BRAND USAGE AND SUBSEQUENT ADVERTISING RECALL

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Abstract

This paper reports the first exploratory steps taken towards quantifying an important empirical generalisation; the link between brand usage and advertising recall. The eventual aim being to specify a model that fits across multiple sets of data, thus providing managers with reliable benchmarks that can be used in varying conditions.

It is a reasonably well established empirical generalisation that users of a brand tend to have a higher propensity to recall advertising for their particular brand than non-users. Consequently, brands with larger market shares generally achieve higher ad awareness scores in advertising tracking surveys. Knowledge of this generalisation is fairly useful but without quantitative norms and benchmarks the interpretation of ad awareness scores can be problematic. In this paper we take the first step towards *quantifying* the nature of this relationship between aggregate levels of brand usage and advertising recall. Quantification of this generalisation offers the potential to identify when advertising has been particularly effective or ineffective in reaching users and/or non-users of the brand.

In order to guide the model specification we examined individual and brand level data covering 2 product categories, 17 brands and more than 20,000 advertising recall observations collected over a two year time period. We found that, (1) users are more than twice as likely to recall a brand's advertising than non-users, and (2) any brand's ad recall score tends to be 20 percentage points higher for users than for non-users.

Introduction: Advertising Awareness and the Need for Grounded Benchmarks

The use of claimed advertising recall to evaluate advertising is not without controversy, with some even arguing that well noticed and remembered advertising might fail to influence brand awareness or purchase behaviour. Some opponents instead advocate 'proven advertising awareness' measures that seek to test if the respondent really did see the advertisement they claimed to have seen. It is not our purpose to review these debates here, we simply note that claimed advertising awareness is commonly used to evaluate advertising performance and this use is supported by respected academic texts (Rossiter and Percy 1997) and specialist industry researchers (Brown 1991).

We also note that different measures of *brand* awareness, (i.e., aided, spontaneous and top-of-mind) have been shown to be systematically related (Laurent et al. 1995) and we suspect that the same may be true of various advertising awareness measures.

Typically, advertising awareness is used in combination with a series of other measures to evaluate advertising effectiveness. The resultant ad recall scores can potentially indicate whether the creativity, execution, media choice, time and weight have achieved 'cut through'. However, comparing various campaigns which may vary on all these factors can be difficult.

Adding to this complexity is the issue of the usage effect; that users of a brand are more likely to recall, or claim to recall, advertising for that brand. Consequently brands with larger market shares tend to gain higher ad awareness scores. This means they typically achieve higher scores for any given level of advertising weight ('share of voice') or creative excellence. They may also record different rates of change in awareness for any given change in advertising weight etc. This makes it difficult to make comparisons across brands of differing sizes, surveys with varying ratios of brand users to non-users, and even across time. It is for this reason that some analysts split users from non-users when tabulating ad awareness data, and a number of market research products adopt approaches based on similar principles eg, The Conversion Model (Hofmeyer and Rice 2000). Marketers also often wish to know if their advertising has reached non-users or users depending on the objectives of the campaign (eg, retention versus acquisition).

Conducting separate analyses for users and non-users allows for some comparisons to be made for these groups across surveys (ie, over time). However, comparisons between these groups are not possible without norms or grounded benchmarks to guide interpretation. The qualitative norm that ad recall will be higher amongst users, and hence higher for larger brands is very useful, but limited - quantification of this benchmark would be a substantial step forward. Hofmeyr and Rice speculate that users are about twice as likely as non-users to recognise advertising for the brands they use (Hofmeyr and Rice 2000 p.47).

In this paper we present the first steps of our descriptive modelling, with the ultimate aim of describing a relationship that holds across multiple sets of data, covering different brands and product categories, and across time (Ehrenberg 1990). We seek to model the relationship between brand usage and advertising awareness.

Descriptive models seek to uncover marketing phenomena and to represent them . . . . This is the classical task of science . . . . Descriptive models without marketing decision variables . . . go back to the work of Ehrenberg (1959, 1988) and others." (Little 1994)

While the practice of descriptive modelling in marketing is now decades old, it is not widely practised (Ehrenberg 1994; Rossiter 1994), and little guidance exists to direct the would-be researcher in their quest. Even Ehrenberg's seminal text on data reduction (2000a) acknowledges that this is not a well documented aspect of science. We hope to make some contribution to the literature by documenting our first steps in this paper, along with presenting some very interesting initial findings.

Our Data Sets

The tracking data collected in the Home Loan and Insurance markets provided both prompted and unprompted advertising awareness of 9 home loan and 8 insurance brands over the last 2 years, split into 8 equal quarters (3 months). The data was collected using a telephone survey methodology conducted continuously over the two year time period.

Seeking to Quantify the Relationship

Firstly, we examined the brand level data aggregated across all quarters for both product categories, giving data based on fairly large samples sizes (2500 and 3300) and minimising variation due to random sampling variation. Drawing on formal prior knowledge (Bound and Ehrenberg, 1993; 1998) we looked for the overall pattern, which was very noticeable, ad recall scores for users were always higher than the scores for non-users. We also looked for a relationship with brand share, ie, that the quantitative nature of the relationship might vary for brands of differing market shares, for this reason we ranked the brands in order of size.

Secondly, we examined the individual level differences in recall between users and non-users across the entire category, and the brand level patterns for each brand. These two approaches gave us (1) a product category level result – how much more likely are users to see advertising than non-users?, and (2) a brand level result – does the relationship vary by brand or brand size? In the next section we report each of these approaches and the relationship models they suggested.

Expectations in Model Specification

Specifying a model that can generalise across varying conditions is not easy. Upon initial investigation many models can seem plausible. Our exploration focused around a linear relationship as there was no real evidence to dissuade us from this approach. Initially we looked for a multiplicative relationship, ie, how many times more likely were users to recall advertising than non-users. We also noted that a simple additive relationship looked plausible, eg, that users' scores were X percentage points higher than non-users. It also seemed reasonable to expect a combination, eg, a classic regression equation, as users' scores may always be some percentage points higher (a 'constant' in the model equation) than non-users even when the brand is not advertising. That is, a zero score for non-users but some small score for users who infer they have seen advertising for the brand because they have used it. It may also be that any user would be more likely to see or recall advertising than a non-user, so increases in advertising produce greater effects for users than non-users (the multiplicative factor in the model equation).

Product Category Level Results

The product category results are based on recall of each brand in the category's advertising by each respondent, over eight quarters. In total the data for both categories, Insurance and Home Loans represents around 20,000+ ad recall observations each.

The home loan advertising recognition levels shown below in Table 1 exhibit a fair level of consistency across time with users being about 3 and a half times more likely to recognise advertising for their brand than non-users.

Table 1: Total user and non-user advertising recall over time – Home Loan

	% Non-users	% Users	Multiple
Q1 (n=342)	7	27	3.7
Q2 (n=243)	6	25	4.0
Q3 (n=247)	9	27	3.0
Q4 (n=276)	7	24	3.4
Q5 (n=292)	8	30	3.6
Q6 (n=289)	7	20	3.0
Q7 (n=342)	7	26	3.5
Q8 (n=295)	6	19	3.3
Average	*7*	*25*	*3.6*

The data also suggests a relationship of users' ad recall being 20 percentage points higher than non-users. When modelled this fits very well.

A 'best fit' (R^2 = 0.35, P = 0.12) OLS linear regression model for this time series result (8 quarters) produced the following model:

Users' ad recall = 2.2 (non-users' ad recall) + 8.9

We noted similar patterns across time for the insurance product category, as shown below in Table 2.

Table 2: Total user and non-user advertising recall over time - Insurance

	% Non-users	% Users	Multiple
Q1 (n=495)	13	37	3.0
Q2 (n=367)	9	27	2.8
Q3 (n=366)	10	29	3.0
Q4 (n=374)	9	31	3.5
Q5 (n=374)	9	27	2.9
Q6 (n=375)	9	28	3.1
Q7 (n=376)	10	32	3.3
Q8 (n=296)	8	26	3.2
Average	*10*	*30*	*3.0*

Again the insurance data suggests the linear models of: (1) users being three times more likely to recall their brand's advertising or (2) having an overall score that is 20 percentage points higher.

This time a 'best fit' (R^2 = 0.83, $P<.0001$) linear regression model for this time series result (8 quarters) produced the following model:

Users' ad recall = 2.2 (non-users' ad recall) + 8.5

The fact that the two different data sets produced 'best fit' models of differing levels of fit, but very similar parameters gives us confidence in this model. However, a simple additive (users = non-users plus 20) model also fits the data very well for both product categories, and across time. This illustrates an important, often neglected, problem with 'best fit' modelling – that there may be quite a number of different models that can fit any one data set with similar degrees of fit but different parameters (Ehrenberg 1963; and 2000).

Brand Level Results

While describing the general product category level result is an important step in understanding the relationship between usage and ad recall, managers are normally faced with brand level data and need norms for interpreting brand level results. We suspected that the nature of the 'usage – ad recall' relationship might vary between brands of differing market shares and/or ad awareness scores (these two variables being strongly related). If so, we would also like to model this variation so that more reliable predictions could be made. We expected that a possible ‘double jeopardy’ pattern, again due to formal prior knowledge, may be observed (eg, Ehrenberg 2000b; 1969; 1990; Goodhardt et al. 1984).

But, we found that again a simple additive (plus 20) model fitted the data, shown below in Tables 3 and 4. Best fit regression ($R^2 = 0.41$, $P<.005$) also produced a model of around:

Users’ ad recall = non-users’ ad recall + 20

Although there is a high level of variation across brands which we would like to address as we further progress this research.

Table 3: Average Home Loan user and non-user advertising recall over time

	% Non-users	% Users (O)	% Users (T)	Deviation
Aussie Homeloans	21	51	41	10
Commonwealth Bank	30	49	50	1
Suncorp	3	42	23	19
Suncorp Metway	7	35	27	8
Westpac	9	27	29	2
Heritage Credit Union	2	25	22	3
National Aust Bank	9	17	29	12
ANZ	7	17	27	10
Bank of Queensland	1	9	21	12
Average	*10*	*30*	*30*	*0*

O=observed, T=theoretical (plus 20)

Table 4: Average Insurance user and non-user advertising recall over time

	% Non-users	% Users (O)	% Users (T)	Deviation
Australian Pensioner	10	42	30	12
AAMI	20	41	40	1
Suncorp Metway	4	32	24	8
GIO	22	31	42	11
Suncorp	8	28	28	0
AMP	5	25	25	0
NRMA	6	21	26	5
FAI	6	19	26	7
Average	*10*	*30*	*30*	*0*

O=observed, T=theoretical (plus 20)

Conclusion

This study has been the initial step towards quantifying the empirical generalisation that users notice advertising more than non-users and has given a stable result that we will continue to test across other markets.

Our initial finding is more stark and simple than we ever imagined. Users seem to be at least twice as likely as non-users to recall the brand’s advertising and ad recall scores for users are typically 20 percentage points higher than the score for non-users.

More work is needed to test the generalisability of this empirical pattern. Our programme of replication research will begin by looking at other types of markets, such as repertoire markets, and continuing to investigate the home loan and insurance markets to gain a more stable brand level result.

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