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Agent-based Simulation of Durables Dynamic Pricing

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Abstract

The market is a complex economic system, in which all members adaptively interact with each other and with the environment to make decisions. Therefore, pricing dynamically due to the real market situation is a system engineering task. This paper developed an agent-based consumer affordability model, trying to observe the durables diffusion with price adjusting according to the evolution of product life cycle (PLC). By creating a large number of heterogeneous consumers in the artificial market, consumer behaviors were dynamically established and predicted. Comparison of sales volume and profit were provided in different scenarios, which could support the business decision-making.

Key words: ABMS; innovation diffusion; dynamic pricing; higher-priced durables; financial engineering

1. Introduction

Price is an important factor for enterprises to survive and develop in complex market environment. How to pricing according to products characteristics is an inevitable topic in marketing activities. To some extend, price dramatically determines the profit. Therefore, adopting the appropriate pricing scheme and strategy to make big profit is a critical direction for enterprises' long-term survival and sustainable development [1]. In recent years, dynamic pricing strategy has gained great attention and adoption in more and more industries, especially in the retail business and service industry, such as airlines, hotels and restaurants [2]. Three factors contributed to this: first, an increased availability of demand data; second, ease of changing prices due to new technologies; third, an availability of decision-support tools for analyzing demand data and for dynamic pricing.

Dynamic pricing is mainly concerned with the changing of costs and demands with time. It focuses on pricing strategy developed with the product life cycle (PLC) [3]. Terms related often are "innovation diffusion" and "experience curve". Bass[4] presented a model that predicted consumer purchase probability at a certain time point during the diffusion process, separating consumers into two groups "Innovator" and "Imitator". On the basis of the Bass Model, many scholars made attempt to improve and extend, such as adding the marketing combination variables[5], considering the competition factor[6], and introducing the supply constraint[7,8]. The main limitation of the Bass model is that it only takes spread into consideration, while it ignores the marketing schemes, consumer affordability, consumer heterogeneity, and so on. Golder at el[9] regards that the purchasing powers of consumers are different, so that they have different affordability to prices. They built model of function taking price, income, consumer sentiment, and market presence as variables. In recent years, more and more complex system theories are

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applied to innovation diffusion, considering that consumers are information updated and heterogeneous, so that their decisions are dynamic. The main modeling methods include complex network modeling and agent-based modeling and simulation (ABMS) [10-13].

This paper focus on the higher-priced durables, such as laptop, digital camera, mobile phone and so on, trying to observe the influence of dynamic pricing on innovation diffusion with the evolution of product life cycle. ABMS is a relatively new and promising method to study complex system problem, and it is widely used in areas such as finance, economics, engineering, military science, etc. It uses a bottom-up approach and builds models of individual characteristics and behaviors [14]. It maps individuals onto agents, individual characteristics onto agent's properties, individual behavioral rules onto agent's methods. With interaction and coordination between agents, it simulates the independent but mutually influential phenomenon of individuals, and so that to study the structures and functions of the system. ABMS is an effective way of studying innovation diffusion and its factors. Three factors contributed to the reason: (1) There are a large number of behavioral subjects (consumers, retailers, manufactures and so on) in the market, and they are heterogeneous (2) Each individual accepts, as well as releases information, and therefore their psychology and behaviors are changing with the updated of information, as in adaptability (3) Influences of elements (price, quality, ads, and so on) are nonlinearly interactive, so that simple interactive behaviors between individuals may cause complicated emergent phenomenon.

2. Agent-based innovation diffusion model

Innovation diffusion in the social system reflects the purchasing decision of consumer individuals [15], which is usually determined by consumer characteristics (income, social status, age, etc), product features (price, brand, function, etc) and social network [12]. Consumers, enterprises, products and interactions among them compose a complex economic system. Gatignon and Robertson [16] proposed the "consumer diffusion paradigm" (see Fig.1).

2.1 Literatures

Based on the congruence of its application strengths and characteristics of diffusion environments, ABMS has great potential to advance diffusion research. Izquierdo et al. [17] used an agent-based model to illustrate how quality uncertainty could lead to market failure, even in the absence of information asymmetric. The paper showed that market interaction with quality uncertainty generally produces underestimation of product quality as well as systematic drops in prices and losses of market efficiency, while spread of information through social networks can greatly mitigate this market failure. By creating a large number of heterogeneous consumer agents in an artificial market, Zhang et al. [10] uses multi-agent simulation (MAS) to exhibit the emergent decoy effect phenomenon. Schramm et al. [12] developed an agent-based diffusion model with consumer and brand agents, and they used the brand and product diffusion curve output to study of diffusion at micro and macro levels, respectively. Delre et al. [18] compared the effect of social influence and word-of-mouth processes on diffusion across different network structures. The simulation showed that innovations diffuse more quickly in clustered networks than in random networks because individuals in clustered networks are exposed to more social influence that may result in a shorter time to adoption. Diffusion occurs more slowly in large networks since in this case more adopters are necessary to influence the individual.

It could be concluded that in the current agent-based diffusion models, research focus either on the whole diffusion process, or on the impact of social network structure on diffusion rate. However, research on price, the most important attribute of a product, are very rare. Golder [9] indicated that most consumers are informed about new durables long before purchasing them. New durables usually appear as very expensive items, only when prices drop substantially do they appeal to the mass market. Moreover, by observing the history of new product introductions over time, consumers can learn that the latest, hottest innovation is not invariably expensive. If they wait long enough, they can get today's hot item at a substantial discount tomorrow. Therefore, many consumers may delay their purchases until prices decline or incomes rise sufficiently. Thus affordability became an important driver of sales growth of a new product.

In the context of fierce market competition and globalization, dynamic pricing is especially important for studying product diffusion. The following reasons may explain this: First, prices are not only the game between enterprises, but also game between enterprises and consumers. The constantly changing game environment forces enterprises to make appropriate price decision to survive and develop in the highly competitive and dynamic market. Second, profit is the ultimate goal of enterprises, and price could not only influence the short-term profit, but also the long-term profit. Fast price changing may increase the short-term profit for a while, however, frequent price changing may add costs, and negatively affects consumer emotions, which may decrease the market share and therefore reduce long-term profit of the enterprise. Therefore, this paper tried to show the innovation diffusion of higher-priced product with the changing of price, trying to observe influence of dynamic pricing on new product development.

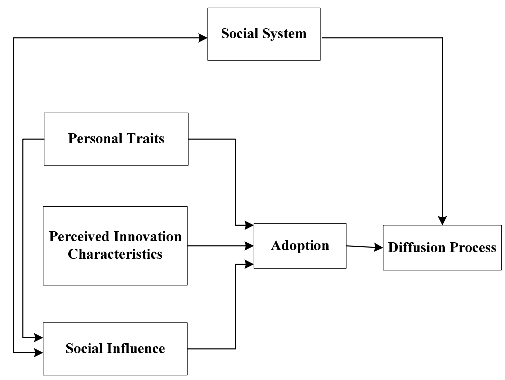

Fig.1. Consumer diffusion model

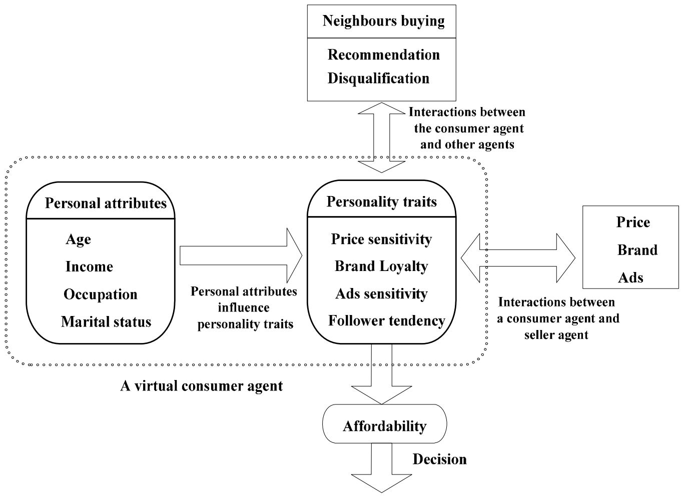

Fig.2. Consumer affordability model

2.2 Model assumptions

(1) Since our paper study higher-priced durables, repeat purchasing is not considered;
(2) There is no supply constraint;
(3) Effective market.

2.3 Consumer affordability model

Consumer purchasing behaviour could be separated into five stages: perceiving requirements, searching for information, evaluating options, purchasing decision-making and post-purchase behavior [10]. Therefore, most of the purchasing behaviors are rational. Requirements produce purchasing motivation with some stimuli, and purchasing motivation produce purchasing behavior with the support of affordability. According to marketing theories, the stimuli include price, brand, quality, promotion and ads, recommendations and disqualifications, etc. Consumer characteristics determine how much consumer would be influenced by these stimuli. These characteristics include age, income, social status, marital status, etc. For instance, a millionaire would not be sensitive to the prices of most products, while a regular worker would possibly be frightened by luxuries.

This paper developed a consumer affordability model (see Fig. 2). Consumers are different in terms of affordability, therefore, each consumer is an agent, and each consumer agent produces purchasing behavior when its affordability reaches the threshold. The affordability function is as follows:

$$S_i = \lambda_1 \times P \times PS_i + \lambda_2 \times B \times BL_i + \lambda_3 \times Ad \times AdS_i + \lambda_4 \times Inf_{i,in} \times ft_i \tag{1}$$

In which, S_i is the affordability of consumer agent i （$i = 1, 2, \cdots N$）. λ_1、λ_2、λ_3、λ_4 are weights of price, brand, ads, and social network to affordability, and $\lambda_1+\lambda_2+\lambda_3+\lambda_4=1$. P is the product price, and PS_i is the price sensitivity of consumer agent i. A larger price sensitivity means a lower affordability to price. Obviously, PS_i is negative. B is brand strength, and BL_i is the brand loyalty of consumer agent i. Ad is ads strength, and AdS_i is the ads sensitivity of consumer agent i. The higher ads sensitivity is, more consumers would be influenced by ads. $Inf_{i,in}$ is the perceived influence exerted by other agent, while ft_i is the agent's follower tendency parameter that represents how easy agent i may be influenced by other people.

2.4 Product life cycle theory

A new product progresses through a sequence of stages from introduction to growth, maturity and decline[1]. This sequence is known as the Product Life Cycle (PLC) and is associated with changes in the marketing situation, thus impacting the marketing strategy and the marketing mix. In the introduction stage, product is rarely known by consumers, and sales increase rata is very low. Little or no competition exists in this stage. Product is widely accepted by consumers in the growth stage. Sales and profit would increase dramatically. However, with the increasing of competitors, consumers have more options, and therefore, the seller is faced with great price pressure. When it comes to the maturity stage, sales volume flattens out. There would be a large number of competitors, so that seller needs to adjust price according to its market position. In the decline stage, sales would decrease remarkably, and products of competitors are less and less. For products such as computer, digital camera, car and so on, the main reason to decline is the outdated technology. Product life cycle of such kind of product is about 2 to 4 years.

However, it is not an easy task to tell which stage of PLC is. The current methods include sales growth rate method, Gongshi curve method, method of analogy, cubic function curve method, etc [19]. The essence is to take sales as the test index. This paper adopted the sales growth rate method for its better operability. $\pm$ 10% month sales growth rate is taken as the boundary. When the sales growth rate is less than 10%, product is in the introduction stage, and when it exceeds 10%, the growth stage is coming; when the sales growths rate falls off to -10% to 10%, product has entered into the maturity stage; sales growth rate of less than -10% indicates that the product is gradually drop out of the market. See Table 1.

Table 1. Stage of product life cycle

Sales growth rate/month	Stage of PLC
0~10%	Introduction
> 10%	Growth
-10%~10%	Maturity
< -10%	Decline

As an economic body that would always purchase the maximum profit, sellers must make their price decisions due to the PLC evolution [20]. Not only situations of their own should be considered, but also the strength of competitors and consumers should be evaluated. From the angle of game theory, sellers need to adjust their prices according to the strength of all parties, searching for new price balance, to maximize the profit.

For higher-priced durables, such as computer, digital camera, car, mobile phone, etc, sellers usually adopt the "skimming pricing method", which means they would make a pretty high price at first so that only a few people, who may strive for a new and fashionable mind, could afford it. When the sellers have earn certain amount of profit, and the product is known by more people, they would decrease the price a bit, so that more people can afford it. Eventually, the price would be low enough so that the mass market could afford it, and the sellers would earn their profit from the large sales volume. But when new upgraded products or substitutes are increasing so that the product does not have much potential, sellers would sell them at a very price to earn the surplus value to the full extent.

Dynamic Pricing

The paper considers the diffusion of only one product, so that there is only one seller agent. Since agents are intelligent, the seller could analyze which stage it is and adjust prices accordingly. Robinson proposed the multistage pricing model based on the Bass model. It came into the mathematical form like this: $P^*_{(t)} = P^*_{m(t)} + dP_{(t)}$. $P^*_{m(t)}$ is the short-term optimum price, and $dP_{(t)}$, function of innovation effect, discount rate, price elasticity and market potential, is the adjusted price. However, many research show that $P^*_{m(t)}$ is not any easier to determine than $P^*_{m(t)}$. Moreover, parameters of $dP_{(t)}$ are very hard to estimate. Therefore, this model is not quite practical.

For simplicity, this paper adopt the percent dropping price policy, as in the seller adjust the price for n% (n$\in$(0, 20)) each time. For products like computers, mobile phone, camera, etc, sellers usually adopt "skimming pricing"—they would set a very high price in the introduction stage, and as the competition became more and more fierce, or the showing up of new technology and upgrade products, price would decline each time when it gets into a new stage of PLC. The seller agent computes sales volume at the end of each month, and when the sales growth rate reaches the boundaries mentioned above ($\pm$ 10%), it gets into a new stage, and then the seller decease the price for n%.

Since the price sensitivity, brand strength, ads strength, as well as the social influence perceived by the agent are changing with time, the consumer affordability model could be reformed as follows:

$$S_{ti} = \lambda_1 \times P_t \times PS_{ti} + \lambda_2 \times B_t \times BL_{ti} + \lambda_3 \times Ad_t \times AdS_{ti} + \lambda_4 \times Inf_{ti,in} \times ft_{ti} \tag{2}$$

In which, $t = 1, 2, 3, 4$, that represents stages of PLC. P_t is the price in stage t , which follows a decreasing tendency during the entire PLC. B_t does not fluctuate much, especially for the regular and creditable brand. The ads strength (Ad_t) would be relatively larger in the introduction and growth stage, because the product need to be known by more people. $Inf_{ti,in}$ would increase with a larger number of consumers that have purchased the product. Since the market is effective, an agent would perceive more recommendation than disqualification.

3. Simulation and result

Currently, numerous software programs exist for modelling ABMs. Netlogo 4.1.2[21], used this study, provides a tool for any manager and researcher—not just those with computer programming skills—to build an ABM. An important feature of this software is its sliders and switches. Sliders are used in models as a quick way to change a variable without having to recode the procedure every time. Instead, the user moves the slider to a value and observes what happens in the model. Switches are a visual representation for true–false variables. The switches can be turned on to add complexity or, in other words, to add contingencies to the model. By setting the sliders to redetermine values and by setting the switches to the off position, a baseline model can be established.

3.1 Parameters setting

Since our research focus on the higher-priced durables, price is definitely a premier influencing factor, so that we set λ_1=0.5. Also, it is not easy for consumers to observe qualities, so that it is more likely they would take brand strength as reference for qualities and services. λ_2=0.3. Considering consumers are rational to purchase higher-priced products, they are unlikely to make impulsive purchase decisions because of ads or neighbours opinions, so we set λ_3=0.1， λ_4=0.1. Assume the price in the introduction stage is P_1=1000, and the cost C=600. Price sensitivity $PS_{ti} = (P_{ei} - P_t) / P_t$, in which P_{ei} is the price expectation of agent i, and is mainly determined by the consumer income, social status, age, etc. Assume P_{ei} is normally distributed, as in $P_{ei} \sim N(800, 300)$. For simplicity, we assume that the brand strength and ads strength keep constant, B_t=800， Ad_t=800. Brand loyalty BL , ads sensitivity AdS and follower tendency ft are uniformly distributed with（0.1, 1）. Consumer agent j exerts influence on others $Inf_{tj,out}$, which is normally distributed, as in $Inf_{tj,out} \sim N(800,300)$. Each consumer agent interacts with other agents within 3 time radiuses from where it is located. Recommendations and disqualifications from consumers that have purchased the product are 7:3—70% consumers are satisfied with the product and give positive evaluation $Inf^{+}_{tj,out}$, while 30% consumers are dissatisfied with the product for some reason so that they make negative assessments $Inf^{-}_{tk,out}$. Therefore, social influence perceived by consumer agent i is $Inf_{ti,in} = \sum Inf^{+}_{tj,out} - \sum Inf^{-}_{tk,out}$.

3.2 Experimental result

1000 potential consumer agents were created in the artificial market, and the computer randomly pick up values for them due to the parameters rules mentioned above. In this way, there are 1000 heterogeneous consumers in the market. In Fig. 4, red agents are those who have not purchased the product, and the yellow ones are those who have already bought this durable. Fig. 3 is the parameter sliders, and all the parameters could be adjusted according to the practical condition of the market.

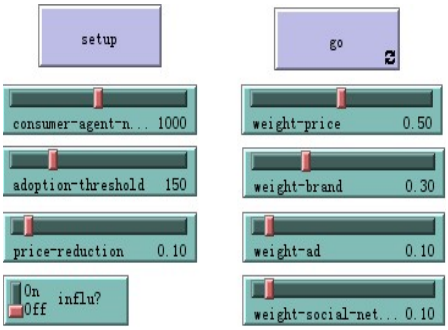

Fig.3. Parameter sliders

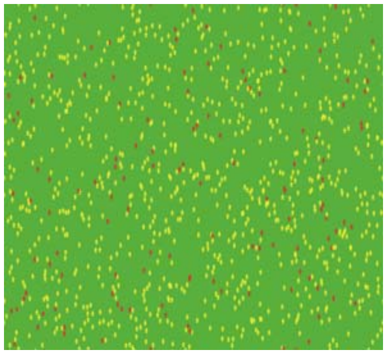

Fig.4. Consumer agents

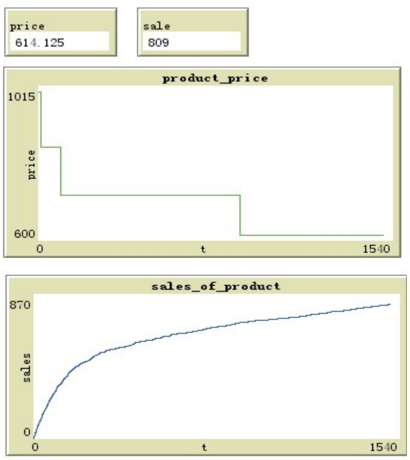

Fig. 5 Price reduce for 15%

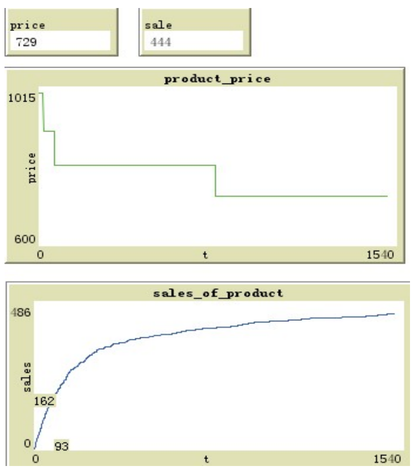

Fig. 6 Price reduce for 10%

Product prices and sales are in Fig.5 and Fig. 6, when the price was adjusted for 15% and 10%. The maximum ticks are set as 1500. It could be seen that the sales increased pretty fast at the first few stages, and then flattened out. Compared to the practical condition, stages of introduction and growth are a bit shorter. It mainly because that consumers who have enough affordability for the product are just a few, and they would purchase as soon as their affordability reached the threshold in the simulation, so that the process of gradually knowing the product is ignore, which needs improvement in the future. Scenario of invariable price is also presented to better compare the influence of price change on diffusion. Assume the price kept 900, according to Fig 7, sales volume was only 286, while it reached 809 and 444 when the price changed for 15% and 10%. Sales volumes of each stage of PLC are easy to observe from Fig. 7. Sales of maturity, which may account 50% of the total volume, are definitely the most. From Fig. 8, profit of growth is bigger than that of maturity, although the sales are much smaller. The main reason is that price in the growth stage is pretty high, and the margins are bigger. In the context of price adjusted for 10%, profit followed the same tendency with the sales volume. In general, sales and profits increasingly decrease when price changed for 15%, 10% and 0. However, it does not mean that the lower the price is, the bigger margins. Simulation experiments show that there is a growing sign of deficit when the price reduced for more than 20%.

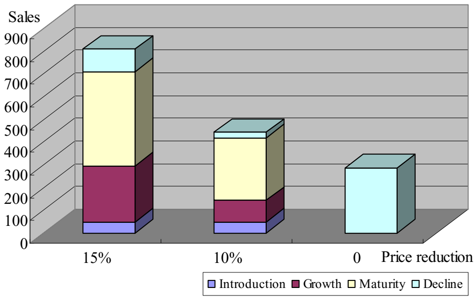

Fig. 7. Comparison of sales volume

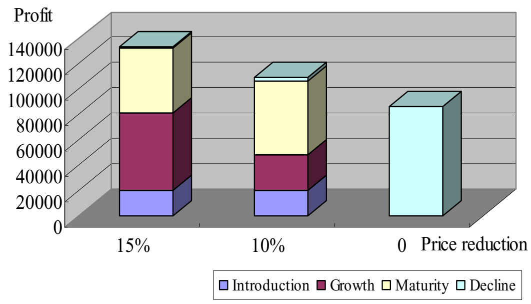

Fig. 8. Comparison of profits

4 Conclusions

In the sophisticated economic world, how to pricing is a decision not only depending on the retailers, but also all the subjects in the industrial system. Therefore, pricing is a system engineering problem that needs both macro and micro level thinking. This paper developed an agent-based innovation diffusion model, in which product price was adjusted with the evolution of product life cycle to achieve profit maximum. Based on the features of higher-priced durables, heterogeneous agents were created with intelligence and adaptively interacted with each other. Simulation results show that ABMS could dynamically establish the market situation when price change in different scenarios. And the simulation could enable users to conduct various experiments in the artificial market by changing parameters to find out how a real market would respond to a certain event and to predict the evolution of the market. In the future research, we will try diversifying the price adjusting scheme, rather than a certain percentage change, to conduct more market closed experiments, which we believe could provide more accurate foundations for business decision-making.

5. Copyright

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