Quantifying an Empirical Generalisation: Usage and Advertising Recall in the International Travel Market

Byron Sharp, Virginia Beal and Jenni Romaniuk
University of South Australia

Abstract

This paper extends our exploratory research aimed at quantifying an important empirical generalisation; the relationship between brand usage and advertising recall. This study of the international travel market in 3 countries covers 21 travel destinations over a 3 year period. We found that users (previous visitors) were twice as likely to recall recent advertising for the travel destinations they had previously visited. Our aim was to specify a model that fits across multiple sets of data, thus providing managers with reliable benchmarks that can be used in varying conditions. We show how such a model can be applied to brand level data in order to assess a brand's advertising performance.

Introduction: Advertising Awareness and the Need for Grounded Benchmarks

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 steps towards quantifying the nature of the relationship between aggregate levels of brand usage, in this case country visitation, and advertising recall. Quantification of this generalisation offers the potential to identify when advertising has been particularly effective or ineffective in gaining ad awareness amongst users and non-users of a brand.

The use of claimed advertising recall to evaluate advertising is not without controversy, with some arguing that even well noticed and remembered advertising might fail to influence brand awareness or purchase behaviour. Yet customarily advertising awareness is seen as the best way of assessing advertising cut-through and unlike measures such as sales volume and brand awareness it is likely to respond to changes in execution of campaign weight (McDonald, 2000). It is not our purpose to review these debates concerning the relative merits of ad versus brand recall, prompted vs proven recall etc. 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 industry research (Brown, 1991). And we suspect that as different measures of *brand* awareness have been shown to be systematically related (Laurent et al., 1995) the same may be true of various advertising awareness measures (eg, aided, spontaneous, top-of-mind, proven and unproven).

Determining what level of ad awareness is acceptable can be difficult. One reason for this difficulty is the usage effect; users of a brand are more likely to recall, or claim to recall, advertising for their brand. Consequently brands with larger market shares (or more users in the survey) tend to gain higher ad awareness scores. This means that they will typically achieve higher scores for any given level of advertising weight ('share of voice'), media strategy or creative excellence. They may also record different rates of change in awareness for any given change in advertising weight etc. This creates difficulty in making 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 because 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 (i.e., 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 (2000 p.47) speculate that users are about twice as likely as non-users to recognise advertising for the brands they use.

We are seeking to quantitatively describe the relationship between brand usage and advertising awareness. We have undertaken exploratory 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).

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 practiced (Ehrenberg, 1994b, Rossiter, 1994), and little guidance exists to direct the would-be researcher in their quest. Even Ehrenberg's seminal text on data reduction (2000) 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. Most marketing models are developed and fitted on a single, historic, data set and no attempt at generalisation is made. Consequently, the predictive ability of the model is unknown and there is a very real danger of over generalisation.

The Data Analysed

Our findings are based on the analysis of tracking data collected in the international travel market. The data consisted of unprompted ad recall for television and magazine advertising and prior country visitation for 3 markets (UK, USA, and Japan) over 3 years (1998 to 2001).

Expectations in Model Specification

Specifying a model that can generalise across varying conditions (the basic work of scientists) is not easy. Upon initial investigation many models can seem plausible. We followed Ehrenberg's 'data reduction' (Ehrenberg, 2000, Ehrenberg, 1994a) approach, rather than apply a 'best fit' modelling approach, as Ehrenberg's approach is specifically designed to create a generalised model that fits multiple sets of data, whereas 'best fit' approaches are not (Ehrenberg, 1990).

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, i.e., how many times more likely were users to recall advertising than non-users. We also noted that a simple additive relationship looked as if it might produce good model fit, e.g., that users scores were X percentage points higher than non-users. It also seemed reasonable to expect a combination, e.g., 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 mistakenly 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).

Quantifying the Relationship

As we began our quest to quantify the relationship, we drew on formal prior knowledge (Ehrenberg and Bound, 1993, Bound and Ehrenberg, 1998) and looked for the qualitative pattern, which was very noticeable. 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 (those that had previously travelled to the destination) to see advertising than non-users? and (2) a brand/country level result – does the relationship vary for individual brands (or their campaigns)?

Product Category Level Results

The product category level results are based on each respondent's, within the seven separate country/time periods, recall of each country's advertising for both television and magazines. In total the data represents around 100,000+ ad recall observations.

Although the level of user and non-user recall varies in magnitude across the countries/ periods and media the relationship between them remains fairly consistent, with users being twice as likely as non-users to recall advertising, as shown below in Table 1. While the sample size of these surveys are reasonable, ad recall is not high and the subsequent split of these respondents into users and non-users can produce a fair degree of random sampling variation on these statistics. By examining the averages, it is possible to see that users are about twice as likely to see the brands' advertising as non-users (11% cf 6% for TV and 15% cf 7% for magazines). After much experimentation we fitted the following two models to the separate media.

For television: Users' ad recall = 1.2 (non-users' ad recall) + 4

For magazines: Users' ad recall = 1.2 (non-users' ad recall) + 6

Table 1: Total User and Non-user Ad recall

	Television				Magazine			
Country and period	Non-user	User (O)	User (T)	Dev	Non-user	User (O)	User (T)	Dev
UK 99 (n=1408)	5	11	10	-1	4	14	11	-3
UK 00 (n=1336)	4	10	9	-1	5	12	12	0
Jap 98 (n=800)	8	13	14	1	5	12	12	0
Jap 99 (n=801)	6	14	11	-3	6	15	13	-2
US 98 (n=1009)	9	16	15	-1	8	16	16	0
US 99 (n=1050)	4	8	9	1	8	16	16	0
US 00 (n=1048)	6	8	11	3	11	20	19	-1
Average	**6**	**11**	**10**	**1.5**	**15**	**7**	**11**	**0.9**

O = observed, T= theoretical

Both models are highly similar in structure and display a good fit across the data sets, the Absolute Mean average deviation being 1.5 and 0.9 respectively, with irregular (non-systematic) residuals.

Such a category level model provides norms against which brand level results can be compared because such a model represents the average brand. Deviations for particular brands from this average provide a starting point for investigation. That is, to explore potential brand specific causes for the deviation, eg share of voice, advertising quality, or distribution effects such as proximity of the country. An illustration of how this would be undertaken in practice follows, applying our preliminary model(s) to UK brand level results.

Brand Level Results

Managers are normally faced with brand level data and therefore need norms for interpreting brand level results. The product category level model provides this norm, in effect describing the propensity of any user to notice advertising ahead of a non-user. Fitting the product category models to the brand level data allows one to identify unusual brands or advertising campaign, an example using the UK ad recall scores for the year 2000 is illustrated below in Table 2. As a reminder, the models we are fitting are as follows:

For television: Users' ad recall = 1.2 (non-users' ad recall) + 4

For magazines: Users' ad recall = 1.2 (non-users' ad recall) + 6

Table 2: UK 2000 TV Brand Level Ad recall

	Television				Magazines			
Destination (brand) Advertising	Non-user	User (O)	User (T)	Dev	Non-user	User (O)	User (T)	Dev
USA	13	24	20	-4	12	26	20	-6
Spain	10	13	16	3	9	10	17	7
France	5	9	10	1	5	13	12	-1
Canada	3	9	8	-1	6	15	13	-2
Greece	3	8	8	0	3	9	10	1
Turkey	3	8	8	0	2	6	8	2
Italy	2	5	6	1	4	12	11	-1
Portugal	2	4	6	2	2	6	8	2
Average	**5**	**10**	**10**	**2**	**5**	**13**	**12**	**3**

O = observed, T= theoretical

Overall the category level models show a good fit at brand level. There is more variation, but this is to be expected as we have a wider variation of observed figures at brand level. We do not expect a perfect fit for every brand, given that many countries undertake quite different levels and types of marketing activities. There does not appear to be any systematic patterns in the deviations, which is a positive indicator of the appropriateness of the model structure chosen.

Table 2 does show some deviations of interest, for example the model under predicts the number of users in the UK that will notice either television or magazine advertising for the USA. This could indicate that advertising for the USA in the UK does particularly well at attracting users' attention (i.e. more than the model would expect), or it could indicate that as the percentage of non-users recalling the brand gets higher (in this case over 10%) the relationship between user and non-user ad recall becomes curvilinear. The relationship is reversed for Spain with the model over predicting the number of users that should recall. Reasons for these deviations may be either incorrect model specification, or the influence of some outside variable (eg advertising weight or brand familiarity). In the interests of developing a simple, parsimonious model we have concentrated on only two variables, user and non-user ad recall figures, at this stage.

Conclusions

We were able to confirm the comment by Hofmeyr and Rice (2000) that users are, in general, about twice as likely to see their brands advertising than non-users. We have further developed this relationship and demonstrated that it is possible to identify a more specific, generalised relationship between the % of users and the % of non-users that recall a brands advertising. This relationship held across markets, countries and time periods, and had the same structure for both TV and magazine advertising. The key difference between the two was a higher constant/baseline for recall of magazines. The relationship can be defined as:

$$\text{Users' ad recall \%} = 1.2\,(\text{non-users' ad recall \%}) + c$$

Where c=4 for TV and c=6 for Magazines.

Matching these findings with other information such as share-of-voice and campaign execution details may allow for cause and effect relationships to be specified. Hence, enabling advertising practitioners to increase the effectiveness of their advertising in the future. This would be especially useful should the campaign have aims of retention or acquisition. The key limitation of this research is that the ad recall figures were all below 30%. This means that it is impossible to discern whether a linear relationship as proposed would be appropriate for higher ad recall levels. Further research on data with higher non-user ad recall levels would help uncover this. Additionally, this research was conducted using spontaneous ad recall, further work needs to be done to see if the same relationship holds for other ad recall measures (eg, proven ad recall, aided recall).

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