Understanding the drivers of customer value: The fusion of macro and micromodelling

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Abstract In this paper, the authors propose that consideration of both macro and micro levels of analysis reveals deep insights into the impact of marketing activity on customer profitability. They contend that brand drivers, such as pricing and advertising, have a different impact on customer segments (such as 'loyalists' and 'switchers'), and that understanding these differences will enable marketers to optimise their marketing strategy in a way that maximises valuable customer behaviour (and hence profitability and shareholder value). Consequently they believe that those marketers who adopt a fused approach to marketing evaluation will have a distinct competitive advantage over those who do not. Therefore their aim is to test two null hypotheses: i) that customers are homogenous; ii) that marketing mix variables (in particular, price promotion and advertising) have the same effect on all customers. Using panel data from the hair colourants category they refute both.

INTRODUCTION

Customer profitability analysis (CPA) provides a measure of profitability at a customer level. One important factor in these calculations is the level of customer demand — increasing sales (by stimulating demand) relative to costs delivers additional profits. Since customer demand can be stimulated by marketing activity, customer profitability can therefore be maximised by ensuring that the marketing budget is being spent in a way that promotes profitable customer behaviour and hence delivers a maximised return on investment. To do this requires an understanding of the causal relationships between marketing and demand, and the tools by which to

evaluate them. In this paper a methodology that marketers can use for this purpose is introduced.

A traditional method in this arena is econometric modelling. For example, the IPA has a large database of case studies where econometric techniques have been employed to isolate and quantify the impact of advertising on measurable key performance indicators (KPIs), such as overall sales, footfall or enquiries.¹ One of the limitations of applying econometric modelling to an aggregate KPI (such as overall sales), however, is the implicit assumption that all sales are the same.

In reality, however, some customer sales are more important than others. As

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Knox highlighted in the mid-1990s, not all customers are created equal, and all customers purchase on a portfolio basis.² And so, although all sales might be the same, different customers, or more accurately, different customer relationships, represent differing values to the business.

By now the principles of customer retention, much as a result of Reichheld's work on loyalty,³ are well established — the more loyal a customer, the more profitable; the cost of acquiring a customer is greater than the cost of retaining them; etc. Equally well established, but worth repeating, is the general applicability of the Pareto Principle to the distribution of customer profitability — it is likely that 80 per cent of a firm's profit will come from 20 per cent of its customers. Thus, having absorbed this idea, it is not surprising that throughout the 1990s, marketers were focusing intently on developing segmented approaches that differentiated marketing expenditure based on a segment's potential value to the firm.

Moreover, work by Ward and Ryals⁴ has shown additional customer-relationship benefits over and above the economic value of the profit generated by that customer. In particular, referrals (word of mouth), referencability, product innovation and learning from customers all add to the shareholder value derived from a customer relationship. In short, although the terminology has changed since 1990, 'loyalty' still matters.

Thus it is obvious to state that a key differentiator of customer value is the individual's pattern of consumption — how much they buy of a product or brand, when and how often. It is also obvious to state that understanding the distinct patterns of consumption behaviour that constitute the total sales figure is a key requisite in both the development of marketing strategies that

maximise shareholder value, and the evaluation of marketing impact.

It is the authors' experience, however, that although marketing strategy development has embraced the differentiation of 'micro'⁵ consumption behaviour, on the whole, marketing evaluation has not. Indeed, a good deal of marketing evaluation has remained remarkably insensitive to the way in which marketing activity is changing underlying customer consumption patterns, often sticking doggedly to assessing its impact on 'macro' KPIs.⁶ It is acknowledged that this may be due, in part, to an overall failure of marketing (and demand-side thinking) to integrate itself into the language and culture of the finance-dominated board. A study by Ambler⁷ highlights the preference of many boards for the metrics of supply-side efficiency, over those of demand-effectiveness. It is perhaps not surprising then that marketing accountability, often conducted by the finance department, tends to take the macroperspective, and only considers marketing's impact on overall sales.

It could also be argued that the predominance of the macro-only perspective is because by taking the macro-level an aggregation of all micro perspectives is provided, and as such, means that evaluation needs only to be conducted at this level. Yet while this is correct in principle, it misunderstands the role of evaluation, taking a 'black or white' approach to effectiveness — 'Is my marketing spend effective (Yes/No)?'. While the answer to this question may be good enough for the board, it is insufficient for the marketer.

A key role of marketing evaluation, beyond that of accountability, is to provide marketers with insights for future strategy development. Marketers need to know more than whether what they did

last time worked, but why it worked. They need to know what elements of the marketing mix are delivering the desired returns, and (perhaps most importantly) their impact on driving customer, and hence shareholder, value.

It is this analysis of the influence of brand and market drivers (marketing activity and other macroenvironmental variables⁸) at a microbehavioural level that are referred to as 'the fusion of macro and micromodelling'.

In this paper, it is argued that a 'fused' approach to marketing evaluation reveals deep insights into the real impact of marketing activity on customer value. The authors believe that brand drivers, such as pricing and advertising, have a different impact on customer segments (such as 'loyalists' and 'switchers'), and that understanding these differences will enable marketers to optimise their marketing strategy in a way that maximises valuable customer behaviour and hence shareholder value. Moreover, they contend that adopting a fused approach is the only way to conduct a comprehensive analysis of customer marketing profitability. Consequently they believe that those marketers who adopt a fused approach to marketing evaluation, will have a distinct competitive advantage over those who do not.

DEFINITION OF NULL HYPOTHESES

In this paper the authors take two null hypotheses. First, that customers are homogenous. And secondly, that marketing mix variables (in particular, price promotion and advertising) have the same effect on all customers. It will be demonstrated, with the aid of panel data analysis from the hair colourants category, that the evidence overwhelmingly supports the rejection of both.

DESCRIPTION OF PANEL DATA

The data used in this study were a 3-year continuous sample of the UK hair colourants sector, for the period July, 1998 to July, 2001 (a continuous panel is one that has zero churn over the sample period). The data were provided by AC Nielsen from their Homescan service. The panel consisted of 1,700 households. The information available on each household can be split into two types:

- purchasing information: (7,288 cases and 22 variables). Each record refers to a single purchasing occasion and contains details about the buyer (household), trip date, store, price, quantity, offer/promotion, nancode, manufacturer, brand, packaging (single, double packs) and sector (permanent, tone on tone ...)
- household information: (1,700 cases and 75 variables). Each record refers to a single household, and contains information about household size, number of children, housewife demographic characteristics, white and black goods ownership, pet ownership, region, lifestyle indicators, income, education, ethnicity, shopping behaviour (store choice, loyalty card ownership ...)

SECTION A: MICROANALYSIS

Given the underlying nature of the investigation — assessing customer value — the first approach to the data was to understand the distribution of sales value by household. Table 1 reports the percentage of buyers, by banded value. On further analysis, it is noted that those households with a total purchase value greater than or equal to £20 accounted for 26.7 per cent of buyers and 61 per cent of value. So for the market as a whole, a disproportionate amount of

Table 1

Sales value band £	Percentage of households %	Cumulative percent %
0–4.99	33	33.0
5.00–9.99	19.9	52.9
10.00–14.99	12.4	65.3
15.00–19.99	8.1	73.3
20.00–24.00	6.0	79.3
25.00–29.99	3.7	83.0
30+	17.0	100.0

Table 2

Shopping trips	Percentage of households %	Cumulative percent %
1	33.4	33.4
2	17.5	50.9
3	11.0	61.9
4	8.4	70.2
5+	29.8	100.0

value can be seen to be residing in a minority of customers.

For this category, however, sales value is a function of sales volume, which is itself a function of shopping trips. The authors therefore wanted to understand the distribution of shopping trip frequency. Table 2 shows this distribution. The mean number of trips per household was 4.26 over the sample period. From this frequency breakdown, it can be seen that the sample can be split in half by considering those households with less than three shopping trips, and those that made three or more. Those 50 per cent of households that made more than three trips accounted for 87 per cent of the sales value. This was an interesting finding: given this skewed distribution, what was happening at a brand level? Were households that made multiple trips staying brand loyal, or were they switching their purchases among brands?

The first point of analysis at the brand level was to look at solus brand purchasing behaviour. (A solus household is defined as one which only buys a single brand.) It was found that the three

leading brands in the hair colourants category, which accounted for 69.3 per cent of total revenue, had different levels. Table 3 provides a breakdown.

What this analysis shows is that, for those households making multiple hair colourants purchases, there is a high degree of brand purchasing promiscuity — for example, only 4.55 per cent of Brand A's multi-buy consumers purchased Brand A on all occasions. In this category, therefore, there is a low level of loyalty — most purchasers are switchers. Indeed, loyalty may be more accurately described as the relative degree of switching. Perhaps the 'loyalists' are akin to Knox's 'habitual' segment?²

By looking at solus buyers it can also be seen that there are differences between brands. This was an important insight, and one the authors wanted to explore further. If loyalty did differ between brands, it was possibly as a result of historical marketing activity. Understanding these differences would be progress towards rejecting the second null hypothesis.

Table 4 takes the three leading brands, and reports the distribution of each brand's share of purchases by percentage

Table 3

Brand†	Solus households (%)
A	14.0 (of which 67.5 are one-off purchasers)
B	31.6 (of which 57.3 are one-off purchasers)
C	28.8 (of which 51.8 are one-off purchasers)

†In accordance with the authors' contractual agreement with AC Nielsen, the identity of the brands have not been revealed. Instead specific brands are referred to with an alphabetic identifier (eg Brand A, Brand B, etc).

Table 4

Share of purchases %	Brand A %	Brand B %	Brand C %
0–10	6.13	5.72	2.22
10–20	16.11	17.16	7.41
20–30	12.78	9.04	8.25
30–40	14.89	12.73	12.70
40–50	25.57	12.18	22.12
50–60	2.80	3.32	4.13
60–70	3.85	5.17	5.93
70–80	2.28	2.40	4.97
80–90	1.23	0.55	2.96
90–100	14.36	31.73	29.31
Total	100	100	100

of households. There are two aspects worth noting. First, the high percentage of buyers across a number of share classes; and secondly, the difference between Brand A's distribution with Brands B and C. Brand A had its highest proportion of customers having only 40–50 per cent of purchases with its brand, whereas Brands B and C had their highest proportion of customers making 90–100 per cent of their purchases with their respective brands. In other words, customers of Brands B and C are more likely to be loyal than those of Brand A.

Given this difference in brand loyalty, the authors were keen to investigate the interrelationship of switching between brands. Not only would this provide useful insights for the marketer, it would also provide an informed steer to the macroanalysis of a brand's competitive set.

An indicator of switching often used in this area is the duplication coefficient.⁹ A

problem associated with the duplication coefficient, however, is that it does not recognise the direction of switching behaviour — ie whether consumers are switching from Brand A to B or vice versa. While it can be a useful measure in a category which has low involvement and high frequency of purchase, for this category and this study, the authors wanted to know which brands customers were switching to. Telser's Switch Matrix was therefore used.¹⁰

The switch matrix is formally defined as follows: let S_{ij} equal purchasers of brand j in period t that were purchasers of brand i in period $t - 1$. These S 's are arranged in the switching matrix so that the row subscript is the brand of origin and the column subscript is the brand of destination. The main diagonal of the matrix (S_{ii}) represents the number of repeat purchasers. The elements within the switch matrix are a description of the direction of switching behaviour by brand.

Table 5

Year 1	Year 2 Brand A %	Brand B %	Brand C %	Brand D %	Brand E %	Other brand %	No purchases %
Brand A	45.62	18.25	24.82	2.92	2.19	17.88	29.20
Brand B	23.58	41.05	29.26	3.06	1.75	17.90	30.57
Brand C	20.47	20.04	45.91	3.23	1.08	15.09	32.33
Brand D	17.39	26.09	23.91	10.87	0.00	19.57	45.65
Brand E	20.63	20.63	17.46	3.17	7.94	20.63	44.44
Other brand	15.82	16.12	24.48	3.58	1.79	30.45	42.09
No purchases	13.43	13.28	17.61	4.18	1.34	18.51	42.09
Year 2	Year 3 Brand A %	Brand B %	Brand C %	Brand D %	Brand E %	Other brand %	No purchases %
Brand A	37.66	15.91	26.62	2.60	0.32	14.29	33.12
Brand B	14.44	36.10	27.80	4.69	0.36	17.69	36.10
Brand C	15.42	14.70	46.27	2.41	0.24	16.14	34.70
Brand D	3.45	10.34	20.69	12.07	0.00	22.41	58.62
Brand E	17.39	13.04	17.39	0.00	4.35	8.70	56.52
Other brand	14.24	15.89	22.52	2.98	0.33	30.46	43.71
No purchases	12.57	12.57	19.65	2.89	0.29	18.93	42.34
Difference	Brand A %	Brand B %	Brand C %	Brand D %	Brand E %	Other brand %	No purchases %
Brand A	-7.96	-2.34	1.81	-0.32	-1.87	-3.60	3.92
Brand B	-9.14	-4.95	-1.46	1.64	-1.39	-0.21	5.53
Brand C	-5.05	-5.34	0.36	-0.82	-0.84	1.06	2.37
Brand D	-13.94	-15.74	-3.22	1.20	0.00	2.85	12.97
Brand E	-3.24	-7.59	-0.07	-3.17	-3.59	-11.94	12.08
Other brand	-1.58	-0.23	-1.96	-0.60	-1.46	0.02	1.62
No purchases	-0.86	-0.71	2.04	-1.29	-1.05	0.42	0.25

Table 5 provides the switch matrix for the key hair colourants brands for Years 1 to 2, Years 2 to 3, and the change between years. Volumes of buyers are given in percentage terms. (S_{ij} is divided by the total number of purchasers of Brand i in period $t - 1$).

The switching analysis clearly shows that not only was there a high degree of interbrand switching going on across all brands, but also that the competitive nature between brands (as defined by consumers choice of switch) was changing year on year.

REJECTION OF THE FIRST NULL HYPOTHESIS

The evidence provided by the microanalysis strongly supports the

rejection of the first null hypothesis — that all customers are the same. The analysis has shown skewed distributions of value, trips and loyalty, both at the market and brand level. Different customers have different consumption behaviour, and hence represent different levels of current and potential value to the brands within the category.

SEGMENTATION

Having concluded that buyers were not homogenous, the authors needed to find a simple, yet meaningful, segmentation of households that split purchasing behaviour into distinct groups. This would enable them to test the second null hypothesis — that marketing has the same effect on all customers.

Table 6 Cumulative % households

Household value £	Before weighting %			After weighting %		
	Brand A	Brand B	Brand C	Brand A	Brand B	Brand C
<5	34.85	48.71	72.11	64.45	67.34	80.64
5–10	60.07	69.93	83.39	82.14	82.66	88.89
10–20	82.14	87.64	92.11	92.29	92.80	94.39
20–40	92.47	96.31	97.37	96.32	97.42	98.25
40–60	96.15	99.08	99.06	97.90	99.45	99.24
60–80	97.90	99.08	99.77	99.65	99.45	99.88
80–100	98.95	99.63	99.88	99.82	99.63	99.88
> 100	100.00	100.00	100.00	100.00	100.00	100.00

To begin with, the authors took an unsupervised approach to the analysis, using K-Means clustering. None of the household characteristics was significant in this task however. It was noted, however, that households were discriminated by their total expenditure and the allocation of purchases between brands (each brand's share of total trips). It was therefore concluded that category brands have customers with similar demographic and socioeconomic characteristics, but different consumption behaviour. Consequently, the authors opted for an *a priori* segmentation, based on their earlier descriptive analysis of consumption. It was decided that the foundation of the segmentation would be the level of loyalty a household had to a brand. The segmentation would be conducted on a derived weighted value variable, which would represent a household's total spend on a brand, weighted by that brand's share of the household's total shopping trips. In this way, a higher value was given to loyal purchasers (where the brand commanded a higher share of the household's portfolio of purchases), and sales to 'switchers' were devalued. This had the effect of reinforcing the separation of the two consumption behaviours.

The segmentation can be formally described as follows. Let e_{kj} denote expenditure on brand j by panellist k . Also let n_{kj} and n_k be the number of

purchases of brand j by panellist k and the total number of purchases (across all brands) by panellist k respectively. Panellist k 's weighted expenditure for brand j is defined as follows:

$$w_{kj} = e_{kj} \star (n_{kj}/n_k)$$

w_{kj} is calculated and ranked for brand A ($j = A$) across all panellists that purchased Brand A. Having done this, it was then possible to retabulate the proportion of buyers by banded value, before and after weighting.

To create the segments, it was decided to split the households into those which had a weighted value less than £5 (eg 64.45 per cent for Brand A), and those with a spend greater than or equal to £5 (eg 35.55 per cent for Brand A). This enabled a simple allocation of households into two groups, with the first group highly likely to contain a high proportion of switchers; and the second group a high proportion of loyalists. (From now on, these segments will be referred to as 'loyalists' and 'switchers'.) Having done this, it was possible to produce a time series of value sales by customer segment. Producing segment sales as a time series enables the investigation of the influence of marketing over time, and as such, the series became the dependent variables for the econometric analyses detailed in the next section.

Table 7 Dependent variable — Sales value brand A, Loyalist segment

Key explanatory variables	Coefficient	Std. error	t-Statistic	Prob.
Constant	2.6658	1.0689	2.4940	0.0182
Brand A above the line advertising AdStock (retention 80%)	9.85E-08	2.94E-08	3.3488	0.0021
Brand A direct price reduction (promotion)	0.0230	0.0044	5.2397	0.0000
Log of Brand A loyal segment real price	0.9352	0.3097	3.0198	0.0050

Table 8 Dependent variable — Sales value brand A, Switchers segment

Key explanatory variables	Coefficient	Std. error	t-Statistic	Prob.
Constant	-1.2308	0.1175	-10.4760	0.0000
Brand A price promotion	0.0409	0.0072	5.7079	0.0000
Brand A non-price promotion	0.0593	0.0154	3.8632	0.0006
Brand C price promotion	-0.0095	0.0053	-1.7920	0.0832
Brand D price promotion	-0.0059	0.0023	-2.4999	0.0181
Brand B price promotion	-0.0177	0.0070	-2.5235	0.0172
Brand B non-price promotion	-0.0557	0.0199	-2.7942	0.0090

SECTION B: MACROANALYSIS (ECONOMETRICS)

In this section, the causal relationships between brand demand and the drivers of brand demand are identified. Of particular interest is the quantification of the effect of various marketing programmes on sales. This is done with the aid of econometric analysis.

Econometrics is a popular technique based on multiple regression that is used to isolate and quantify key drivers of a dependent variable. In this analysis the dependent variable was sales value for Brand A by customer segment (loyalists/switchers). The key drivers of sales value in this sector were assumed *a priori* to be price, promotions, above-the-line advertising and new product development. During the period under investigation, however, Brand A did not increase the range of core products under its brand portfolio. The hypothesis that economic growth would have an impact on sales of Brand A was also tested, but an income effect was not found to be significant in the equations

below. In the spirit of Hendry, a general to specific methodology was adopted.¹¹ Full technical details of the models including diagnostic tests results can be found in the technical appendix.

The dependent variable in both models is sales value. In this category, it is more appropriate to use value sales instead of volume sales as the dependent variable because when aggregating the sales of different products (within a brand portfolio) some products are high value/low volume, while for others the reverse is true.

The key explanatory variables, their respective parameter values, *t*-statistics and associated *p*-values are presented in Tables 7 and 8.

The most apparent difference between the two segments is the impact of promotions. Purchases by switchers are driven purely by price and non-price promotions — when Brand A promotes, an uplift in sales occurs; whereas a promotion by a competitor brand has an adverse effect on sales. The absence of above-the-line advertising from the

switchers equation suggests that brand advertising does not motivate customers in the switchers segment to purchase. It can be inferred that switchers of Brand A are promotion-seeking bargain hunters who have low levels of brand loyalty.

The loyalist segment is more driven by above-the-line brand advertising, as shown by the presence of the advertising adstock term in the first equation. Although promotion-led price reductions can increase sales, the response to promotions is less sensitive for loyalists than for switchers (the price promotions coefficient is less for loyalists (0.0230) than for switchers (0.0409)). Competitive promotions do not have an impact on the loyalist segment of Brand A — ie they do not switch to a competitor brand for the sake of a promotion.

It is interesting to note that real price has a positive coefficient for the loyalist segment. This may seem counter-intuitive at first. Since, however, it is sales value that is being modelled, the coefficient does not represent price elasticity. By rearranging the equation, the price elasticity for loyalists is estimated to be -0.06 ,¹² which suggests that demand is price inelastic. Caution should, however, be exercised when interpreting this result. Price promotions for brand A occurred in every single four-week period over the sample and since the price variable is derived from the ratio of value sales to unit sales, it implicitly includes promotions. Furthermore, it is known from other sources, such as audit data, that for Brand A, underlying price (defined as the non-promotion price) was fairly stable over the period. It is therefore difficult to distinguish general price changes from promotion-driven price changes. A possible inference nevertheless is that while loyal customers of Brand A are sensitive to price promotions, they are less sensitive to modest changes in the underlying price.

REJECTION OF THE SECOND NULL HYPOTHESIS

From the above evidence, it is clear that the consumption behaviour of the loyalist and switchers segments were driven by different marketing mix factors. It is therefore proposed that the second null hypothesis, that marketing mix variables have the same effect on all customers, is false.

CONCLUSION

The aim of this paper was to introduce the concept and benefits of fusion analysis in understanding the drivers of customer value, and its relevance to customer profitability analysis. By employing this approach to the hair colourants category, some interesting marketing insights have been generated:

- that not all customers are the same, with many purchasing on a portfolio basis, representing differing current and potential value to the brands within the category
- that the contribution of different variables in the marketing mix has varying impacts on different customer segments
- that brand loyal customers are less motivated by promotions, but are influenced by brand advertising; and brand switchers are motivated purely by promotions.

These are powerful insights: although they confirm ‘gut instinct’, the advantage is that as a result of the analysis, they are now quantified. It is also noted that this could only have been achieved through the fusion of macro and microanalysis. Knowing accurately how sales respond to demand drivers at a customer level can now be employed at a planning level to optimise brand strategy.

In terms of marketing evaluation, the natural next step would be to consider the costs of running promotions and brand advertising. This would enable the return on investment to be calculated for both promotions and brand advertising, by customer segment, and provide deeper insights into customer profitability.

References

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- 3 Reichheld, F. and Teal, T. (1996) 'The loyalty effect: The hidden force behind growth, profits, and lasting value', Harvard Business School Press.
- 4 Ward, K. and Ryals, L. (2001) 'Latest thinking on attaching a financial value to marketing strategy: Through brands to valuing relationships', *Journal of Targeting, Measurement and Analysis for Marketing*, Vol. 9, No. 4, pp. 327–340.
- 5 By micro, the authors refer to a perspective where the individual provides the level of analysis.
- 6 By macro, the authors refer to a perspective where the brand or market provides the level of analysis. In a similar vein, they note that where evaluation is conducted at the micro-level, it very rarely takes the macro factors into consideration.
- 7 Ambler, T. (2000) 'Marketing and the bottom line', Prentice Hall.
- 8 These 'environmental factors' will be category dependent: for example, in the banking sector, interest rates will be key. Other example macro factors include weather, state of the economy, Internet penetration etc.
- 9 Ehrenberg, A. (1996) 'Repeat buying: Facts, theory, and application', Charles Griffin & Co Publishing.
- 10 Telser, L. (1962) 'The demand for branded goods as estimated from consumer panel data', *Review of Economics and Statistics*, pp. 300–324.
- 11 Hendry, D. (1993) 'Econometrics: Alchemy or science?', Oxford University Press.
- 12 If the log of sales value is the dependant variable, the estimated equation is of the form:
 $\ln(\text{val}) = \ln(\text{vol} \times \text{price}) = c + b\ln(\text{price}) + \text{other explanatory variables}$ where $b = 0.9352$.
 The left-hand side of the equation can be written as $\ln(\text{vol}) + \ln(\text{price})$. By subtracting $\ln(\text{price})$ from both sides of the equation yields:
 $\ln(\text{vol}) = c + (b - 1)\ln(\text{price}) + \text{other explanatory variables}$, $(b - 1) = -0.0648$ is the coefficient of price.

TECHNICAL APPENDIX

Two models (one for each customer segment) have been estimated for Brand A using OLS. The estimation sample consisted of 39 four-weekly observations. The models perform satisfactorily over a range of statistical tests that are reported below.

Most of the variables in the models are self-explanatory. Two of them, however, require an explanation of how they were constructed:

Adstock

The purpose of adstock is to treat advertising as a 'cumulated' variable. It can be thought of as a stock of advertising which decays over time. The amount of adstock retained from one period to the next is represented by the retention rate. Adstock in period t can be represented formally as follows:

$$\text{Adstock}(t) = \text{Adstock}(t - 1) \times \text{retention rate} + \text{advertising spend}(t)$$

Promotions

Each panellist records when a purchase is made on promotion and the type of promotion (ie price promotion or non-price promotion). It is therefore possible to create a promotions time series per panellist by brand as a one-zero dummy variable. By aggregating across panellists, time series for the number of promotions by type of promotion and by brand is derived. (Strictly speaking, such a derived variable cannot

be interpreted as causal, since it is more of a truism. However, for a descriptive model of sales, this is sufficient.)

BRAND A LOYAL SEGMENT MODEL

Dependent Variable: log of Value of Sales to Brand A loyal segment deflated by:

Retail Price Index
Log(BrAS2val/RPI)
Method: Least Squares

Sample(adjusted): 2 39

Included observations: 38 after adjusting endpoints

Variable	Coefficient	Std. error	t-statistic	Prob.
C	2.665829	1.068906	2.493979	0.0182
Brand A adstock (retention rate 80%)	9.85E-08	2.94E-08	3.348761	0.0021
Brand A price reduction promotion	0.022964	0.004383	5.239719	0.0000
Log of Brand A price deflated by RPI	0.935163	0.309675	3.019826	0.0050
Period 11 dummy variable DUM11	0.435318	0.149222	2.917245	0.0065
Period 12 lagged dummy variable DUM12	0.357349	0.156226	2.287389	0.0292
Period 20 dummy variable DUM20	-0.449708	0.149342	-3.011263	0.0051
R-squared	0.725299	Mean dependent var		-0.130184
Adjusted R-squared	0.672131	S.D. dependent var		0.244366
S.E. of regression	0.139923	Akaike info criterion		-0.930621
Sum squared resid	0.606935	Schwarz criterion		-0.628960
Log likelihood	24.68180	F-statistic		13.64165
Durbin-Watson stat	1.657757	Prob(F-statistic)		0.000000

Further diagnostic tests

Normality Jarque Bera: 1.31 ($p = 0.52$)

Serial correlation LM1: 1.17 ($p = 0.28$), LM2: 1.21 ($p = 0.55$), LM4: 3.17 ($p = 0.53$), LM8: 5.91 ($p = 0.66$), LM13: 7.73 ($p = 0.86$)

Heteroskedasticity White test: 6.08 ($p = 0.73$), White X test: 9.05 ($p = 0.70$)

ARCH1: 0.005 ($p = 0.94$), ARCH2: 0.54 ($p = 0.77$), ARCH4: 3.17 ($p = 0.52$), ARCH8: 10.51 ($p = 0.23$), ARCH13: 13.79 ($p = 0.39$)

Specification error Ramsey RESET1: 0.37 ($p = 0.54$), Ramsey RESET2: 0.52 ($p = 0.77$), Ramsey RESET3: 2.76 ($p = 0.42$)

BRAND A SWITCHERS SEGMENT MODEL

Dependent Variable: Log of value of sales to Brand A switchers segment deflated by:

Retail Price Index
 $\text{LOG}(\text{BrAS1VAL}/\text{RPI})$
 Method: Least Squares

Sample: 1 39

Included observations: 39

Variable	Coefficient	Std. error	t-statistic	Prob.
	-1.230823	0.117490	-10.47600	0.0000
Brand A price promotion	0.040893	0.007164	5.707912	0.0000
Brand A non-price promotion	0.059304	0.015351	3.863213	0.0006
Brand C price promotion	-0.009509	0.005306	-1.792019	0.0832
Brand D price promotion	-0.005858	0.002343	-2.499873	0.0181
Brand B price promotion	-0.017656	0.006997	-2.523471	0.0172
Brand B non-price promotion	-0.055719	0.019941	-2.794242	0.0090

Variable	Coefficient	Std. error	t-statistic	Prob.
Period 6 dummy variable DUM6	-0.887866	0.216282	-4.105126	0.0003
Period 32 dummy variable DUM32	-0.853128	0.221442	-3.852601	0.0006
R-squared	0.837729	Mean dependent var		-1.134156
Adjusted R-squared	0.794457	S.D. dependent var		0.448758
S.E. of regression	0.203453	Akaike info criterion		-0.147590
Sum squared residuals	1.241793	Schwarz criterion		0.236309
Log likelihood	11.87800	F-statistic		19.35947
Durbin-Watson stat	2.186244	Prob(F-statistic)		0.000000

Further diagnostic tests

Normality Jarque Bera: 3.02 ($p = 0.22$)

Serial correlation LMI: 0.61 ($p = 0.43$), LM2: 0.84 ($p = 0.66$), LM4: 1.16 ($p = 0.89$), LM8: 16.20 ($p = 0.04$), LM13: 18.60 ($p = 0.14$)

Heteroskedasticity White test: 15.48 ($p = 0.42$), White X test: insufficient number of observations

ARCH1: 0.26 ($p = 0.61$), ARCH2: 0.73 ($p = 0.69$), ARCH4: 1.8 ($p = 0.77$), ARCH8: 3.08 ($p = 0.93$), ARCH 13: 3.61 ($p = 0.99$)

Specification error Ramsey RESET1: 0.88 ($p = 0.35$), Ramsey RESET2: 1.33 ($p = 0.51$), Ramsey RESET3: 1.40 ($p = 0.70$)