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Dynamic price competition market for retailers in the context of consumer learning behavior and supplier competition: Machine learning-enhanced agent-based modeling and simulation

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A B S T R A C T

This study analyzes the impact of consumer learning behavior and supplier price competition on retailer price competition in a complex adaptive system. Using machine Learning-enhanced agent-based modeling and simulation, the study applies fuzzy logic and genetic algorithms to model price decisions, and reinforcement learning and swarm intelligence to model consumer behavior. Simulations reveal that different learning behaviors result in different retailer competition patterns, and that supplier price competition affects the strength of retailer price competition. Simulation results demonstrate that consumer learning behavior influences retailer competition, with self-learning consumers leading to higher-priced partnerships, and collective-learning consumers leading to a shift in price competition among retailers. In contrast, perfect rationality consumers result in low-price competition and the lowest average margin and profit. Additionally, the competitive price behavior of suppliers impacts retailers' price competition patterns, with supplier price competition reducing retailer price competition in the perfect rationality consumer market and enhancing it in the self-learning and collective-learning consumer markets, leading to lower average prices and profits for retailers. This study presents a simulated market for price competition among suppliers, retailers, and consumers that can be expanded by subsequent scholars to test related hypotheses.

A R T I C L E I N F O

Keywords:
Pricing competitive model;
Complex adaptive system (CAS);
Agent-based modeling and simulation (ABMS);
Machine learning (ML);
Genetic algorithms (GA);
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1. Introduction

Competitive markets are often complex because they are the emergent result of many individual agents (e.g., consumers, retailers, supplier) whose motivations and actions combine so that even simple behavioral rules can result in surprising patterns [1, 2]. Agent-based modeling and simulation (ABMS) is a rich platform for studying complex evolving systems to test behavioral economics theory and bridge micro and macro models. Many studies are beginning to apply ABMS to investigate how individual agents interact during the competitive process and achieve a balanced outcome from the perspective of a dynamic evolutionary game [3-8]. ABMS frameworks are applied to design artificial adaptive agents to simulate the decision-making and learning behaviors of real-world individuals and their interactions with incomplete information and partially rational decisions. In this way, the payoffs and final equilibrium outcomes of individuals can be observed over time to support and assist marketing strategies [9]. The advantage of ABMS is that it can produce results similar to those of the analytic model under the same assumptions and can be further extended and relaxed to analyze dynamic simulation results in more complex situations, test and develop theories, and provide strategic implications [10-14].

The earliest assumptions of the price-competitive model were to explore the equilibrium of the final price-competitive situation when oligopolistic competitors sell homogeneous products without regard to their capacity, when they have the same cost function, when demand is certain and known, and when consumers choose only the lower-priced products [15]. Hunt's general theory of competition describes the complexity and evolutionary nature of competitive markets from a different perspective [16]. The theoretical view is that competition in the market is caused by market imbalances. Competitive behavior stems from the endogenous learning behavior of suppliers. Tay and Lusch applied ABMS to construct a producer competitive market and observed the price competitive dynamics and equilibrium of suppliers. The results validate Hunt's general theory of competition [17].

The subsequent development of the price competition model includes a number of considerations, such as consumer different cognitive decisions [18], heterogeneous consumers with objective supplier preferences [19] and switching behavior [20], consumers' sensitivity to price information [21], consumers' demonstrated loyalty [22], consumers' social network word-of-mouth [23], consumers' different levels of learning ability [24], consumers' ability to demonstrate strategic purchasing behavior etc. [25]. In summary, previous studies that have examined the price competitive market from a dynamic perspective have focused on price competition among suppliers and incorporated consumer learning behavior to construct an ABMS market to observe the dynamic effects of learning behavior on overall market prices but have neglected the role of retailers in the price competitive market [26].

In a price competitive market characterized by independent suppliers and retailers, the dynamics of price setting and adjustment are influenced by three main competitive forces. First, there is the competition that occurs at the supplier level, as each supplier seeks to offer the most attractive price for the product they produce relative to other suppliers in the market. Second, there is the competition that occurs at the retailer level, where retailers seek to set the most attractive prices for the set of goods they offer, taking into account the prices set by their competitors. Third, there is the vertical interaction competition that occurs between the suppliers and retailers, where the two parties negotiate and adjust prices in response to each other's decisions and actions. Together, these three forces shape the competitive landscape of the market and ultimately influence the price decisions of the firms involved [15, 27]. The price decisions of retailers nowadays have a significant degree of influence on the market. The impact of retailer competition on the price competitive market is an issue worth clarifying [14, 28].

In this study, ABMS is applied to construct a price competition simulation market involving retailers, suppliers, and consumers, where each retailer, supplier, and consumer can establish their behavioral decision rules as adaptive agents. Individuals will interact with each other to maximize their rewards and be given learning behaviors to observe over time in a complex adaptive system (CAS) simulation to understand the intricate competitive relationships between retailers, suppliers, and consumers [29].

Evolutionary game theory has been applied to price competition, emulating the behavior of human deductive reasoning and inductive reasoning, where suppliers and retailers have price decision rules and learned behavior mechanisms that apply fuzzy logic (FL) to their price decisions and genetic algorithms (GA) to the price rules adjustment [27, 30]. In constructing consumer purchase learning behavior, reinforcement learning (RL) from psychology was used to model self-purchase learning behavior [12, 30], while swarm intelligence from biology was used to model collective learning consumers [32].

This study will answer the question: from a price competition perspective, is it possible to observe how different *consumer learning behavior* and *supplier price competition behavior* affect the price competition process of retailers and the eventual price equilibrium outcome that may result? This study will examine the following:

- The impact of three different *consumer learning behaviors*, namely *perfect rationality*, *self-learning*, and *collective learning* on retailers' dynamic co-opetition strategies.
- The impact of the *non-price competitive* and *price competitive* behavior of suppliers on retailers' dynamic co-opetition strategies.

2. Pricing competition model

The price competitive market in this study comprises a number of suppliers, retailers, and consumers. The suppliers produce a single product, and their price decisions are primarily setting the wholesale price of that product. The suppliers' products are homogeneous, and there is price competition between suppliers. Retailers are responsible for selling the products produced by their respective suppliers. The retailer's pricing decisions primarily determine the margins of the supplier's products, which are also price-competitive with each other. The supplier's wholesale price and the retailer's margins are added together to form the retail price. There is still a so-called price competition between suppliers and retailers. In this price-competitive interaction, suppliers and retailers make price decisions with the aim of maximizing their own profit. In addition, they follow human deductive reasoning and inductive reasoning behavior, apply fuzzy logic as the basis for their price decisions and genetic algorithms as a way of adjusting price rules through empirical learning, resulting in an evolutionary game of price competition between retailers, between suppliers, and between suppliers and retailers.

In competitive markets, consumers engage in purchase learning behavior. In a market, the price of each retailer is a form of incomplete information to the consumer. As a result, consumers judge which retailer they can get the best price from based on their past purchasing experience. Once in the retailer's shop, the consumer can directly compare prices between suppliers and choose the lower price. Consumers can use the rewards of this purchase to form an experience and adjust their choice of retailer for the next time through learned behavior. In addition, consumers can model self-learning behavior about purchases through reinforcement learning in psychology [12] and the learning behavior of a group of consumers through swarm intelligence in biology [32].

Price competition means that suppliers will consider the wholesale prices of other suppliers and margins of downstream retailers when making price decisions. Retailers will consider the margins of other retailers and wholesale prices of upstream suppliers when making price decisions. *No price competition* means that there is peaceful co-existence *between suppliers* and *between suppliers and retailers*. As a result, suppliers' price decisions remain fixed throughout the simulation period. At the same time, the retailer's price decisions are made without regard to the supplier's price.

2.1 Price competitive market

The price competitive market in this study consists of supplier S_i $(i = 1, \dots, i^*)$ that each produces its own supplier's product and has the same fixed cost c_i^f. Retailer R_j $(j = 1, \dots, j^*)$ sells each supplier S_i*'s* product with the same fixed cost c_j^f. At each point in time t, supplier S_i determines the wholesale price w_i for the product. The w_i set for the period applies to all retailers R_j $(j = 1, \dots, j^*)$. Next, retailer R_j determines the margin m_j for that product. The m_j set for the period applies to all suppliers S_i $(i = 1, \dots, i^*)$. The sum of m_j and w_{ij} determines the retail price *of* S_i *at* R_j, R_{ij}. In the market, there are many heterogeneous consumers C_k $(k = 1, \dots, k^*)$. Consumers have different price sensitivities, forgetting rate, degree of rationality and different propensities towards retailers $\theta_{k,j}$ $(j = 1, \dots, j^*)$. The profit of S_i $(i = 1, \dots, i^*)$ and R_j $(j = 1, \dots, j^*)$, as well as the accumulated capital *profit*$_i$, *profit*$_j$, can be calculated based on the demand q_{ij} for retailer R_j*'s* product S_i generated by the consumer's purchase behavior.

The price competitive market simulation works as follows: At each point in time t, the interactive steps described below are included:

Step 1: In the mode, the simulation time is t^*, which contains multiple time points t. Each time point t contains multiple rounds r^*. Each round r contains multiple encounters ε^*.

Step 2: For each round r, the supplier and retailer select a price decision rule from a library of price decision rules to conduct an ε^* encounters test.

Step 3: For each round ε, the supplier refers to the previous price interaction with other competing suppliers and retailers and applies fuzzy logic to determine its own wholesale price, and proposes its wholesale price to each retailer.

Step 4: The retailer takes into account its margin with other competing retailers and the supplier's wholesale price in the previous round and applies fuzzy logic to determine its own margin.

Step 5: Consumers will be able to evaluate and choose a retailer based on their purchasing decisions. The consumer does not have access to the current prices set by the retailer for each supplier's product but must enter the retailer's shop in order to obtain price information. After deciding on a retailer, the consumer can directly choose the supplier with the lower price, which in turn generates the demand q_{ij} for the supplier M_i among the retailers R_j and the profit of each retailer and supplier in that transaction.

Step 6: Consumers use purchase learning behavior to adjust their purchase decisions based on the rewards generated by this epsilon purchase decision. The learning behavior is modified using self- and collective learning.

Step 7: When $\varepsilon < \varepsilon^*$, return to step 3 and $\varepsilon = \varepsilon + 1$. Otherwise, determine if $r < r^*$ is valid, and if it is, go back to step 2 with $r = r + 1$, and if it is not, go to step 8.

Step 8: Retailers and suppliers evaluate the performance of their price decisions based on profit and apply genetic algorithms to adjust their price decisions.

Step 9: Determine whether t reaches the maximum simulation time t^*, and stop if it does. Otherwise, go back to step 2, $t = t + 1$.

2.2 Price competitive behavior of supplier and retailer

The study explores the modeling of human deductive and inductive reasoning through the continuous adjustment of pricing strategies by suppliers and retailers using fuzzy decision rules, with the ultimate goal of enhancing their survival. The FL-GA theoretical framework provides an excellent opportunity to showcase the effectiveness of ABMS in this context. A schematic representation of the FL-GA architecture is illustrated in [17]. The process of fuzzy rules adjustment for improved decision-making involves two methods: exploitation, which involves the recombination of existing genetic material in novel ways via crossover, and exploration, which involves the adoption of new genetic material via mutation. Selection and reproduction are used to keep and replicate successful decision-making approaches while discarding those that are ineffective. Both exploitation and exploration strategies rely on the use of selection and reproduction to optimize decision-making performance.

These rules are constantly evaluated and adjusted based on their predictive accuracy in forecasting market behavior. Successful rules are retained and acted upon while poorly performing rules are discarded. The discarded rules are replaced with new hybrid rules generated from the effective ones. Additionally, new rules are generated and tested in response to emerging market information. This iterative process of learning and adaptation allows suppliers and retailers to continually adapt to the constantly evolving market conditions. Please refer to the study by Tay and Lusch for details on the FL-GA theoretical framework [17].

2.3 Consumer learning behavior

Each consumer is an artificial adaptive agent and will exhibit bounded rationality learning behavior in the face of incomplete information about prices. After each purchase, the individual will calculate the price difference based on his or her past purchase experience or observation of other people's purchases as a reward for the purchase and adjust his or her propensity to buy from each retailer. The aim is to get the same product at a lower price the next time. The study distinguishes three types of purchase learning behavior as follows:

Type I *Perfect Rationality*: This type was designed as a control group. The consumer is provided with all price information prior to purchase. There is no price information search cost for the consumer and the lowest price for each purchase, so there is no learning behavior, and it can be used as a basis for comparison with other learning behaviors.

Type II *Self-Learning*: Because this type of consumer has the highest price search costs, they will only adjust their purchase decisions after each purchase by comparing them to their last purchase price. The consumer decides which retailer to go to this time to get a better price based on his or her past purchase experience and decides which retailer to go to this time. The self-learning behavior is based on reinforcement learning (RL) algorithms.

Type III *Collective-Learning*: Collective-Learning emphasizes a way of learning by comparing purchasing experiences with those of others as a basis for future revision decisions. Consumers use the swarm intelligence algorithm to compare prices between groups after making a purchase decision to see if the purchase is more expensive or cheaper, and then adjust their propensity for the retailer to facilitate a higher return on their next purchase decision.

2.3.1 Self learning behavior

RL means that actions that produced good results in the past will be reinforced, making them more likely to be taken again in the future. Actions that produced bad results in the past will be weakened, making them less likely to be taken again in the future. Action means that the consumer decides which retailer to buy from. The result is a *price differential* in the price paid for the product purchased. With incomplete information, the current price is only known after the consumer has chosen the retailer, and the price information for other retailers is still not available and must be recalled from past memory. When the return on price differential is perceptually positive, the likelihood of choosing that retailer next time increases, and vice versa. Such a learning model is based entirely on one's own experience and fully expresses the spirit of self-adaptive learning. Therefore, RL algorithms were used to model this self-learning behavior. The relevant behavioral patterns and algorithm flow are as follows.

Step 1: Initial action

RL is the conversion of past experience into a propensity to act on that decision. The level of propensity is seen as a preference for a particular *Action*. A consumer's propensity is his or her preference for a retailer θ_j. For example, a consumer who chooses between two retailers and whose purchase action is either to shop at retailer R_1 or to shop at retailer R_2, is given an $\theta_{j=1}$ and $\theta_{j=2}$ to indicate the consumer's propensity for each of the two actions. Parameters are set for each consumer, including their initial propensity to shop at the retailer, upper and lower limits of propensity, rationality, price sensitivity, etc.

Step 2: Rules of selection

According to the rules of selection for retailers, the *rules of selection* are used to determine the retailers that consumers decide to buy from at this stage, based on their current propensity for each retailer. The higher an individual's propensity for a particular action, the more likely that individual is to choose that action. The choice of retailer is determined by the ratio of each retailer's propensity to the total propensity. This ratio indicates the probability of each retailer being selected. The formula for the *choice of action* rule is as follows:

$$x_j(t) = \begin{cases} max \quad \theta_j(t) \quad \text{if } rand < \beta \\ \frac{\theta_j(t)}{\sum_{j=1}^{n}\left(\theta_j(t)\right)} \quad \text{else} \end{cases} \tag{1}$$

The variable $x_j(t)$ is the consumer's choice of retailer j at time point t, and β is the degree of rationality of the consumer's purchase decision. A higher β value indicates a higher probability of choosing a retailer with a higher propensity to buy. Random variable $rand$: between 0 and 1. When $rand < \beta$, the consumer directly chooses the retailer with the highest propensity; otherwise, the consumer is given a chance to choose the retailer with the highest propensity according to the ratio of each retailer's propensity and then directly chooses the supplier with the lowest price.

Step 3: Calculation of reward

The price at which the consumer purchases at this point in time t is compared to the price of the previous purchase $(t-1)$ to calculate the return on the consumer's choice of retailer for this purchase. The formula for calculating the reward at time point t is as follows.

$$u_{k,j}^{t} = \alpha_k (p_j^{t-1} - p_{k,j}^{t}) \tag{2}$$

The variables are defined as follows. $u_{k,j}^{t}$ is the reward from retailer j arising from consumer k's choice to buy from retailer j. α_k is price sensitivity of the consumer k. The greater the price sensitivity, the greater the effect on the price differential. $P_{k,j}^{t}$ is the price at which consumer k buys at this time at retailer j. p_j^{t-1} is the price of the consumer k's last purchase. $p_j^{t-1} - p_{k,j}^{t}$ is price differential.

Step 4: The propensity to update decisions

The reward generated by a consumer action is the key factor that allows for the *reinforcement* of learning. Each time a decision is made, RL updates the reward to a propensity for that strategy. The remaining strategies that are not selected are not updated because of the learning effect. Past propensities are partially lost over time. Therefore, through repeated purchases, each propensity will increase or decrease after each purchase, making it more or less likely to be chosen next time. The propensity update method for each retailer is:

$$\begin{gathered} \theta_s(t+1) = (1-\delta)\theta_s(t) + u_s(t) \\ \theta_u(t+1) = (1-\delta)\theta_u(t) \end{gathered} \tag{3}$$

$\theta_s(t)$ indicates the propensity to update for the selected retailer s and $\theta_u(t)$ is the propensity to update for the unselected retailer u. $1 \geqq \delta \geqq 0$ is a memory parameter (recency), which indicates that past experiences or memories are forgotten over time. A larger δ value indicates a greater emphasis on the most recent memory. Over time, consumers will have a relatively high propensity to buy from retailers that generate high returns. The probability of being selected is relatively high. In the end, the consumer's action set tends to be simple, and learning tends to be stable.

2.3.2 Collective learning behavior

Collective learning is generally conceptualized as a dynamic and cumulative process that results in the production of knowledge. Such knowledge is institutionalized in the form of structures, rules, routines, norms, discourse, and strategies that guide future action. This study uses Swarm Intelligence to model consumer collective-learning behavior. Swarm Intelligence primarily mimics the process of a bird's collective flight in search of a food location. Each individual modifies the intensity of the flight by taking into account both their own past experience and the experience of other individuals in the flock to determine the direction of the next flight.

In collective purchasing learning behavior, consumers also decide which retailer to buy from based on the rules of retailer choice. Under the retailer choice rule, consumers decide which retailer to choose at this stage based on their current propensity for each retailer through the *choice action rule*. The higher an individual's propensity for a particular action, the more likely that individual is to choose that action. The choice of retailer is determined by the ratio of each retailer's propensity to the total propensity. The ratio indicates how likely each retailer is to be selected, where the rules of selection are the same as for self-learning. After each purchase, consumers adjust their propensity to buy from a particular retailer by calculating rewards based on their past purchasing experience and the experience of others, as expressed in the following equation:

$$u_{k,j}^{t+1} = \alpha_k \times rand()\left[(p_{k,j}^{t-1} - p_{k,j}^{t}) + (p_g^t - p_{k,j}^{t})\right]$$
$$\theta_{k,j}^{t+1} = \theta_{k,j}^{t} + u_{k,j}^{t+1} \tag{4}$$

$u_{k,j}^{t+1}$ is the reward generated by the consumer k's choice of retailer i, which can be used as a basis for adjusting the consumer's propensity for each retailer. α_k is the price sensitivity of consumer k. $rand$ is The degree of randomness indicates an extraneous environmental variable, a random number between 0 and 1. $p_{k,j}^{t-1}$ is the retailer price at which consumer k purchased in the previous purchase. $p_{k,j}^{t}$ is the retailer price at which consumer k purchased this purchase. p_g^t is the retailer whose price is the lowest among the group at time point t. $\theta_{k,j}^{t}$ is consumer k' propensity for various retailers j at this stage. $p_g^t - p_{k,j}^{t}$ is consumer perception of the price difference.

3. Experimental results

3.1 Setup for price competitive market simulation

In this study, the Matlab programming language was used to implement the ABMS system. The parameters of the simulation were set as shown in the table 1. The number of retailers n_r is set to 2, the number of suppliers n_m is set to 2, and the number of consumers n_c is set to 100. The simulation was conducted 25 times in each market environment setting. Simulation time t^* = 1000. A time point t consists of 10 rounds (r^*). Each retailer competes on 4 encounters (ε^*) per round, and the average margin, average profit, and the cumulative profit of the two retailers are recorded for each time point t. Finally, the average of the 25 experiments is taken to produce the experimental data. This study found that equilibrium was reached after 1000 simulation time t^*. Retailers' price competition patterns are repeated. It was therefore decided that 1000 simulation time t^* would be the time for the simulation.

Table 1 Parameter settings for the price competitive market

	Initial Settings for the Variables/Parameters	Setup Values/Range
Retailer/ Supplier	Number of retailers n_r / Number of suppliers n_m	2／2
	Fixed costs (c_i & c_j)	400
	Initial assets	1000
	Initial wholesale price ($w_i^{t=0}$)	8
	Initial margin $m_{i,j}^{r}(t=0)$	8
	Upper and lower price limits	6-10
	Number of rules for the library (n_{rule})	16
	Number of semantic values of input variables under fuzzy rules	4
	Number of semantic values of output variables under fuzzy rules	8
	Mating rate	0.8
	Mutation rate	0.2
	Code	Binary encoding
	Fitness function	Total sales
	Mating operator	Two-point mating
Consumer	Number of individual consumers (n_c)	100
	Initial retailer propensity of consumers (θ_j): Normal distribution	$\tilde{u}$ = 8 $\sigma = 0.5$
	Upper bound of consumer propensity to retailer	10
	Lower bound of consumer propensity to retailer	2
	Price sensitivity (α)	1
	Degree of rationality (β)	0.8
	Consumer forgetting rate (δ)	0.2
System settings	System implementation language	Matlab
	Simulation time (t^*)	1000
	Number of consumer purchases per cycle (r^*)	40
	Number of experiments per market environment	25 times

The retailer determines the unit margin for the product. The unit margin is summed with the wholesale price of the product and becomes the selling price. The unit margin is set at a maximum of \$10 and a minimum of \$6 per unit. The retailer's fixed cost per operation is (c_i) \$400. The initial unit profit $m_{i,j}^{r}(t = 0)$ is set at \$8. In a non-competitive situation, the wholesale price is set at a fixed price of \$8 per unit of product. In the case of a competitive supplier, the wholesale price is determined using fuzzy logic. The wholesale price per unit is also set at a maximum of \$10 and a minimum of \$6 per unit. The supplier's fixed cost (c_i) per production run is \$400. The initial wholesale price $w_i(t = 0)$ is set at \$8. The initial propensity of consumers toward retailers presents θ_i^k a normal distribution, where $\tilde{u} = 8$ and $\sigma = 0.5$. The lower bound of consumer propensity towards retailers ranges from 2 to 10. Consumer price sensitivity α is designed to be 1, and consumer forgetting rate δ is 0.2. The degree of rationality of consumers' purchase decisions was set at 0.8.

3.2 Impact of price competition among retailers

In this study, three different consumer learning behaviors and two different suppliers competitive behaviors were simulated to obtain a total of six market environment settings. Table 2 presents that the different *consumer learning behavior* and *supplier price competition behavior* affect the overall average margin, the overall cumulative profit, and the profit gap at the retailer end.

First, we looked at the impact of three different *consumer learning behaviors* on retailers' coopetition relationship. Market 1 shows that the overall average margin (6.7842) and cumulative profit (-2,845,861) at the retailer end are the lowest when consumers demonstrate *perfect rationality* and suppliers do not engage in price competition. It can be inferred that retailers are more likely to make higher profits through low-price strategies when consumers have immediate access to price information, therefore, more likely to engage in low-price competition among retailers. As a result of low-price competition, the average cumulative profit of retailers is also the lowest.

If we further analyze the price competition pattern in Fig. 1, we can see that during the price competition between the two retailers, margin tend to fall quickly to the lowest price (\$6) under low price competition. After that, both parties have the opportunity to see the benefits of cooperation, and prices are gradually raised to \$8, but only for a relatively short period of time (50 rounds). The retailer learns that it is more rewarding to set lower price than its rival. As a result, the retailer will begin to compete at a lower price. The cycle goes on and on, with no equilibrium of low-price convergence. The validity of the basic price competition model can be verified by the results of the experiment in which consumers exhibit *perfect rationality* behavior, which is the same as the Bertrand model of competition, as mentioned in the previous literature. Under the same assumptions, it can be found that price competition among producers eventually approaches the equilibrium price of the lowest price.

Market 2 shows that the overall average margin price (\$9.7216) and cumulative profit (\$3,435,891) at the retailer end are highest when consumers exhibit *self-learning behavior* and suppliers do not engage in *price-competitive behavior*. According to the company, consumers who do not have immediate access to price information must rely on their past purchasing experience to make purchasing decisions. As a result, retailers set prices high for long periods of time and only occasionally run low-price promotions to retain consumers and reduce price competition among retailers.

Further analysis of the price competition pattern in Fig. 2 shows that in the early stages of price competition between the two retailers, those who adopt a low-price strategy are able to make higher profits. The retailer with a high-price strategy continues to lose money but does not compete at lower prices. After a certain period, the retailer with the low-price strategy finds that higher prices will lead to higher profits and gradually raises its prices. Thereafter, the two retailers positioned their prices at a high level. Even when prices are adjusted, only sporadic low-price fluctuations occur.

Table 2 Experimental results

Market environment	Consumer learning behavior	Competitive behavior of suppliers	Overall average margin on the retailer side	Overall cumulative profit on the retailer side	Overall cumulative profit gap on the retailer side	Chart coding
1	Perfect rationality	N/A	6.7842	-2,845,861	1,932,295	Fig. 1
2	Self-learning	N/A	9.7216	3,435,891	3,686,571	Fig. 2
3	Collective-learning	N/A	9.6558	3,282,325	2,776,079	Fig. 3
4	Perfect rationality	Yes	7.1787	-2,060,160	4,451,600	Fig. 4
5	Self-learning	Yes	9.3794	2,633,278	7,582,923	Fig. 5
6	Collective-learning	Yes	9.3208	2,472,801	6,780,293	Fig. 6

Market 3 shows that with consumers exhibiting *collective-learning behavior* and suppliers not engaging in *price-competitive behavior*, the overall average margin ($9.6558) and cumulative profit ($3,435,891) at the retailer end is slightly lower than *self-learning behavior* but not significantly different. This is a more interesting result. From a practical point of view, if consumers adjust their purchasing propensity for retailers by making inter-group comparisons after making a purchase, this should result in more intense competition among retailers for lower prices. Further analysis in Fig. 3 reveals that the difference in competitive patterns between Markets 2 and 3 is that: Whilst retailers' prices are positioned at a high level, and there is sporadic and very short-lived low-price competition (2-5 rounds) between retailers in self-learning, collective-learning is likely to experience more frequent and short-lived medium-price competition (lasting 20-50 rounds). However, the modeling results do not suggest that long-term low-price competition will occur.

Comparing Fig. 2 and Fig. 3 on the comparison of consumer propensity and cumulative profit patterns at the retailer end, it can be seen that there is little difference between the propensity of consumers who can engage in self-learning behavior towards the two retailers and the change in propensity is relatively gentle. This means that consumers show a more gradual adjustment when their propensity for retailers changes. In contrast, consumers who are able to engage in collective-learning have a high frequency of change and a steeper curve of change in their propensity for retailers. This means that consumers tend to adjust their propensity for both retailers in a wide range of ways, immediately, quickly, and frequently. Then we looked at the average profit pattern of retailers per round. The self-learning behavior presented shows that retailers take longer (more rounds) to make a lead transition per round. Collective-learning shows that retailers often have short lead transitions. This is due to post-facto group price comparison by consumers. Price information can still be spread over a short period of time. A one-time low-price strategy can sometimes have an effect.

Next, we looked at the impact of the *non-price competitive* and *price competitive* behavior of suppliers on retailers' co-opetition relationship. The study found that there were similarities with the *non-competitive behavior* of suppliers. For example, the retailer with the lowest average price and cumulative profit ($7.18) was found in the case of *perfect rationality* behavior by consumers. Retailers presented an overall average margin price ($9.35 vs. $9.32) and cumulative profit ($2,633,278 vs. $2,472,801) that were fairly similar under self-learning and collective-learning, with retailers under self-learning still being slightly higher than retailers under collective-learning.

Market 4 shows that overall average margin and cumulative profit at the retailer end are lower than the overall average margin and overall profit, given the *perfect rationality* of consumers and the *competitive pricing practices* of suppliers. Looking further at Markets 1 vs 4, it can be seen that *price competition* by suppliers increases the overall average margin and overall cumulative profit at the retailer end. However, when comparing Markets 2 vs 5 and Markets 6 vs 3, it can be seen that the overall average margin price and cumulative profit at the retailer end decreases when suppliers engage in *price competition*. The reason for this is inferred to be that if there is price competition from suppliers, this will result in more drastic price changes in the market, which in turn will require longer purchase learning behavior on the part of consumers to recognize the pattern of price competition among retailers. As a result, retailers would need to increase the learning rewards for consumers by offering more low prices.

If we further analyze Figs. 1 and 4, we can see that if suppliers are competing on price, the price competition pattern does not drop in the short term and remain locked at the lowest price ($6) for a long period of time. Instead, the price will fluctuate in a relatively gentle cycle between $6 ~$8. This pattern is also reflected in the profit patterns of retailers in each round. Price competition from suppliers has resulted in less lead shifting and wider lead gap for retailers.

If we further analyze Figs. 2 and 5, we can see that if suppliers are competing on price, the price competition pattern does not rise in the short term and remain locked at the higher price ($10) for a long period of time. Instead, the price will fluctuate in a relatively gentle cycle between $9 ~$10. In terms of consumer propensity and retailers' profit patterns in each round, consumer propensity to swap leadership becomes more frequent, the gap becomes wider, and the speed of adjustment in propensity increases if suppliers engage in price competition. Retailers' profit patterns show an increase in the likelihood of mutual and significant profit leads, which is unlike the high price levels over time, fewer lead swaps, and less of a profit gap seen in Market 2.

If we further analyze Figs. 3 and 6, we can see that if there is competition from suppliers, the price competition pattern does not produce the same short-term increase in price competition and long-term lock-in at high prices that would occur if suppliers did not compete. Instead, there would be several short-term price competitions at prices falling between $8.50 and $9.

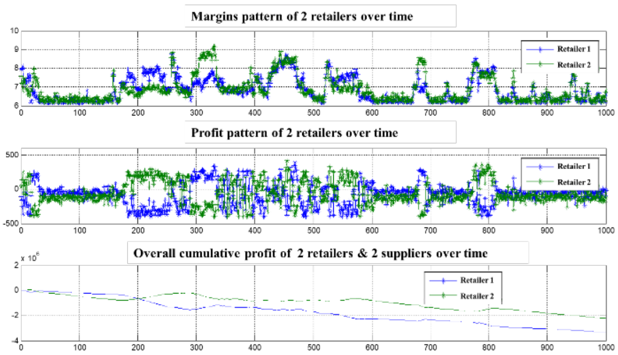

Fig. 1 Market 1: Non-competitive suppliers & perfect rationality consumers

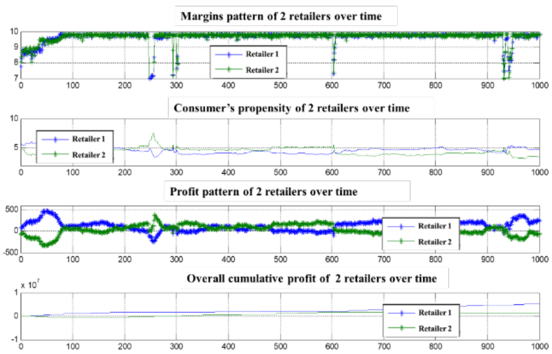

Fig. 2 Market 2: Non-competitive suppliers & self-learning behavior consumers

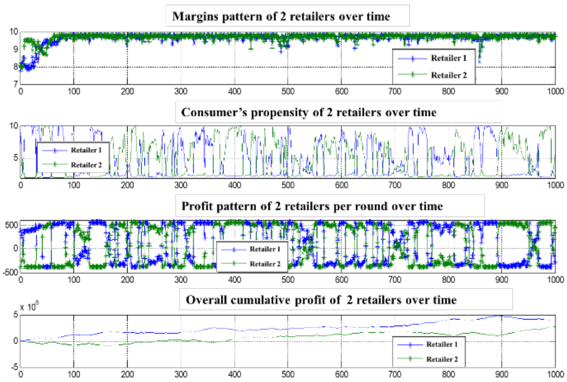

Fig. 3 Market 3: Non-competitive suppliers & collective-learning consumers

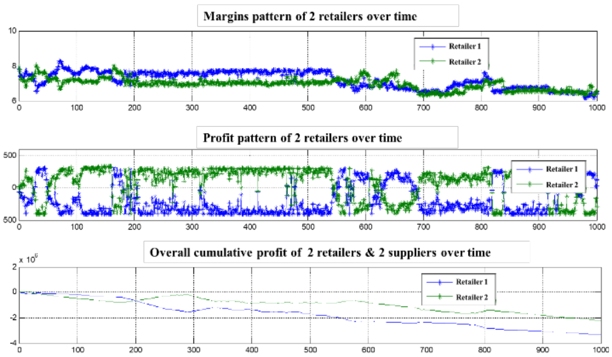

Fig. 4 Market 4: Competitive suppliers & perfect rationality consumers

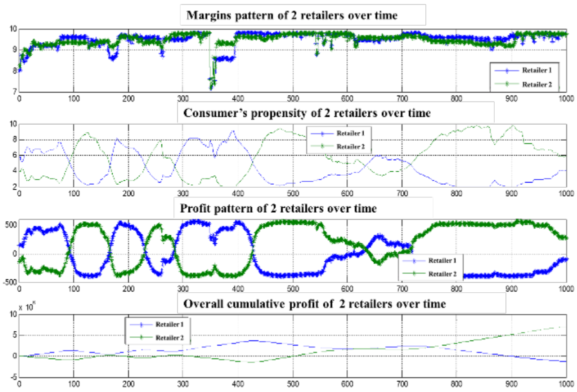

Fig. 5 Market 5: Competitive suppliers & self-learning consumers

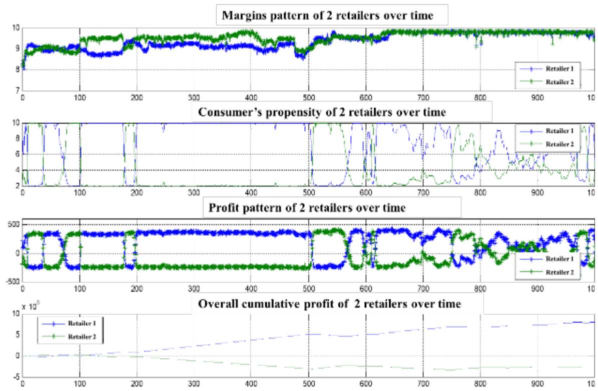

Fig. 6 Market 6: Competitive suppliers & collective-learning consumers

In terms of consumer propensity and the profit pattern of retailers in each round, the propensity and profit of retailers in Market 3 changes most sharply in the absence of competitive behavior by suppliers. The adjustment in propensity is steep, and there is a high degree of frequent switching of leadership. Where suppliers compete, the change in propensity and profit tends to moderate. Retailers with a profitable lead remain steadily and significantly ahead for a period of time, but lead changes can still occur in very short periods of time.

Overall, there is competition for the lowest price at the retailer's end as consumers display p*erfect rationality* behavior. In the case of self-learning behavior, if suppliers do not compete on price, retailers will cooperate, and all adopt a high price strategy. The overall average price and overall cumulative profit at the retailer end will be the highest, with the least amount of interchange between retailers and the least change in profit. However, if suppliers were to compete on price, this would increase the intensity of market change. In the absence of price competition by suppliers, the most dramatic changes in retailer propensity and profit patterns occur in the absence of Collective-Learning behavior, although retailer price competition can result in high prices, including large leads, the most frequent lead switching, and the steepest lead transitions. Price competition by suppliers can help to mitigate the intensity of market change.

4. Conclusions

The contribution of this study is to present a simulated market for price competition involving suppliers, retailers, and consumers and observe how different 'consumer learning behavior' and *supplier price competition behavior* affect the price competition process of retailers and the eventual price equilibrium outcome.

For the retailer side, this study found that consumers engaged in self-learning behaviors that were most beneficial to the retailer side of the competition. Collective-learning has the potential to become a major learning method at a time when e-commerce and online communities are becoming more prevalent. The impact of this could also bring the overall profit of the retailer side closer to that of the consumer market where self-learning is present. It is important to note, however, that if consumers engage in collective-learning, this will lead to increased competition for the retailer as a whole. Therefore, individual retailers need to be cautious in dealing with collective-learning consumers and be aware of market dynamics and be flexible in adjusting their pricing strategies to avoid becoming loss-making retailers due to rigid pricing strategies.

In the face of price competition from suppliers, only in the control group (i.e., the *perfect rationality* consumer market) can the overall retailer side see an increase in profit. Other environments will result in lower profit. Therefore, in a market where consumers are likely to *self-learning* and *collective-learning*, it is more advantageous for retailers as a whole to stabilize the wholesale price of suppliers. From a retailer's perspective, where suppliers do not compete, if consumers engage in self-learning behavior, this will result in the highest overall average price for the retailer and maximize overall cumulative profit. Therefore, from a practical point of view, a retailer can achieve higher profits if it can keep supplier prices stable and induce consumers to engage mainly in self-learning behavior.

The price competitive market proposed in this study also models the price competitive behavior of retailers under the basic assumptions of the Bertrand model (no competition among suppliers, *perfect rationality* among consumers). The experimental results are not only identical to the Bertrand model of competition but also show the dynamic process of price competition. In the further, the price competitive market can be extended or expanded by subsequent scholars to include specific factors to observe the results of the interaction and test related hypothesis.

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