] Qin Kaida. Study on the price fluctuation in the auction market of fresh agricultural products[D]. Kunming University of Science and Technology, 2012. (in Chinese)

[14] Zheng Hanxiong, K. Y. Goh, and K. W. Huang. "Evaluating the Impacts of Auction Bidding Restrictions on Consumer Surplus and Behaviors - An Empirical Study of Penny Auctions." International Conference on Information Systems, Icis 2011, Shanghai, China, December DBLP, 2011:3546-3556.

[15] Ma Xichen. Analysis of the promotion effect based on the theory of consumers' learning[D]. Shanxi University of Finance and Economics, 2014. (in Chinese)

[16] Li Xingmei, Zhang Qian, Zhao Xinchao, Qi Jianxun. Research on the project network model based on the double effect of learning effect and time conversion constraint[J]. Journal of Industrial Engineering and Engineering Management, 2015, (02): 63-69. (in Chinese)

[17] Hu Ziwei. The application of mathematical statistics in data analysis[J]. Economic & Trade,2016. (in Chinese)

[18] She Lingling. Consumers' psychological factors effect on the result of two different sales promotion tools[D]. Huazhong Agricultural University, 2010: 84. (in Chinese)

[19] Liu Yang, Zhu Hui. Research on consumer behavior under modern electronic commerce[J]. China Journal of Commerce, 2010,25:133-134. (in Chinese)

[20] Katok E, Kwasnica A M. Time is money: The effect of clock speed on seller’s revenue in Dutch auctions[J]. Experimental Economics, 2008, 11(4):344-357.