Explaining Retail Brand Performance – An Application Of 'Prior Knowledge'

Byron Sharp (Director), Erica Riebe (Senior Research Associate) and Monica Tolo (Research Associate)

Marketing Science Centre University of South Australia, City West Campus

Abstract

In this paper, we document the application of formal prior knowledge about brand performance and buyer behaviour in analysing typical brand tracking data. We present both our approach and the findings of our analysis of the grocery market. Our findings include that the market performs in line with predicted patterns and that small deviations from these patterns can be explained by using more prior knowledge concerning the impact of pricing policies on the composition of a retail store's customer base. That such differences in brand performance were predictable was surprising to the managers of these brands and their market research provider who supplied the data. Particularly surprising was that fairly complete explanations of brand performance differences between brands were able to be made without reference to the brands' respective marketing strategies, brand images, advertising execution etc.

Keywords - consumer behaviour, retail, data analysis

Introduction

Recently, Bound and Ehrenberg (1998) have highlighted the vital role that 'prior knowledge' plays in turning data into meaningful information. The application of prior knowledge is a key aspect of science, and yet is often neglected by marketing engineers who instead develop new models for each new set of data. Likewise, it is not unusual for market researchers to present managers with semi-digested raw data and provide little context or meaning for such data. In this paper, we analyse the sort of brand performance data that is typically presented from large commercial consumer tracking panels, but we give it context and meaning through applying prior knowledge of predictable patterns of buyer behaviour.

Our Purpose And Approach

Our analysis (of brand performance differentials in the grocery market) sought to exploit prior knowledge in order to identify and explain these performance differentials. Our purpose here is to provide a case study of the use of prior knowledge, as well as to present some useful generalisable findings concerning supermarket brand performance.

This research is based on panel data of supermarket shopping patterns. We were concerned with typical brand performance statistics such as market share, how many customers each brand had, how often these customers repeat-purchased the brand, and how much they spent on each shopping trip to the supermarket chain (basket size).

The analysis used these aggregate statistics to provide conclusions in light of known empirical patterns. These expected patterns made it possible to draw significant and useful conclusions. In general, the market conformed to the expected patterns and, with knowledge of these patterns, we were able to identify the few specific brand deviations. These, in turn, were explainable by additional prior knowledge about consumer reaction to particular brand feature differences.

We found that brand share was largely explained by the number of stores in the chain and the average store size. Other brand performance statistics, eg loyalty statistics, generally conformed with predicted patterns given each brand's respective market share. Small deviations from these patterns were associated with differences in pricing policy, use of coupons, and average store size – again this was in line with expectations given our formal 'prior knowledge'.

Research Data

It is very common for marketers to commission research to examine the performance of their brand, usually compared with competitors. Often this data comes from panels or large buying behaviour surveys. We took aggregate statistics from a commercial panel that gathered supermarket repeat-buying data. The panel data were presented to us from a very large commercial market research provider in the same format that clients received it, ie presented in the form of tables or charts showing the key aggregate statistics. This was quite typical. Market researchers may also sometimes attempt to give the data some meaning by making comparisons to past tracking results, or by undertaking statistical modelling to identify and describe relationships. Far less usual is to adopt a scientific approach and compare the data to existing, well established, empirical models. In this research, we took supermarket repeat-buying data and analysed it in light of known empirical generalisations concerning brand performance and buyer behaviour. By showing what was normal and expected the analysis changed many of the interpretations that had previously been drawn from the data by commercial market researchers.

Using Prior Knowledge

Prior knowledge is knowledge of findings that have been empirically validated and then brought together as an intuitive or formal model (Uncles and Hammond 1995). Using prior knowledge is an essential component for providing more empirically generalisable and sensible findings. When analysing data, using prior knowledge of what has been supported before extends the validity of findings and of our understanding of data, more so than statistical techniques alone are able to do (Ehrenberg and Bound 1993).

The prior knowledge we used included the double jeopardy pattern of repeat purchase and the affect of pricing policy on basket size. Double jeopardy is the phenomenon where smaller brands suffer in two ways. Not only do smaller brands have fewer customers but, these fewer customers, tend to buy less frequently (Uncles and Hammond 1995). Our prior knowledge about pricing policies indicates that generally large basket shoppers prefer 'Everyday Low Pricing' and small basket shoppers prefer Hi-Lo retail pricing strategies (Bell and Lattin 1998). Those brands which adopt 'Everyday Low Pricing' strategy should be expected to have a relatively larger basket size per customer.

Analysis & Discussion

Our first step was to use the known law-like relationships to guide table layout. This is a simple, but often neglected, step (Ehrenberg, 2000 provides guidelines). For example, data is usually presented to commercial clients in alphabetical order, or the order that the brands feature in the survey questionnaire.

Market Share And Penetration

Table one presents the data on each brand's market share and their market penetration, in which the brands are ranked by their market share ¹. When this data was presented with brands ranked in alphabetical order the strong relationship between penetration and share was difficult to see. Now the relationship is starkly clear - smaller brands get visited by fewer customers.

Table 1 market share and penetration arranged in market share order

Chain	MktShare (visits)	Penetration (proportion who visited at least once)
Category	100%	100%
Total		
Fresh	32%	70%
Pay Less	22%	55%
Market Galore	16%	38%
Wonder Foods	13%	40%
Food World	6%	21%
Delicious	5%	24%
Grocers		

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¹ The brand names have been disguised to protect commercial confidentiality and, due to space constraints, we only present the six top brands. Our analyses are based on the full set of brands.

Having ordered the data by this expected pattern, it is now possible to identify small deviations from the general pattern. For example, in the above table, Wonder Foods and Delicious Grocers appear to have a slightly higher number of customers (market penetration) for their level of share of the total number of supermarket visits. For some reason, these chains must have a relatively higher proportion of customers who visit only once (or a few times). Thus, the brands have a surplus of light buyers (they don't visit very much), perhaps these are 'top up' shoppers or occasional buyers of the brand lured by particular specials/promotions. Table one shows that proper and simple presentation of data and prior knowledge can, lead to the discovery of important information. Using further prior knowledge we were able to explain these brand differences in terms of the pricing policies of these two brands - heavy use of promotions rather than "everyday low prices" was attracting small basket 'top up' shopping (Bell and Lattin 1998).

Market Share And Share Loyalty

Table two shows the expected Double Jeopardy pattern – smaller brands have lower market penetration and purchase frequency. Again, with knowledge of this pattern, we can now spot deviations from the expected - Market Galore has unusually high purchase frequency given its market penetration/market share. This is the only brand in this market that uses coupons. Such specials attract frequent (and small basket) shoppers such as the retired or unemployed.

Table 2 market penetration and loyalty

	Market	Av
Chain	Penetration	Purchase
		Frequency
Category	100%	19.4
Total		
Fresh	70%	7.6
Pay Less	55%	6.7
Market Galore	38%	7.2
Wonder Foods	40%	5.2
Food World	21%	4.4
Delicious	24%	3.7
Grocers		

Market Share And Number Of Stores

Given the market share of the brands, the brand performance statistics generally reflect the expected patterns of repeat-purchase. It therefore seems sensible to seek explanations of their market share differentials. Number of stores in the chain and store size seem to be obvious factors. Table three shows a strong relationship between each brand's share and its number of stores. Pay Less is one exception, having only a few stores for its market share, but these are all very large stores.

Table 3 Marketshare and number and size of stores

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	Mkt	Number	Average	
Chain	Share	of stores	Store size	
	(visits)	in region		
Fresh	32%	25	Large	
Pay Less	22%	8	Extremely	
			large	
Market Galore	16%	16	Medium	
Wonder Foods	13%	12	Large	
Food World	6%	5	Medium	
Delicious Grocers	5%	4	Extremely	
			large	

Market Share And Basket Size

We know of no documented relationship between market share, and average basket size and table four shows no clear relationship. This lack of 'Triple Jeopardy' in itself is a useful finding (for instance see Sharp and Riebe 2000).

Table 4 Marketshare and basket size

Chain	Mkt Share (visits)	Av \$ per visit (basket size)	Average Store size
Category		\$61	
Total			
Fresh	32%	\$56	Large
Pay Less	22%	\$81	V. large
Market Galore	16%	\$62	Medium
Wonder Foods	13%	\$45	Large
Food World	6%	\$68	Medium
Delicious Grocers	5%	\$75	V.large

However, store size seems an obvious factor that should affect average basket size. This hypothesis does appear to fit the data reasonably well (Table 4), though not perfectly. Our prior knowledge on the effect of pricing policy provides an acceptable explanation of the few discrepancies. Wonder Foods and Fresh, who both have low basket sizes for their size of stores both have extreme 'Hi-Lo' pricing policies.

Given the research on this topic (Bell and Lattin 1998) we would expect store size and pricing policy to also show up in the demographic profiles of the stores' customer bases. Though we would not expect large differences since research has shown that competitive brands generally have very similar customer profiles (Hammond et al. 1996). Table 5 shows that Delicious Grocers and Pay Less, the stores with the largest average basket size, have the greatest proportion of families in their customer base. Market Galore, the one brand that uses couponing and which has slightly unusual high average purchase frequency, has a greater proportion of their customer base aged 65 years and over.

Table 5 Demographic differences

Brand	Families (%	Proportion
	of customer	of shoppers
	base)	over 65
Pay Less	60	11%
Delicious	51	7%
Grocers		
Food World	46	13%
Market Galore	45	23%
Wonder Foods	45	16%
Fresh	43	17%
Average	48.33	14.5%

Implications

Our research has supported previous findings and has given the data context and meaning. Our research suggests that it would be fruitful for grocery retailers across countries/markets to employ these generalisations to analyse brand performance data in light of these patterns.

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