Retailer Marketing Strategy and Consumer Purchase Decision for Local Food –
An Agent-Based Model

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Abstract Price and assortment are two market decision variables that are firmly under the retailer’s control. There is a need for a deeper understanding of the roles of price and assortment in shaping consumers purchasing behavior and how price and assortment can be an effective marketing weapon used by retailers. This study uses agent-based modeling method to simulate a retail system in which retailers and consumers are modeled as a set of software agents who optimize their behaviors. By using empirical data from Relay Food and parameter estimates from previous literature, we effectively validate the model. Several experiments are designed to examine the sensitivity of the fruit price and assortment. Our findings have direct implications for retailers to improve their market position when marketing local food.

1. Introduction

Growing segments of world consumers seek improved quality, healthiness, and variety in their food (Verbeke2005; IDDBA2008). Accordingly, demand for agri-food products with credence attributes (e.g., place of origin, organic, locally grown, environment-friendly, and fair trade) is increasing rapidly Many studies suggest that credence attributes have an impact on some consumer groups’ buying intentions (Dentoni et al. 2009). Specifically, increased consumer demand for food produced, sourced, or grown locally is perhaps one of the most important food-industry developments in the past 20 years (Richards et al. 2017). With a growing body of consumers interested in local food, it becomes critical for marketers to understand the different types of consumers based on their characteristics. To this end, exploring whether local food has a direct or indirect effect on consumers’ attitudes towards a product has important implications for marketers, public agencies, and nongovernmental organizations. Researchers have a strong commitment to work to understand a range of consumer purchase behavior and strategic retailing issues, through a host of theoretical and methodological lenses.

Previous research on store choice and store sales has shown the importance of retailer prices and promotions on shopping behavior (Arnold, Ma, and Tigert 1978; Arnold and Tigert 1982; Arnold, Oum, and Tigert 1983; Walters and Rinne 1986; Kumar and Leone 1988; Walters and MacKenzie 1988; Walters 1991; Barnard and Hensher 1992; Bell, Ho, and Tang 1998; Bell and Lattin 1998; Fox, Montgomery, and Lodish 2004). Supermarket retailers are actively
engaged in formulating pricing strategies. Some retailers position themselves on the basis of “Low Prices, Everyday” across a wide assortment of product categories, while others offer temporary deep discounts in a smaller group of categories (Bell and Lattin 2017). In a pricing context, a recent empirical study by Desai and Talukdar (2003) as well as findings from Bell and Lattin (1998) suggest that some grocery categories are more influential than others in shaping a retailer’s store price image.

Another marketing policy that has been shown to affect shopping behavior and patronage patterns is product assortment (Reilly 1931; Huff 1964; Brown 1989). Assortment strategy is important because assortment drives both store positioning and store choice (Corstjens and Corstjens 2002). The most widely used theory implies that shoppers prefer larger assortments. Shoppers consistently report that retail assortments affect their store choice decisions, ranking it third in importance behind convenient locations and low prices as a choice criterion (Arnold, Ma, and Tigert 1978; Arnold, Oum, and Tigert 1983; Arnold and Tigert 1982). Fox, Montgomery and Lodish (2004) calculate assortment elasticities for grocery (and nongrocery) retailers and find that assortment size positively affects the probability that shoppers will patronize their stores. Zeithaml (1988) argues that consumers form quality perceptions not only about products but also about product categories and a retailer’s overall store assortment. Several studies, based on surveys, lab experiments and panel dataset analysis, have revealed that product assortments are key determinant of consumers’ store evaluations and store patronage decisions (Arnold, Oum, and Tigert 1983; Craig, Ghosh, and McLafferty 1984; Louviere and Gaeth 1987; Meyer and Eagle 1982; Rhee and Bell 2002).

This study focuses on these two retailer marketing strategies: pricing and product assortment. These two market decision variables are firmly under the retailer’s control. Through charging lower prices and offering more varied assortment, retailers can expand their market shares (Dhar, Hoch and Kumar 2001). However, what is less obvious is the exact importance of each of these marketing decision variables and how their impact might vary by category. Specifically, because consumer behavior and motivations can differ dramatically given what role the product plays in everyday life, the effectiveness of marketing actions should differ systematically across assortments and categories. Given the widespread use of assortment and price strategies across retailers, managers and academicians have a great interest in understanding how consumers react to such strategies as well as what types of strategies retailers should focus on in order to improve their store performance and to what extent those
strategies can influence key store level metrics such as patronage, basket sale, market share and profit. Our investigation will focus on the retail assortment and price effect on consumers purchasing behavior. By applying an ABM methodology, we provide a framework to examine the assortment and price effect on consumer store choice and basket choice behavior. Our results are likely to be of interest to retailers and manufacturers trying to optimize pricing and promotion strategies across many categories as well as in designing micro-marketing strategies.

The remainder of the paper is organized as follows. First, we introduce the application of ABM to model a dynamic retail system. Subsequently, we identify agents’ behaviors including consumer’s basket selection behavior and retailer’s profit maximization behavior. Next, we demonstrate the model specification in the context of the proposed approach along with the variable and parameter operationalization. Then simulation of price and assortment effect on consumer purchasing behavior will be performed and discussed. The paper ends with a brief conclusion. We describe the data, the model specification and variable and parameter operationalization.

2. Application of ABM

Advances in computing efficiency and affordability have been important catalysts for increasing researchers’ ability to access simulation analyses. When tractable analytical functional forms cannot be derived, simulation analyses can help understand and characterize these nonstandard functions and distributions (Bekkerman 2015). By using an agent-based modeling (ABM) method, this study will endeavor to identify the purchasing pattern of a large number of consumers and estimate the effect of the change in retailer food assortment and price on shaping the consumer’s purchasing behavior. The results of this study is useful in the solution of an array of retailer’s marketing problems.

The supply chain participants will be modeled as a set of autonomous (software) agents. By simulating the participants’ behavior in a realistic manner, the computer program itself represents the processes that are thought to exist in the actual world. Understanding of participant behavior will provide insight into identifying strategies on how marketers may assist in creating more demand for local food products and how to better tailor products and services meeting the needs of these potentially diverse consumers and maximizing their profits.

It is beneficial to have a realistic simulation model to explore and evaluate various supply chain improvement policies before their implementation. This study simulates customer’s food
purchasing behavior in a realistic manner to assess the effect of food assortment and price on their shopping basket selection decisions. Simulation allows one to provide estimates of efficiency and effectiveness of systems and to assess the impact of changed input parameters on the resulting performance before implementing any decisions into real systems (Harrison et al. 2007). The generated data in this study provide critical input into possible unforeseen consequences of a retailer’s change in food assortments and prices. Our simulation results are suggestive of a range of marketing strategy issues surrounding the local food promotion and marketing.

This paper highlights the key features of agent-based modeling. Rather than focusing on stable states, the ABM considers a system’s robustness and captures the emergent behaviors, decisions and interactions of the autonomous, intelligent and interconnected human actors that inhabit them. It provides a natural framework to harness the system heterogeneity, nonlinearity and dynamics out of the reach of analytic or mathematical methods.

3. Model Specification

Like all modeled representations of reality, we must rely upon a set of realistic behavioral algorithms to render the simulation tractable: (1) define the physical, and social-economic environment through which agents interact; (2) define autonomous and heterogeneous decision-making agents (retailers and consumers, suppliers are not represented as agents at this stage and operates in the background instead); (3) specify rules that define the relationship between agents and environment; (4) specify rules that define interaction between agents. According to the rules defined for the simulation, agents assess their personal situations and make decisions appropriate to their objectives.

The simulation typically integrates a physical system, represented by a raster grid of spatially distributed and uses within the landscape, with a human system, represented by a collection of agents making individual decisions. The landscape divided into cell regions presented by retailers and households locating in those cells characterized by different state variables. Every cell has explicit coordinates in an imaginary coordinate system, determining the distance between cells which helps define the relationship between them (store choice).

The supply chain network is characterized as a dynamic system consisting of various participants (growers, retailers and consumers) who optimize their behavior in an economic environment and interact and respond to the unpredictable system over time. The ABM will be
designed to identify the motivational factors influencing long-term (one-year timeline) food purchasing behavior and retailers’ strategies. A consumer will go shopping once one week and purchase one shopping basket, in total 52 shopping trips across one year.

3.1. Consumer Behavior

One important aim of this study is to ascertain who buys where, what, when and how. We apply rational choice theory to define consumer’s behavior from the bottom up. Individuals choose the best action to maximize their utility. It is proposed that food consumers are not a homogenous group and not all of them will have similar traits. The heterogeneity of consumers is defined by the individual context of each agent’s unique combination of experiences, biases, assets and perceptions. Such heterogeneity determines consumers’ individual utility function, varying behavioral patterns and their different responses to both environmental stimuli and the actions of others, which in turn influences consumers’ purchase decision in categories, including the consumer store selection, and shopping basket selection. The model will be designed to accommodate different specifications of individual shopping behavior.

Our model assumes that, after deciding to make a shopping trip, the process by which the customer chooses a shopping basket at a store can be summarized in the following four steps,

1) Determine all combination of items for shopping baskets. A household’s choice in shopping basket must fall into the basket sets.

2) Calculate the utility of shopping for those household needs at each competing store. The utility depends on travel distances to each store as well as demonstrated preference and loyalty for that store (fixed component). The utility also depends on retail prices, and assortments for categories that the household needs at the time of the visit (variable component).

3) Select the store that offers the shopping basket with the highest utility. Consumers will compare the utility of shopping basket offered at each store and select the best shopping basket candidates across three stores and form an ideal shopping basket pool with 53 baskets that come from either of the three stores.

4) Consumers’ utility maximization behaviors determine their basket choices and thus their store choices. It is assumed that the consumer has full or perfect information about all the alternatives, i.e. categories and assortments offered by each store and their prices. Thus the consumer can rank among all alternatives involves no uncertainty. The final choice of basket
and store will be determined by solving a discrete choice model of consumer purchasing behavior.

Consumers are more willing to shop at retailers that offer a wider range of product variety and thus a wider range of shopping basket. In addition, lower prices expand the geographic radius of customers served by the store. The lower the price of local food the greater the radius of attraction. Consumers attracted to the store by low price food will also likely to purchase other grocery items to fulfill a shopping basket on a single shopping trip. Strategically, a retail should be structured to optimize store-choice through offering local categories at appropriate prices and no-local categories that substitute or complement local food purchases in the shopping basket.

Figure 1 shows an activity diagram of our simulated retail system. Each participant in the market. The system is driven by both the physical movement of fruit (indicated by solid arrows) from retailers to consumers, as well as with information flows across agents (indicated by dotted arrows). Each participant in the system collects relevant information for synchronizing the retailing or purchasing processes, leading to operational decisions. A consumer dynamically adjusts the store choice and basket choice based on perceived assortment and price information of retailers and optimizes the purchasing behavior. In turn, the retailer adjusts assortment and pricing strategy in a manner to be driven by perceived information about consumer’s purchasing behavior. By simulating the consumer and the retailer’s behavioral optimization behavior, we attempted to answer some key questions pertinent to what retailers may want to know such as what assortments should be offered and how to price the products properly for enhancing sell.
We start by defining the consumer utility function, which represents consumer preference toward items that are available on the market. It is suggested that the consumers’ preference to purchase and consume food could be linked to their attitude toward food attributes and their personality traits. Based on prior literature (Rhee and Bell 2002; Briesch, Chintagunta and Fox 2006; Bell and Lattin 2017), we assume that the utility of consumer for items at purchase occasion is dependent upon several factors including intrinsic preference for the item, price, store loyalty and shopping distance. The proposed formulation represents a random coefficient discrete choice model that assumes consumers act rationally and choose the product that gives

Figure 1. Agent Activity Simulation Diagram.
them the greatest utility. The utility equations for a representative consumer $n$ for $i$ categories at store $j$ can be compactly represented as

$$U_{nij} = V_{nij} + \varepsilon_{nij}$$  

where $\varepsilon_{ni}$ is the error term that represents the residual unobserved heterogeneity after accounting for observed heterogeneity of consumer $n$, which is assumed independently and identically distributed according to extreme value distribution, and $V_{ni}$ is the observed part of utility to be linear in parameters with a constant. The baseline utility for each category is defined as a linear utility function over the determinants (Eq. (2)). The specification allows for the influence of preference, price, shopping distance and loyalty to store.

$$V_{nij} = \alpha_{ni} + \beta_{nij}^1P_{ij} + \beta_{nij}^2L_{nj} + \beta_{nij}^3D_{ij}$$  

where $\alpha_{nij}$ donates consumer $n$’s preference for item $i$ at store $j$, $P_{ij}$ denotes the price of item $i$ at store $j$, $L_{nj}$ denotes consumer $n$’s loyalty to store $j$, where item $i$ are available, $D_{ij}$ denotes the distance between consumer $n$ and store $j$, and $\beta$ represent a vector of coefficients of these variables.

The importance of distance in affecting consumer purchasing behavior has been highlighted in previous studies. Briesch, Chintagunta, and Fox (2009) found that convenience (operationalized as travel distance) has a greater effect on store choice size than price and product assortment. Virtually all models of retail competition (Hotelling 1929; Reilly 1931; Huff 1964; Hubbard 1978; Brown 1989; Fox, Montgomery, and Lodish 2004) and shopping behavior (Barnard and Hensher 1992; Arentze, Borgers, and Timmermans 1993; Bell, Ho, and Tang 1998; Dellaert et al. 1998) specify store patronage as a function of the distance from the store to the shopper’s home. Our model includes a measure of distance in the form of travel distance, which is operationalized as the distance in mile it takes to travel from the household to the shopping store.

The loyalty variable in Eq. (2) adjusts for the household $i$’s long-run propensity to buy the items in a store. Many studies investigated the role of customer loyalty in regulating consumer purchasing behavior. Survey studies by practitioners (The Hartman Group Inc. 2014) found that consumers prefer to a diversity of stores and divide their shopping across retailers instead of being loyal to a single “primary store”. Similarly, Talukdar, Gauri, and Grewal 2010 suggested that consumers seem to have much to gain from not being loyal to a single store.
Through analyzing observed consumers’ shopping statistics, Rhee and Bell (2002) found that a consumer’s loyalty to the favorite store was determined by the store’s geographical proximity, and the consumer’s knowledge of the store’s assortment and prices. Bell, Ho and Tang (1998) categorized two kinds of store loyalty into two kinds: category-independent and category-specific. A household's category-independent store loyalty captures its habitual preference for a store, independent of the shopping list (category and assortment). Due to assortments and categories in stores are defined as two variables in our model. The focus of this study is to evaluate their effect on consumer purchasing behavior. To facilitate segregating the assortment and category effect, we avoid making the loyalty evolve with the assortment and category change in stores. For simplicity, we only consider the independent store loyalty, i.e. assume that the loyalty is exogenously determined by the geographical proximity of customers to stores involved in the model. The loyalty varies from shopper to shopper and is initialized using the geometrical distance between shoppers and stores.

Different attributes should be weighted differently by individual consumers with respect to the importance of attributes to the consumers. We use a vector of coefficients \( \alpha_n \) and \( \beta_n \) to indicate consumer \( n \)’s evaluation for certain attribute of a food category. A consumer has different evaluations for attributes of a category (different parameter values in the vector \( \alpha_n \) and \( \beta_n \)). Different consumers have different evaluations regarding these attributes. To capture the heterogeneity in category preference, loyalty to store and price-responsiveness, we specify the coefficients of variables as randomly distributed to represent consumer heterogeneity related specifically to a number of unobservable characteristics of consumers,

\[
\alpha_{ni} = \alpha_{0i} \delta_1 \sim N(1, \sigma_1)
\]

\[
\beta_{ni1}^1 = \beta_{0ij}^1 \delta_2 \sim N(1, \sigma_2)
\]

\[
\beta_{ni2}^2 = \beta_{0ij}^2 \delta_3 \sim N(1, \sigma_3)
\]

\[
\beta_{ni3}^3 = \beta_{0ij}^3 \delta_4 \sim N(1, \sigma_4)
\]

Consumers make multicategory decision in a variety of context such as choice of multiple categories during a shopping trip. There is interdependence in demand between categories (cross-category purchase effect) in a shopping basket. Recent research in marketing has seen a considerable emphasis on understanding the cross-category effects of marketing activities. Accordingly, researchers have proposed a variety of alternative model specifications to understand the nature of these cross-category effects (Manchanda et al. 1999; Richards et al.)
We use $\theta_{ij}$ to represent a vector of consumer-specific parameter that captures the degree of interdependence (externality) in demand between categories $i$ and $j$, such that if $\theta_{ij} < 0$, the pair of categories are substitutes, if $\theta_{ij} > 0$, the categories are complementary, and if $\theta_{ij} = 0$, they are independent in demand. Richards et al. (2017) found that there are a significant set of cross-effects for items in the same shopping basket.

Consistent with empirical studies (Kwak, Duvvuri, and Russell 2015; Song and Chintagunta 2006), the model assumes that households evaluate assortments of products by summing valuations of individual items and then adjusting the joint value for demand interactions. The conditional utility consists of two parts: (1) a baseline utility dependent on item characteristics and (2) demand interactions with other items in the assortment. Consumer $n$’s utility for a shopping basket composed of assortment $k$ of item $i$ and/or $j$, conditional on the observed purchase outcomes of other items under consideration, is formulated as,

$$U_n^g = \sum_{i=1}^a \sum_{j=1}^b (V_{nij}) + \sum_{i=1}^a \sum_{j=1}^b \left( \frac{1}{2} \theta_{nij} \right) + \epsilon_n^g \quad (3)$$

We derived Multi-Variate Logit (MVL) formula under the assumption that the unobserved factors are distributed extreme value. The distributed extreme value is independent of $n$, $i$ and $j$. Mixed logit probabilities are the integral of standard logit probabilities over a density of parameters. Stated more explicitly, the probability of consumer $n$ purchase a shopping basket $g$ can be presented as a mixed logit formula,

$$P_{n}^{g} = \frac{e^{\sum_{i=1}^a \sum_{k=1}^b \left( V_{nij}^a + \sum_{i=1}^a \sum_{j=1}^b \left( \frac{1}{2} \theta_{nij} \right) \right)}}{\sum_{g=1}^G e^{\sum_{i=1}^a \sum_{k=1}^b \left( V_{nij}^a + \sum_{i=1}^a \sum_{j=1}^b \left( \frac{1}{2} \theta_{nij} \right) \right)}} \quad (4)$$

where $a$ is the total number of categories, $b$ is the total number of assortments in each category. Here $0 < P_n^j < 1$ and $\sum_{g=1}^G P_{n}^{g} = 1$ ($G$ denotes the total number of baskets). In the simulation, a consumer will necessarily fulfill one shopping basket at each shopping time. The consumer may need to go shopping to more than one stores for fulfilling the basket. As in the baseline utility function, we allow for unobserved heterogeneity to allow for unobserved heterogeneity in purchase effect by allowing each $\theta_{ij}$ parameter to be randomly distributed across consumers, following independent normal distributions,

$$\theta_{ij} = \theta_{0ij} \delta_5 \quad \delta_5 \sim N(1, \sigma_5)$$
It is assumed that consumers maximize their utility in choosing which categories to buy from on each trip to each store in assembling a shopping basket (multi-category choice in local and non-local). By focusing the simulation on shopping basket choices, the data generated from this simulation will enable us to examine the marginal effect of including local content in categories on the probability that consumers choose shopping baskets and make their particular store choices to maximize their utility.

### 3.2. Retailer Behavior

Product assortment and price are two of the most important determinants of store performance. The implementation of product pricing and assortment strategies has to be planned and conducted carefully because it is believed that it affects consumer perceptions and behavior. Using various methods such as laboratory and natural experiments, researchers have reported that a change in product assortment can influence consumer perceptions about the variety of products (Broniarczyk, Hoyer and McAlister 1998), store choice (Briesch, Chintagunta, and Fox 2009), sales (Boatwright and Nunes 2001), and customer retention (Borle and colleagues 2005). Researchers have also investigated cross-category price effect where prices in one category influence purchasing in other categories (Manchanda et al. 1999; Chib et al. 2002; Russell and Petersen 2000; Wedel and Zhang 2004; Song and Chintagunta 2006; Van Heerde, Leeflang, and Wittink, 2005; Wedel and Zhang, 2004). An understanding of how consumers respond to price and assortment would be important to a retailer who sells products in many categories as store profit maximization would involve coordination of activities across categories as well as across products within each category. Determining optimal product assortment and price is an important issue from a managerial standpoint.

In this study, the retailers’ objective is to maximize their profit. The model is designed to examine the tradeoff between increase or decrease in prices, and increase or decrease of assortments. Any change in category prices or food assortments in stores will change consumers’ utility outcomes and thus lead to different basket selection decisions. The simulation will identify the effect of retailers’ pricing and assortment strategies on consumers’ purchasing pattern and retailer market share and profit. Our results can provide useful insights for retailers to formulate effective pricing and assortment strategies.

Profit levels accumulated through time provide a basis for comparing efficiencies between different assortment or pricing strategies. To facilitate comparison, fixed costs or setups are not
included as a component of costs. Only variable costs are considered in this research, which implicitly assumes that fixed costs equal across retailers. The profit equation for a retailer \( r \) is written as,

\[
F_r = \sum_{i=1}^{n} [Q_{ri}(p_{ri} - c_{ri})]
\]

where \( n \) denotes the total number of food categories offered at retailer \( r \);
\( p_{ri} \) denotes price of food category \( i \) that consumer pays to retailer \( r \);
\( Q_{ri} \) denotes the total volume of category \( i \) that consumer purchases at retailer \( r \);
\( c_{ri} \) denotes the price that retailer \( r \) pays to grower;

4. Experimental setting

The model includes three retailers and one thousand representative consumers. Consumers choose among four food categories, banana (=1), apple (=2), graph (=3), and berry (=4). Each category has local (=1) and non-local (=2) assortments. It is noted that local banana is excluded because is not grown in the U.S. Each shopping basket contains from one to four different categories and each category can be either local or non-local assortment. We define shopping baskets with different combination regarding the category and the assortment. In total there are 53 shopping baskets \((C_2^1 \times C_3^1 \times C_3^1 \times C_3^1 - 1)\).

Instead of using the multinomial probit model which only allows the choice of one alternative from a set of mutually exclusive alternatives (MacCulloch and Rossi 1994), we develop our model of multi-category choice to model multi-category demand. The MVL model is particularly suited for our investigation as it allows for more than one category to be purchased simultaneously. The MVL model facilitates modeling both the size of the basket (the number of items) and the composition of the basket (which items). Consumers are assumed to maximize utility in choosing which baskets to buy from on each trip to each store.

The choice of one category may affect the selection of another category due to the complementary or substitute nature of two categories (Manchanda, Ansari, and Gupta, 1999; Chib, Seetharaman, and Strijnev, 2002). Alternatively, two categories may co-occur in a shopping basket because of a host of other unobserved factors, including unobserved household

\[1 \text{ We exclude visits that result in a null basket, so our model is conditional on a purchase of some sort of fruit for each shopping trip.}\]
preference or observed household demographics that are not integrated into the model delicately. To allow for those ignored household characteristics to make our model more effectively the mirror the actual retail system, we justify the distribution of basket choice to meet observed statistics over three years from Relay Food. The total number of purchase occasions for households in the sample was 12,439. Out of these one-category shopping baskets were purchased on 3,988 occasions, two-category was purchased on 4,935, three-category was purchased 2,655 and four-category was made on the remaining 859 occasions, which represents 32 percent, 40 percent, 21 percent and 7 percent of all occasions respectively. We assume that each consumer’s selection in shopping basket falls into the same distribution as the observation.

To predict expenditures across households and stores, we have defined a set of coefficients involved with Eq. (2). Richards et al. (2017) build a MVL demand model to establish the level of specificity necessary to model the household-level demand for fruit categories, including local content. The model generates serval estimates that can be used by our model. A consumer’s baseline preference ($\alpha_i$) to items and price coefficient ($\beta_{il}^1$) is shown in Table 1.

Table 1. Baseline preference and price coefficient for items

<table>
<thead>
<tr>
<th></th>
<th>12</th>
<th>21</th>
<th>22</th>
<th>31</th>
<th>32</th>
<th>41</th>
<th>42</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preference ($\alpha_{0i}$)</td>
<td>0.5128</td>
<td>1.9800</td>
<td>0.6383</td>
<td>1.5970</td>
<td>0.6710</td>
<td>1.6896</td>
<td>0.7991</td>
</tr>
<tr>
<td>Price ($\beta_{0il}^1$)</td>
<td>-0.9977</td>
<td>-0.8147</td>
<td>-0.8147</td>
<td>-0.8077</td>
<td>-0.8077</td>
<td>-0.6608</td>
<td>-0.6608</td>
</tr>
</tbody>
</table>

Source: Richards et al. (2017).

Note: 12-banana non-local, 21-apple local, 22-apple non-local, 31-grape local, 32-grape non-local, 41-berry local, 42-berry non-local (the same hereafter)

Table 2 lists the sale prices and buy prices for fruit categories/assortments, and fruit quantity per order. The prices and quantity are averaged from the long-term retail data from Relay Food over a 3-year period. These values will be used in the basic experiment for benchmark results used for model calibration or comparison. However, to attract consumers from its rivals, a retailer may change the price. In the following section, different experiments will be designed to examine the optimal prices for assortments.
Table 2. Retailer sale price/buy prices ($/pound) and quantity per order (pounds)

<table>
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<th>12</th>
<th>21</th>
<th>22</th>
<th>31</th>
<th>32</th>
<th>41</th>
<th>42</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sale price</td>
<td>0.5954</td>
<td>2.9594</td>
<td>1.2333</td>
<td>3.1552</td>
<td>4.0735</td>
<td>4.6371</td>
<td>4.4671</td>
</tr>
<tr>
<td>Buy price</td>
<td>0.5258</td>
<td>2.1168</td>
<td>0.9071</td>
<td>2.5608</td>
<td>4.5761</td>
<td>3.6142</td>
<td>4.6291</td>
</tr>
<tr>
<td>Quantity/order</td>
<td>2.2715</td>
<td>1.4799</td>
<td>3.6230</td>
<td>1.2934</td>
<td>1.1803</td>
<td>1.1790</td>
<td>1.2512</td>
</tr>
</tbody>
</table>

Source: Relay Food (2017)

The magnitude of the coefficient of distance influences a consumer’s utility for purchasing a shopping basket at different stores. To calibrate the simulation, we sought parameter values such that the outcomes of the model replicate some empirical regularities. Through numerous computer trials, we identified parameter values that appear reasonable for the simulation. We set the coefficient value at 0.1, which means the influence of distance on utility will locate in an interval [0.017, 1.015] (note the longest and shortest distance from customers to stores is 10.15 miles and 0.17 miles respectively). In this way, consistent with empirical observations, each consumer in the model has loyalty to multi-stores. The further away a store is from potential customers, the less they are loyal to the store. As shown later, this coefficient value works well in this context.

Based on results for interdependence values are from Richards et al. (2017), we develop a matrix to indicate the cross-category purchase effect between either two categories purchased (Table 3). In the matrix, all $\theta_{ii} = 0$ and symmetry is imposed on the matrix of cross-purchase effects, i.e. $\theta_{ij} = \theta_{ji}$.

Table 3. Cross-category purchase effect

<table>
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<td>12</td>
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<td>0</td>
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<td>0.5996</td>
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<tr>
<td>32</td>
<td>3.5915</td>
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<td>0.9981</td>
<td>0</td>
<td>0</td>
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<tr>
<td>41</td>
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<td>-0.5674</td>
<td>0.8513</td>
<td>-0.7390</td>
<td>0.5996</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>42</td>
<td>3.7333</td>
<td>0.8513</td>
<td>0.8513</td>
<td>0.5996</td>
<td>0.5996</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: Richard et al. (2017)

Note: 12-banana non-local, 21-apple local, 22-apple non-local, 31-grape local, 32-grape non-local, 41-berry local, 42-berry non-local
The consumers are heterogeneous, i.e., they have different perceptions for the utility of certain category or shopping basket purchased. To allow for the heterogeneity, we generate perception coefficients for each individual consumers regarding different attributes of a product. The product of the coefficient and an attribute represents a specific consumer’s perception of the attribute when the consumer evaluates the utility of the attributes. The normal distribution with given standard deviation provides a measure of the strength of the impact of unobserved factors in inducing or dissuading joint purchasing activity.

We assume that the coefficient of preference, the coefficient of price, coefficient of loyalty and the coefficient of distance fall into a normal distribution. To generate different effect parameters for heterogeneous consumers, we multiply the preference coefficient by a vector of normally distributed values with mean 1 and standard deviation 0.05.

$$\delta_1, \delta_2, \delta_3, \delta_4 \sim N(1, 0.05)$$

We also assume that the cross-category effect parameter is randomly distributed across consumers, following the independent normal distributions. In the same way, each effect parameter is multiplied by a coefficient $$\delta_5 \sim N[1, 0.05]$$.

### 5. Model Calibration and Verification

This study considers simulation as a way in system modeling and analysis. It is a challenging work to model the stochastic and uncertain characteristics in real-time supply chain systems. An effective simulation model should be able to capture the key features of the supply chain. Therefore, it is necessary to effectively abstract the most important elements and mechanisms of the system. Based on prior literature, as well as interviews and discussions with experts, we design a realistic food retail system with structure and characteristics similar to the real system and use it to model the store retailing and consumer purchasing behaviors.

The basic model assumes that each store offers all four categories with seven assortments. Using given values of parameters variables in the previous section, we run the model and obtain the preliminary results for the retailer’s consumer patronage, basket distribution and market share. There are 52 shopping trips for each consumer through the simulation. Figure 2(A) shows the customer’s store choice pattern at the end of the simulation. A consumer may visit different stores to purchase the shopping basket. A chosen store by a consumer shown in the figure is the one that is most frequently visited by the consumer through the simulation period.
Figure 2(B) shows the sold number of the 53 baskets individually. Figure 2(C) shows the market share of three stores. Figure 2(D) show the sold number of summarized baskets. In total there are fifteen summarized baskets².

The simulation results are contrasted with observed statistics from Relay sale data. Figure 3(A) shows the summary of simulated basket vs the summary of Relay Foods basket data. Figure 3(B) shows the share of sold volume by assortment. Figure 3(C) shows the share of sold volume by category. With the given retail system structure defined in this study, the simulation results of participant behaviors are robust and largely consistent with the real-world situation. The explicitly modelled retail system and well-designed participant behaviors contribute to the effectiveness of behavioral analysis subsequent. Thus, the model could serve as a rigorous basis for setting real-world categories/assortments and prices. Generated results offer direct implications for the practical assortment and pricing strategies under given operational conditions.

² Fifteen basket combination: 1-Banana, 2-Apple, 3-Grape, 4-Berry, 5-Banana/Apple, 6-Banana/grape, 7-Banana/Berry, 8-Apple/Grape, 9-Apple/Berry, 10-Grape/Berry, 11-Banana/Apple/Grape, 12-Banana/Apple/Berry, 13- Banana/Grape/Berry, 14-Apple/Grape/Berry, 15-Banana/Apple/Berry
6. Results and Analysis

To evaluate the price effect of local products, we run experiments to identify the price effect of those products. We assume that the optimal price of those individual local product price at store 2 maximizes the profit earned by the store. We also examine the optimal price of the non-local product and compare the effect with that of the local product. Figure 4-10 show the price effect of the local product along with its non-local counterpart in pairs.

When the price for local apple is $2.39, maintaining the prices of the remaining items in store 2 and all prices in the other store constant, store 2’s profit reaches the maximum, $24,727 (see Figure 4(A)). At the price premium, store 2 gains greater market share 52 percent and its competitors are ousted. Such a result is consistent with empirical evidence. Mulhern and Leone (1990) found that all things equal, a deeper price cut should have a greater effect on sales because it leads to more saving to consumers. The market share expansion is attributed to the increase in sold baskets that contain the local apple item, i.e. basket No. 2, 5, 8, 9, 11, 12 and 15. A lower price of local apple steals customers and market share from the competitors. While those customers are induced to buy more local apple, they also purchase local apple related basket, especially those baskets combining local apple and banana, i.e. basket No. 5, 11, 12 and 15. Further reduction in the price will increase store 2’s market share while decreasing its profit. There is a tradeoff between the increase in market share due to price reduction and...
the profit loss due a lower price. The optimal price just catches appropriate balance. A reduction of the price of non-local apple also expands store 2’s market share. At the optimal price $1.03, store 2 reaches 40 percent market share and profit maximum $22,608 (Figure 4(B)), lower than those achieved at the optimal local apple price. The cross category effect of non-local apple is not as strong as that of local apple product. As a result, the price effect of non-local apple is not as effective as that of local apple to motivate consumer’s incentive to purchase related baskets.

Figure 4. Optimal price of apple (local/non-local)

When store 2 only changes the price of local grape, as shown in Figure 5(A), the price is $2.55 at the optimum. Such a price is lower than the buy price, $2.56. Correspondingly, the market share is 46 percent and the profit is $23,255. This is not a surprising result. Once customers are attracted to the store, they can buy local grape, which can induce additional purchases of related items in other categories from which the store can generate incremental revenues to offset the price cut, e.g. incremental sales for basket No. 6, 8, 11, 13 and 15. Such a result is consistent with the previous empirical finding from Mulhern and Padgett (1995), who found that customers who reported visiting one of two home improvement stores due to a promotion and buying a promoted item bought a combination of promoted and non-promoted items that was profitable on average. Many theoretical and empirical studies have investigated this so-called loss leader pricing in which selected items are priced below their market costs and provide evidence that this strategy can draw consumers to the store where they contribute to retailer profits primarily through purchases of other categories (Blattberg and Fox 1995; Fox, Postrel

Alternatively, when store 2 only changes the price of non-local grape instead, as shown in Figure 5(B), the optimal price is $4.76, higher than the benchmark price 4.07. Because the cross category effect of non-local grape is not as strong as its local counterpart, the role of non-local grape to attract consumers is not as significant as that of local grape. A $0.69 increase in price only slightly shrinks the market share of store 2 (1 percent lower than the benchmark share) while raising the profit by 2 percent.

![Figure 5. Optimal price of grape (local/non-local)](image)

Similarly, for the berry product, a reduction of the local berry price by $0.84 (Figure 6(A)) or a rise of the non-local berry price by $0.13 (Figure 6(B)) is deemed optimal for store 2. In the former case, the local berry price cut increases the market share of store 2 by 14 percent and increases the profit by 7 percent. In the latter case, the increase in the non-local price decreases the market share by 1 percent but increases the profit by 2 percent.

![Figure 6. Optimal price of berry (local/non-local)](image)
Figure 6. Optimal price of berry (local/non-local)

To attract customers from the rival, a retailer might prefer deep price cuts on a small number of items to averaged price cut over a large number of items. A reduction in prices for complementary items within the store facilitates cross-category sales. The effect of price cut on items depends on their ability to generate enough incremental sales from established customers in the price cut category to offset the price cut, and also on their capacity to generate incremental profit in other categories. Our model is designed to leverage the pricing strategy to catch the optimal balance of tradeoffs. A price cut on items less complementary or substitute with items in other categories, e.g. non-local grape and non-local berry, has less opportunity to offset the item price reduction with sales of higher price margin items in other categories. Our results extend the empirical finding by showing that an appropriate increase in the price of those items could contribute to incremental profit in spite of the undercut market share by the rivals.

To further to explore the price effect, we run experiments to examine how the market performs if the prices of a couple of contents in the same categories are changed. A search method was used to identify the optimal price set that maximizes the store 2’s profit. Using MATLAB, a routine was designed to globally examine a wide range of value combinations of the local and non-local prices in the same category in order to identify a narrow-range of optimal price combinations. After a number of trials, we identified regions in the price space where the best price sets were likely to be located. This led to simulating the model with value ranges for prices of local and non-local content in each variety, i.e. $2.40-$2.60 for local apple, $0.95-$1.20 for non-local apple; $2.40-$2.70 for local grape, $3.90-$4.30 for non-local grape; and $3.75-$4.00 for local berry, 4.45-$4.90 for non-local berry. The computational executions were performed on a computer with 2.84 GHz CPU and 2GB RAM. It took 0.05 - 2 hours to accomplish the computation for those executions.

Further simulation results showed that the best price for local and non-local apple is $2.42 and $1.02 respectively, maintaining the rest prices of store 2 and prices of other stores constant.
The generated optimal price is $0.53 and $0.21 lower than its benchmark price respectively. Store 2’s profit under the best price combination is $26,789, higher than that if there is no change in prices, 20,288, or if the local or non-local price is changed solely, $24,727 and $22,608. The change in two item prices introduces more flexibility for store 2 to coordinate price change between local and non-local items and better leverage tradeoffs between costs (profit loss due to lower prices) and benefit (profit increase due to a higher market share (51 percent) under lower prices). The increase in the market share of store 2 is attributed to the increased number of sold baskets that contain apple item (basket No. 3, 6, 8, 11, 13 and 15 in Figure 7).

Figure 7: Results at apple price optimum (local $2.42/non-local $1.02)

A similar conclusion can be applied to the other two varieties, grape and berry. Simulation results suggest that the optimal price is $2.57 for local grape (see Figure 8). The price reduction contributes to the increase in the sold baskets in which grape appears (basket No. 3, 6, 8, 11, 13 and 15 in Figure 8) The optimal price is $4.16 for non-local grape, $0.09 higher than its benchmark price. There is a limited number of shopping basket with the item of non-local grape sold in store 2. An increase in non-local grape price only results in a slight reduction in shopping baskets sold in the store while the increase in the price of non-local grape increases the store earnings. Finally, under the optimal prices, store 2 has 45 percent of the market share makes a profit of $23,378. Such a profit value is higher than $23,255 at the optimal local grape price only, i.e. under a condition that only local grape price is changed, or $22,624 at the optimal non-local grape price only.
Similarly, when examining the sensitivity of the price of local berry along with the price of non-local berry, we find that local price falls to $3.80 while the non-local price rises to $4.78 to reach the optimum (see Figure 9). The former contributes to improved store patronage (from 32 percent to 41 percent) and the increase in the number of sold baskets that contains local berry at store 2 (basket No. 4, 7, 9, 10, 12, 13 and 15 in Figure 9). At the optimum, store 2’s profit reaches $24,356, higher than that if there is no change in prices or if the local or non-local price is changed solely, $22,848 or $22,500.
From a retailer's perspective, it would be particularly valuable to know the differential effects of local assortment on non-local assortment and vice versa, not only within but also across related categories. The effects are achieved through shifting consumers’ demand for assortments/categories. To assess the assortment effect on the consumer’s store selection and basket selection behavior, we first run a benchmark experiment that assumes all three stores only homogeneously offer four non-local assortments (B2, A2, G2 and R2 in Figure 10). Next, we assume that local apple product is added to store 2. Subsequently, local grape and local berry are introduced respectively instead of local apple. In each case, we run an experiment to identify the effect of an increase in local assortment on the consumer and retailer behaviors and retailer market share and profit.

In the benchmark experiment, the distribution of the sold basket number and market share are shown in Figure 10(A). Here the market share is calculated by taking the store's sales in dollars over the period and dividing it by the total sales of all three stores over the same period. When local apple product is added to store 2, its market share significantly rises from 32 percent to 65 percent and its profit rises from $11,732 to $33,525. The strong cross category effect of local apple with other assortments increases the sales of baskets with local apple content in store 2 (basket No. 2, 5, 8, 9, 11, 12, 15 in Figure 10(B)), and, holding constant the inherent potential of the market that three stores serve, reduces the sales of baskets with apple content in other stores, contributing to the higher market share of store 2. As shown in Table 4, the share of the unit of apple product sold in store 2 increases from 30.83 percent to 33.42 percent. Grape and berry sales slightly go down while banana sales almost remain unchanged. This is because local apple has a stronger cross category effect with banana than with grape and berry. A similar conclusion applies to a situation if local grape or local berry is added to store 2 instead of local apple (Figure 10(C)&(D)). Comparatively, local apple product can more strongly motivate the customer to purchase baskets with local content than local grape and local berry do. Local grape ranks second and local berry ranks last. Generally, the introduction of a new item affects current market shares in a sense that the new item will draw a large portion of consumer consideration from its close competitors. Comparing with the price effect, our results suggest that assortments play a more important role than prices in consumer store and basket choice decisions.
Table 4. Share of sold units of fruit in store 2 (percentage)

<table>
<thead>
<tr>
<th></th>
<th>Banana</th>
<th>Apple</th>
<th>Grape</th>
<th>Berry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>43.54</td>
<td>30.83</td>
<td>11.09</td>
<td>14.54</td>
</tr>
<tr>
<td>Local apple added</td>
<td>43.27</td>
<td>33.42</td>
<td>10.17</td>
<td>13.14</td>
</tr>
<tr>
<td>Local grape added</td>
<td>42.59</td>
<td>26.02</td>
<td>21.68</td>
<td>9.70</td>
</tr>
<tr>
<td>Local berry added</td>
<td>42.99</td>
<td>27.99</td>
<td>8.46</td>
<td>20.76</td>
</tr>
</tbody>
</table>

Next, we let store 2 change both the assortment and the price to see how the retail system will perform. We simulate a situation in which store 2 has local apple and the other two stores do not have it. We assume that store 2 changes the price for all the non-local assortment simultaneously. The optimal prices for the all four non-local assortments are listed in Table 5. To facilitate comparison, we also run a benchmark experiment to simulate the optimal price of
the non-local assortments by assuming that store 2 only offer the same four non-local assortments as the other stores do. Obviously, the increase in local apple assortment in store 2 softens price competition of non-local assortments (exclude non-local apple which is substitute for local apple) between competitors. A similar conclusion can be applied to the situation where store 2 exclusively offers local grape or local berry instead of local apple. An additional local assortment in a store raises the optimal prices of those non-local assortments that are not in the same variety as the additional local assortment, especially for the local assortment that is strongly complementary with local assortments, e.g. non-local banana. In other words, the unavailability of local assortment will intensify price competition regarding those non-local assortments. From this point of view, consistent with the conclusion from Bliss (1988), a retailer offering more local content than others can set a higher price for one or more items and increase its profits. On the contrary, as Bell and Lattin (1998) indicated, failure to carry items that are typically on the consumer's shopping list can lead to store switching. To be competitive in a market segment, a store should avoid having a fewer number of assortment and a high price of category simultaneously. That is, a retailer offering less assortment than others, a low-price strategy may be applicable to increase market share and profit.

Table 5. Optimal prices for non-local assortments (unit: $/pound)

<table>
<thead>
<tr>
<th></th>
<th>Banana-NL</th>
<th>Apple-NL</th>
<th>Grape-NL</th>
<th>Berry-NL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without apple local</td>
<td>0.55</td>
<td>1.16</td>
<td>4.62</td>
<td>4.83</td>
</tr>
<tr>
<td>With apple local</td>
<td>0.79</td>
<td>1.12</td>
<td>4.70</td>
<td>4.98</td>
</tr>
</tbody>
</table>

7. Conclusions

We use an ABM to evaluate the effects of assortments and price on consumer purchasing behaviors. We investigate the effects of marketing activities on multicategory choice behavior. While our analysis utilizes a retail chain’s store-level data, we are able to account for consumer heterogeneity in category preferences, loyalty to stores and distance and price sensitivities. Our investigation has focused on the effect of retail assortments and prices on consumer purchasing behaviors. Our results reveal incentives behind the retailer marketing strategies. This provides rich information can be used by retailers to allocate their resources and formulate effective strategies.
Our results show that both assortment and price play a significant role in determining consumer store and basket choice. Although appropriate prices and larger assortments generally improve the retailer’s profit level, the effects of the price and assortment strategies vary depending upon the role the category plays in the portfolio of the retailer and-the consumer. A reduction in prices for complementary goods within the store can disproportionately affect cross-category sales. For local assortments with stronger cross category effect with other categories, a low-price strategy facilitates category performance. For some non-local items which have less cross category effect and a lower share in total sale volume, such as grape and berry, a high-price strategy helps improve the profit. Assortment can be a competitive weapon and is more important than price in shaping consumer store and basket choice decisions. Among all local items, local apple has the strongest assortment effect on improving market share and profit. Interestingly, we find that a retailer with additional local content can set a higher price for one or more items to increase its profits. From this point of view, offering a wider range of assortments can soften price competition with competitors. We also find that the price justification applied to a wider range of assortments contributes to higher profit.

Our results provide a foundation for further research on consumer store choice and shopping basket choice, as well as retail assortment and pricing strategies. One can use the assortment and price to diagnose the relative competitiveness of a store and understand why competitors are doing better or worse than they are. A detailed understanding of their and their competitors’ competitiveness enables retailers to enhance the effectiveness of pricing and assortment strategies, and the coordination of those marketing efforts across categories. In addition, although we have focused on the retailer's perspective, our approach can also provide insights into developing marketing strategies for manufacturers. For example, it may help identify which local assortments generate positive spillover effects within or across categories, which can increase a manufacturer's bargaining power for negotiating more favorable trade deals with retailers. The model can also be used by public agencies and organizations to assess the effectiveness of their promotion programs that aim toward shifting consumer demand and enhancing consumption of products with specific credence attributes, e.g. local food products.

References


