An agent-based simulation for a trade-off between frequency and depth in retail price promotion strategy

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Abstract. *A good pricing strategy helps retailers generate profits, increase sales, and set a strategic position in the market. However, the interactions between retailers and customers add complexity to retailer pricing decisions. This study aims to model retail pricing complexity and analyse retail pricing strategies using an agent-based simulation approach. Two types of agents are modelled: customers and retailers. Customer buying decisions are influenced by several customer preferences factors, while product prices are set according to the retailer's promotion strategy. The promotion is applied based on the frequency and depth of the price cut. A functional product market is considered in this simulation, representing daily necessities that are purchased regularly, such as foodstuffs and toiletries. The results show that the limited rationality and interactions of each agent drive the unique behaviour of the system, and that each pricing strategy has a different impact on retailer profit and market share. This study provides insights into pricing decision strategies related to price promotion.*

Keywords: pricing decision, price promotion, agent-based simulation, retail, customer behaviour.

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Introduction

Retailers have an important role in supply chains; they are the final stage that delivers the product to the customer's basket (Busu et al., 2020). As retailers interact directly with the end customers of the supply chain, and their business decisions influence consumer satisfaction, the retailer's decisions will ultimately affect the profits of the supply chain.

One strategic decision for retailers is pricing—where a firm sets the value in the exchange of goods and services. An appropriate pricing strategy can increase sales and win market share for a retailer because price is an essential source of information for customers when making purchase decisions (Vrânceanu et al., 2020). However, many factors must be considered when making pricing decisions, including understanding consumer behaviour and the competition between retailers (Monroe, 2003).

Consumer behaviour is influenced by consumer preference, which drives customer actions in choosing a retailer and determining the buying quantity (Bell, 2015).

Consumer preferences can be defined as the buying priorities of consumers (Tadellis, 2013), where each consumer has a different preference. Preferences can be induced by many factors, including: socio-demographic factors, such as age and income; personality, including sensitivity to price, distance, and quality; and factors related to interaction—the exchange of information with the retailer (Zhang and Zhang, 2007). In addition to customer preferences, it is also necessary to pay attention to reference prices that affect customer reactions (Mazumdar et al., 2005). The reference price is the standard value of the product to the customer that influences their decision to buy (Monroe, 1973).

Several previous studies have addressed the issue of pricing strategies. Several recent studies address multi-channel pricing strategies using a mathematical approach that considers supplier relationships, inter-channel competition, and customer behaviour (Chen et al., 2016; Ding et al., 2016; Giri and Roy, 2016; Liu et al., 2016; Xie et al., 2016). Qu et al. (2017) have developed a mathematical approach to accommodating consumer behaviour that aims to ensure that luxury goods do not remain in the warehouse for long. Another avenue of research on pricing strategy is determining the optimal rebate strategy (Hu et al., 2017). Meanwhile, Luo et al. (2018) have shown how retailers can make product choice decisions and determine pricing policies by considering heterogeneous customer demand based on different customer values. Chen et al. (2018) have created four dynamic pricing models for deteriorating products based on different pricing adjustment frequencies, with and without menu costs. A design of revenue sharing contracts by Haji et al. (2018) coordinated pricing and inventory control decisions in a serial supply chain consisting of one supplier, one manufacturer, and one retailer. Furthermore, Chung (2019) has shown how determining the right price also greatly affects the business environment related to perishable products. Money-back guarantees (MBGs), which allow customers to return products that do not meet their expectations, are widely used in the retail industry (N. Chen and Liu, 2019). Another model has designed a two-stage dynamic pricing strategy when sellers face strategic consumers in the presence of a reference price effect (Chen et al., 2020). Customers with different time-sensitivities need different approaches and Golrezaei et al. (2020) have investigated the right pricing strategy to address this problem. However, none of these studies allow for modelling the interactions between consumers and retailers—an important part of the decision-making process in the trade of a product or service.

This study takes a new approach, namely to investigate the effect of price strategies on retailers using agent-based simulation. The simulation approach considers consumer behaviour and competition between retailers, and the scope is complex due to these dynamic interactions. As suggested by Fassnacht and El Husseini (2013), profit is an appropriate measure of a retailer's performance as an intermediary. Therefore, profit and sales are used to evaluate the resulting emergent behaviour. This paper considers functional products that are used daily, such as food ingredients and toiletries, and presents several preliminary results of the agent-based model. It also intends to provide a novel approach to understanding the effect of pricing strategies on retailers. Although there are limitations to agent-based simulation models, the freedom of cost and time in the simulation approach enables optimisation of a pricing strategy. Finally, the results of the model will support the feasibility of the study and can be used as an initial solution if the model is to be applied in the actual market environment.

Literature Review

Price is an important source of information customers may use to make purchase decisions (Vrânceanu et al., 2020). Retailers need to pay careful attention to pricing

strategies, which are not only important but also challenging, being influenced by a variety of factors. According to Monroe (2003), when setting prices, retailers need to analyse the competition, their customers, and the rules and regulations. Suppliers and wholesalers to the retailer also need to be taken into consideration as a reference for determining product prices.

Research developments in the area of pricing strategy have had a variety of different focuses. Ding et al. (2016) centred on the relationship between wholesalers and retailers, resulting in the creation of a hierarchical pricing decision. This supports joint optimal pricing between the wholesaler, the traditional retailer, and direct channels. Similarly, Xie et al. (2016) established two scenarios: (1) the wholesaler charges the same price for each retailer and (2) the wholesaler charges different prices for each retailer. Both studies were conducted in a dual-channel business environment. Different approaches to the relationship between wholesalers and retailers are described in the study of Haji et al. (2018), which tries to determine the appropriate contract design in the management of Vendor Managed Inventory (VMI) and mutually beneficial revenue sharing. Although these studies provide valuable insight into pricing decisions, they are limited to the wholesaler–retailer relationship.

Research on retail prices must also consider competition between retailers. Chen et al. (2016) have considered the situation mix between online and offline channels, which adds a new dimension of competition. The central issue in this situation is to decide the best pricing strategies between channels, with important managerial implications for retailers to develop proper pricing strategies. Cao et al. (2017) have applied three scenarios, namely basic, competition, and uncertain advertising effectiveness, in retailers' efforts to implement marketing and operational strategies to obtain long profitability. Chung (2019) has claimed that developing effective ways to manage perishable foods is crucial for food retailers to survive in the highly competitive retail food industry. The results of Chung's study show the potential impacts of different pricing strategies by considering perishable food issues. Although we already know that competition between retailers affects price decisions, with implications for retailer profits, the situation and the indirect impact also vary.

Next, we discuss the influence of the customer in pricing decisions. Qu et al. (2017) try to determine the appropriate price for luxury products by considering the customer's assessment of the product. The model uses a regression tree or random forest-based machine learning algorithm to predict weekly demand. Luo et al. (2018) have investigated how customers' assessment of goods affect their purchase decisions in retail markets. In their paper, a market consisting of one manufacturer and one retailer is investigated. The manufacturer produces two substitute products, while the retailer determines his product choice decisions and pricing policies by considering heterogeneous customer demand based on different customer valuations. Chen and Liu (2019) have studied a retailer's money-back guarantees (MBGs) policy with the dynamic pricing of a limited inventory, where a key decision for the retailer was to decide whether to offer MBGs to customers or not. Meanwhile, Golrezaei et al. (2020) have examined the pricing of goods in the presence of strategic customers who are heterogeneous with respect to their initial valuations of goods and their time sensitivities. Finally, Chen et al. (2020) have considered retail pricing in the context of understanding consumer desires. The consumers establish two sequential periods—with time utilities on the current retail price in the first period, and an anticipated future retail price in the second period as the reference price—and then choose their purchasing timing, representing strategic

behaviour. Retailers will determine the price that has the smallest difference to the average reference price for the most consumers.

Customer reactions to the price of goods can also be influenced by the characteristics of the goods, such as perishability. Tiwari et al. (2018) have considered perishable products contained in a two-echelon supply chain with unlimited capacity. The customer demand rate is assumed to be dependent on the retailer's selling price and the displayed stock level. Moreover, Chen et al. (2018) have proposed four dynamic pricing models for deteriorating products based on different pricing adjustment frequencies, with and without menu costs. The study elucidates the role of the customer and proves that the decision to set prices needs to consider the influence of consumers. Furthermore, these prices and customer reactions influence each other.

Based on a retail pricing strategy that considers many aspects, situations, and conditions, this paper takes a different focus to previous studies. We aim to determine the effect of price promotion strategies, as one of the strategies for pricing decisions, on retailers, using agent-based modelling. Agent-based modelling is a simulation approach that explains phenomena by the interactions of agents with other agents or the environment. Agents in the model are autonomous individuals or objects that have actions, properties, and goals. The environment is the landscape in which agents interact and can be geometric, network-based, or drawn from real data. The interactions that occur between these agents or with the environment can be quite complex and approach real conditions (Wilensky and Rand, 2016).

In this paper, we further investigate the interactions between consumers and retailers—an important part of the decision-making process in the trade of a product or service. This paper presents several preliminary results of the agent-based model, and provides a novel approach to understanding the effect of pricing strategies on retailers. Although there are limitations to agent-based simulation models, the freedom of cost and time in the simulation approach allows for optimisation of a pricing strategy. The results of the model will support the feasibility of the study and can be used as an initial solution if they are to be applied in the actual market environment.

Model design

We adopted the modelling framework suggested by Robinson (2004), which addresses the following elements of a conceptual model: the model content, inputs or experimental factors, outputs or responses, and assumptions and simplifications of the model. The model content incorporates the main features of the agent-based modelling approach, as set out by Macal and North (2010) and by Robertson and Caldart (2009), which describe the model's scope and level of detail.

The model consists of agents, environment, interactions, and rules of behaviour. There are two types of agents in the model: retailers and customers. The customers' decision to shop is influenced by the distance model as well as price. Retailers are located relatively close to each other, while customers are located randomly and dynamically in the environment. The agent's behaviour was constructed based on several economic theories: consumer price reference theory for the gain and loss aspect, consumer behaviour theory, and price promotion theory.

Two retailers were modelled, and can be set to have either homogenous or heterogeneous behaviour in making pricing decisions. The retailer's pricing decisions are related to price promotion, defined by the frequency and level of price reduction. The pricing method applies a cost-plus strategy, while the price promotion reduces the target profit. The promotion strategy is delineated into three levels: high-shallow, moderate,

and low-deep (Sivakumar, 1996). The high-shallow strategy represents a high frequency, shallow price cut, where the price reduction is around 20% with 40% of occurrences. The moderate strategy reflects a moderate frequency and level of price cut, which provides a price reduction of about 40% in 20% of occurrences. The low-deep strategy consists of a low frequency, deep price cut, with a price reduction of about 80% in 10% of occurrences. When retailers are set to be homogenous, they both adopt a similar price promotion strategy; when they are set to be heterogeneous, the retailers apply different pricing strategies.

Meanwhile, each customer agent is characterized by its buying preferences, which include price, distance, gain and loss tolerance, and budget. Each consumer possesses a different weight for each type of preference, so the consumers are set to be heterogeneous. For example, some consumer agents can be highly sensitive to price, while others have different features. Consumers also have various budgets that follow a normal distribution, so that each consumer has a diverse budget. This rule gives each consumer a different level of demand, i.e. each consumer can generate a different number of items to buy.

The interactions between agents are illustrated as follows. The consumer agents select a retailer that fits their preference. For instance, if a consumer agent is more sensitive to price than retailer distance, then it needs to consider the gap between the desired price and the lowest price offered by the retailer. If the gap is still within its loss tolerance, the consumer will select the retailer that provides a lower price. Otherwise, the consumer will not decide to buy from any of the retailers. When the consumer decides to buy from one of the two retailers, the next decision determines the number of items to buy, depending on the budget of the consumer. This consumer's autonomy can be presented in a simple chart shown in Figure 1.

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Start
  For each consumer
    set preference price =  $\alpha_1$ 
    set preference price
    set preference distance =  $\alpha_2$ 
    set preference gain =  $\alpha_3$ 
    set preference loss =  $\alpha_4$ 
  Start buying cycle
    set budget round random-normal (100,20)
    set p1 [price] of retailer 1
    set p2 [price] of retailer 2
    set d1 [distance] from retailer 1
    set d2 [distance] from retailer 2
  Calculate the gain and loss consumers that are obtained from each retailer
  Set gain for retailer 1 = max {reference price - p1,0}
  Set loss for retailer 1 = max {p1- reference price ,0}
  Set gain for retailer 2 = max {reference price - p2,0}
  Set loss for retailer 2 = max {p2- reference price ,0}
  Calculate the price normalization from each retailer
  Yp1= P1/ P1+ P2
  Yp2= P2/ P1+ P2
  Calculate the distance normalization from each retailer
  Yd1= d1/ d1+ d2
  Yd2= d2/ d1+ d2
  Calculate the gain normalization from each retailer
  Yg1= g1/ g1+ g2
  Yg2= g2/ g1+ g2
  Calculate the loss normalization from each retailer
  Yl1= l1/ l1+ l2
  Yl2= l2/ l1+ l2
  Calculate each retailer's score
  Set Retailer 1's score =  $\alpha_1*Yp_1 + \alpha_2*Yd_1 - \alpha_3*Yg_1 + \alpha_4*Yl_1$ 
  Set Retailer 2's score =  $\alpha_1*Yp_2 + \alpha_2*Yd_2 - \alpha_3*Yg_2 + \alpha_4*Yl_2$  If
  Retailer 1's score < Retailer 2's score
    Choose Retailer 1
  Else
    Choose Retailer 2
  Buy product at retailer with quantity = Budget / price of selected retailer
  Leave retailer
  Update reference price
  Repeat the buying cycle
End

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Figure 1. The rule of consumer agents

Source: Authors' own research

The retailer's behaviour is presented as the pricing strategy used. The promotion strategy is set to be the key input or experimental factor of the model that affects the consumer's buying behaviour. In this study, the emergent outcome of the simulation is measured by three indicators: retailer profit, total sales, and market share. The time unit is weeks, and the number of replications is 100 with a simulation length of 52 weeks. Figure 2 shows the display of the Netlogo software used. We compared the resulting emergent behaviour to the result of Hotelling's law (Hotelling, 1929) as the basis of model validation. The results show that when both retailers have a homogeneous competitive behaviour, the emergent outcomes are in accordance with Hotelling's law. The second validation process against the model is seen from the consumer behaviour in choosing retailers. From the customer model, it can be seen that customers are making decisions according to their respective preferences, in accordance with real conditions (Chang et al., 2016). The final validation is that the retailer's behaviour in determining the price promotion has illustrated the transition between frequency and price cut (Sivakumar, 1996).

Figure 2. The computer representation of the simulation

Source: Authors' own research

Experiment and preliminary results

This paper presents the preliminary results of the model, covering a small number of experiments analysing the effect of price promotion strategy on retailers. There are six scenarios performed in this study, all of which allow retailers to use a price promotion strategy. In Scenario 1 (S1), both retailers apply the high-shallow strategy. In Scenario 2 (S2), both retailers adopt a moderate strategy. Scenario 3 (S3) depicts both retailers using the low-deep strategy. Scenario 4 (S4) reflects one retailer using a moderate strategy while the other employs a high-shallow strategy. Scenario 5 (S5) indicates one retailer making use of the high-shallow strategy and the other applying the low-deep method. Finally, in scenario 6 (S6) one retailer utilizes a moderate strategy while the other uses the low-deep approach. The scenarios are presented in Table 1 and the results of each scenario are discussed below.

Table 1: Simulation scenarios

Pricing Scenario	Description
S1	high-shallow vs. high-shallow
S2	moderate vs. moderate
S3	low-deep vs. low-deep
S4	moderate vs. high-shallow
S5	high-shallow vs. low-deep
S6	moderate vs. low-deep

Source: Own representation

The first three scenarios (S1–S3) represent homogeneous retailer agents, employing similar strategies. The results of the scenarios indicate that the difference in average profit between the two retailers is insignificant. This was proven using Welch's t-test with a confidence level of 95%, using replicated data from the simulation results of 100 replications as input. A similar emergent pattern also applies to the total sales. The reason for this small difference in profit and sales between retailers could be because of the identical price promotion strategy used by the retailers. This is supported by Ridley (2016), that if two retailers have the same price, promotion, product, and adjacent location, the benefits received by the two do not have a significant difference.

Meanwhile, the remaining scenarios (S4–S6) represent heterogeneous agents. Welch's t-test for S4–S6 showed a significant difference in the average profit received by the two retailers. For S4 (moderate strategy vs. high-shallow strategy), each strategy alternated in dominating profit and sales during the simulation run. However, if the simulation length was extended to be more than 52 weeks, the moderate strategy was the dominant strategy in terms of profit and total sales. For S5 (high-shallow vs. low-deep), the results show that a high-shallow strategy leads to higher profits and sales than a low-deep strategy. Finally, for S6 (moderate vs. low-deep) no strategy consistently dominated in terms of profit and sales during the simulation run. Compared to S1–S3, the stability between the two retailers has collapsed for S4–S6 as they are implementing different strategies. This encourages consumers to choose the retailer that provides the maximum benefits for the prices offered.

The profit summary for both retailers is shown in Table 2 and Table 3. From Table 2, it can be seen that retailer 1 reached its highest profit under S5, where retailer 1 used a high-shallow strategy and retailer 2 took a low-deep approach. Conversely, S2, where both retailers employed a moderate strategy, resulted in the lowest profit for retailer 1. Table 3 shows that the highest profit for retailer 2 was achieved under S1, where both retailers applied the high-shallow strategy. The lowest profit for retailer 2 was experienced under S5. As both retailers take a similar strategy under S1–S3, and the differences in results seem to be insignificant, the result of S1–S3 can be neglected for the analysis. Therefore, it can be concluded that S5 leads to a significant difference in both retailers' profits.

Table 2: Profit summary for retailer 1

Profit	Retailer 1					
	S1	S2	S3	S4	S5	S6
Mean	\$11.809,9	\$11.026,9	\$11.564,0	\$12.025,1	\$15.256,0	\$11.740,5
Median	\$11.818,1	\$11.019,5	\$11.545,9	\$12.015,5	\$15.262,1	\$11.734,5
Minimum	\$11.410,6	\$10.586,6	\$11.266,1	\$11.803,0	\$14.965,4	\$11.496,0
Maximum	\$12.214,4	\$11.335,8	\$11.960,4	\$12.276,0	\$15.585,8	\$12.039,0

Source: Own representation

Table 3: Profit summary for retailer 2

Profit	Retailer 2					
	S1	S2	S3	S4	S5	S6
Mean	\$11.783,6	\$10.997,1	\$11.533,4	\$11.449,9	\$7.938,5	\$10.790,1
Median	\$11.775,8	\$10.990,6	\$11.546,3	\$11.443,5	\$7.925,7	\$10.790,5
Minimum	\$11.368,1	\$10.650,9	\$11.104,7	\$11.232,0	\$7.622,7	\$10.466,0
Maximum	\$12.155,5	\$11.503,5	\$11.876,2	\$11.691,0	\$8.296,0	\$11.150,0

Source: Own representation

The summary of the total sales for each scenario is presented in Table 4. From the table, it can be seen that S5 resulted in a significant difference in sales, with the highest sales for retailer 1 and the lowest sales for retailer 2. Even though this result seems to be consistent with the profit analysis, by comparing Table 4 with Tables 2 and 3, we can see that a higher sales level does not always lead to a higher profit. For example, retailer 2 had the highest profit with S1, but the highest level of sales for retailer 2 occurred in S6.

Table 4: Sales summary for retailers 1 and 2

Total sales (000 unit)	Retailer 1						Retailer2					
	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6
Mean	27	28	28	30	35	28	27	28	28	26	23	29
Median	27	28	28	30	35	28	27	28	28	26	23	29
Minimum	26	27	27	29	34	28	26	27	27	26	22	28
Maximum	28	29	29	30	36	29	28	29	29	27	23	30

Source: Own representation

The type of price promotion strategy had an influence on consumer demand, particularly in the quantity of goods purchased. When neither retailer applied any promotion, the total consumer demand was about 52,000 units. The demand increased when the price promotion strategies were applied. The six scenarios (S1–S6) generated demand for about 54,000 units, 56,000 units, 56,000 units, 56,000 units, 57,000 units, and 57,000 units, respectively. If stated as a percentage increase in demand, then there was an increase in demand of 3.9% for S1; 7.7% for S2, S3, and S4; and 9.6% for both S5 and S6. In this context, S5 and S6 resulted in higher demand generation.

The market share between the two retailers was also analysed, and is summarized in Table 5. From the table, it can be seen that S5 resulted in the most significant difference in market share. In this scenario, retailer 1, with a high-shallow strategy, dominated the market share (60.80% share), while retailer 2, with a low-deep strategy, became subsidiary (39.20% share).

Table 5: Resulting market share

Agent	Market Share					
	S1	S2	S3	S4	S5	S6
Retailer 1	50.06%	50.07%	50.05%	53.15%	60.80%	49.56%
Retailer 2	49.94%	49.93%	49.95%	46.85%	39.20%	50.44%

Source: Own representation

These outcomes are a result of the bounded-rationality of the agents in the model. The consumer agents updated their behaviour over time, but the retailers did not have any information about the future actions of the consumers. The consumers also could not predict when the retailers would apply a promotion and so refreshed their decisions in each time unit of the simulation. Moreover, the retailers did not have enough information about the pricing decisions made by their competitor, or when the competitor would apply its own promotion strategy.

Discussion

The decision to determine prices is a problem faced by all business actors, including retailers. Careful consideration is needed in setting retail prices, based on the situation and conditions at hand, and there are different strategy choices available. Consequently, this paper attempts to provide insights into decision-making for pricing strategies by considering price promotions, which are defined by the frequency and depth of cuts to product prices. This paper takes a novel approach in choosing an agent-based model simulation. The model considers the competitive situation between two retailers when applying either homogenous or heterogeneous promotional strategies, and considers customer preferences and the effects of customer reference prices.

This paper shares some similarities with Sivakumar's (1996) work, but differs in the methods and approaches used. Similar approaches were also used by Chang et al. (2016) and Chen et al. (2018), who conducted agent-based simulations to test dynamic pricing for perishable products. These studies applied a competitive business environment in which each actor applies a different pricing strategy. He et al. (2014) designed agent-based simulations for a market environment consisting of one manufacturer and multiple retailers, all competing to sell the same product. Retailers applied a metaheuristic genetic algorithm approach to determine the ideal price and inventory location when there was competition. During the process, retailers applied different prices to each other and disappeared when they were unable to make a profit. This process continued until a retailer that could survive during the simulation period was obtained. The price set by this retailer was later selected as the optimal price. None of the aforementioned studies, however, have tested the effect of price promotion on retailer profits.

In this paper, the use of an agent-based simulation model approach allowed us to discern the interaction between customers and retailers, and the influence of competition between retailers on the business environment. Future research could consider the interactions between suppliers and wholesalers, retailers, and customers in a competitive environment. The competition that occurs will therefore not solely be competition between retailers but competition between supply chains.

Conclusions

This paper presents an agent-based modelling approach to analysing the effect of pricing strategies on retailers for functional product markets. Price promotion is the focus of the pricing strategies analysed. Three strategies are evaluated: a high-shallow strategy, a moderate strategy, and a low-deep strategy. Economic theories were considered for the model development, including: consumer price reference theory to determine the variable gain and loss for the consumers; consumer behaviour theory, on which distance, price, gain, and loss preferences were based; and price promotion theory. These theories have been proven to be suitable for developing a simulation model that generates useful information for the analysis of retailer price promotion strategies. The preliminary results show that not all price promotion strategies are effective under most circumstances. The high-shallow strategy is found to be the only approach that has a significant result in improving retailer profits, sales, and market share. However, this situation only applies when the other retailer adopts a low-deep strategy. This emergent behaviour is due to the bounded-rationality of the agents.

The model incorporates market complexity that allows for heterogeneous agents. It provides a new way to understand the impact of pricing strategies on retailers, while consolidating various features of consumers. However, the heterogeneous agents make it difficult for the analysis to trace which customer preferences are sensitive to each of these price promotion strategies. Another aspect to be considered for future research is the limited number of simulated retailers. More competing retailers may lead to different emergent results.

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