Modeling an Organizational Decision Support System To Improve Retailers’ Decisions

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Abstract

Retail organizations (grocery stores, department stores, etc.) have access to rich data, based on scanner technology at store check-out counters. Most experts acknowledge that these data are under-utilized for lack of sophisticated organizational decision support systems to transform the scanner data into useful information that can be disseminated and used across the many stores of a retail organization. This paper offers a mathematical model that can be used in conjunction with scanner data in a retailer’s decision support system. The proposed model can help retailers maximize individual store profits by helping choose "optimal" brands for the price promotions. By maximizing store profits, the overall profit potential of the organization is enhanced. Additionally, the proposed model has substantial theoretical appeal as it is based on the literature from the field of ecology.

1: Introduction

Retail organizations today have access to sophisticated scanner-based data on customer purchase behavior. However, for the most part, these data are under-utilized and their potential to help retailers increase their profitability has not been completely realized (Cooper [3]; Gold [7]; Harbert [8]; Overhultz [22]). This situation is largely due to retail organizations’ present decision support systems that lack sophisticated models to make optimal use of the available scanner data (Hume [11]). This research offers a model that focuses on profitable pricing decisions; specifically, the model can help retailers’ choose the “ideal” brands for price promotions so that store profitability is maximized and organizational profit goals are achieved.

From a business perspective, retail organizations (for example, grocery retailers) focus on the key marketing function of making goods available to customers. The degree to which these organizations are profitable depends to a large extent on how they manage their suppliers (the manufacturers) and their customers. Further, the profitability of a retail organization is closely linked to maximizing the profitability of each store in the organization. Profits will be maximized in each store if the profits generated from every product category in the store (for example, in a grocery store, product categories vary from fresh produce to disposable diapers) is maximized.

However, maximizing the profit of each product category is a challenging task because retailers receive varying profit margins among the different brands in product category. Further, demand for each brand in the product category varies depending on which brands are “price promoted”. Such price promotions include (1) temporary price discount, (2) temporary price discount with an in-store display, and (3) temporary price discount accompanied with a local advertisement (Blattberg and Neslin [11]). These price promotions are extremely successful in directing demand to specific brands (Blattberg and Neslin [11]).

Thus, the choice of brands for price promotion is critical not only because profit margins vary by brands, but also because retail price promotions have the capability to shift demand in brand sales. These sales increases come from a variety of purchase mechanisms, including brand switching, stockpiling, and increased consumption (see later).

This paper offers a model that utilizes scanner data and which can be incorporated in a retailer’s organization decision support system to identify those brands that enhance store profitability during price promotions. Additionally, the model has substantial theoretical appeal as it is based on the rich literature on competition from the field of evolutionary ecology. As such, it is based on sound theoretical principles from an area (i.e. ecology) that is receiving substantial attention in the marketing literature.
2: Organizational DSS: The Case of Retail Organizations

Organizational decision support systems (ODSS) has received substantial attention in the recent past (Bots and Sol [2]; Dondi, Migliarese, Moia, and Salamone [4]; George [6]; Miller and Nilakanta [19]). Various definitions of ODSS have been offered in the literature, (for example see King and Star [13]; Watson [26]). George [6] reviews these definitions and notes that the common themes underlying the definitions of ODSS include a focus on organizational tasks that affects several organizational units or corporate issues, and an emphasis on cross-functionality, cutting across hierarchical layers and involving computer based technologies and communication technologies.

Researchers have also attempted provide architectures for ODSS (for example, Philippakis and Green [23]; Watson [27]). Philippakis and Green’s architecture has particular appeal to retail organizations. They offer a hierarchical organizational pyramid based on the scope of decision support: from a long term, corporate-wide scope to a short term, functional and localized scope. The specific components of the organization decision support system are: corporate planning systems (CPS), executive information systems (EIS), functional decision support systems (FDSS), and local decision support systems (LDSS).

The Philippakis and Green [23] hierarchy can be used to describe retailer organizations; systems such as CPS and EIS cut across functional areas and are focussed on long term issues. However, FDSS or functional DSS include short term decisions of the retailer such as moving inventory, advertising campaigns, pricing decisions, etc. - all of which impact the profitability of the stores and therefore, the organization. One key FDSS that is critical in retailer profitability is the choice of brands offered on price promotions in a retail store; as described below, this decision directly impacts store profitability, and thus profitability of the retail organization.

The overall objective of a retailer is to maximize store profits (Blattberg and Neslin [1]). This objective will be realized if the profit for every product category in the store is maximized (Kumar and Leone [14]). As an example, a grocery store’s overall profit objective will be realized if the profit for every category in the store (e.g. beverages, soups, salted snacks, disposable diapers, etc.) is maximized.

For the retailer to maximize profits in every product category, the retailer must maximize the sales of that brand in each product category which provides the largest profit margin. Of concern to the retailer is the fact the brand that sells the most in any product category may not always be the one that provides the largest profit margins. Brand sales are driven by a variety of factors revolving around product issues (brand name, quality, etc.), manufacturer’s national advertising, and price (manufacturers coupons, competing brand’s price, etc.). As such, retailers have little control over many of the factors that affect sales; however, one factor that can directly impact purchase behavior and therefore sales, is retail price promotions.

Past research reveals that price promotions have the potential to bring about substantial sales increases (for a comprehensive review see Blattberg and Neslin [1]). The sales increase during a retail price promotion is made possible by a variety of mechanisms. Research has illustrated that a given increase in sales during a price promotion is brought about by any or all of the following mechanisms: (1) increased consumption of the promoted brand, (2) stockpiling of the promoted brand, (3) brand switching from the non-promoted brand to the promoted brand, and (4) category switching to the promoted brand (Moriarity [21]).

Thus, the ability of price promotions to produce sales for the promoted brand is well recognized and reported. However, today few retailers have the ability to manage these price promotions to maximize their profitability, particularly as demand patterns vary across the different store locations, and profit margins vary across the different brands. Retail organizations need decision support systems that store managers can use to exchange data between stores and identify those brands that when promoted will enable each store to maximize its profits, thus helping the overall retail organization to achieve its profit objectives. The challenge for retailers is to have a system that identifies the "correct" or optimal brands for price promotion; however, that may not be a simple task as a brand’s price promotion impacts not only the promoted brand, but also other brands in the product category, as discussed below. As such, the ODSS, or more specifically the FDSS must be set up to model the purchase dynamics of price promotions and help retailers identify brands that when promoted will maximize store profits.
3: Choice of Brands for Retail Price Promotion

The profit margin that a retailer receives from the manufacturers varies substantially across the brands in a product category. As discussed above, ideally, the retailer would like the see all sales of a product category to come from that brand that provides that largest profit margin. However, in reality, sales come from a mix of brands, with a corresponding mix of profit margins. As such, the challenge to the retailer is to choose those brands for retail price promotions that will maximize the following: (1) encourage brand-switching from low profit margin brands to high profit margin brands (2) discourage brand-switching from high profit margin brands to low profit margin brands (3) stockpile high profit margin brands and thus, preempt sales of low profit margin brands in the future. Identifying those brands that produce the above effects (brand switching and stockpiling) and those that do not, is difficult. During a price promotion, a retailer’s scanner data will typically indicate a substantial increase in sales for the promoted brand. However, most retailers today cannot identify the degree to which the above three effects occur (or the relevant brands involved). This is largely because today’s retailers do not have sophisticated models in their FDSS that provide such information from the scanner data.

What retailers need is a model that will provide information on the different brands that are affected (in terms of brand switching and stockpiling) when a particular brand is offered on price promotion. Ideally, the model should measure the effects of a retail price promotion over time for a particular brand, on its own sales performance, over time, and on the sales performance of each of other brands in a product category, over time. Such a model will enable the retailer recognize which brands are affected by the price promotion of a given brand, and help manage category profitability. This paper offers such a model that can be incorporated in a retailer’s FDSS and which will be specifically useful in identifying the brands that are affected by a given brand’s retail promotion. As such, the model will help identify the extent to which any given brand affects every other brand in a product category through brand-switching during price promotions.

Further, the model offered in this paper is appealing because it is based on sound theoretical concepts from the literature in evolutionary ecology. As discussed in the next section, theoretical principles of ecology are used to conceptualize product categories as competitive systems, where competing brands exist in dynamic equilibrium. Such a conceptualization provides a model of brand competition within product categories that can be utilized by retailers to manage brand switching and thus, the profitability of each product category.

4: Theoretical Foundations of Model

The field of evolutionary ecology (Pianka [24]) has a long and rich tradition of research on the dynamic effects of competition. Henderson [9] provides a strong case that business competition at the most fundamental level is natural or ecological competition. The potential of ecological theories in understanding and analyzing business competition has been recognized by many marketers (Henderson [9],[10]; Lambkin and Day [15]). Ecology theory offers a very useful method for describing, explaining, and measuring competition among many competitors (Milne and Mason [20]).

The above mentioned researchers strongly encourage marketers to exploit the extensive literature in ecology to better understand the dynamics of competition in today’s marketplace. Few studies (e.g. Milne and Mason [20]) have risen to this challenge and attempted empirical work in this area.

We will first examine the basic principles of ecological competition and their relevance to business competition (Henderson [9], [10]; Milne and Mason [20]). We then draw on these concepts to introduce a model of brand competition that can be usefully applied to examine the competitive effects of a brand’s price promotion.

From an ecological perspective, competition is the struggle for scarce resources. The intensity of competition is determined by the extent to which two or more species compete for the same scarce resources. Through their interaction, competitors "crowd out" or displace each other. "Crowding out" or displacement occurs based on a central tenet in ecology: Gause’s Principle of Competitive Exclusion (Gause [5]). According to Gause [5], no two species can coexist that make their living in the identical way. For two species to coexist and survive, each must be different enough to have an unique advantage. Such unique advantage, is based on the concept of niche.

The niche is important for the study of competition because it is defined as the range of scarce resources for which species compete. The overlap or sharing of niche space (or the range of scarce resources) is the essence of competition. The larger the overlap indicates the more similar the species, and more
intense the competition. If there is perfect niche overlap between two species, it will mean that both species compete for exactly the same resources, and depending on the scarcity of resources, and density of the species, one species will "crowd out" or displace the other.

The analogous situation in business competition has been drawn by researchers such as Henderson [9],[10] and Milne and Mason [20]. Brands can be thought of as competing species. Brands need a variety of resources to survive, including the critical resource of customers. Typically, the customer resource is finite and limited, and hence a scarce resource. Using concepts from niche theory, we can consider two brands to be close competitors if they have a large niche overlap, or if they target similar customers. On the other hand, if they do not share the same resource, (i.e., they are differentiated from each other and target different segments), they are not direct competitors. This analogy between species and brands can be used as the basis for building a model of brand competition.

4.1: Competitive Dynamics in Product Categories

This study proposes the brand competition in each product category can be considered to be in dynamic equilibrium, based on the following discussion.

If competing brands coexist in a product category, then they must be in dynamic competitive equilibrium. Such an equilibrium can exist in each product category only if any change in the competitive environment in that category triggers other changes that tend to restore the conditions prior to the disturbance. Thus, in a case of two highly competitive brands, if one is offered on retail promotion and the other is not, competitive disequilibrium may result. To ensure competitive equilibrium is restored, changes in the environment that affect any competitor will require some degree of response and adaptation. This means that continual change is required, and competitors that adapt best or fastest can either reverse the disequilibrium in their favor or at least, restore equilibrium.

Using an extreme example, in the case of two brands that are perfect substitutes (i.e. complete niche overlap), continuous promotions for one that is unchallenged by the other, means growth in sales for the former, and decreasing sales and market share for the latter, until its sales are nil. Thus, a restoration of equilibrium requires responses in terms of forces similar to those that triggered the disequilibrium; in this case, promotions.

We do not see brands "crowded out" of the market, because realistically there are no perfect substitutes, and promotions are not exclusive to a selected group of brands only. Rather, promotions for brands vary, and are met with similar promotions from competing brands. Thus, there is continuous activity of initiating and reacting promotions between brands in a product category.

Based on the above discussion, we propose a model of brand competition within a given product category. The proposed model of brand competition models changes in sales (increase, decrease) of a particular brand by modifying and adapting a well established model of competition in ecology called the Lotka-Volterra model (Lotka [17]). This model has been successfully used to model the population changes of competing species with large niche overlap, competing for scarce resources. More important, it enables a measure of the competitive impact of one species growth on the growth of another species. Hence it can be applied to a retail promotion context and help measure the competitive impact of one brand on another during price promotions.

4.2: Building the Model

The model is based on the fundamental notion that the change in sales for any given brand \( i \) in a retail chain, with sales \( S_i \) at time period \( t \):

\[
\frac{dS_i(t)}{dt} = \lim_{\Delta t \to 0} \frac{S_i(t) - S_i(t-\Delta t)}{\Delta t}
\]

We assume that the continuous form in (1) can be approximated by the discrete form (i.e., \( S_i(t) - S_i(t-1) \)):

\[
S_i(t) - S_i(t-1) = r_i S_i(t)
\]

However, (2) may be an incomplete specification as sales at time \( t \) \( (S_i(t)) \) is affected by stockpiling from time \( (t-1) \) as well as brand switching at time \( t \) - both of which affect sales at time \( t \). We can incorporate both these effects in (2), as discussed below.

**Stockpiling:** Assume that \( K_i \) is the maximum sales possible for Brand \( i \) over two periods. In other words, the more of \( K_i \) that is "used-up" in the first period, there is less available in the second period. Thus, if
stockpiling of brand 1 occurs at time t-1, then its sales at time t is affected. More precisely, the sales at time t, \( S_{1(t)} \), will interact with \( [K_1 - S_{1(t-1)}]/K_1 \). Thus, equation (2) can be modified as follows to accommodate stockpiling:

\[
S_{1(t)} - S_{1(t-1)} = r_1 \cdot S_{1(t)} \left[ K_1 - S_{1(t-1)} \right]
\]

(3)

**Brand Switching:** To incorporate the effects of brand switching, assume that there are only two competing brands, brand 2 and brand 3, and their respective sales at time period t are \( S_{3(t)} \) and \( S_{3(t)} \). Again, sales of brand 1 at time t (\( S_{3(t)} \)) may not be independent of sales received by competing brands at time t; more likely \( S_{3(t)} \) will interact with \( S_{2(t)} \) and \( S_{3(t)} \). Equation (3) can be modified to include the competitive impact of these two brands:

\[
S_{1(t)} - S_{1(t-1)} = r_1 \cdot S_{1(t)} \left[ K_1 - S_{1(t-1)} - C_{21} \cdot S_{2(t)} - C_{31} \cdot S_{3(t)} \right]
\]

(4)

Where:

- \( C_{21} \) = competition coefficient, measures brand switching, the impact of brand 2’s sales at period t on brand 1’s change in sales from period (t-1) to period t.
- \( C_{31} \) = competition coefficient, measures brand switching, the impact of brand 3’s sales at period t on brand 1’s change in sales from period (t-1) to period t.

Thus, the model states that the change in sales between two time periods is a function of the sales at time t, which interacts with stockpiling effects, and brand switching effects. The above model can be conveniently expanded to include n competitors; i.e. the effect of all competing brands can be taken into account, providing \( C_{12}, C_{13}, \ldots, C_{1n} \). Further, the model can be used for every brand in the product category; for example, for brand 2:

\[
S_{2(t)} - S_{2(t-1)} = r_2 \cdot S_{2(t)} \left[ K_2 - S_{2(t-1)} - C_{21} \cdot S_{2(t)} - C_{32} \cdot S_{3(t)} \right]
\]

As discussed below, the competition coefficients (\( C_{ij} \)) provide useful information.

**4.3: Competition Coefficients**

The competition coefficient provides a measure of the extent of inter-brand competition, in a product category. More specifically, it is the measure of the degree to which a competing brand’s sales interact with a particular brand’s attempt to grow in sales from one period to another. As such, it is a measure of the degree of brand switching between the given two brands. As an example, a large value for \( C_{12} \) will indicate that brand 2 impedes the growth in sales of brand 1, indicating that brand 1 cannot draw sales away from brand 2. In other words, price promotions of brand 1 do not generate brand switching from brand 2.

Thus, retailers can use the competition coefficients to identify the degree of brand switching for every pair of brands in a given product category. Using this information, the retailer can decide which brand’s promotions will enhance profitability and which brand’s promotions will decrease profitability. However, to make such inferences, the model must be estimated as described below.

**5: Model Implementation**

The model proposed is estimated at the retail chain level; as such stores within a retail chain are aggregated to the chain level. Such aggregation will produce biased estimates if the estimated response coefficient does not represent on average, the sum of the response coefficients across stores. As shown by Theil [25] the expected value of the estimated aggregate promotion coefficient will be a weighted average of each true store coefficient, plus the weighted average of the true coefficients of other variables in the model. However, this bias will not occur if the promotion schedules in each store of the retail chain are the same.

Given that the promotion schedules between stores within retail chains of a geographic market can be expected to be the same, this study uses store level data, aggregated to the chain level. Further, as an added measure, each store’s sales are indexed by the average all commodity volume (ACV) for that store. Such weighing by store volume has two benefits. First, the weighing counteracts the potential problems of aggregating across stores if aggregating is not appropriate (Theil [25]). Second, it counteracts the problem of counting the impact of a promotion as the same whether it takes place in a store with one third the size of the average store or three times the average - the result is a wide variation in promotion response for the same level of promotion.

**5.1: Methodology**

The Competition Coefficients are estimated for
each pair of brands, using weeks of price promotion data, including one week before each price promotion and one week after each price promotion. As an example, in a 52 week period, if week 8 is a price promotion, we include weeks 7 and 9 too. By adding the extra weeks, we are able to model the increase in sales from a non-promotion week to a promotion week, plus checking for stockpiling in the week after the promotion. Following the notation used earlier, equation (7) for brand 1 in any given product category with one competing brand can be re-written as:

\[ S_{10} - S_{10+1} = r_1 S_{10} - z_1 S_{10+1} - b_{12} S_{10+1} S_{20} \]  

(8)

And for brand 2:

\[ S_{20} - S_{20+1} = r_2 S_{20} - z_2 S_{20+1} - b_{21} S_{20+1} S_{10} \]  

(9)

Where \( z_1 \) and \( z_2 \) are \( r_1 + K_1 \) and \( r_2 + K_2 \) respectively, and \( b_{12} \) and \( b_{21} \) are \( z_1 C_{12} \) and \( z_2 C_{21} \), respectively.

Therefore:

\[ C_{12} = (b_{12} + z_2) \]  

and \( C_{21} = (b_{21} + z_1) \). Equations (8) and (9) are estimated using ordinary least squares for each product category.

6: Model Validation: Preliminary Results

Given proprietary issues, it was not possible to run the model in a specific retailer’s DSS and evaluate its usefulness in improving profitability for that retailer. However, Information Resources, Inc. (IRI), Chicago provided scanner data on a randomly sampled retail chain from New York, Chicago, and Los Angeles. Data on three product categories were provided: Saltine Crackers, Baking Chips and Disposable Diapers.

We use the data to run some preliminary analysis to help validate the proposed model. The model was run on 52 weeks of store level scanner data on every major brand in each of the three product categories. The results are interesting, as discussed below.

We use the model to test the hypothesis that there are asymmetric competitive effects in a product category. That is, we would expect that the brand switching impact of brand k on brand i will not be equal to the brand switching impact of brand i on brand k. Such differences are expected from past research in price promotions. The rationale is that differences in market share will produce asymmetrical effects, in the sense that small share brands get more “bang for their promotional buck” than large share brands. Thus, we can expect asymmetrical competitive effects (i.e. \( C_{ik} \neq C_{ki} \)) to occur when the difference in market shares between any two brands \( (M_i - M_k) \) is significantly different from zero. Today’s retailers expect this effect; it would be interesting to see if the proposed model substantiates this expectation.

To test this hypothesis, a T-test for paired comparisons is used to: (1) test the mean difference in market share for every pair of brands is significantly different from zero, and (2) test the mean difference in competitive impact (i.e. \( C_{ik} - C_{ki} \)) for every pair of brands is different from zero. As such, our hypothesis will be supported if \( C_{ik} \neq C_{ki} \) in those cases where \( M_i \neq M_k \).

Table 1 provides the results of the analysis. As seen, the results are mixed. The hypothesis is not supported at all in the saltine cracker category, is partially supported in the baking chip category, and is fully supported in the disposable diaper category. In the saltine cracker category, although we see significant differences in market share between every pair of brands across the three markets, no asymmetrical competitive effects are seen in any of the cases. In the baking chip category, of the nine cases analyzed, eight cases have market shares that are significantly different from zero. However, out of these eight cases, only three indicate asymmetrical competitive effects. Interestingly, the three cases belong to the same pair of brands (Nestle and Hershey), from each of the three markets. With regard to the disposable diaper category, there is strong support for the hypothesis. In every case where a pair of brands exhibited significantly different market shares, asymmetric effects are noted.

The pattern of support (or lack of support) of the hypothesis provides some interesting insights into the brand switching dynamics present in the market place. For example, it seems that asymmetric competitive effects are more prevalent in higher priced product categories (such as disposable diapers) in contrast to lower priced product categories (such as saltine crackers). It could also mean that retail promotions are more powerful in negating market share differences at lower priced product categories than in higher priced product categories.

7: Conclusion

The profitability of retail organizations is closely linked to the profitability of the individual stores of the organizations. A given store’s profitability is
TABLE 1
ASYMMETRICAL COMPETITIVE IMPACT

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<thead>
<tr>
<th>Product</th>
<th>Market Share Difference</th>
<th>Asymmetry Effect</th>
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<tr>
<td>SALTINE CRACKERS</td>
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*: significant at α=0.05; actual market share figures cannot be provided for proprietary reasons.
ns: not significant

determined by a variety of factors including the effective management of pricing policies, particularly temporary price changes—called price promotions. Today few retailers are able to manage their price promotions such that they maximize store profits. This is unfortunate given that the typical retail organization today has access to store scanner data that provides rich information on purchase behavior. However, most experts acknowledge that these data have been underutilized for lack of sophisticated models that transform the data to useful information.

This paper provides a model that can be incorporated in retailers’ decision support systems. Specifically, it can be incorporated into the functional DSS which is considered a component of the organizational DSS (Philippakis and Green [23]). Once implemented, this model will enable store managers of a retail organization to communicate with each other on the purchase dynamics of price promotions and help them better manage the profitability of price promotions. As such, this decision support system will be particularly useful in large retail organizations where stores are widely dispersed across the country. If effectively used, the system will enhance the profitability of each store and thereby, the profitability of the organization.

References


