Effective Retail Promotion Management: Use of Point of Sales Information Resources

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The increasing availability of customers' transaction level data at the point of sale (POS) in electronic form in various stores in India is opening up important arenas in marketing analytics that can enhance business dicision-making process. This paper discusses the strategic role that management of customer information resources can play for the growth and sustenance of business. This paper also provides examples of simple analysis using POS data that can directly aid practising managers in their strategic and tactical decision-making.

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India has witnessed a surge in organized retailing in the recent past. While the retailing industry is still in its infancy stage and growth opportunities are significant, the lessons from more developed markets suggest that increased competition in this area will demand better operational efficiencies to remain viable in the long run. To be able to support good decision-making for the future, retailing organizations need to equip themselves, among other things, with the infrastructure to develop and manage customer databases which can be effectively mined in the future to help drive strategy-building. Investing in Point of Sales (POS) data has been a reasonable success story in the, western markets and this paper attempts to highlight some of the plausible applications of such data. It also emphasizes the areas in which retailing majors could possibly invest to reap the benefits of market information in the future.

The use of POS data in developing analytical models that provide insights into managerial decision-making in the context of retailing has been well-documented in marketing science literature. A recent article on this issue (Bucklin and Gupta, 1999) articulates the progress made in the consumer packaged goods industry in the US in the past 20 years in harnessing POS data both in academic research as well as in developing effective industry practices in the area of retail promotion management. Some of the decision areas under retail promotions that have been extensively researched are:

- Product pricing at retail outlets which includes decisions on timing and depth of discounts.
- In-store display planning which includes issues

on what brands/product categories to display and location of such displays.

- In-store communication and advertising management — issues on design of ceiling signs, mobiles, inflatable, floor graphics, danglers, instant redeemable coupons, etc.

- Local area advertising decisions to promote products that build store traffic.

- Decisions regarding shelf space allocation and arrangement of brands to command optimal visibility.

- Decisions regarding store coupon circulation for various product categories.

What is POS Data?

As the name suggests, POS data is information collected at the retail store that provides volumetric information on every transaction made, i.e., the quantity sold, both in numbers and value, the price at which the transaction was made, and any added information regarding promotional programmes which the store ran at the time the transaction took place. POS provides marketers with direct behavioural information on what consumers buy.

POS data has been recorded in a systematic manner in India for over a decade now, albeit at a modest scale. ORG-MARG has an' extensive operation in India that conducts a monthly retail audit on a sample of stores for a limited number of brands/Stock Keeping Units (SKUs). The information recorded has been primarily volumetric data, which has been used by Fast Moving Consumer Goods (FMCG) companies to track market share over time. While third party data collection practices at the retail store have been around for a while in India, the fragmented nature of retail industry has inhibited the collection of individual transaction level data at the retail store. With the coming of organized retailing in India in the past three to four years and its projected spiralling growth (Rs 160,000 crore by 2005[1]), transactional level

1. Economic Times, March 18, 2000. ET Interactive, Interview with Simon Bell, Principal, A T Kearney, New Delhi.

POS data availability has been on the increase, especially with most retailing giants having electronic check out in their retail outlets which facilitate easy recording and storage of data.

Why is POS Data an Important Source of Managerial Information?

POS provides a rich source of behavioural data on the customers' purchase characteristics. It is the most disaggregate form of behavioural data available from the retail outlet. In comparison, the monthly retail audit data collected by ORG-MARG aggregates brand sales over a period of a month. Therefore, the details of the purchases made on every transaction are not available at this higher order of aggregation. POS data has been used to develop various analytical frameworks that have provided important insights into consumer retail purchase behaviour. In marketing science literature, a seminal paper on modelling brand choice (Guadagni and Little, 1983) with marketing mix variables using consumer panel data marked the initiation of a spate of research on consumer behaviour using panel as well as store level retail transaction data.

In the developed countries, especially in the US, research companies such as AC Nielsen and IRI have established businesses collecting both store level (POS) and consumer panel level information. The information collected is used primarily for tracking studies of market share, but over the past 12 years, consumer data has been systematically analysed to generate value added insights on consumer reaction to various marketing mix initiatives. The SCAN*PRO model (Wittink *et al.,* 1988) and its variants have been extensively used by practising managers, especially in the packaged goods industry in the US to develop an understanding of the causal effects of price and retail promotion. Some of the areas which have been extensively researched, both in academic institutions as well as in industry, are discussed below.

Analysis of Key Drivers of Sales

Price and in-store promotion variables have

traditionally captured the attention of both retail store managers and brand managers. What brands to promote and when, for how long, which will drive profitability of the store or the brand, has been of prime importance to managers in this industry in the US for long. To evaluate the relative importance of various promotional vehicles, like temporary price reductions, coupon offers, in-store special displays, freebies, and local area feature advertising of price-offs, the SCAN*PRO model (Wittink *et al.,* 1988) has been extensively used. Managers across various companies ranging from Kraft, Coca Cola, Pepsi and Procter & Gamble, to name a few, have used this modelling technique to examine the effect of various trade promotion initiatives. The end objective has been to develop normative models that help make decisions regarding optimal promotional spending — how much to spend, on what brand to spend, and what specific promotions to run. Promotional price elasticity and base price elasticity are estimated using the SCAN*PRO model output to make pricing decisions, wherein issues regarding the long-term impact of price changes are weighed against short run promotional price effects.

A very effective managerial tool developed by market research organizations specializing in the retail industry using POS data has been the *Sales Rate Chart*. This is simply a distribution of sales volume generated at a retail outlet across various price points. The chart is simple but provides important information on sales spikes due to price changes. Sales rate charts have their limitations in terms of analytical rigour; however, they have proven to be a successful tool in making broad pricing decisions both in the long and short run.

Analysis of Category Management Issues

Three specific decision areas that have benefited by the use of POS information analysis are:

- Optimal product portfolio size at the retail outlet and retail shelf space optimization.

- Optimal retail promotion initiatives to maximize retail category contribution.

- Optimal trade allowance package to be offered to retailers by manufacturers with the objective of maximizing manufacturer's category contribution.

While the first two areas are primarily retail management issues and are of prime importance to store managers, brand and category management specialists in manufacturing organizations are necessarily concerned about optimizing their own brand portfolio contributions. Sometimes, these objectives may work against each other, for example, if promotion of brand A in the store brings in high volume share for the particular brand, which is good for the manufacturer of brand A; however, promoting brand A cannibalizes sale of other brands in the category in the retail store to such an extent that it causes a fall in the total contribution for the product category in the retail store.

With retailing dominated by large organized corporations in the US who have the leverage to negotiate better terms with manufacturers to maintain brand visibility in the store, manufacturers have been forced to devise promotion mechanisms that harmonize retailer's category profit objectives along with their own.

In the context of using POS data for developing analytical frameworks for resolving category management issues, brand and category managers in the US have constructed causal models which determine not only the direct effect of own price and promotional mix elements on sales of the brand, but also the cross effects of marketing mix elements of other brands which are deemed to be direct competitors. Own price/promotional elasticities and cross price/promotional elasticities elements are inputs to build category profit simulators which are typically scenario building tools which help in designing effective promotional programmes which maximize contribution.

Such exercises are carried out quite regularly at large packaged goods companies. In the beer category, extensive use of this simulator has been made by the second largest brewery in the US market. The specific purpose of this project has been to convince retailers across the

US markets that promoting their brand of beer on key holiday weeks maximizes profits for the retailers compared to promoting the market leader brand.

Rationalizing on portfolio and shelf space management requires additional inputs in terms of layout design of retail stores (planograms) which when integrated with POS sales information can provide significant insights into optimal portfolio size as well as the area and shelf location to be allotted to different product categories with the objective to maximize the retail sales or profits. Exercises of this nature are performed regularly with fair degree of success in developing appropriate marketing decisions. Several research companies have developed syndicated analytical models which have had limited success in resolving issues across the board. They go by nomenclature such, as Portfolio Manager or Category Manager; however, based on our experience, developing customized solutions using POS data has had significant potential in resolving product assortment and shelf space management issues.

Advertising

POS data along with media exposure data as collected by research agencies in the US, such as Nielsen Media Research (ORG-MARG collects media exposure data in India) have been used by brand managers to calibrate their long-term advertising spendings. There have been attempts at studying the short-term effects of advertising on sales; however, the impacts estimated have been fairly low (0.1 to 0.12 for established brands, 0.2 to 0.4 for new brands). There has been moderate success at estimating advertising impact on sales in the long run (1.5 to 2 times more than short run effects).

An explanation for these lukewarm results may rest with the characteristics of data resources used to construct the analysis. Research agencies such as AC Nielsen and IRI favour the use of store level data (POS) to study advertising effects, which they claim is consistent with the analysis conducted to study the effect of store promotions (Bucklin and Gupta, 1999). This point is, however, debatable since

other agencies (presumably not having access to store level data) have argued for the appropriateness of using market level data to estimate the impact of what they call market level phenomenon such as advertising. Readers should note that market level sales data is obtained by aggregating POS data across all stores in a market over an appropriate time window. Using appropriate projection factors that account for the population of stores the store level data can be projected to get an estimate of the overall market offtake.

While brand managers are concerned about the effectiveness of their advertising budget, retail managers also need to know about the impact of advertising on brands, especially advertising campaigns of new brands and new product categories.

The Retailing Environment in India

With her population touching a billion, India is working at the doorsteps of becoming one of the world's foremost consumer markets. About a quarter of this huge mass of consumers live in towns and cities and the remaining in villages. Over the years, the retailing infrastructure that has proliferated in India is characterized by a high degree of fragmentation as compared to many developed nations. A recent estimate puts the figure at 10 million operational retail outlets in India, 32 per cent of these being in urban areas. Small stores (about 300-400 sq.ft.) accounted for 64 per cent of the retail outlets in the country whereas very large stores (about 800 sq.ft.) constituted only 3 per cent of the establishments. FMCG stores accounted for nearly 75 per cent of these retail outlets. According to a CMIE[2] forecast, total retail sales in India is likely to exceed Rs 9200 billion by the year 2002, of which about 73 per cent is expected in the food sector. Therefore, it is obvious that the great Indian retailing revolution is not waiting for the size of the business opportunity. The challenge lies in identifying the key drivers that steer the Indian consumers' perception and behaviour when it comes to their shopping needs.

[2]Centre for Monitoring Indian Economy.

In this context, market enthusiasts are crystal gazing on the 'fate' of large format and/or organized retailing in India. There are interesting trends by way of statistics, e.g. the friendly neighborhood mom&pop stores have increased per 1000 population as per an ORG study, and large format and specialty retailing is also on the increase (though their absolute numbers are still quite small). This is at the expense of perhaps the middle-sized-middle-value shops[3]. The reality is that every retailer has to "understand his customers" more discerningly than ever before and make strategic choices to pursue the right target (customer) with the right proposition. Also, the reality is that every retailer today is unanimous in his appreciation that he needs to "deliver value" to his customers.

The final reality is that in today's retailing environment in India, the sheer complexity of the product-market matrix is posing 'mental-model' based decision-making a real challenge. This exponential change, started during the early 90s, is arising essentially out of two sources. First, in pursuit of the proverbial 200 million strong Indian middle class, the manufacturers have been continually adding new products in the market place. For instance, in the FMCG sector, there were 57 core categories of products in 1990, which grew to 76 by 1996 (and the trend continues). These 19 new categories boasted of 1378 brands and 2579 SKUs. Furthermore, the number of SKUs in the erstwhile 57 categories also grew from 7715 to 15160 during the same period (Banerjee *et al.,* 1999).

The second change agent, and the most important, is the consumer who has become vastly discerning through rapid exposure to the global business environment. The Indian consumer today reflects a strong preference for imperatives such as evaluating choices from among large assortments of products, a pleasurable shopping experience, and a shopping experience that would provide the maximum "value" per rupee spent.

Herein lies the opportunity of utilizing the POS data to model consumer response to marketing mix variables at the retail level. With increasing competition, both at the manufacturer level and the retail level, it is obvious that there are distinct advantages of being the first mover in harnessing information resources to drive the marketing strategy building exercise, both for retailers and manufacturers. The latter, it is hypothesized, will increasingly feel the pressure of building strategies that are in congruence with the retailers' business objectives.

The rapid changes in the retailing environment are currently quite evident at least in some of the metropolitan pockets of the country. A fairly extensive review of the expanding retailing sector in India is available in prominent trade publications.[4] Competition has set in from multiple sources. In the Chennai market, competition in food retailing is multi-faceted with the neighborhood *(kirana)* stores facing direct competition from more than one organized retailing chain: FoodWorld, Nilgiri's, Subhiksha, and Vitan. With such intense competition in the market, newer retailing chains are forced to adopt significantly differentiated POS strategy to make customers change their shopping habits. For instance, the specific trade publication reports that Subhiksha adopts a blanket policy of discounting prices by selling less than MRP, similar to the textbook definition of an Everyday Low Pricing (EDLP) strategy. "You have to give customers a solid reason to change their shopping behaviour. One which conventional stores like the *kirana* can't duplicate," says the director of Subhiksha chain of supermarkets.

The above instance corroborates our assertion that retailers of the future will have to rapidly employ differentiated marketing strategy based on customer response information. Utilizing customer behaviour data at POS to develop effective pricing strategies, EDLP or otherwise, will certainly be an imperative for long-term survival and growth.

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3 *The Hindu Business Line,* "Responding to Modern Retailing Formats," May 23, 1998.

4 Brand Equity, *The Economic Times,* April 26 - May 2, 2000.

Status of POS Data in Retail Management in India

As was pointed out earlier, ORG-MARG has operated a retail store audit in India for many years. The data primarily consists of actual stock movement data at sample stores. Collection of corresponding marketing mix elements has been minimal, and only very recently has some effort been made to collect price and promotion data. AC Nielsen is also reported to be planning to develop an audit infrastructure. However, none of these organizations is capable of fully collating the rich transaction level data that exists at the retail point of sales. AC Nielsen and IRI claim to provide census data on store sales, but only in a few geographic regions in the US.

A typical source of POS transactional data will have information on the following:

- Wider range of SKUs.

- Tracking of generic/store brand sales.

- Ability to handle consumer panels through loyalty programmes.

    Ability to conduct product basket analysis.

- Ability to generate information on optimal "loss leader" promotion strategy.

A recent study document prepared on this topic (Raghuram *et al.,* 1999), highlights some of the analytical capabilities of this type of information. However, a detailed assessment of a typical POS transactional level database available today shows the limited amount of information collected currently (Table 1). This is not surprising given that use of the data has been primarily to generate simple accounting reports. In order to develop the full potential of POS data for decision-making, the future managers have to proactively think of information bytes that need to be systematically collected which can be used along with the transaction level data in the future to help making better store level decisions.

One area that conventional grocery stores like the small *kirana* stores cannot replicate is

Table 1: Type of POS Data Available

* Item Files
    • Bill Date, Bill Number, Bill Time, Product Code, Cost, MRP, Sold Value, Quantity
* Product Master
    • Product Code, Product Name, MRP, Group Code
* Group Master
    • Group Code, Group Name
* Campaign Files
    • Product Code, Campaign Start Date, Campaign End Date, Cost, MRP, Selling Price, Campaign Number

Source: Raghuram *et al,* 1999.

the investment in infrastructure that organized retailing chains have made in collecting transaction level data. An *ad hoc* survey in the Ahmedabad market, which is in the infancy stage of the retailing revolution compared to its counterparts in the south, revealed that a significant number of-supermarket stores collected transaction data at the cash register. Yet, no significant efforts are made currently to "mine" this database to reveal insights on customer behaviour. Even with limited information availability, these databases have enough data to understand market level drivers of store sales. The reasons for this perceived apathy may be varied; lack of expertise in mining data may be an important reason but more often it is the issue of prioritization of initiatives that has kept developmental projects such as database mining a back burner. This is most unfortunate since we predict that with rapid entry of competition, players who understand customer psyche, through its manifestation of overt behaviour, will dictate the future course of the retailing industry.

An Example of a Potential Analysis

We used a database obtained from a store of a large retail food chain based in South India to identify specific "category-driven" transactions that generate more revenue for the store. The purpose of the study was to identify customer segments that, on an average, gener-

ated more revenue for the store compared to others. Customer segments were identified based on their main purchase category as exhibited by the nature of their transaction.

Transaction data over a four-month time period across all recorded product categories in the store was used for the analysis. Five major category purchases were identified for the study based on the frequency of purchases made (weighted by the value of the purchase). These categories were: a) staple, b) spices, c) cooking oils, d) pulses, and e) toilet soap. A sixth category was formed clubbing sales from all the other categories. The number of categories chosen for the study was kept at six to avoid unnecessarily complicating the study, but the analysis could be done at any level of detail. It must be pointed out that while this type of data has been available in India only in the past three to four years, there does not seem to be a scarcity of transaction data in electronic form in the organized retailing sector currently.

In our analysis each individual transaction in the store (identified as all purchases made during one store visit based on a unique bill number) was categorized as either a particular category driven purchase or not (e.g. staple driven purchase or not staple driven purchase) based on the rupee value spent on the category in the specific transaction. To control for variation in average value spent across categories, the purchases were categorized based on their relative value compared to the maximum value recorded in that category across the entire database. This is a limitation, since without any customer-related characteristics in the database, it is impossible to identify the drivers of individual purchases and hence one has to resort to approximations.

SAS software was used to manipulate the data and the results obtained are presented in Table 2. The direct interpretation of the results is that customers that came into the store primarily to buy staples spent on an average Rs 517 compared to customers who did not have staples as a major category in their shopping list (average spending per transaction is Rs 160).

Table 2: Average Transaction Value (in Rs)

Category	Key Purchase[1]	Minor Purchase
Staple	517	160
Spices	445	130
Cooking Oils	620	153
Pulses	556	140
Soap	475	152

[1] When the key purchase is of the corresponding category.

Similarly, the average transaction, which was driven by spice purchase, was valued at Rs 445 compared to Rs 130 that was spent by customers[5] who did not have spices as a major category in their shopping list.

The largest difference in the transaction value occurs between transactions that record significant purchase of cooking oils versus the transactions that do not record significant purchases of cooking oil (Rs 620 versus Rs 153).

This result throws some light on the type of customers that bring in more value to the store in terms of revenue (Chen *et al.,* 1999). If store managers were to make decisions about promotions in the local area to draw more customers, the typical output obtained from this analysis may be used to identify the "right" destination category to be featured in the local area promotion to increase store traffic of high valued customers. In the present case, high propensity of using cooking oil as a promotion category will attract the highest revenue customer.

Designing Proper Information Resource to Help Better Decision-Making in the Indian Context

There are limitations in the analysis described above given the approximations made in categorizing transactions into specific category driven purchases due to the lack of customer descriptors. Also, the results obtained are not statistically robust enough to pass a test of technical rigour. Although technical rigour is needed,

"The same transaction may be classified as driven by multiple category purchases — staples, spices, etc. This is true since many consumers make monthly purchases in bulk across major consumption categories.

often, appropriate data analysis (even without passing the litmus test) provides a higher level understanding of consumer behaviour which can shape better decision-making.

What is critical to drive the process is availability of the right information/data resource that can be mined. In this respect, FoodWorld (C) (Banerjee *et al,* 1999) touches on the need to "IT-enable" operations for smooth running of the retail operations. We would suggest that retail organizations of the future do need to go beyond envisioning IT integration. They will benefit by adopting a proactive stance in designing and developing an IT-enabled information warehouse for both customer and operational information, which can significantly drive strategic decision-making in the future. As a starting point, an assessment of the type of decisions that one needs to take in more advanced stages of the business life cycle is necessary. Lessons from the developed markets of the west and the type of decision problems that they have faced may provide leads to the type of information requirements of the future.

Some Broad Level Initiatives

Initiating customer loyalty programmes is a pragmatic way of collating customer level transactional data that can be linked to customer characteristics. Segment level analysis of customer likes and dislikes drive most marketing decision-making and this type of database provides ample opportunity to customize store promotional programmes based on the type of consumer segments who frequent the store. An effective way of utilizing this behavioural information is to generate customized coupons and promotional features at the check-out counters based on the customer characteristics and current purchases made. Catalina Corporation, a Chicago-based research agency has evolved such coupon generating machines that have been set up at several retail food stores across the US. Manufacturers have also availed of this service at retail counters to induce brand switching with limited success. However, the

true value of this loyalty programme is to provide individualized promotions to customers which enhances perceived service quality at the store.

There are a number of non-food departmental store chains in Mumbai and Delhi, which have introduced loyalty programmes and are tracking purchase data on these customers. Proper design and mining of these databases can yield significant insights to develop direct mail promotion campaigns.

There is tremendous opportunity to enhance the scope of in-store promotions and to capture the information at the most disaggregate level. In-store displays, whether they are end of aisle displays, within aisle or front of store, have been recorded to have varying effects on sale spikes. A deeper understanding of the drivers of in-store sales will help retail store managers plan their space utilization more effectively in conjunction with the most appropriate marketing programme. It is important to invest in an initial period of testing various innovative marketing options and recording them religiously, such as one would do in conducting a pilot test programme. After the initial phase of testing, managers would have a sufficiently large information base to fine tune their programmes according to the market needs. However, this latter stage does make the created database redundant. Effective ongoing decision-making demands continuous building and mining databases as well.

Conclusions

Retailing is entering an active phase in its business life cycle in India. This note has attempted to address a dimension of this business, which has a strategic role to play in the growth and development of its constituents — the management of information resource. Like many other service industries which have become intensely focused on information resource management, for example, consumer finance, insurance and hospitality, survival in the long run will depend upon smart management of market information resources. Unfortunately,

developing marketing information resources needs a significant lead-time and there is a natural advantage of being the first off the block. Large retail chains have a definite advantage with respect to the available infrastructure that they have in place. They simply have to initiate a proactive process of investing in appropriate information that will yield the right kind of marketing insight for the future.

References

Banerjee, Bibek; Raghuram, G and Koshy, Abraham (1999). "FoodWorld (C): The Road Ahead," Working Paper, Ahmedabad: Indian Institute of Management.

Bucklin, Randolph and Gupta, Sunil (1999). "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives," *Marketing Science,* Vol 18, No 3, pp 247-273.

Chen, Yuxin; Hess, James D; Wilcox, Ronald T and Zhang, John Z (1999). "Accounting Profits vs Marketing Profits: A Relevant Metric for Category Management," *Marketing Science,* Vol 18, No 3, pp 208-229.

Raghuram, G; Banerjee, Bibek; Jain, A K; Koshy, Abraham and Bhatt, Gunjan (1999). *Retailscope '99, Retail Sales Data: The Hidden Treasure,* Draft Report, Ahmedabad: Indian Institute of Management.

Guadagni, Peter M and Little, John D C (1983). "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science,* Vol 2 (Summer), pp 203-238.

Wittinik, Dick R; Addona, Michael; Hawkes, William and Porter, John (1988). *SCAN*PRO: The Estimation, Validation and Use of Promotional Effects Based on Scanner Data,* Working Paper, AC Nielsen, Schaumburg, IL.