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The Structure of Switching: An examination of market structure across brands and brand variants

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Abstract

This paper examines the competitive structure of two consumer packaged goods markets, namely breakfast cereals and canned soup in the UK. The purpose is to present and use a straightforward approach that identifies market structure, and reports on what features it is based. Only two categories are examined due to space constraints. Brands are analysed along with functional features (e.g. flavour, type) using a quasi-independence model of consumer purchase data. This is intended to be a first step in cataloguing the structure of multiple markets. The two markets investigated here are found to be quite different in structure. Canned soup is structured very much by 'brand' with far more switching between each brand variant (e.g. Campbells chicken to Campbells tomato) than between flavour variants (e.g. Campbells chicken to Heinz chicken). In contrast, switching is much more in-line with overall market share in the Breakfast Cereal category. That said, a fairly strong 'high sugar' partition is found in cereals, and this is not due to purchases for children, as the cereal analysis is restricted to no-child households. The partitions are confirmed in additional data sets.

Introduction

It is well known that consecutive purchases, many customers will re-purchase the same brand they bought last time, while many others will buy a different brand. Marketers are interested in both aspects of this phenomena. Repurchasing is measured as a behavioural loyalty metric, while brand switching is one of a number of methods used to identify competitive market structure. Examination of competitive market structure provides an understanding of the intensity of competition between particular brands or product variants. For example, the marketing manager for *Ford* in the UK is interested to know which brands Ford loses sales to when a current Ford buyer buys a competitor brand on their next purchase. Likewise, which brands does Ford take sales from. If there is a particular brand that Ford competes against very intensely, then Ford can try to determine the cause of this heightened intensity, because the other brand represents a particular threat. Therefore it can prioritise its competitive intelligence pertaining to that brand. Similar questions apply to product variants. If say, SUV's are gaining market acceptance, the marketer wishes to know which other variants they are taking market share from (e.g. Cooper and Inoue, 1996).

The answers to questions of competitive structure can also be used to plan new product introductions. For example, Urban, Johnson and Hauser (1984) found that Nestle instant coffee brands did not compete intensely against ground coffee brands, therefore entering that product-market would result in little cannibalisation of Nestle share. Bauer and Herrman (1995) were able to recommend new product introduction moves based on an analysis of switching in the German car market.

The literature on competitive market structure is considerable, and dates back to the 1970's (e.g. Kalwani and Morrison, 1977, Ehrenberg and Goodhardt, 1974). Many papers have presented techniques ranging from simple to complex, to portray the pattern of competition among brands and product types. Examples of these approaches are: graphical representations (Hoffman et al., 2001); tree structures (DeSarbo et al., 1993) and tabulations (e.g. Bennett and Ehrenberg, 2001). Many of these techniques were compared in a paper by Colombo, Ehrenberg and Sabavala (2000). A range of data types has also been used to analyse competitive structure: actual purchase behaviour from consumer records, as well as stated choice sequence as part of surveys or experiments. Judged similarity is also a way of identifying brand or variants that will compete more directly with each other (Lehmann, 1972). Note that the term *switching* in this paper is used in a purely behavioural sense, namely that a person buys A, then B. No inference as to choice processes is made, or that such a switch indicates a change in underlying purchase propensity (see Bass, 1974) or that a brand bought last time has been *rejected*. It is evident that considerable strides have been made in developing *techniques* for analysing CMS. There has also been some progress in developing managerially useful findings that can apply across more than one isolated case. Two consistent findings have emerged:

1. *Market share* is an overwhelming factor in determining which brand buyers switch to. Ehrenberg, Uncles and Goodhardt (2004) state this as the ‘duplication of purchase law’. This phenomena is consistent with Luce’s choice axiom (Luce, 1959), which states that the probability of selecting one brand *over another* from a group of brands is not affected by the presence or absence of other brands in the group. In other words, the ratio of popularity of brands *C* and *D* should be the same among *A* buyers as it is among *B* buyers. Urban Johnson and Hauser (1984) use the term Aggregate Constant Ratio Model (ACRM) as essentially an aggregation of the Luce theorem. Empirically, the effect of market share on switching is very strong.

2. There is *heightened switching* (partitioning) among functionally similar product types. For example, there is far more switching within instant coffee brands, and within ground coffee brands, and lessened switching *across* the instant / ground types. In the car market, there are partitions formed by price / quality level as well as by local brand / foreign brand (Colombo et al., 2000) and product type (e.g. Bauer and Herrmann, 1995). It also appears that *unless* a subset of brands or products share a functional similarity (or some other straightforward similarity such as common distribution) there tends *not* to be partitioning (Sharp and Sharp, 1997), at least an absence of evidence of this occurring.

While a number of studies have identified the presence of market partitions, there is a lack of reporting on the general magnitude of partitioning found over various markets, and on the basis for the partitions. For example: how strong are partitions usually ? Are there markets in which a partition completely overturns the effect of market share, whereby a brand loses more sales to a small but functionally similar brand and less to larger, less functionally similar brands ? Another question is, on what bases are markets structured ? If there are some partitions, and we know this is often based on functional differences (e.g. product type), what *sorts* of functional differences form partitions ? There can be multiple product-based differences in a market, for example in soft drinks there are flavour (cola, lemonade, orange) as well as formula differences (diet v non diet). A fruitful area for research is therefore to document the way in which a large number of markets are structured. This could yield potential empirical generalizations about the nature of competition.

Therefore, the objective of this paper is not to present a new approach, but to use an existing approach, then present the results as a template for replication. Due to space limitations, only two categories can be analysed here, but the simple approach used can form a basis for further investigation. The two product categories used are breakfast cereal and canned soup.

Data

Data was kindly provided by TNS UK from its Superpanel, a panel comprising approximately 15,000 consumers. I extracted a two-purchase switching matrix for each category. For the breakfast cereal category, a sample of the seven largest manufacturer brand / product variants was chosen, comprising approximately 25% of total sales. For canned soup, three leading manufacturer brands Heinz, Campbells and Weight Watchers were used. While two of these share common ownership (Heinz and Weight Watchers) this selection enables a perfectly matched comparison of three brands, crossed with the three most common flavour varieties (tomato, chicken, vegetable). This facilitates an examination of switching by brand and variant. The resultant nine brand variants collectively comprise approximately 15% of total canned soup sales. Note, however, that the comparison is not perfect as the three brands differ in pack size – Heinz variants are 400 g whereas the Campbells and Weight Watchers variants are all 305g. Note that a criticism of the use of consumer panel data for this purpose is that brand switching can be confounded with purchasing multiple brands or types to cater for varying tastes in the household. I minimised this problem by using data from no-child households for breakfast cereal, and single or 2-person households for canned soup. Some cell counts were zero, these were converted to a count of 0.1 for the purpose of model fitting as per Agresti (2002, ch 7). The unit of analysis was the brand / product variant. There are other potential variants that can be analysed, such as pack size, but this examination is at the brand / product level. Canned soup brands use corporate branding (Laforet and Saunders, 1994) with a product descriptor, for example *Heinz* tomato. This is similar in the cereal market, for example *Kellogg's* Cornflakes; *Nestle* Shredded Wheat, *Nestle* Shreddies. There was no a priori expectation of what the resultant structure would be.

Analysis Method

There are many techniques to analyse such data. The simplest and clearest is Ehrenberg's 'purchase duplication' table (e.g. Ehrenberg, 2000b ch. 9). This approach simply tabulates the proportion of each brand's customer base that bought each other brand in a time period. An appealing feature of this method is that the figures in the duplication columns of such a table should be approximately the same. Therefore partitions are easily identified. I used a slightly more complex technique, namely log-linear analysis. This is a widely used method for analysing contingency tables, of which this matrix is of one type. Loglinear analysis has these advantages: (a) it provides conventional goodness of fit statistics such as a likelihood ratio test, (b) can allow an examination of possible asymmetries in switching, (c) provides standardised residuals, which indicate the statistical significance of partitions, and (d) is potentially a more sensitive test for partitions than the purchase duplication table. This is because purchase duplications places equal weight to A buyers who occasionally also buy B with those who often buy B. Another very appealing feature of the approach is *transparency* – the raw cell counts are presented, which allows any other researcher to check or conduct their own analysis on the data. The analysis steps are as follows:

1. Order the data in rows and columns by market share for clarity (e.g. Colombo et al., 2000, Ehrenberg, 2000a).
2. Disregard the diagonals of the matrix (ie the repurchases of the same brand/variant), because it is the pattern of switching that is of interest.
3. Apply a quasi-independence loglinear model to the data (e.g. Agresti, 2002 ch. 10). The quasi-independence model ignores the diagonal cells in the matrix. It creates 'theoretically expected' switching frequencies, as well as a goodness of fit measure and standardised

residuals. The goodness of fit measure is the log-likelihood chi-square G^2 (not χ^2). Inspect and report the standardised residuals, as those +/- 1.96 (2.0 rounded) are statistically significant at $p<0.05$ (see Iacobucci and Henderson, 1997 for discussion and application). Report the statistically significant occurrences of excess / under switching in a separate matrix, as percentage differences to expected.
4. Check the results for each category on new data for consistency. Sound knowledge development requires validation of results from multiple data sets (Evanschitzky et al., 2007).
5. Report the correlation between observed cell counts and fitted estimates in the form of a scatterplot and related r statistic. This clarifies the 'market share' effect on switching and graphically illustrates the magnitude of partitioning.

Results

For **Breakfast Cereal**, the effect of brand size on switching is very pronounced. In other words, the relationship between brand size and how many buyers switched to/from that brand is more predictable than for soup (below). That said, there is markedly higher switching between two 'high sugar' brands – Kellogg's Frosties and Crunchy Nut Cornflakes. This is not a 'children's' partition because these data are from households without children. There are some other instances of excess or under-switching, but they are not marked. The data were checked against a subsequent time period and the 'high sugar' partition was again apparent. In contrast, **Soup** is noticeably partitioned by brand. There is much less switching across each brand compared to the switching levels between flavour variants within those brands. We can see this from the clusters of large positive deviations around the diagonals of Table 2. It is interesting to note the size (in proportional terms) of the deviations increase as brand size diminishes. This is conjectured to be purely a size effect, for example a small brand comprising all small-share variants can have 500 percent more switching than expected between them, but this is not arithmetically possible for a large brand comprising large-share variants. It is also worth noting that this result is not due to distribution differences, as a sub-set of the data comprising purchases made only at Sainsbury's exhibited the same pattern. Analysis of data for a subsequent time period showed over 90% of the statistically significant deviations occurred again. The final step in the analysis can show more clearly what we can call the 'size effect' – the variation in cell counts explained by the 'main effect' of brand size (e.g. expected switching from A to B = function of the size of A and B). This is shown in two scatterplots following Table 2.

Table 1 Breakfast Cereal (Likelihood Ratio 84, d.f. 29, $p<0.001$))

	Second purchase						
First Purchase	1	2	3	4	5	6	7
1 Kell CF	421	198	77	51	67	29	43
2 Weetabix	199	287	43	57	44	36	28
3 Nestle Shr Wht	92	48	111	12	14	7	11
4 Kell Frosties	49	50	15	95	25	26	14
5 Kell Rice Krisp	67	34	15	18	51	12	13
6 Kell Cr Nut CF	27	22	14	24	12	82	7
7 Shreddies	49	19	16	13	7	9	45

	*% over or under expected switching**						
	1	*2*	*3*	*4*	*5*	*6*	*7*
1			-25		-34		
2							
3	26						
4	-31				+117		
5							
6	-33		+128				
7							

* for cells that have a std. residual of -2.0 > Z > +2.0

For example: 198 people bought Kellogg's Cornflakes on purchase 1 and then Weetabix on purchase 2.
(note Kell = Kellogg's, CF = Cornflakes).

Table 2 Soup (Likelihood Ratio 1196, df 55 , p<0.001)

First purchase	*Second purchase* 1	2	3	4	5	6	7	8	9
1 Heinz Tom	391	158	90	22	25	9	13	1	0
2 Heinz Chick	148	136	60	5	15	1	1	1	0
3 Heinz Veg	105	64	122	2	5	5	1	2	2
4 Campbell Tom	29	10	8	103	85	19	2	2	0
5 Campbell Chick	27	13	9	92	128	17	4	3	1
6 Campbell Veg	5	2	4	31	24	27	0	1	0
7 WW Tom	7	0	0	1	5	0	42	18	15
8 WW Chick	4	0	2	2	3	0	17	15	3
9 WW Veg	2	0	1	0	0	0	10	6	8

*% above / below expected switching**

	1	2	3	4	5	6	7	8	9
1 Heinz Tom		+67	+43	-59	-56			-91	-100
2 Heinz Chick	+62		+53	-85	-58	-90	-90	-85	-100
3 Heinz Veg	+55	+46		-92	-81		-86		
4 Campbell Tom	-48	-72	-66		+293	+204			
5 Campbell Chick	-55	-66	-65	+316		+152			
6 Campbell Veg	-77	-86		+282	180				
7 WW Tom	-53	-100	-100					+1537	+2127
8 WW Chick		-100					+1524		568
9 WW Veg							+1473	+1247	

* for cells that have a std. residual of -2.0 > Z > +2.0

Summary and conclusions

This paper used a conventional analysis approach to commence a wider study examining market structure. It examined the competitive structure of two product categories. It controlled for the well-known problem of brand switching being confounded with household buying. One category, canned soup, was found to be far more strongly partitioned than the other, namely breakfast cereal. What possible reasons might there be for varying structures across categories ? More specifically, what reasons could be examined with switching data ? Two avenues of future investigation will be pursued. First, it is reasonable to think that category layout differs somewhat across retailers. Separate analysis across retailers could help to establish if competitive structure is affected by in-store layout. Secondly, to compare the same category in different geographic markets. This would establish whether an observed switching structure was inherently due to the nature of the product (e.g. canned soup) or a local market (e.g. U.K. specific) factor. These are the next steps for this research.

Figure 1. Plot of observed v expected counts, Breakfast Cereal r=0.97

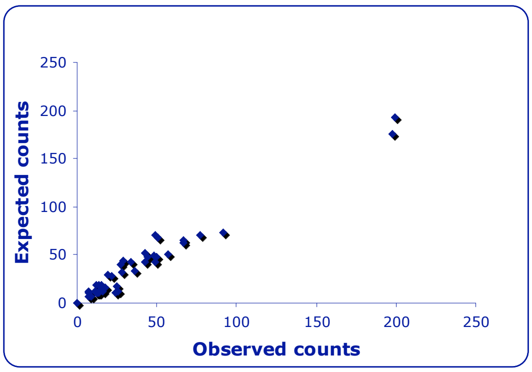
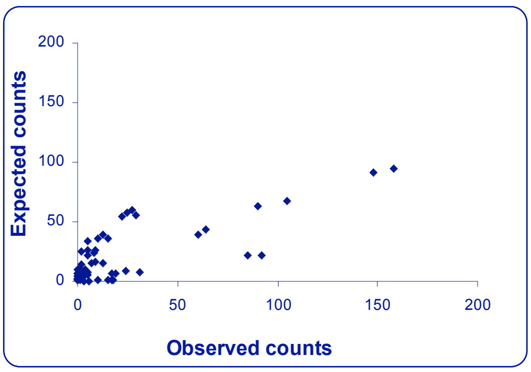


Figure 2 Plot of observed v expected counts, Canned Soup r=0.78



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