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Competition and evolution in multi-product supply chains: An agent-based retailer model

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ABSTRACT

Facing such issues as demand uncertainty and in- and cross-channel competition, managers of today's retail chains are keen to find optimal strategies that help their firms to adapt to the increasingly competitive business environment. To help retail managers to address their challenges, we propose in this paper an agent-based retail model (ARM), grounded in complex adaptive systems, which comprises three types of agents, namely suppliers, retailers, and consumers. We derive the agents' optimal behaviours in response to competition by evaluating the evolutionary behaviour of the ARM using optimisation methods and genetic algorithm. We find that consumers' ability to collect pricing information has a significant effect on the degree of competition in retail chains. In addition, we find that the everyday low price (EDLP) strategy emerges from the evolutionary behaviour of the ARM as the dominant pricing strategy in multi-product retail chains.

1. Introduction

A supply chain is composed of a large number of autonomous entities, e.g., suppliers, manufacturers, distributors, retailers etc., which work together in a dynamic business environment. Generally, firms in a supply chain collaborate with their upstream and downstream partners, and need to react to their rival firms' competition as well. Both competition and collaboration are the driving forces of supply chain evolution.

Retailers, which are at the end of supply chains, sell goods or commodities directly to consumers. In today's competitive and fast-changing retail markets, there are issues that retailer managers need to adequately address for their firms' survival and prosperity. The issues include: (1) demand uncertainty. Consumers having different preferences seek to minimise their cost of obtaining goods and maximise their utility from these goods (Bell et al., 1998). Therefore, variability in consumer behaviour makes it difficult for retailer managers to accurately forecast consumer demand. (2) In- and cross-channel competition. Many products are transferred and distributed to a great number of retailers, e.g., fast-moving consumer goods (FMCG) like soft drinks can be bought from different retailers, such as supermarkets, convenience stores, mom-and-pop shops, and even street hawkers. The wide variety of alternatives for distributing similar products leads to fiercer competition among retailers, making pricing a key marketing element in peer competition. (3) Optimal pricing of multiple products. In a store, there are many homogeneous or heterogeneous products that are substitutable for consumers because their preferences for each product vary. Consequently, multi-product pricing is getting much more complex along with the rapid development of new products. (4) Inventory policy. The introduction of products with shorter life cycles, together with decreasing brand loyalty of consumers, has presented great challenges of inventory management to retailers. From the retailer's standpoint, these issues make the supply chain a highly dynamic and competitive environment with ever growing complexity.

Over the past years, researchers have made a lot of attempts to model and optimise the retailer's decisions. Previous research on the above issues has been predominantly based on the methods of Operation Research (OR). Under given assumptions, OR-based modelling of the retailer's operations has focused on finding optimal solutions for such issues as pricing strategy, inventory management, and competition effects (Kwon et al., 2007). However, analytical methods are impractical in today's retailing context, which is extremely complex (as the problems concerned are often non-linear and non-convex with mixed integer and continuous variables), because the mathematical model requires excessive computing time when realistic cases are considered (Mele et al., 2006; Thierry et al., 2008). Therefore, simulation-based

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modelling methods, such as agent-based modelling (ABM), have been introduced to deal with complex issues by dynamic modelling of the behaviours of firms in supply chains. Drawing on OR and game theory, integrating supply chain management with ABM captures many of the challenges met by changing supply chain practices (Chaib-draa and Müller, 2006). Moreover, some researchers propose treating a supply chain as a complex adaptive system (CAS) in order to understand how the supply chain adapts to and co-evolves with the dynamic environment in which it exists (Li et al., 2010; Surana et al., 2005).

In this paper we propose an agent-based retailer model (ARM) from the CAS perspective, in which there are two products and three types of agents, namely suppliers, retailers, and consumers. We solve the ARM using a genetic algorithm (GA) to address the following research questions: (1) what is the optimal pricing strategy for the retailers in such a competitive market environment? (2) What is the optimal inventory control policy for retailers in the presence of price-sensitive consumers? (3) If the two products differ in their wholesale prices and consumers' preferences, what are the differences in pricing and inventory control for them? (4) Some retailers may be eliminated in an increasingly competitive environment over time, which can be considered as "evolution". What kinds of retailers can survive in the evolution? (5) From the consumer's standpoint, how does his utility change with the evolution? We make a contribution by resolving the above challenging research and practical issues.

The remainder of the paper is organised as follows: In Section 2 we give a concise review of the related studies in the literature. In Section 3 we present the ARM, including the assumptions and technical details, in detail. In Section 4 we design a series of experiments to observe the evolution of the ARM under different scenarios. In Section 5 we present the data analysis and discuss the results. In Section 6 we conclude the paper and discuss the research and managerial implications of the study. We also acknowledge the research limitations and make suggestions for future research.

2. Literature review

This paper is closely related to three streams of research, namely ABM, supply chain evolution, and retailer competition effects.

ABM, which is a new analytical method for computational social science, combines elements of game theory, complex systems, emergence, computational sociology, multi-agent systems, and evolutionary programming (Briscoe, 2010). The term "agent" denotes an individual or organisation that has the following characteristics: autonomy, social ability, reactivity, and proactiveness (Wooldridge and Jennings, 1995). Therefore, a firm in a supply chain, which carries out tasks by itself and interacts with other companies, is fit to be modelled as an agent using computer programs to simulate its behaviour and gain insight into supply chain management. Recently, the multi-agent system (MAS) approach, a sub-domain of ABM that comes from the discipline of distributed artificial intelligence (DAI), has been widely adopted as an intelligent IT support tool to study various SCM issues such as decision making of supply chain partners (García-Flores and Wang, 2002; Li, 2007), supply chain coordination (Kanda and Deshmukh, 2008), planning and scheduling optimisation problems in manufacturing processes (Caridi and Sianesi, 2000; Monostori et al., 2006), resource allocation (Brandolese et al., 2000) etc. In fact, only a few studies have been conducted on the retail market using MAS. For example, Chang and Harrington (2000) examined the relationship between the degree of discretion given to store managers and the rate of innovation at the store level. In their study, they modelled distributed organisations as multi-agents, each of which is capable of generating new ideas. Yu et al. (2004) proposed an agent-based retail electricity market consisting of four kinds of participant agents and used coloured Petri net technology to represent communication and cooperation of the agents in the market. By simulating their trading procedures in modern power systems, they obtained results that the proposed retail electricity market could increase efficiency, reduce operational cost, and give consumers more alternatives. Heppenstall et al. (2007) designed a multi-agent model to simulate the petrol retail market, and employed a geographical information system (GIS) and GA to explore the parameterisation and verification of the model. Despite increasing studies on MAS-based SCM, there have been few agent-based models proposed to investigate the effects of competition among retailers in a bottom-up way.

Supply chain evolution treats a supply chain as a continuing evolving dynamic process driven by a number of factors. Common methods to study supply chain evolution include case study, evolutionary game theory, and ABM from a CAS perspective. Examples of works employing the first two methods include the following. Fearne (1998) suggests that establishing trust in supply chain partnerships is important by describing the evolution of supply chain partnerships in the British beef industry using a case study. Fujita and Thisse (2006) find that the development of new information and communication technologies is one of the major forces that should be accounted for in order to better understand globalisation and the evolution of the supply chain. Zhu and Dou (2007) propose an evolutionary game model between governments and core enterprises in greening supply chains, and find three evolutionary stable strategies in three cases. Jalali Naini et al. (2011) employ evolutionary game theory and the balanced scorecard (BSC) for environmental supply chain management (ESCM). To understand the complexity of supply chains, CAS theory, proposed by Holland (1996), has been applied to model the dynamic and evolutionary behaviours of SCM systems. Choi et al. (2001) argue that supply chains should be recognised as a CAS for managing supply networks. Li et al. (2010) provide a complex adaptive supply network (CASN) based on CAS and fitness landscape theory to investigate the evolutionary complexity issues such as emergence, quasi-equilibrium, chaos, and lock-in of CASNs. These works, especially CASN studies, have enriched our understanding of the evolution of supply chains. However, previous research has largely neglected consumers' evolutionary behaviours and often assumes that the consumers exist in a static environment. On the contrary, consumers in fact have the power through their fast-changing behaviours to change the evolution direction of the retailer's network in today's dynamic business environment.

As regards research on the competition effects of retailers, there exists a large body of works. For the sake of conciseness, we do not provide a comprehensive review of the literature in this area. For excellent surveys on this topic, we refer the reader to Kopalle et al. (2009) and Bijvank and Vis (2011). Besides, as increasing numbers of firms enter the retail market in which consumers with heterogeneous tastes exist, product differentiation and price competition should be considered. Therefore, we refer the reader to Soon (2011) for a detailed survey of the existing literature on multi-product pricing models. The vast majority of these studies are OR-based or empirical in nature, which focus on the design and optimisation of the retailer's pricing strategy and inventory control policy based on the assumption that the retail chain is an integrated, static organisation. Although specific optimal solutions can be obtained from analytical models via mathematical analysis, these models are often limited in their ability to map the dynamics of the retail chain that is non-linear and complex (Pathak et al., 2007).

Motivated by the above observations, we set out to study a retail chain consisting of two suppliers, n retailers, and N consumers with two products ($N > n$ in general), and model their behaviours from the CAS perspective. Investigating both scenarios of homogeneous and heterogeneous products in this paper, we use GA to find the retailer's optimal pricing strategy and inventory policy in response to competition throughout the evolution of the proposed ARM. Our model moves beyond previous work in several aspects. First, we apply ABM to study the effects of competition and evolution of a multi-product supply chain. Second, we derive the optimal decisions from the ARM, which is based on relaxed (and hence more realistic) assumptions, using GA rather than traditional mathematical analysis. Finally, we model consumers as heterogeneous agents that are able to react to retailers adaptively.

3. Model description

3.1. Overall structure

Our ARM explicitly models micro-scale interactions among suppliers, retailers, and consumers, and macro-scale feedback of market transactions. Fig. 1 shows the overall market structure of our retail chain model, which consists of two suppliers, n retailers, and N consumers.

Underlying the ARM are the following basic notions. First, each supplier only provides one unique product for all the retailers, i.e., Supplier 1 provides Good 1 while Supplier 2 provides Good 2. Second, retailers purchase Goods 1 and 2 from suppliers at wholesale prices, and sell them to consumers. Third, consumers get price information about the two products from the retailers' advertisements and choose to shop with one retailer to buy both products, which are substitutable for the consumers. Fourth, there is no information or material exchange among agents at the same level. In other words, each agent, which makes decisions independently, only reacts to its upstream or downstream partners, if any. Considerable information sharing or collection among consumers and retailers is likely in practice, but the above notions capture the key elements of competition among retailers and, as we will see later, help us to capture the evolutionary process in the retail chain.

In the following we discuss the various components of the model in detail and explain the behaviours of three types of agents in a static time step as a snapshot of the ARM. Appendix A summarises all the parameters and variables used in the ARM.

3.2. Consumers' behaviours

At the beginning of a time step in the ARM, a consumer collects price information from several retailers randomly through their advertisements. So the consumer knows the selling prices of the two goods before deciding on a retailer from whom to buy the goods (Kumar and Rao, 2006). However, in the ARM, we assume that each consumer can only choose to shop with one and only one retailer at each time step because of the high transportation cost, which is neglected in the model.

After consumers collect the price information, we model their purchase behaviours using consumer choice theory in classical microeconomics. We assume that the consumer is a rational decision-maker who seeks to maximise his utility under a budget constraint to achieve equilibrium between preference and expenditure. In terms of the parameters and variables of the model shown in Appendix A, we formulate the consumer's decision problem, in which the consumer's goal is to maximise his utility at time t, as follows:

$$\text{Maximize } U_{it}(q_{jt}^1, q_{jt}^2) = (q_{jt}^1)^{\alpha_i}(q_{jt}^2)^{\beta_i}$$

$$\text{Subject to } P_{jt}^1 q_{jt}^1 + P_{jt}^2 q_{jt}^2 \le B_i.$$

In the above formulation, we use the Cobb–Douglas utility function to model consumers' convex preferences. Parameters α_i and β_i denote a consumer's preferences for G_1 and G_2, respectively, given that consumers differ in their preferences for different products in the real world. So we can assign random values to α_i and β_i in order to generate heterogeneous consumers (see Section 4) in the simulation experiments.

Using the Lagrange multipliers method, we can easily derive the optimal quantities of G_1 and G_2 that consumer C_i buys from retailer R_j respectively, as follows:

$$\begin{cases} q_{jt}^{1*} = \frac{\alpha_i}{(\alpha_i+\beta_i)} \frac{B_{it}}{P_{jt}^1} \\ q_{jt}^{2*} = \frac{\beta_i}{(\alpha_i+\beta_i)} \frac{B_{it}}{P_{jt}^2} \end{cases}.$$

We can then use the utility function to find the maximum utility U_{it}^{j*} that C_i is able to gain from retailer R_j given prices P_{jt}^1 and P_{jt}^2. For a consumer at time t, the retailers from which the consumer gets the price information can be sorted in descending order of U_{it}^{j*}. Then the consumer will choose the retailer that offers him the maximum utility. At the same time, the sum of all the consumers' q_{jt}^{1*} and q_{jt}^{2*} makes up the total demand for retailer R_j, which we will be further discussed in the section on retailers' behaviours.

Besides, variable γ_i, the number of retailers from which the consumer gets price information, is fewer than or equal to the sum of all the available (surviving) retailers at time t, and denotes the degree of the searching ability of consumers enhanced by information technology in the market. If $\gamma_i = 1$, the consumer chooses one retailer randomly. As γ_i increases, the competition among the retailers becomes fiercer because consumers have more retailers

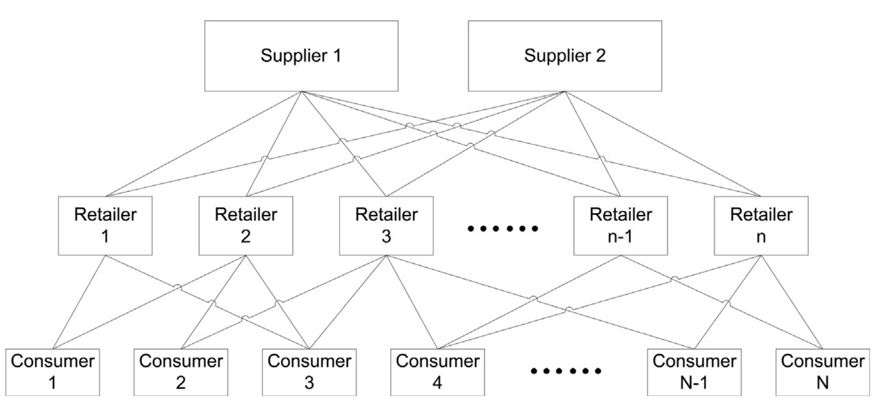

Fig. 1. The market structure of the ARM.

to choose to shop with, which reflects channel competition in the retail market.

In sum, consumer agents in the ARM are able to collect price information on products from several retailers randomly, and compute their maximum utility based on their individual preferences and the retail prices offered by the retailers. To maximise his utility, each consumer agent will choose the retailer that offers him the maximum utility to shop with in the current time step.

3.3. Suppliers' behaviours

Only two suppliers S_1 and S_2 are modelled in the ARM. Good 1 and Good 2, provided by S_1 and S_2 respectively, are substitutable for the consumers. The input variables for suppliers are the order quantities O_{jt}^1 and O_{jt}^2 from retailer R_j, and the output variables, decided by the suppliers, are the wholesale prices WP_{jt}^l offered to R_j based on its order quantity. Explicitly, we state WP_{jt}^l as follows:

$$WP_{jt}^l = \max(k^l O_{jt}^l + b^l, WPmin^l),\ \text{where } k^l \le 0,\ l = \{1, 2\}.$$

The above wholesale price function is the simplest case of incremental discount, which means the wholesale price decreases as the order quantity increases, but no less than a certain level. This assumption reflects the fact that price discounts have long been used as a common strategy for improving the profitability and cost effectiveness of distribution channels (Viswanathan and Wang, 2003). Incremental discount, one of two types of quantity discount to offer, has been studied for a long period from the viewpoints of marketing and operations management (Chen and Ho, 2011; Li and Liu, 2006). Therefore, it makes sense to employ incremental discount in the suppliers' pricing strategies.

Another important aspect about the suppliers in the ARM is transportation from the suppliers to the retailers. First, we assume that the suppliers provide infinite amounts of products for the retailers. Second, cargos will be loaded in the supply line as soon as the orders from retailers are confirmed by suppliers at time t, and will be transported into retailers' inventory at time $-t$+1. Finally, we exclude the transport cost from the ARM. Despite these assumptions, which imply high delivery efficiency, no lead time, and no transport cost in our model, the model still captures the key elements in mapping the supply line of retailers that face keen competition in today's retail market.

To recap, we apply the incremental discount strategy to model suppliers' pricing behaviours to simplify the model and to focus on retailers' behaviours. Moreover, we assume the lead times of the two products to be zero, and the product transport costs negligible in the ARM for the same reasons. Besides, we can vary the exogenous variables such as k^l and b^l to make the two products differ in purchase cost for the retailers (see Section 4).

3.4. Retailers' behaviours

Borrowing the generic stock-management system proposed by Sterman (1989), we model the retailer's inventory structure, illustrated in a system dynamics flow chart with profit formation, as shown in Fig. 2.

Appendix B provides the detailed mathematical expressions for the above functions of the retailer's structure. Concisely, we express the objective function of retailer R_j in the ARM as follows:

$$\text{Maximize } PR_{jt} = Profit(P_{jt}^1, P_{jt}^2, EI_{jt}^1, EI_{jt}^2).$$

Setting the selling prices and expected inventory levels of the two products are the key decisions of a retailer, which aims to maximise its profit. Although most mathematical functions are given in a static time step, it is difficult to directly express the profit function, given $P_{jt}^1, P_{jt}^2, EI_{jt}^1$ and EI_{jt}^2 as independent variables,

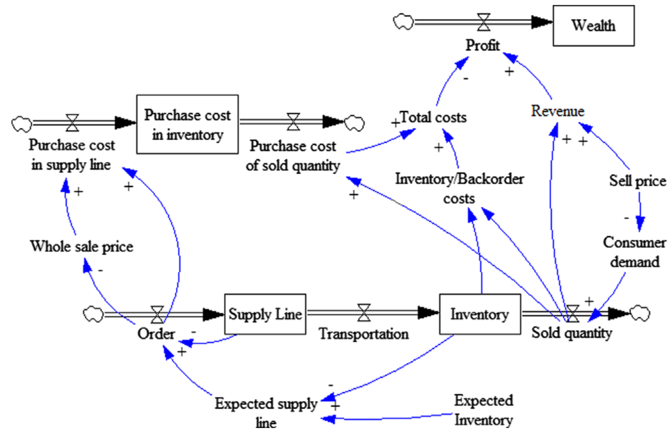

Fig. 2. The retailer's structure in the ARM.

and to optimise the profit in a dynamic context using traditional OR methods for the following two reasons: (1) it is difficult to derive the optimal selling prices to maximise retailers' profits because of uncertainty in the quantities of the products sold. Although the quantity of a product sold is a decreasing function of its selling price according to supply-demand theory in classical microeconomics, which is true for most of the cases of the ARM, consumers are able to compare the prices of the two products offered by different retailers and choose a single retailer to shop with. A surviving retailer's prices of the two products are also independent variables of the retailer's sold quantities, and the elasticity of consumer demand is hard to estimate because the demand function is non-linear and imprecise. (2) It is very difficult to control inventory to match consumer demand to minimise cost. Inventory cost or backorder cost incurs if inventory does not equal consumer demand. Not only consumer demand, but also inventory is a variable because inventory at time t depends on the inventory left at time $t-1$ and the supply line at time $t-1$ (see Appendix B). Therefore, the delay in transportation from suppliers to retailers creates complexity in controlling inventory precisely. To sum up, because of the complexity, dynamics, and non-linear feedback in the ARM, OR-based mathematical methods cannot be applied to find the optimal decisions of the retailers in the absence of precisely defined objective functions.

To address this problem, we apply genetic algorithm (GA) to produce approximate optimal solutions to maximise profit through heuristically searching possible solution spaces. Comparing with other heuristic techniques for optimisation, GA mimics the “natural selection” process and the mechanism of population genetics. It uses probabilistic rather than deterministic rules for solving many types of complex problems, and possesses a remarkable ability to focus on the most promising parts of the entire solution space, which is a direct outcome of its ability to combine strings containing partial solutions (Holland, 1992). These features make GA a promising technique to find the optimal decisions of the retailers by evaluating the evolutionary behaviour of the ARM, given that retailers are selected by consumers and may be eliminated over time in a highly completive environment.

To solve the ARM, we apply a GA that follows the following steps:

Step 1: Generate an initial population of possible solutions randomly by assigning random values to $\{P_{j0}^1, P_{j0}^2, EI_{j0}^1, EI_{j0}^2\}$ as individuals.

Step 2: Compute PR_{j1} as the fitness of each individual in that population.

Step 3: Select the best-fit $(PRmax_{jt})$ individual $\{P_j^{1*}, P_j^{2*}, EI_j^{1*}, EI_j^{2*}\}$ for reproduction at time t.

Step 4: Encode $\{P_j^{1*}, P_j^{2*}, EI_j^{1*}, EI_j^{2*}\}$ in binary as strings of 0 s and 1 s.
Step 5: Breed new individuals $\{P^{1'}_{j(t+1)}, P^{2'}_{j(t+1)}, EI^{1'}_{j(t+1)}, EI^{2'}_{j(t+1)}\}$ through the crossover and mutation operations to give birth to offspring.
Step 6: Evaluate the individual fitness $PR_{j(t+1)}$ of new individuals $\{P^{1'}_{j(t+1)}, P^{2'}_{j(t+1)}, EI^{1'}_{j(t+1)}, EI^{2'}_{j(t+1)}\}$ at time $-t$+1.
Step 7: Replace the least-fit population with new individuals.
Step 8: Go to Step 3 until termination.

With GA, retailers are able to “memorise” their good pricing strategies and inventory control policies that generate high profits in the past time steps. Moreover, retailers are intelligent agents that evolve towards better strategies to optimise their objectives.

Not only the pricing strategy and inventory control policy, but also the number of available (surviving) retailers is able to change in the ARM, since we incorporate an elimination mechanism as evolution. Each agent is endowed with the same wealth at the beginning of each simulation run and able to make a profit (loss) that accumulates (depletes) wealth. However, the ARM will eliminate all the retailer agents with a negative wealth when the next time step starts, which reflects the bankruptcy of under-performing retailers in the real world.

In conclusion, based on the GA procedures, retailers generate better pricing strategies and inventory control policies to maximise their profits, and they may demise and be eliminated from the ARM when they lose all their wealth. These settings help us to examine the best strategies of the retailers, especially survivors with high performance reacting to the competitive market, and to gain managerial insights from observations of the evolutionary behaviour of the ARM.

3.5. Summary

Fig. 3 summarises the sequence of events in the ARM in the form of UML behaviour diagrams. The scheme is quite straightforward and all the components have been discussed above.

In the next section we discuss the simulation experiments we have performed to examine the interactions among the consumers, retailers, and suppliers, and derive insights from the simulation results.

4. Simulation

4.1. Experimental design

We performed several experiments using the ARM under three different scenarios: benchmark case (Scenario A), consumer enhanced price information collection ability case (Scenario B), and heterogeneous products case (Scenario C). Table 1 presents the parameter settings of the three scenarios.

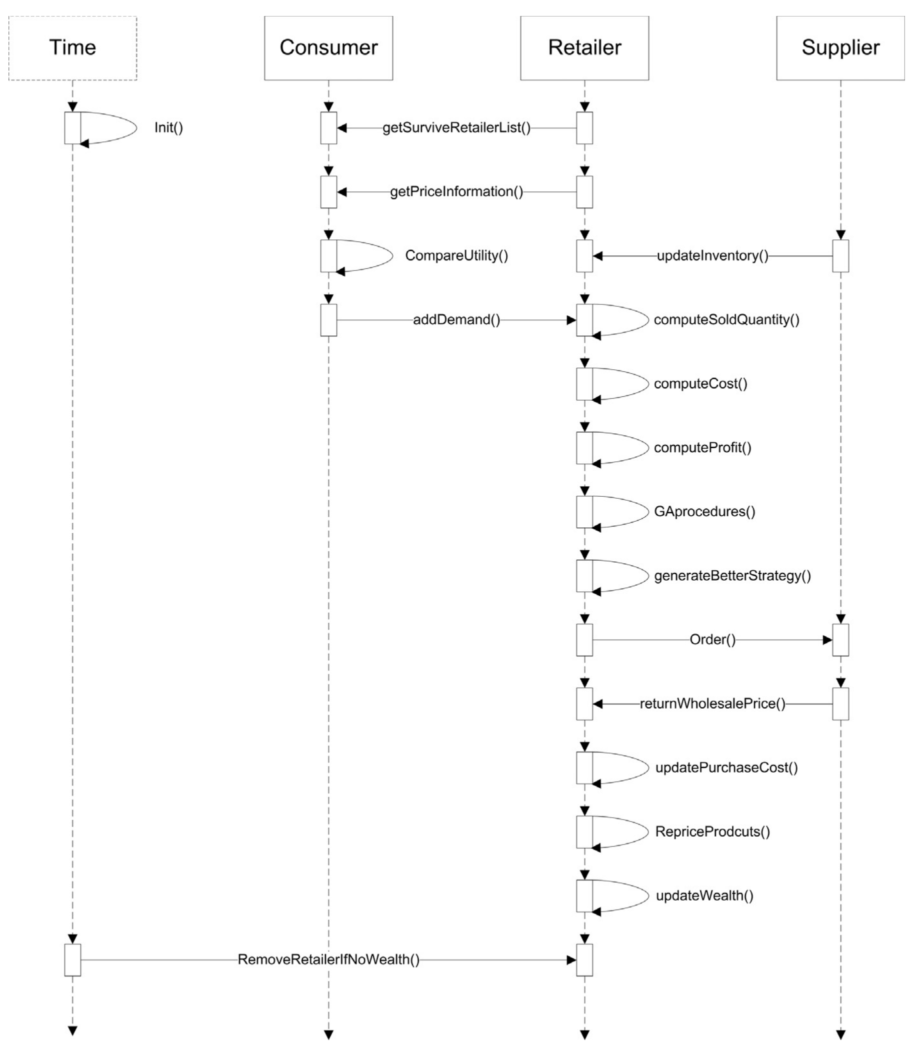

Fig. 3. .UML time sequence diagram of the ARM.

Table 1
Parameter settings of three scenarios.

Parameters	Remark	Scenario A	Scenario B	Scenario C
α_i	Preference for G_1	$U(0,1)$	$U(0,1)$	$U(0,1)$
β_i	Preference for G_2	$1-\alpha_i$	$1-\alpha_i$	$1-\alpha_i$
B_i	Budget of consumers	500	500	500
γ_i	Number of retailers from whom consumer gets price information	2	4	2
h_j^l	Inventory cost per unit	0.5	0.5	0.5
g_j^l	Backorder cost per unit	1	1	1
pm	Probability of mutation	0.1	0.1	0.1
W_{j0}	Initial wealth	10,000	10,000	10,000
$WPmin^l$	Minimum wholesale price	10	10	{10, 20}
k^l	Wholesale price function parameters	−0.1	−0.1	−0.1
b^l		20	20	{20, 30}
NC	Number of consumers	20	20	20
NR	Number of retailers	5	5	5

Under Scenario A – the benchmark case – consumers are able to make a choice between the two retailers and have the same expected preference for each product. Regarding the suppliers, they have the same discount policy. Therefore, Goods 1 and 2 are homogeneous under Scenario A.

The only difference between Scenarios A and B is the variable γ_i, i.e., the number of retailers from which consumers are able to get price information. Under Scenario B, consumers can collect more price information from the retailers, which means the retailers face greater competition.

Besides, we design a scenario with two heterogeneous products to study products' impacts on competition and the evolution of the retail chain. Under Scenario C, consumers prefer G_2 to G_1 because $E(\beta_i) > E(\alpha_i)$. However, the wholesale price of G_2 is greater than that of G_1 in the distribution channel. For the retailers, Good 2 may be more attractive to consumers, but appropriate pricing is essential to maximise their profits.

4.2. Implementation and performance measures

We conducted simulation experiments using the ARM on the Swarm v2.2 platform with Java programming codes. We performed 300 experiments with the ARM under the three scenarios to ensure robust outputs. We carried out the steps presented in Fig. 3 over 1000 time steps for each experiment to examine and analyse the evolutionary behaviour of the ARM. Specifically, we focused on the dynamic changes of the following variables in order to generate insights:

(1) number of surviving retailers: NSR,
(2) wealth of the retailers: W_{jt},
(3) best solutions of the pricing strategies and inventory control policies: $\{P_j^{1*}, P_j^{2*}, EI_j^{1*}, EI_j^{2*}\}$, and
(4) utility of the consumers: U_{it}.

5. Results and discussion

5.1. Scenarios A and B

Observation 1: variable γ_i has a significant effect on NSR, U_{it} as well as retailers' optimal behaviours and performances.

Note that Scenarios A and B only differ in one variable γ_i, i.e., $\gamma_i = 2$ under Scenario A versus $\gamma_i = 4$ under Scenario B. However, the evolutionary results of the two scenarios differ significantly. First, as we see from Fig. 4, which shows the number of surviving retailers after 1000 time steps for 100 experiments under Scenarios A and B, all the five retailers survived 83 times when consumers made a choice only between two retailers; while under Scenario B, a similar result just happened once in 100 experiments. There were 42 times that only two retailers survived, 27 times for one retailer, and 25 times for three retailers if consumers were able to collect more information. These results indicate that consumer choice is a key factor that intensifies competition in the retail market. In reality, various information technologies including the Internet, TV, mobile APPs, and other

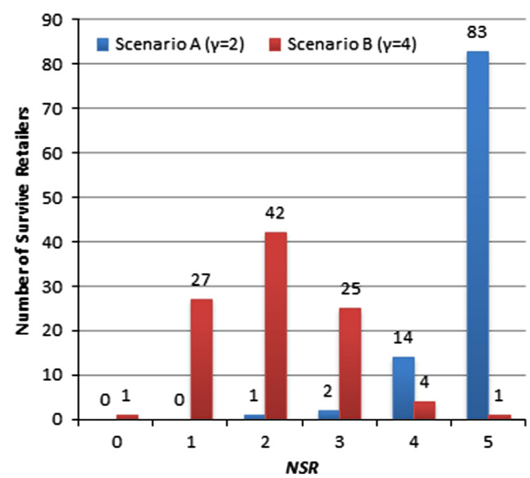

Fig. 4. Histograms of NSR (Number of Survive Retailers) under Scenarios A and B ($t = 1000$).

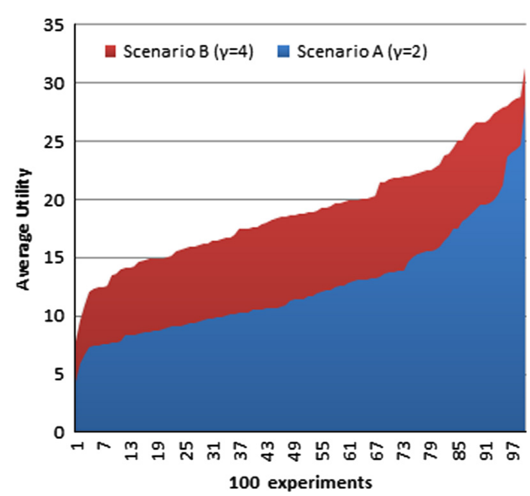

Fig. 5. Area charts of consumers' average utility under Scenarios A and B ($t = 1000$).

telecommunication services that distribute commercial information (such as advertisements, pricing information, promotion etc.) to numerous consumers in a convenient and efficient way lead to fiercer in- and cross-channel competition in the retail market.

Second, from the consumer's viewpoint, it seems that they could gain more utility from the competition among retailers, as illustrated in Fig. 5. Therefore, this hypothesis is tested and accepted according to the output of the ARM, as shown in Table 2.

To discover the reason that consumers gain larger utility under Scenario B, we present the optimal order quantities q^1 and q^2 at $t=1000$ in Fig. 6. We see that consumers were able to buy more products under Scenario B even though they were subject to the same budget under the two scenarios (see Appendix C for detailed statistical test results). Therefore, we speculate that the prices of the two products were lower due to fiercer competition under Scenario B.

Finally, we turn our attention to retailers' pricing strategies and inventory control policies, as well as their wealth, to examine the evolutionary adaptation of retailers and examine the above speculation. As expected, under Scenario B, retailers pursued a low price strategy with a higher expected inventory policy, and made more profit than that under Scenario A, as presented in Figs. 7, 8, and 9.

Fig. 9 shows that in 100 experiments under Scenario B, retailers were very likely to accumulate much more wealth under keen competition. We provide two reasons in the ARM to account for this phenomenon. First, although some retailers were eliminated in the competition brought about by the selectivity of price-sensitive consumers, the surviving retailers could achieve better performance because the number of competitors decreased, so each of the surviving retailers could craft a bigger share of the whole demand of the consumers, which means more profits. Second, as shown in Fig. 7, the prices of the two products were less than those in the benchmark case, so were the profits per unit of G_1 and G_2. However, Fig. 8 shows that the low price strategy is attractive to consumers; retailers adjusted their inventory levels to

Table 2
Summary of statistical test results on consumers' utility (sample size = 100).

Null hypothesis (H_0)	Statistical test methods	Significance	P-value	Result
Consumers' average utility under Scenario A $\sim N(\mu_A, \sigma_A^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.0960	H_0 accepted
Consumers' average utility under Scenario B $\sim N(\mu_B, \sigma_B^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.4797	H_0 accepted
$\sigma_A^2 = \sigma_B^2$	Two-sample F test (two-tailed test)	0.01	0.7315	H_0 accepted
$\mu_A \geq \mu_B$	Two-sample t-test (left-tailed test)	0.01	2.9917e-19	H_0 rejected

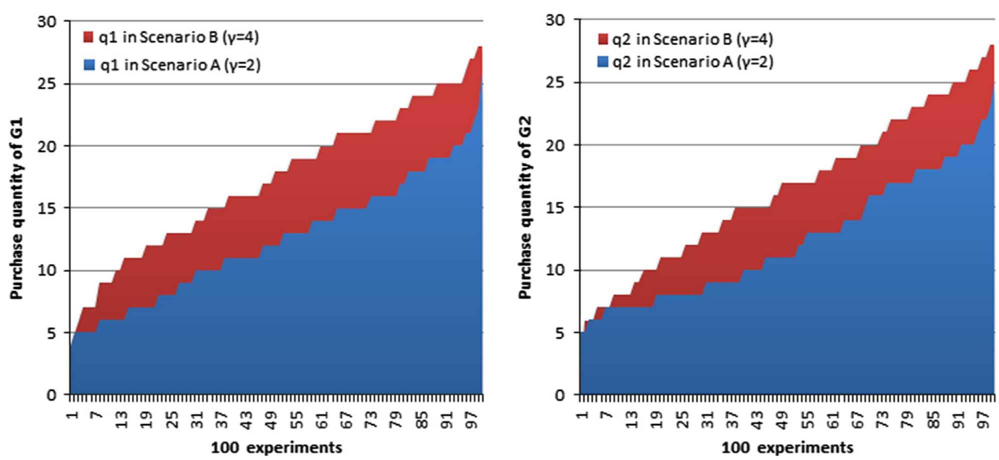

Fig. 6. Area charts of consumers' optimal order quantities under Scenarios A and B ($t=1000$).

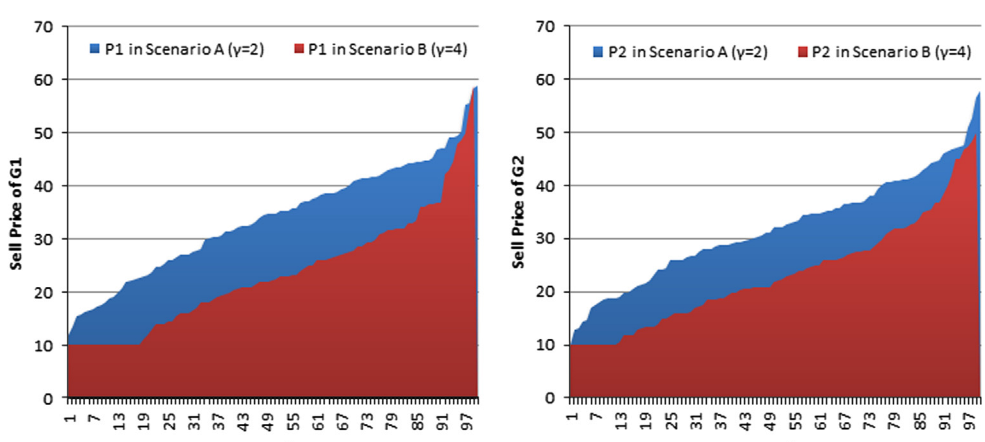

Fig. 7. Area charts of retailers' pricing strategies under Scenarios A and B ($t=1000$).

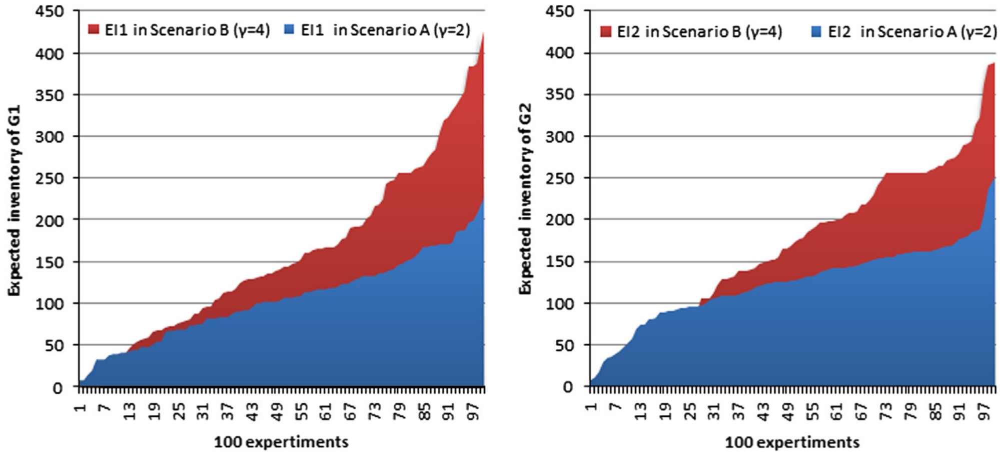

Fig. 8. Area charts of retailers' inventory control policies under Scenarios A and B ($t = 1000$).

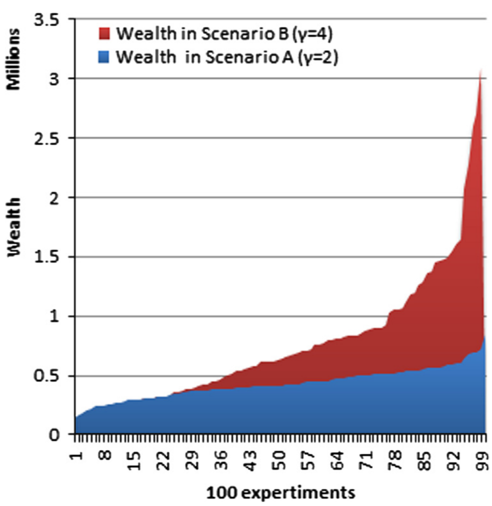

Fig. 9. Area charts of retailers' wealth under Scenarios A and B ($t = 1000$).

meet the greater demand of the consumers, as illustrated in Fig. 6. In conclusion, the evolutionary strategies emerging from the surviving retailers under Scenario B can be classified as the "Low Prices, Everyday" (EDLP) strategy, i.e., the retailer charges a constant, lower everyday price with no temporary price discounts (Hoch et al., 1994).

Retailers like Wal-Mart have adopted the EDLP strategy successfully to encroach on the turf of other retailers such as supermarkets, department stores, and drugstores by advertising that their everyday prices are "always the lowest" to be found (Hoch et al., 1994). This phenomenon is just the practical reflection of our model, especially under Scenario B. Not only practitioners, but also researchers have found that EDLP is the dominant pricing strategy in the retail market. However, comprehensive studies on EDLP are predominantly examining store choice, format choice, or both, without considering how individual consumers choose between different retailing formats (Kopalle et al., 2009). Our ARM adopts the CAS perspective to model the optimal responses of retailers to consumers and vice versa in a bottom-up way, and identifies that the evolutionary and optimal behaviours of retailers in competition is the driving force of the emergence of the EDLP strategy in the retail market. Our approach provides a promising framework to study the competition effects in retail chains from an academic standpoint, and our findings generate valuable practical insights for practitioners based on realistic modelling of their optimal behaviours in today's fast-changing, increasingly competitive, and complex business environment.

5.2. Scenarios A and C

Observation 2: retailers lowered the price of Good 1, and transferred the purchase cost of Good 2 to consumers with a higher preference for Good 2; other indicators are also affected.

Under Scenario C, we are interested to know what will emerge from the retail chain with two heterogeneous products. As mentioned in Section 4, consumers prefer Good 2 to Good 1 with a higher expected preference for the former. However, the purchase cost from Supplier 2 increases accordingly. Therefore, retailers in the ARM have to consider the trade-off between competing for consumer demand and minimising total cost, which is an important issue that retailer managers need to address in the real world.

According to the simulation output of Scenario C, the number of surviving retailers was fewer than that in the benchmark case, and the average utility of consumers decreased as well, as shown in Fig. 10. These results indicate that both the retailers and consumers needed to pay more for the increased cost to purchase Good 2.

For consumers, they reduced their demand for Good 2 but kept the demand for Good 1 to maximise their utility. Fig. 11 shows that q^2 under Scenario C was much less than that under Scenario A, which led to a decrease in the average utility of consumers.

For retailers, they lowered the price of Good 1 to attract the price-sensitive consumers, and transferred the purchase cost of Good 2 to consumers with a higher preference for Good 2. As shown in Fig. 12, the selling price of Good 2 increased by almost ten, which equalled the value of $WPmin^2$ under Scenario C minus that under Scenario A. In other words, retailers, which were forced by the increasing purchase cost and decreasing discount from Supplier 2 of Good 2, had to adopt the EDLP pricing strategy as well to maximise their profits.

Besides, the expected inventory level of Good 2 decreased under Scenario C to match the lower demand, as shown in Fig. 12. Therefore, lowering the selling price of the two products, together with a reduced discount from Supplier 2, reduced the wealth of the retailers, as shown in Fig. 13.

To conclude, with the rapid development of new products and the wide variety of consumers' preferences for products nowadays, the EDLP pricing strategy is the best strategy for retailers with no or little prior knowledge about consumers' personal information and other retailers' pricing information due to high information collection costs. Retailers' inventory control policies are affected by consumers' demand for goods and suppliers' discount policies. The principle to control inventory in a competitive environment is to keep matching demand as best as possible.

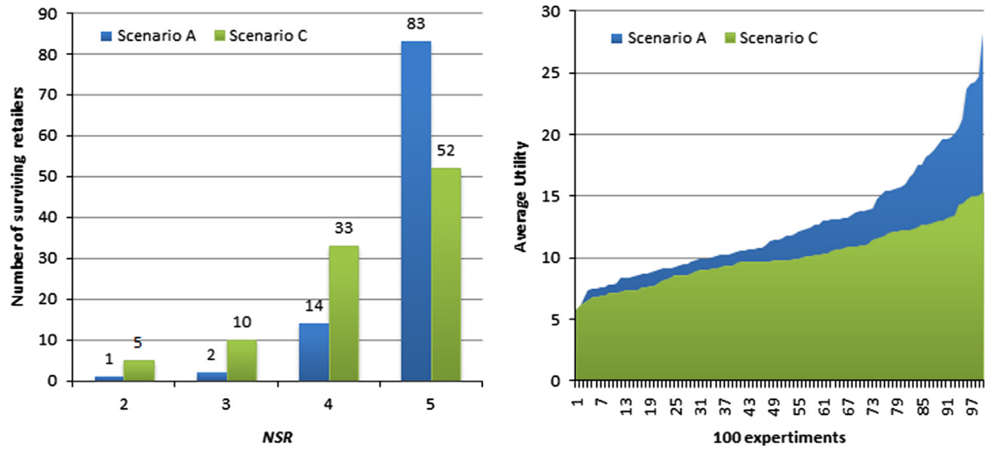

Fig. 10. Charts of *NSR* and consumers' average utility under Scenarios A and C ($t=1000$).

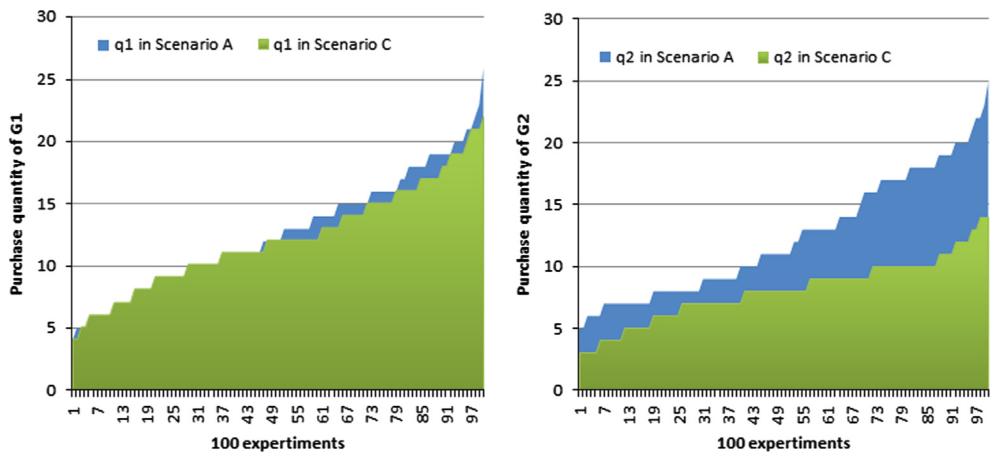

Fig. 11. Area charts of consumers' optimal quantities under Scenarios A and C ($t=1000$).

6. Conclusions

In this paper we propose an agent-based retailer model (ARM), grounded in complex adaptive systems, to model a retail chain with three types of agents, namely two supplier agents that provide two kinds of goods independently, several retailer agents that order goods from suppliers and sell them to consumers to maximise their profits pursuing suitable and evolutionary pricing strategies and inventory control policies, and many consumer agents that have individual preferences for the two goods and are able to collect price information on the products from several retailers randomly to maximise their utility by choosing one retailer to shop with in each time step. We derive the agents' optimal behaviours in response to competition by evaluating the evolutionary behaviour of the ARM using optimisation methods and genetic algorithm.

Our findings from the simulation outputs of 300 experiments under three scenarios can be concluded as follows: (1) Consumers' ability to collect pricing information has a significant effect on the degree of competition in a retail chain. From the consumer's standpoint, this result explains the internal factors driving channel competition and evolution in the retail market. (2) The EDLP strategy emerges from the evolutionary behaviour of the ARM as the dominant pricing strategy in the retail market. This finding is consistent with the findings in previous theoretical research, and substantiates the success of some retailers that adopt the EDLP strategy well such as Wal-Mart in practice. (3) In the case that retailers have no or little prior knowledge about consumers' personal preferences for heterogeneous products and rival retailers' pricing information, EDLP is the best strategy to survive in a competitive market.

We suggest several future directions for this model. First, it is worth modelling suppliers' optimal behaviours. Each firm in the supply chain has its individual objective, so we could model a supplier as an intelligent agent in detail to simulate its adaptation and evolutionary behaviours. Second, the transportation cost and other elements omitted in our model for simplicity purposes can be taken into account in an extended version of the ARM, which would make agents' behaviours much more realistic. Finally, it is desirable to improve the structure of the ARM by, e.g., incorporating the possibility that new retailers can enter the market.

Acknowledgements

We thank two anonymous referees for the positive and constructive comments and suggestions. This research was supported in part by the Hong Kong Polytechnic University under grant number G-UA39.

Appendix A. Variables and parameters in the ARM at time *t*.

See Table A1.

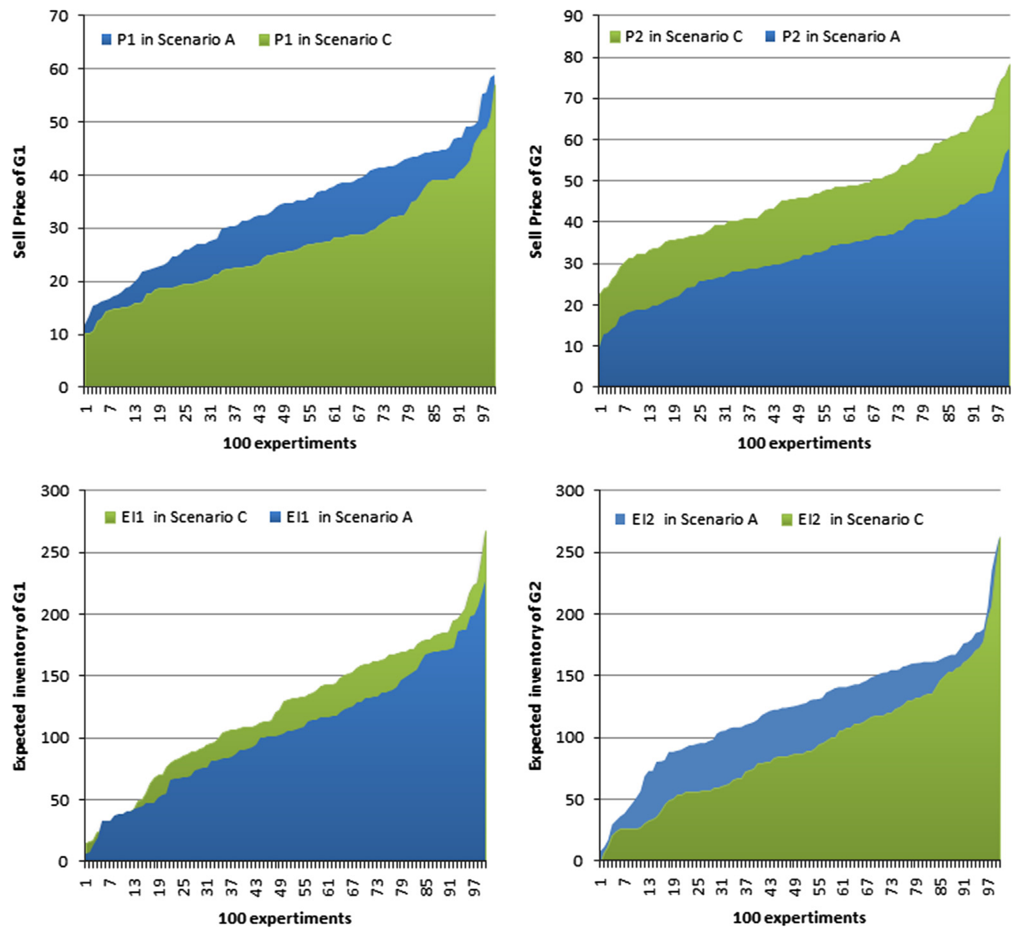

Fig. 12. Area charts of retailers' pricing strategies and inventory control policies under Scenarios A and C ($t = 1000$).

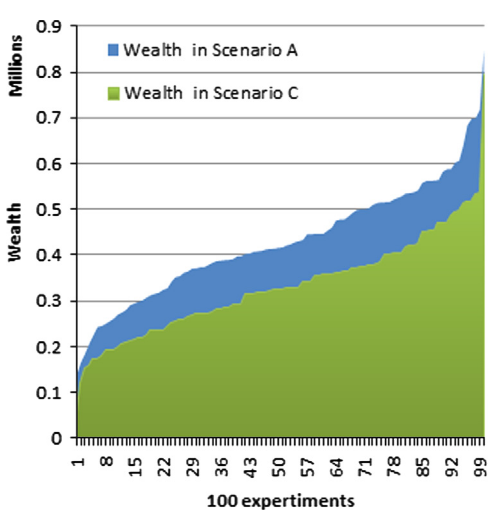

Fig. 13. Area charts of retailers' wealth under Scenarios A and C ($t = 1000$).

Appendix B. Mathematical expressions of retailers' behaviours.

Maximise $PR_{jt} = Profit(P_{jt}^1, P_{jt}^2, EI_{jt}^1, EI_{jt}^2)$

Subject to $P_{jt}^l \geq WP_{jt}^l$, $O_{jt}^l \geq 0$

$W_{jt} = W_{j(t-1)} + PR_{jt}$ //Wealth accumulation

$PR_{jt} = \sum_{l=1,2} (RV_{jt}^l - TC_{jt}^l)$

$RV_{jt}^l = P_{jt}^l SQ_{jt}^l$

$SQ_{jt}^l = \min(I_{jt}^l, Q_t^l)$

$I_{jt}^l = I_{j(t-1)}^l + SL_{j(t-1)}^l$ //transportation from supply line to inventory

$TC_{jt}^l = h_j^l \cdot \max(I_{jt}^l - SQ_{jt}^l, 0) + g_j^l \cdot \max(Q_t^l - SQ_{jt}^l, 0) + PCI_{jt}^l \cdot \min\left(\frac{SQ_{jt}^l}{I_{jt}^l}, 1\right)$ //inventory/backorder costs plus purchase costs

$PCI_{jt}^l = PCI_{j(t-1)}^l + PCSL_{j(t-1)}^l$

$I_{jt}^l = I_{jt}^l - SQ_{jt}^l$ //update inventory

$O_{jt}^l = \max(EI_{jt}^l - I_{jt}^l, 0)$ //order quantity

$SL_{j(t+1)}^l = O_{jt}^l$ //no lead time assumption

$PCSL_{j(t+1)}^l = O_{jt}^l \cdot WP_{jt}^l$ //update purchase cost in supply line

$PCI_{jt}^l = PCI_{jt}^l - PCI_{jt}^l \cdot \min\left(\frac{SQ_{jt}^l}{I_{jt}^l}, 1\right)$ //update purchase cost in inventory

Table A1
Variables and parameters in the ARM at time t.

	Consumer	Retailer	Supplier
One sample	C_i	R_j	S_l, provides Good G_l
Inputs	Sell price of G_1 in R_j: P_{jt}^1 Sell price of G_2 in R_j: P_{jt}^2	Demand from consumers: Q_t^1, Q_t^2 Wholesale price from supplier: WP_t^1, WP_t^2	Order quantity of G_l from R_j: O_{jt}^l
Outputs	Purchase quantity of G_1 in R_j: q_{jt}^1 Purchase quantity of G_2 in R_j: q_{jt}^2	Sell price of G_1: P_{jt}^1 Sell price of G_2: P_{jt}^2 Order quantity of G_1: O_{jt}^1 Order quantity of G_2: O_{jt}^2	Wholesale price of G_l for R_j: WP_{jt}^l
Constraints	Budget: B_i	$P_{jt}^l \geq WP_{jt}^l$, $O_{jt}^l \geq 0$	$WP_{jt}^l \geq WPmin^l$
Object	Utility: U_{it}	Profit: PR_{jt}	
Endogenous variables		Inventory: I_{jt}^l Supply line: SL_{jt}^l Sold quantity: SQ_{jt}^l Expected inventory: EI_{jt}^l Purchase cost in inventory: PCI_{jt}^l Purchase cost in supply line: $PCSL_{jt}^l$ Total cost: TC_{jt}^l Revenue: RV_{jt}^l Wealth: W_{jt}	
Exogenous variables	Preference for G_1: α_i Preference for G_2: β_i Number of retailers from which consumers get price information: γ_i	Inventory cost per unit: h_j^l Backorder cost per unit: g_j^l Probability of mutation: pm	Min wholesale price: $WPmin^l$ Wholesale price function parameters: k^l, b^l

Table C1
Summary of statistical test results on consumers' optimal q^1 under Scenarios A and B (sample size = 100).

Null hypothesis (H_0)	Statistical test methods	Significance	P-value	Result
q^1 under Scenario A $\sim N(\mu_A, \sigma_A^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.5581	H_0 accepted
q^1 under Scenario B $\sim N(\mu_B, \sigma_B^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.3131	H_0 accepted
$\sigma_A^2 = \sigma_B^2$	Two-sample F test (two-tailed test)	0.01	0.0677	H_0 accepted
$\mu_A \geq \mu_B$	Two-sample t-test (left-tailed test)	0.01	1.7213e − 09	H_0 rejected

Table C2
Summary of statistical test results on consumers' optimal q^2 under Scenarios A and B (sample size = 100).

Null hypothesis (H_0)	Statistical test methods	Significance	P-value	Result
q^2 under Scenario A $\sim N(\mu_A, \sigma_A^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.6299	H_0 accepted
q^2 under Scenario B $\sim N(\mu_B, \sigma_B^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.0284	H_0 accepted
$\sigma_A^2 = \sigma_B^2$	Two-sample F test (two-tailed test)	0.01	0.0194	H_0 accepted
$\mu_A \geq \mu_B$	Two-sample t-test (left-tailed test)	0.01	2.7317e-07	H_0 rejected

Table C3
Summary of statistical test results on retailers' optimal P^1 under Scenarios A and B (sample size = 100).

Null hypothesis (H_0)	Statistical test methods	Significance	P-value	Result
P^1 under Scenario A $\sim N(\mu_A, \sigma_A^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.1590	H_0 accepted
P^1 under Scenario B $\sim N(\mu_B, \sigma_B^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.9290	H_0 accepted
$\sigma_A^2 = \sigma_B^2$	Two-sample F test (two-tailed test)	0.01	0.7777	H_0 accepted
$\mu_A \leq \mu_B$	Two-sample t-test (left-tailed test)	0.01	7.7092e-11	H_0 rejected

Table C4
Summary of statistical test results on retailers' optimal P^2 under Scenarios A and B (sample size = 100).

Null hypothesis (H_0)	Statistical test methods	Significance	P-value	Result
P^2 under Scenario A $\sim N(\mu_A, \sigma_A^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.3235	H_0 accepted
P^2 under Scenario B $\sim N(\mu_B, \sigma_B^2)$	Kolmogorov–Smirnov Test (two-sided test)	0.01	0.9969	H_0 accepted
$\sigma_A^2 = \sigma_B^2$	Two-sample F test (two-tailed test)	0.01	0.9296	H_0 accepted
$\mu_A \le \mu_B$	Two-sample t-test (left-tailed test)	0.01	2.6074e−09	H_0 rejected

Appendix C. Summary of statistical test results.

See Tables C1–C4.

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