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SWITCHING BEHAVIOR IN ONLINE AUCTIONS: EMPIRICAL OBSERVATIONS AND PREDICTIVE IMPLICATIONS

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ABSTRACT

There has been substantial work exploring strategies, both theoretical and empirical, for selling and buying in online auctions. However, much of this work has considered single auctions in isolation, partially because it is hard to examine multiple simultaneous auctions using traditional math modeling approaches. In reality, many auctions occur simultaneously, so there is competition not just among bidders, but also among auctions. In this paper, we use simulation to explore bidders' switching behavior between auctions for similar products. Using an empirical dataset, we first examine the distribution of switching and associated bidding behavior in real auctions. We use this data to create an agent-based model that reproduces the price process observed in the empirical data. Using this model we then explore the effects of: (1) different switching distributions, (2) the switching rule, i.e., which auction to switch to, and (3) different auction start rates. In the end, we show that in order to maximize the final price and to minimize the price disparity, auction platforms should encourage users to switch to a low-price auction that is ending soon.

1 INTRODUCTION

Price dispersion of online auctions exists even among auctions selling the exact same item. In this research, we discuss one of the possible causes of this phenomena – bidders' resistance to switch auctions. The reason behind bidders' resistance is associated with search costs (Haruvy and Leszczyc 2010), i.e., the information about similar auctions that is readily available to bidders is limited, which requires bidders to put in significant time to search for another auction that matches their needs.

There has been intensive investigation of bidders' behavior and various proposed strategies for Internet auctions, but very little of it has investigated multiple auctions and switching behavior in these auctions. Bapna et al. (2004) developed a taxonomy of bidding behavior in online auctions, in which early bidders and snipers are identified through empirical data of online auctions. Roth and Ockenfels (2002), and Easley and Tenorio (2004) focus their studies on sniping behavior and jump bidding respectively. Haruvy and Leszczyc (2010) discussed bidders' search and choice in simultaneous online auctions and their impact on price dispersion. Ariely and Simonson (2003) talked about bidders' value assessment and decision dynamics in online auctions. Jank and Zhang (2011) proposed a functional forecast model of auction price to assist bidders' bidding decision. Chu and Shen (2006) concluded that the best strategy is bidding one's

Table 1: Frequency table of bidders' number of auction participated.

Num of Auctions	1	2	3	4	5	6	7	8	9	10	11	12
Frequency	4295	865	311	142	79	48	32	8	17	3	7	10
Num of Auctions	13	14	15	16	18	19	22	27	28	35	43	53
Frequency	6	4	3	4	4	2	3	1	1	1	2	1

maximum willingness to pay (WTP) derived from theory of game mechanism design. Gray and Reiley (2007) discussed whether there is any benefit of early bidding and sniping through real-world experiments. Shmueli, Russo, and Jank (2007) proposed a BARISTA model for bid arrivals in online auction, which capture the deadline and earliness effects. Bradlow and Park (2007) modeled the bid amount and timing of bidders through Bayesian estimation of a record-breaking model. Most of this work has been in the space of single auctions, where our work examines multiple competing auctions. Even when researchers have investigated multiple auctions, they have usually done it in the context of sequential auctions, and not simultaneous auctions. For instance, Zeithammer (2007) examined forward-looking strategies through theoretical models and concluded that with perception of future auctions, bidders would strategically shade their bids down comparing to the single auction setting. Our work differs from all of this previous work in that we are examining why users decide to switch between multiple auctions. Moreover, our goal is not purely descriptive, but instead we also hope to offer prescriptions for auction platforms interested in encouraging users to stay on their platform.

In this research, we design a multiple auction agent-based model (ABM) (Page 2005) to examine the influence of bidders' switching behavior on price dispersion by providing bidders' with information of contemporary auctions. This study provides three useful insights for auction platforms and participants. First, by reducing the price difference between auctions selling the same item, the risk for both bidders and sellers is reduced, which will lead to an increase of customers' satisfaction for both groups of users. Second, providing information about additional auctions will give the auction platform better customer retention, by successfully promoting bidders' switching behavior, because participating in a new auction serves as an incitement for bidders to check back and stay on the same auction platform. Third, increasing switching behavior will increase the average closing price, since more bidders will stay in the auction platform which will increase the level of competition. This in turn will lead to increasing the profits of sellers and online auction websites.

The remainder of this paper is organized as follows. In Section 2, we give an overview of the data and describes exploratory analyses. Section 3 describes the simulation model of multiple online auctions used to test the effect of bidders' switching behavior. In Section 4, we present the simulation experiment test results, and Section 5 presents conclusions.

2 DATA DESCRIPTION

Our research is based on a dataset of digital camera auctions obtained from eBay.com. We examine auctions that were selling brand new Canon SD1000 digital cameras without accessories. There are 1155 auctions and 19,007 bidding records. On average, there are ~ 8 different bidders and ~ 16 bids per auction. In total, 5849 bidders participated in the auctions and 1554 (26.6%) of them participated in more than one auction. Also, $\sim 40\%$ (2428) of bidders only placed 1 bid while the other $\sim 60\%$ (3421) of bidders placed all other 16,579 bids. Table 1 shows the frequency with which bidders' participated in auctions. $\sim 73\%$ of all the bidders left the platform after participating in just one auction. However, there are some very enthusiastic bidders who participated in more than 10 auctions.

We are particularly interested in bidders' switching behavior. If a bidder bids on another auction before her previous auction ends, then this bid is considered to be a *switching bid*. There are 1320 bidders who placed returning bids before the previous auctions ended, which means they were facing the option of continuing to bid on the same auction or switching to another auction, i.e., they could have place a switching bid. The proportion of switching bids for each bidder is calculated as in Equation (1).

$$\text{p.switch} = \frac{\text{Num. switching bids}}{\text{Num. staying bids + Num. switching bid}} \tag{1}$$

3 MULTI-AUCTION MODEL DESCRIPTION

In this section, we describe the general set-up of our simulation framework. We conduct our simulations using an agent-based model.

An agent-based model is a framework that consists of computational, autonomous decision-making entities, which often represent individuals, who interact repetitively within the framework (Bonabeau 2010). Each individual, called an agent, evaluates the information they have about the environment and makes decisions based on rules set by the modeler. The goal of using ABM is to experiment and observe the phenomena or consequences generated from the collective behavior of agents. In the last few years, agent-based modeling has become a useful and popular tool to carry out experiments in social science studies.

One of the main reasons for the recent increase in the popularity of agent-based models is that it enlarges the set of questions researchers can explore (Page 2005). In contrast to classical statistical models which rely on restrictive – and at times unrealistic – assumptions (such as linearity, homogeneity, normality and stationarity) which are often imposed for mathematical analysis and proof rather than realistic applicability, agent-based models operate within a framework of minimal, simple and realistic rules. As a result, agent-based modeling (ABM) allows researchers to examine issues that have been avoided previously in theoretical disciplines and for which mathematical and analytical derivation is impossible (Bankes 2002).

3.1 Switching Design

The multi-auction model is designed based upon a single online auction model as described in a previous paper (Guo, Jank, and Rand 2011). The bidders' arrival process to an auction is kept the same in the multi-auction setting. And each arriving bidder is given a designated auction, when they arrived in the multi-auction system. Different from the single auction model, upon each arrival, the bidder could switch to other auctions. For each visit to an auction, a bidder will first check if she is still the current winner of the auction. If so, he/she will not take any action, except coming back at the next scheduled time. If she is not the current winner, she will make decisions according to the following rules. Let P_{D} denote the price of the designated auction, P_i's denote price of other auctions and w denote the arrival bidder's willingness to pay for the item.

1. If $P_{\text{D}} \leq \min(P_i)$, i.e., the bidder's designated auction has the lowest price, then the bidder won't switch.
   (a) Given (1) then if $w > P_{\text{D}}$, the bidder will place a bid and come back on scheduled revisit time.
   (b) Given (1) then if $w \leq P_{\text{D}}$, the bidder will leave the system and will not come back.
2. If $P_{\text{D}} > \min(P_i)$, i.e., there is at least one auction j with $P_j < P_{\text{D}}$, then the bidder might switch.
   (a) Given (2) if $w > P_{\text{D}}$, the bidder will switch with probability q_1 to another auction and with probability $1 - q_1$ stay in the same auction.
   (b) Given (2) if $w \leq P_{\text{D}}$, the bidder will switch with a probability q_2 to another auction and with probability $1 - q_2$ leave the system.

This specifies whether or not a bidder will switch, but we also need to discuss to which auction the bidder will switch. We call the rule for making this decision a *switching strategy*. There are several switching strategies we test in this model. Each switching strategy corresponds to a potential auction recommendation

Table 2: List of variables of multi-auction model.

Level	Notation	Definition	Distribution & Parameters
Auction	$P_{t=0}$	Starting price	$180{\cdot}\mathrm{Beta}(\alpha_p = 0.17, \beta_p = 0.59)$
	N_b	Number of bidders	$\mathrm{Poisson}(\lambda_b = 12.35)$
	T_s	Start Time	Poisson Process($\lambda_a = 6.08$)
Bidder i	w_i	Evaluation of the good	$\mathrm{Normal}(\mu_w = 180, \sigma_w^2 = 21)$
	ρ_i	Bid increment	$\mathrm{Beta}(\alpha_\rho = 1.2, \beta_\rho = 4.2)$
	$t_{i,1}$	First decision time	$10{\cdot}\mathrm{Beta}(\alpha_t = 0.58, \beta_t = 0.34)$
	n_i	Number of revisits	$\mathrm{Poisson}(\lambda_{\mathrm{re}} = 0.97)$
	$t_{i,j}$	Revisit times $j \geq 2$	$\mathrm{Uniform}[t_{i,1}, 10]$
	$p_{\mathrm{switch}i}$	Probability of Switching	Empirical distribution
			Normal distribution
			Constant value

strategy of the online auction website. The switching strategies listed below are conditional on two things: (1) the bidder has decided to switch based on the switching decision discussed above; (2) only auctions with price P_j lower than (a) the price of the bidder's curet auction P_D and (b) the bidder's willingness to pay w are considered as possible targets to switch to for bidding.

1. *MinPrice*: The bidder switches to the auction with lowest price.
2. *Earliest*: The bidder switches to the auction with earliest closing time.
3. *Random of MinPrice*: The bidder randomly switches to one of the n auctions with lowest price. n can be consider as the recommendation limit of the auction platform. When $n = 1$, this switching rule degenerates to the *MinPrice* rule.
4. *Random of Earliest*: The bidder randomly switches to one of the n auctions with the earliest ending times. When $n = 1$, this switching rule degenerate to the *Earliest* rule.
5. *Earliest of MinPrice*: The bidder switches to the auction with earliest time among the n auctions with lowest price.
6. *MinPrice of Earliest*: The bidder switches to the auction with lowest price among the earlest ending n auctions.

3.2 Simulation Framework

We complete the model description section by presenting the simulation process of the multi-auction model. The multi-auction model simulation starts with generating all the random variables as listed in Table 2. Auction starting time is simulated by a Poisson process with parameter λ_a matched to eBay data. As discussed in Section 2, different distributions of bidders' switching probability are tested later in this paper to see if the shape of the distribution has significant influence on the closing price (both the average and standard deviation). For the second step of the simulation, all the auctions starting and ending events, bidders' visit and revisit events are ordered according to the event times. Then the online auction model begins with the earliest event and iterates through each event until the ending time of the simulation. When it comes to auction starting and ending events, the auction status will change to "open" or "close" according to the event type. Therefore, when a bidder visits the auction platform, it is clear which auctions are available for the bidder to choose from. When a bidder places a bid in an auction, the auction's price will change according to the eBay price rules as well as the bids of the current winner and the underlying highest bid of the auction. If a bidder decides to switch auctions, his/her frequency of future revisits

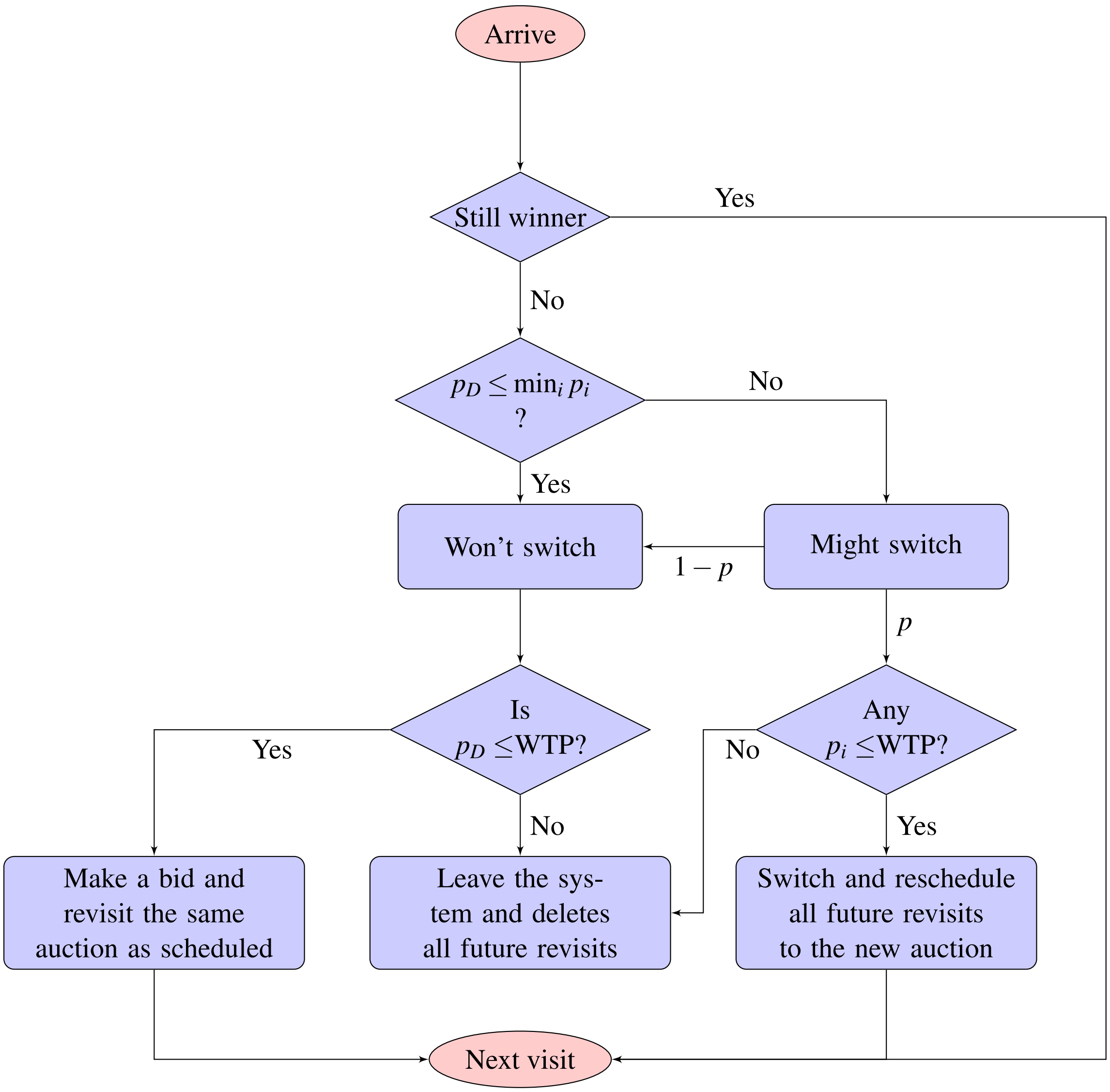

Figure 1: Flowchart of one bidder's bidding decision process.

Table 3: Mean and standard deviation of switching probability with non-linear increments on empirical distribution.

C Value	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1.0
Mean	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90
Std.	.38	.34	.30	.26	.23	.19	.16	.13	.11	.10	.11

and corresponding revisit times to the new auction will be regenerated and the event queue of the whole simulation will be updated accordingly. Also, if a bidder decides to leave the auction platform, his/her future revisits will be deleted from the event queue of the simulation. Figure 1 illustrates a bidder's bidding decision process for one visit.

4 EXPERIMENT TESTS AND RESULTS

In this section, we endeavor to investigate and answer several questions. The first question is whether promoting switching behavior will increase the profit of an online auction website and decrease price dispersion. If so, does any switching rule have a more significant effect on price dispersion than any of the other switching rules? In other words, which auctions should the auction platform recommend to the bidders? Also, as discussed earlier, we want to test if the distribution of switching probability affects the modeling results or only the average switching probability affects the auction prices. In this section, we answer these questions using the multiple auction agent-based model.

4.1 Effects of Distribution of Switching Probability

To answer the question whether there is any benefit of promoting switching for online auction website, we experiment with the model by increasing the switching probability. Here we use a non-linear increment on empirical distribution: $\Delta p_i = C(1-p_i)^2$, where C represents the maximum increment and varies from 0.1 to 1.0 by 0.1. Table 3 shows the mean and standard deviation of the switching probability corresponding to different increments added to the empirical distribution. It can be seen from the table that the mean of switching probability increases linearly and standard deviation decreases, when the C value increases.

Before investigating the benefit of promoting switching behavior, we need to answer a preliminary question, whether the distribution of switching probability makes any difference to the simulation results of the average and standard deviation of auction closing price. This will allow us to examine the robustness of our model to different switching assumptions, and help us to identify a baseline distribution to use. We test three distinct distributions: the empirical distribution from eBay data, a normal distribution and a constant value. Upon examination of the eBay switching distribution it was observed that the empirical distribution had a tri-mode shape, with three modes at 0, 0.5 and 1, which is very different from a normal distribution or a constant value. To test the effect of the different distributions, the three distributions were scaled to have the same mean and the same standard deviation for empirical and normal distributions.

In Experiment 1, we examined the 3 different switching distributions with 11 increments, i.e., changes in switching probability (as listed in Table 3), under 3 switching rules. The 3 rules in this experiment represent three extreme situations (deterministic minimum price, earliest ending time and random switch) and serve as illustrations for examining the influence of switching probability and its distribution. All the switching rules discussed below are conditional on the bidder deciding to switch and will only switch to the available auctions for him/her. The available auctions for each bidder is defined as the auctions that have price less than the price of bidder's current auction and the bidder's willingness to pay.

1. Choose the auction with the minimum price (Minimum rule in Section 3)
2. Choose the auction with the earliest closing time (Earliest rule in Section 3)

Table 4: Experiment settings.

Experiment 1	3 Switching Rules	3 Probability Distribution	11 Probability Increments
99 settings	1. MinPrice 2. Earliest 3. Radom	1. Empirical distribution 2. Noraml distribution 3. Constant Value	All 11 increments as in Table 3
Experiment 2	14 Switching Rules ($n = 1,3,5,10$)	1 Probability Distribution	11 Probability Increments
154 settings	1. Random of MinPrice 2. Random of Earliest 3. Earliest of MinPrice 4. MinPrice of Earliest	Empirical distribution	All 11 increments as in Table 3
Experiment 3	5 Switching Rules	3 Auction Start Rate	6 Probability Increments
90 settings	MinPrice of Earliest with $n = 1,5,10,15,20$	$\lambda_a = 6,12,18$	$C = 0,0.2,0.4,0.6,0.8,1$ as in Table 3

3. Randomly choose from all available auctions (equivalent to the 3rd/4th random rules but all auctions are considered)

In sum, there are 99 settings in Experiment 1 as shown in Table 4. For each setting, 200 days of auctions are simulated and approximately 1200 auctions occur during this period, because the mean of the auction start rate per day is 6. We exclude extreme values and keep track of the trend for both mean and standard deviation of closing price. Experiment 1 provides insights on both the effect of the switching distribution and the influence of promoting switching behavior. From the result, the means and standard deviations of closing price from the three different distribution are essentially within confidence intervals of each other and share the same trend. Therefore without losing generality, We use the empirical distribution with non-linear increment in all future experiments. In addition, we observe that increasing switching probability will increase average closing price with all the three switching rules, while the random switching rule results in lower price compared to the other two rules. Furthermore, by increasing the switching probability with minimum price and earliest ending rule, the price dispersion is reduced, while with the random switching rule there is barely any effect on price dispersion. In the next section, we investigate the effect of each switching rule and begin to answer the question, what is the optimal recommendation strategy for an online auction website?

4.2 Effects of Switching Rule

In this section, we investigate which switching rule has the most significant effect on the closing price, i.e., what kind of auctions should a website recommend to bidders to increase closing prices. To answer this question, we test the last 4 switching rules (Random of MinPrice, Random of Earliest, Earliest of MinPrice and MinPrice of Earliest), with recommendation limit $n = 1,3,5,10$. When $n = 1$, Random of MinPrice and Earliest of MinPrice degenerates to the first rule MinPrice; and Random of Earliest and MinPrice of Earliest degenerates to the second rule Earliest. Therefore, we only need to test the first 2 rules and the last 4 rules with $n = 3,5,10$. As listed in Table 4, Experiment 2 contains 14 different switching rules with 11 increments of the empirical distribution resulting in 154 combinations. The simulation is run for the equivalent of 200 days.

Figures 2 and 3 demonstrate the experimental results by presenting the average and standard deviation of the closing price for each setting. Each graph represents one family of switching rules (Random of

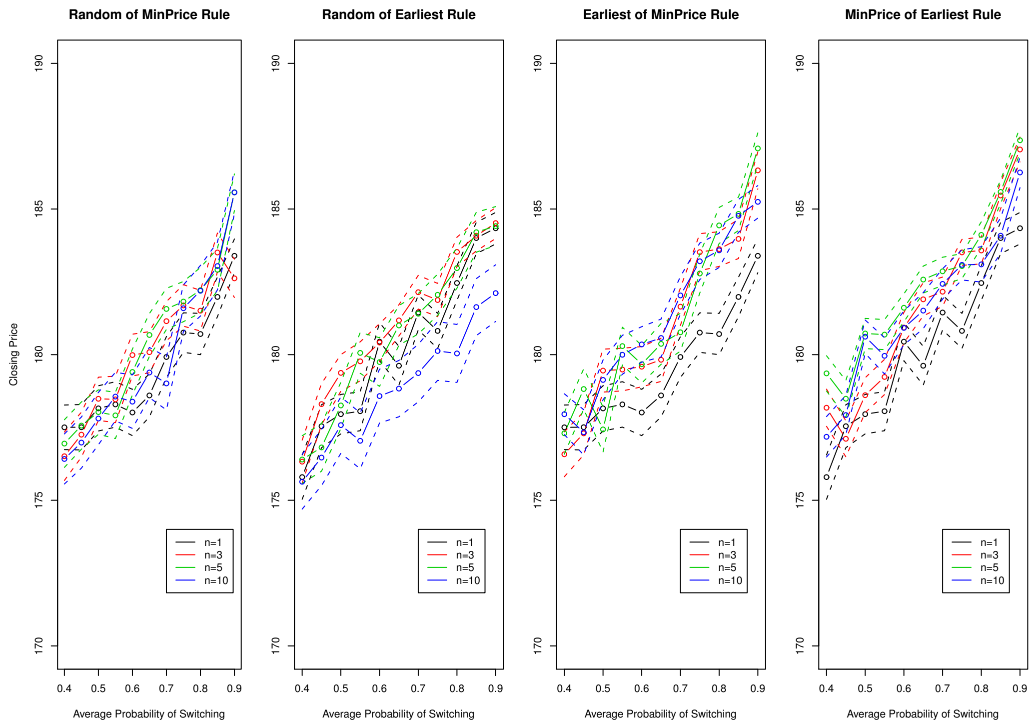

Figure 2: Average closing price in Experiment 2.

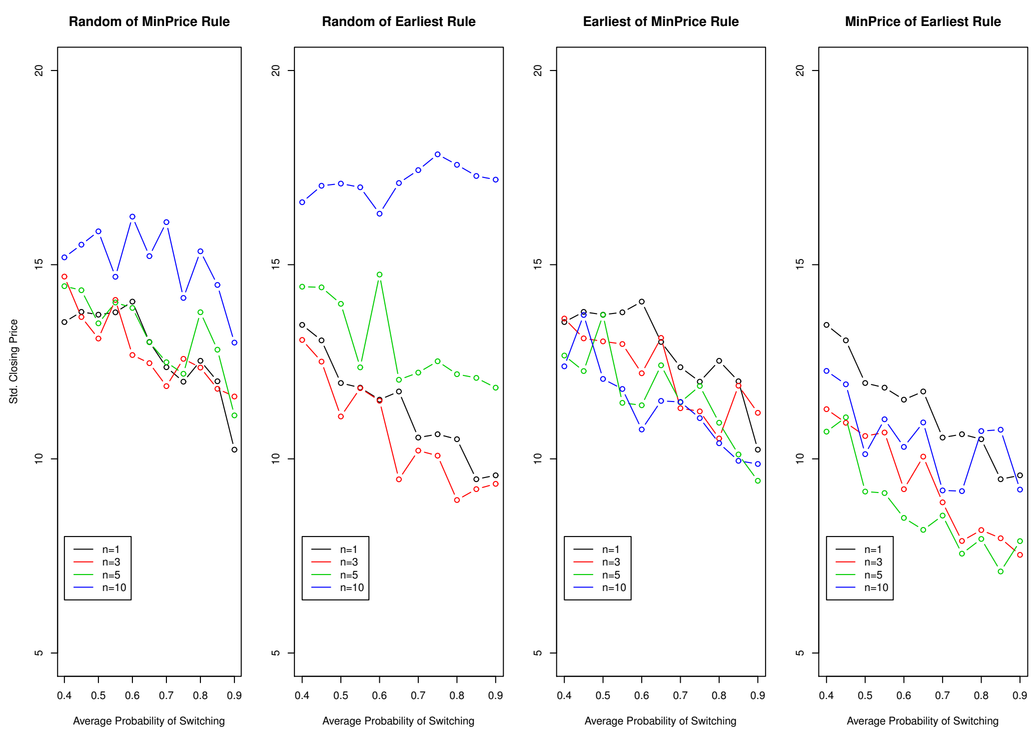

Figure 3: Standard deviation of closing price in Experiment 2.

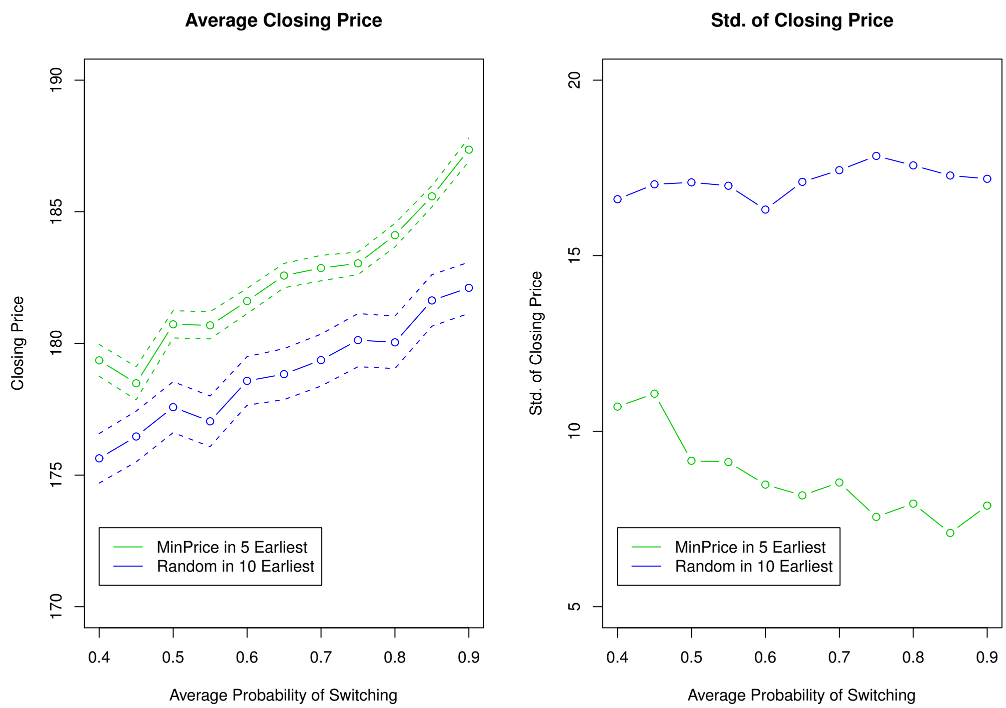

Figure 4: The most distinct two settings in Experiment 2.

MinPrice, Random of Earliest, Earliest of MinPrice and MinPrice of Earliest), and each color represents a value of the recommendation limit n. It is worth noting that the black lines in the first and third graphs are the same and the second and fourth are the same, because the switching strategies in the first and the third graph degenerate to the same rule when $n = 1$ and so do the second and the fourth ones. With an increase in the probability of switching, the increasing trend of average closing price is clear in Figure 2. By careful comparison, the lowest curve of all 14 curves is the blue line ($n = 10$) in the second graph (Random of Earliest rule) and the highest line is the green line ($n = 5$) in the fourth graph (MinPrice in Earliest rule). The confidence intervals of the lowest and highest curves of average closing price have no overlap as shown in the left graph of Figure 4. This indicates that there is a significant difference among auction recommendation strategies. If the website intends to increase auction closing price, then the highest curves of average closing price should be preferred, i.e., the green line in the left graph of Figure 4 is the best for the auction platform, while the blue line is the least favorable one. In addition, the decreasing of price dispersion is clear in most of the experiment settings as seen in Figure 3. One thing interesting is that the lowest standard deviation curve is the blue line ($n = 10$) in the second graph (Random of Earliest rule) and the highest standard deviation curve is the green line ($n = 5$) in the fourth graph (MinPrice in Earliest rule), which are the same two most distinct settings identified for average closing price. For comparison purposes, the two standard deviation curves are plot in the right graph of Figure 4. As discussed earlier, having lower price dispersion will decrease the risk for both bidders and sellers, thus will leads to better customer satisfaction. Therefore, the most beneficial auction recommendation system for the auction platform would increase the average closing price while at the same time reducing price dispersion. According to this simulation the best rule to do so is the *MinPrice in 5 Earliest* Rule among the 14 settings.

Experiment 3 focuses in more depth on the optimal switching rule *MinPrice of Earliest* identified in Experiment 2. This switching rule chooses the auction with minimum price among n earliest closing auctions. When $n = 1$, this switching rule degenerates to the *Earliest* rule, i.e., choose the earliest closing

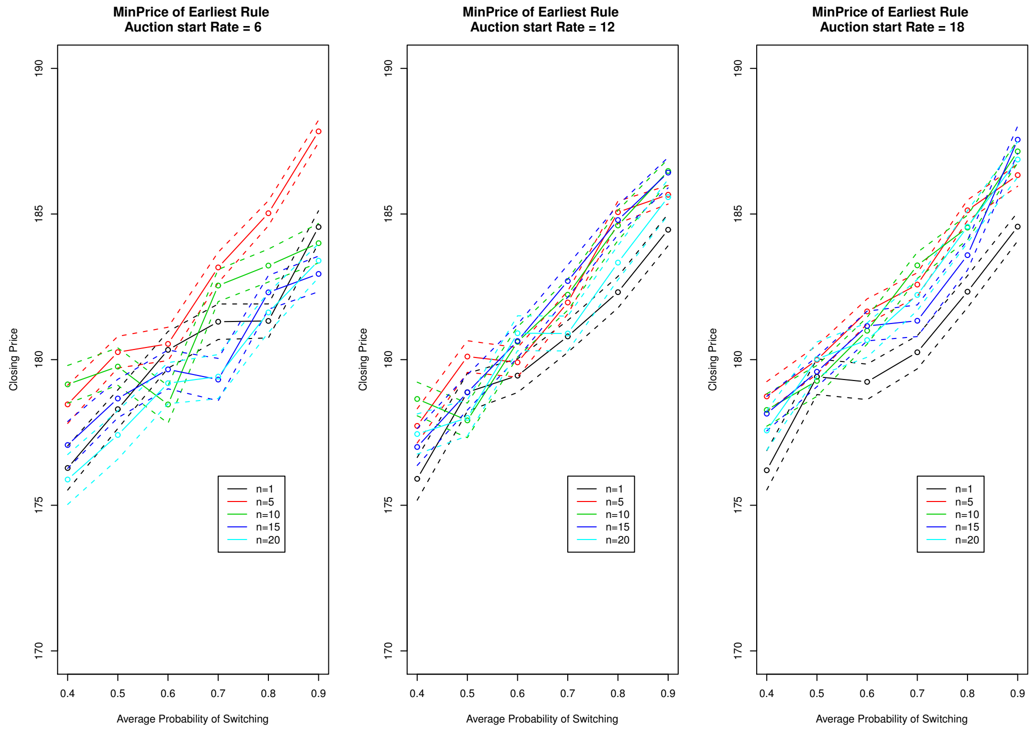

Figure 5: Average closing price in Experiment 3.

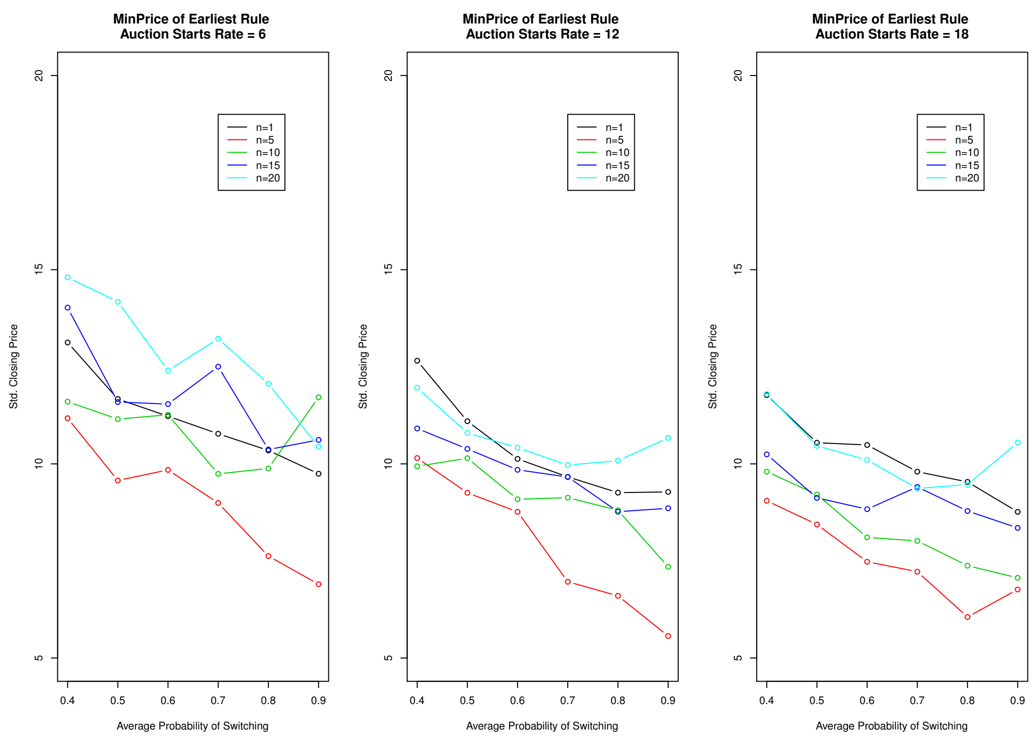

Figure 6: Standard deviation of closing price in Experiment 3.

auction among all available auctions. When n increases to (or is greater than) the number of available auctions, this switching rule becomes the *MinPrice* rule, i.e., choose the auction with minimum price among all auctions. When n is between 1 and the number of available auctions, this rule can be consider as a conditional *MinPrice* rule, i.e., conditional on the fact that the minimum price auction is one of the n earliest closing auction, the one with minimum price will be chosen. This scenario is close to the actual online auction situation. When a bidder sees a list of auctions selling the exact same items, the first thing that might attract his/her attention might be the price, especially when the closing times are similar. From Experiment 2, the optimal n of the *MinPrice of Earliest* rule is 5. In this Experiment 3, we test if the optimal n stays the same, when the number of available auctions varies. In the simulation experiment, the auction start rate is directly related to the number of available auctions. In this experiment, we test 5 recommendation limits $n = 1, 5, 10, 15, 20$ and 3 different auction start rates $\lambda_a = 6, 12, 18$, which are the start rate calculated from data and its two to three times that value. For each combination of auction recommendation limit and auction start rate, 6 incremental increases in the distribution of switching probability are tested with $C = 0, 0.2, 0.4, 0.6, 0.8, 1$. To get approximately 1200 closed auctions per setting, the simulated durations are set to 200, 100 and 70 days according to the auction start rates $\lambda_a = 6, 12, 18$ so that the the average number of auctions remains constant. As listed in Table 4, there are 90 settings tested in Experiment 3.

The simulation results of Experiment 3 are shown in Figure 5 and 6. From both figures, the performance of $n = 5$ (red lines) is robust. In the average closing price graphs, the $n = 5$ line remains one of highest curves across all three graphs. And in the price dispersion curves the $ncc = 5$ lines are clearly the lowest line in each graph. It is also interesting to see that when n increases, the price dispersion first decreases and then increases again. According to the discussion earlier, it is beneficial for the online auction website, when the average closing increases and the price dispersion decreases. Therefore, from Experiment 3, we have the same conclusion as in the Experiment 2 that the *MinPrice in 5 Earliest* Rule is the best strategy for online auction website.

5 CONCLUSION

In this paper, we have described and examined a multi-auction agent-based model to examine switching behavior in auction platforms. Using this model, we show that it is possible to reduce the price disparity among auctions by encouraging users to switch between auctions of a similar type product on an auction platform. We also have made a concrete suggestion about what this recommendation should be, namely that the platform should recommend the 5 auctions with the minimum price that will be ending the soonest. We also show that this rule is robust to a variety of starting rates of auction prices.

It is interesting that the recommendation rule that is discovered to be optimal is to recommend auctions that are ending soon and have a *minimal* price, but this results in the highest average final closing price. This is because by recommending auctions that are ending soon, but that have a low price the auction platform encourages the bidders to stay in the platform. This in turn increases competition and drives up the overall prices. As a result, the recommendation system the is discussed would have three major benefits: (1) it would reduce the price disparity among auctions, (2) it would encourage bidders to stay on the auction platform, and (3) it would increase the final price of the auction. Competition between auctions is inevitable, and a savvy auction platform can use that fact to engage their users, which has a benefit for all parties involved.

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