

# Getting Real About Prediction in Marketing Research

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## Abstract

I begin this paper with a meta-analysis of the predictive performance of customer satisfaction, purchase intention, and advertising recall. I show that it is poor. Developments in cognitive neuroscience and evolutionary psychology help us to understand why. I suggest two routes to improvement: first, through the development of better advertising diagnostics using a new measure of emotional engagement coupled to text mining tools; and second, through the development of a new measure of attitudinal equity based on the Zipf distribution. I finish the paper with a brief discussion about the conservatism of our industry and suggest the need for some changes in orientation.

## Introduction

For all its complexity, a lot of attitudinal marketing research can be summarised very simply: find the number that needs to go up!

- Find the brand attribute that will make the biggest difference to sales.
- Find the advertising execution that will communicate the desired brand attributes most effectively.
- Find the media mix that will make the biggest difference to advertising impact.

Whatever the diagnostic variables – brand attributes, touch-point experiences, advertising recall, perceived media exposure, barrier effects – this ‘find the number’ logic requires a dependent variable against which to model... which leads to the question: how well do typical numbers do?

The answer is discouraging. In a meta-analysis of the customer satisfaction literature, Szymanski and Henard (2001) found an average correlation between customer satisfaction and claimed loyalty (measured using purchase intention) of  $R = 0.52$ ; i.e.,  $R^2 = 0.27$ . The results relating customer satisfaction to ‘word of mouth’ were not much better; i.e.,  $R = 0.57$ ,  $R^2 = 0.32$ . And in what is still the largest reported test of the performance of multiple advertising executions (Lodish et al, 1995), no relationship was found between advertising recall and sales.

In this paper I ask the question: can we do better? And if so, why do we continue to use marketing metrics that are clearly flawed?

The paper begins with an analysis of three of the most widely used measures in marketing research. All perform poorly. I discuss the reasons and suggest remedies based on what are now only relatively new learnings about how the world works - non-linear dynamics, small world networks, cognitive neuroscience. I test two new measures; and close with a discussion of the conservatism of our industry and what must be done to fix it.

## A reminder: The validity of key marketing measures

One reason why it's difficult to develop valid attitudinal marketing measures, is because we seldom have data which compares our measures to real behaviour in controlled environments. Research based on real behaviour is so sparse that Szymanski and Henard don't even reference it in their meta-analysis. Yet, it can be found. Perhaps we just prefer to ignore what's there?

### *i). A critical review of ‘purchase intention’*

Along with customer or brand satisfaction, there is probably no more widely used measure in marketing research than purchase intention. It's central to most loyalty measurement systems. It's used as a measure of ‘persuasion’ in many ad-testing systems. And it's at the core of most concept and product tests systems. So - how well does it relate to what people actually do?

Table 1 is based on a survey of published research on the relationship between purchase intention and real behaviour that dates back to 1966.

**Table 1**

Results from Longitudinal research linking Purchase Intention to subsequent Behaviour

Author(s)	Product Categories	Nature of Study	Results
Juster, F.T. (1966)	Motor cars, appliances	Measure purchase intention using 11-point probability scale. Correlate with whether or not product subsequently bought.	R = .43 (motor cars), .24 (appliances). R <sup>2</sup> = .18 and .06 respectively.
Bonfield, E.H. (1974)	Brands of grape juice	Measure purchase intention using 7-point likelihood scale. Correlate with whether or not the brand subsequently bought.	Results are significant. Average correlation: .40. R <sup>2</sup> = .16
Sewall, M.A. (1981)	Women's apparel	Mall intercept. Measure purchase intentions using 5-point scale. Compare with subsequent purchases.	Results are significant but poor. R = .27; R <sup>2</sup> = .07
LaBarbera, P.A. and D. Mazursky (1983)	Margarine, coffee, toilet paper, paper towels, macaroni	Diary study: Purchase intention measured every two weeks for 20 weeks. Correlated with subsequent brands bought.	Purchase intention <sub>t</sub> → Purchase <sub>t+1</sub> : R = .24 Average R <sup>2</sup> = .06
Morwitz, V.G., E, Johnson and D. Schmittlein (1993)	Motor cars, PC's	Measure intention to buy in next six months, every six months. Longitudinal research measures actual behaviour.	No correlations reported. On average, 29% of those who say they will buy, do; which means that 71% don't.
Bemmoar, A.C. (1995)	Multiple durable categories	A meta-analysis of published studies in which PI was measured and subsequent behaviour was observed.	No correlations. 64% of those who say they will definitely buy, don't. Most purchases come from those who say they will not buy.
Chandon, P., V.G. Morwitz and W.J Reinartz (2005)	On-line grocers, motor cars, PC's	Measure purchase intention. Observe next purchase or purchase within six months	Correlations: .44 (grocer), .12 (motor cars), .16 (PC's). Average correlation: .24 (R <sup>2</sup> : .06)
Seiders, K., G. Voss, D. Grewal, and A. Godfrey (2005)	High end clothing and home furnishings	Measure purchase intention. Correlate with 52 weeks of behaviour in a data-base.	Purchase intention → No of visits: R = .11, R <sup>2</sup> = .01; and Amount spent: R = .10, R <sup>2</sup> = .01
Perkins-Munn, T., I.Aksoy, T.L. Keiningham, D. Estrin (2005)	Trucks, Pharmaceuticals	Measure respondent attitudes. Record subsequent behaviour over a 15 month period.	Intention <sub>t</sub> → Repurchase <sub>t+1</sub> : R = .44 and .65 respectively. Average R <sup>2</sup> = .31 Intention <sub>t</sub> → SoW <sub>t+1</sub> : R = .47, .45 respectively. Average R <sup>2</sup> = .21

These results can only be described as 'bad': the average correlation between what people say they intend to do and what they actually do, is R = 0.30, R<sup>2</sup> = 0.09. In other words, 91% of the variance is not captured by purchase intent. Two of the cited papers report no correlations. Both report that more than half of the people who say they will 'definitely buy' something - don't.

ii). Customer satisfaction: just how predictive is it?

In this case we go back to 1983.

**Table 2**

Results from Longitudinal research linking Customer Satisfaction to Retention and Share of Wallet

Author(s)	Product Categories	Nature of Study	Results
LaBarbera, P.A. and D. Mazursky (1983)	Margarine, coffee, toilet paper, paper towels, macaroni	Diary study: Satisfaction measured every two weeks for 20 weeks. Correlated with subsequent brands bought.	Satisfaction <sub>t</sub> → Purchase <sub>t+1</sub> : R = .20 Average R <sup>2</sup> = .04
Jones, T.O. and W.E. Sasser (1995)	Manufacturer of industrial supplies	Longitudinal study: Measures customer satisfaction and compares with subsequent retention-defection.	Extremely satisfied customers six times less likely to defect – but doesn't report overall retention-defection rates.
Bolton, R. N. (1998)	Telecommunications	Longitudinal survey of customers: Two waves. Models satisfaction and other inputs against length of customer duration.	Satisfaction accounts for most of the variance explained (42%). But Bolton fails to report percent variance explained!
Mittal, V. and W.A. Kamakura (2001)	Motor cars	Customer satisfaction in 33 <sup>rd</sup> month of car ownership – compared with whether brand switched or not when new car bought	Repurchase rate of dissatisfied customers = 48%; repurchase rate of satisfied customers = 72%.
Verhoef, P. C. (2003)	Financial services	Measure attitudes inc. satisfaction. Modelled against subsequent retention-defection.	Regression model acceptable: R = .43; R <sup>2</sup> = .18. But satisfaction fails to make the model.
Capraro, A.J., S. Broniarczyk, and R.K. Srivastava (2003)	University health plans	Measure attitudes inc. satisfaction, one month before decision. Re-contact after decision.	Regression model including satisfaction is significant but R <sup>2</sup> is only .08.
Keiningham, T.L., T. Perkins-Munn, and H. Evans (2003)	Financial services	Measure attitudinal satisfaction. Obtain customer share of wallet from 3 <sup>rd</sup> party sources. Fuse the data and analyze.	A dichotomized satisfaction scale (1-8; 9-10) lifts SoW from about 10% to 15%. Average R = .27; R <sup>2</sup> = .07
Bowman, D. and D. Narayandas (2004)	Processed metals	Measures attitudes inc. Satisfaction. Compares with subsequent data-base information.	Satisfaction correlates poorly with SoW; and does not correlate with profitability.
Gustaffson, A. M.D. Johnson, and I. Roos (2005)	Telecommunications	Measure attitudinal satisfaction. Correlate with churn defined as 'time spent as a customer'	Satisfaction → Churn: R = .13, R <sup>2</sup> = .17
Seiders, K., G. Voss, D. Grewal, and A. Godfrey (2005)	High end clothing and home furnishings	Measure attitudinal satisfaction. Correlate with 52 weeks of behaviour in a data-base.	Satisfaction → No of visits: R = .07, R <sup>2</sup> = .00; and Amount spent: R = .07, R <sup>2</sup> = .00
Perkins-Munn, T., I.Aksoy, T.L. Keiningham, D. Estrin (2005)	Trucks, Pharmaceuticals	Measure respondent attitudes. Record subsequent behaviour over a 15 month period.	Satisfaction <sub>t</sub> → Repurchase <sub>t+1</sub> : R = .24 and .22 respectively. Average R <sup>2</sup> = .05

These results are so bad one wonders what we have been doing over the years. The average correlation between customer or brand satisfaction and behaviour is  $R = 0.13$ ,  $R^2 = 0.02$ . Notice how many authors avoid reporting the percent variance explained. I once corresponded with one of these authors and noted that they hadn't reported the percent variance explained. They wrote back that they'd lost the results!

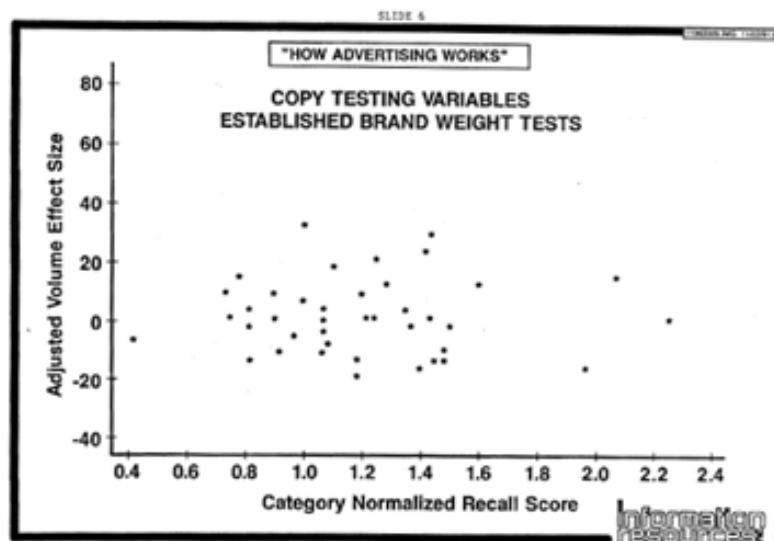
While on this subject, let's note an attempt to link the American Customer Satisfaction Index (ACSI) to shareholder value (Anderson et al., 2004). The article was published in 2004, yet it only covered the relationship between the ACSI and shareholder value in the years 1994 - 1997. Anyone who knows the history of securities will know that markets were volatile from 1998 (Russian crisis) to 2002 (dot-com bubble). I wondered why the authors' analysis ended just before the volatility? Is it because the volatility broke the relationship?

The problem with articles like these, is that publication in a highly respected journal tends to lead to uncritical citing - and so it lays the foundation for the uncritical acceptance that the ACSI is linked to shareholder value (e.g., Cooil et al, 2007).

*iii). Advertising testing: recall and persuasion*

It is probably true to say that measures of recall and persuasion dominate communications measurement - still. Yet one of the most thorough analysis of advertising effects ever conducted (Lodish et al, 1995) showed that there was no relationship between either recall or 'persuasion' and subsequent sales (See figure 1).

**Figure 1:** Advertising recall and subsequent sales  
(from Beth Lubetkin presentation: Marketplace Advertising Research Workshop, 1991)



*iv). To summarise*

Our meta-analysis of satisfaction, purchase intention, and ad-testing and tracking metrics (recall, persuasion) suggests that the links between these measures and what people really do are tenuous at best. Given the extent to which they still dominate marketing measurement, it is worth repeating the validation results here:

- Purchase intention:  $R = 0.30$ ;  $R^2 = 0.09$
- Customer/brand satisfaction:  $R = 0.13$ ;  $R^2 = 0.02$
- Advertising recall/persuasion: No relation to sales, 389 split cable tests

We ought to be embarrassed. Some may find consolation in the fact that our industry is not alone in having poor models. Economists come to mind. Still, as I will show, we can do better. The question then becomes: why don't we?

## Identifying the causes of our poor models

*i). The root of our problems: Fishbein and Ajzen*

I blame some of our industry's addiction to poor measures to the lasting influence of the following equation due to Fishbein and Ajzen (1975):

$$\text{Behaviour} \approx \text{Behavioural Intention} = \sum_{i=1}^n B_i a_i(\omega_0) + \sum_{j=1}^k P_j C_j(\omega_1)$$

**Eq.1**

The equation is based on the view that there should be a strong relationship between what people intend to do and what they actually do, circumstances permitting. From the results of our meta-analysis, however, we know that behavioural intention is a poor guide to behaviour in markets.

But it's not only the left-hand side of the equation that is problematic. Consider the right-hand side: the strength of a behavioural intention is seen to be a function of two factors. The first is an evaluation of the outcomes of the behaviour (for example, a product, service, or brand choice). The second is an estimate as to whether or not relevant others would approve of the behaviour (a cognate of loyalty metrics like recommendation, positive/negative word-of-mouth). The ' $\omega$ ' capture the idea that the lists of outcomes and 'relevant others' should be weighted according to their importance to a person.

The entire approach is what cognitive scientists call 'computationally intensive'. It requires the brain to behave like a very exact calculating machine. Let's take the first term. Getting to a 'number' involves the following steps: list all the attributes that are relevant, attach a brand performance level to each attribute, assign a level of desirability (or importance) to each attribute, weight each performance rating by the level of desirability - and finally, add the results to produce a summary number. Store in memory.

Now turn to the second term. List all the people whose opinions you value. Estimate what you think they would say about the choice. Assign an importance to the opinion of each person. Weight what you believe their opinion would be by how much you value their opinion. Add the numbers to produce a second summary number.

Add the two numbers. The higher the result, the stronger the intention should be. The stronger the intention, the more likely the behaviour should be.

This computationally intensive but logically simple algorithm is at the heart of almost all equity, loyalty, and driver research in marketing. It's known in the cognitive decisions literature as the 'weighted additive' model of brand choice (See Bettman et al, 1998). But is it how the brain works? Increasingly we're realising that the answer is 'no'; and that if it were, we probably would not have survived into the 21<sup>st</sup> century.

Human beings are 'ecologically rational' (See Gigerenzer and Todd, 1999). Our brains have evolved to be maximally efficient under constraints of energy, information, and time. This efficiency involves the use of 'decision short cuts' which work because they're matched to the way the world is. In the brand domain, two great examples of this kind of short cut, are the choice of the most visible brand, or the choice of the market leading brand. Why waste time testing every brand for yourself when you can benefit from the implicit experience and endorsement of everyone else by choosing what most of them choose?

The evolutionary view of human choice coincides with what we're learning about the brain when we watch it under fMRI scanners. To quote the neuroscientist, Read Montague (the first person to look at how the brain behaves when tasting Coke and Pepsi labelled or blind): '[The brain is] ... almost perfect: it's slow,

noisy, and imprecise'. What he means is that we have evolved to do as little computation as possible when making a choice; and that we do so with as little information as possible and only 'just in time'. In this way we make choices and pursue goals effectively in what, for most of our evolutionary history has been (and still is) a resource- and time-poor environment.

In sum: we are heuristic decision makers. We may sometimes feel that we're agonising over a decision. But mostly we decide fast and effectively; with minimal use of energy and little reference to multiple attributes (Deep Blue might have beaten Gary Kasparov in their chess match-up, but Kasparov was by far the most efficient computer). We decide holistically and on the basis of summary evaluations. We do not create long lists (not even subconsciously) and then laboriously plough through them to a summative evaluation. The implications for modelling and research design are clear:

- Attribute intensive methods do not reflect the way decisions are made.
- Questions should be designed to capture the mind's summary decision heuristics.
- Focus only on brands that are relevant to a respondent.

#### ii). *The problem of habituation*

If the weighted additive model of brand choice is one of the ways in which marketing research and real people part ways, a second comes from what we now know about reinforcement learning.

Learning is a 'trial and error' process guided by evolutionary acquired brain mechanisms of which one of the most important is looking at what other people do. The sign in the mind that a particular choice has worked - whatever the choice might be, be it product, service, or brand - is pleasure; which goes with the release of 'reward' substances like dopamine. But initial success doesn't stop the learning process. What the brain does next, is to shift the reward away from the choice itself, to precursors of the choice. In other words, we start to gain more pleasure from working out how to achieve what we want, than from actually getting there. This process of reinforcing 'right' choices; and then withdrawing the reward as soon as we've learnt what works, is an irrevocable part of our natures - and here's the point: it fundamentally undermines product, service, or brand satisfaction because it constantly displaces the reward that is first felt when the right brand is chosen. In psychological terms, it's the process of habituation.

Every marketer knows that people become habituated to what's being done for them. Every marketer knows that there is literally no end to what people will come to expect. And yet, most marketers continue to focus on 'satisfaction' (or even worse, 'delight') as the key to achieving loyalty.

Fortunately, as providers of brands and services we do not have to delight people all the time. For another aspect of life which is obvious but which we overlook when we put on our marketing 'hats', is that people form long-term commitments. *The fact that a choice has become routine - boring even - does not mean that we will stop making the choice.* If it works; and if it allows us to move on and devote time and energy to other things that we really care about - then there is every chance that the original choice will survive. It becomes an automatic part of the way in which we get through daily life.

Our new understanding of the neural mechanisms behind learning, help us to understand why the narrow focus on satisfaction has led to relatively poor returns. The real challenge when it comes to selling, is two fold: first, how to be the first choice; and second, how to maintain loyalty once initial satisfaction has worn off. Paradoxically, there are two primary routes. The first is - to make it an unthinking decision precisely because it's not important; and the second is - to make it so important that it survives moments of disappointment (See Hofmeyr and Rice, 2000).

From the marketing and measurement point of view, the implications are:

- Loyalty can be had without involvement when a decision becomes a habit.
- Loyalty can also be had when high involvement leads to commitment.
- Establishing the level of involvement is therefore key to fixing loyalty metrics.

*iii). We are comparative animals and regularly experience ambivalence*

It ought to be obvious that what matters is not how highly a product, service, or brand is rated per se, but how highly it rates relative to others. It ought to be obvious therefore, that it is better for a brand to score low, but win; than for it to score high, but lose. Yet comparative modelling appears to be the exception rather than the rule. Most models are based on what I call 'straight line' thinking. In other words, they model directly from a brand's score, to its use. Even when multiple brands are included in a survey, each brand still tends to be modelled against its scores alone.

When methods include comparative metrics (See Hofmeyr and Rice, 2000; Bowman and Narayandas, 2004), it's usually the comparative metrics that account for the greatest variance.

If 'straight line' thinking is one of the aspects of our modelling approach that gets us into trouble, then a second is failing to allow people to be ambivalent. Although we are comparative animals and prefer to be able to make a choice based on a winner, the psychology of the comparative process doesn't guarantee that there will always be a winner (See Cacioppo and Berntson, 1994). Ties happen - and they should therefore be allowed in measurement.

These considerations lead to two modelling and research design principles:

- Modelling needs to be done at an individual level. It is the 'within respondent' comparison of brand scores that best predicts what people will do.
- Modelling needs to allow for ambivalence and indecision. It is a feature of people, that they may rate two or more brands equally well.

*iv). A mistaken focus on retention*

Most validation in marketing has focused on retention or recruitment. Reichheld's work in the mid- 1990's (Reichheld, 1993) helped to reinforce this and narrow the focus to retention alone. Increasingly, marketers are realising that it's unhelpful. Most changes in a brand's fortunes, both up and down, come not from people defecting from (or initiating use of) a brand, but from people 'sliding' - in other words, from increases or decreases in the level of use, *no matter what that level is* (Coyles and Cokey, 2002). Sheer use is an artificial threshold. Whether a brand be a packaged good whose use is captured in a series of purchase transactions, or a subscription service which may have to fight for a person's business with other simultaneously owned services, what matters is share of wallet.

These considerations lead to the following principle when developing marketing models:

- Sheer churn is a poor dependent variable. Point-in-time purchase probabilities; or over time 'share of wallet' are what matter as outcomes.
- Validation as 'retention/acquisition' is therefore unimpressive. The true test of a measures of brand strength, is its correlation with share of wallet.

*v). To summarise: the reasons many marketing models are poor*

Let's summarise the ways in which many of the practices and doctrines of marketing research fail to reflect what we now know about people:

- People are not exact mechanical calculators. The weighted additive model of choice, which underpins a lot of quantitative motivational analysis, does not reflect the way people make choices.
- People are comparative animals. A poorly rated 'winner', still wins. A highly rated 'loser', doesn't. Modelling therefore ought to be based on how brands rate relative to each other. 'Straight line' algorithms cannot but be weaker.

- The process of habituation dooms customer satisfaction as the basis for loyalty models. Loyalty has two foundations, namely, convenient, unthinking habit, or involvement driven commitment.
- It's not about retention or acquisition, it's about purchase propensity and share of wallet. Database research shows that it is when people change how much they are using a service or brand, that businesses gain or lose.
- Ambivalence is a fact of customer/consumer life. The comparative decision process doesn't always produce clear winners. Sometimes two or more brands may be rated equally. Modelling should accommodate that.
- It is the individual decision maker that needs to be modelled. Attribute lists should not be endless; and brand lists should zero in on the unique set of brands that are relevant to each respondent.

Let's turn now to the development of new tools. I will focus on two areas: advertising performance and attitudinal brand equity.

## Better Measurement of Advertising Performance

### *i). Ad-testing metrics: emotional engagement*

Figure 2 is a list of typical diagnostics used in advertising research. The first three fall into conventional groupings: first, there are statements about the advert itself - e.g., boring, irritating, liking, etc.; second, there are statements about whether or not the advert might create 'buzz' - e.g., sticks in the mind, will get people talking, etc.; and third, there are statements about what the advert says about the brand - e.g., conveys new information, makes the brand more interesting, etc. But the group that performs best is a group seldom seen in advertising testing - it's the fourth which has to do with the extent to which the ad successfully embeds the brand in relevant personal experience.

**Figure 2:** A list of typical advertising diagnostic questions

Attributes of the advert		
It is believable	}	Average correlation with brand impact: 0.30
It is understandable		
It is boring		
It is irritating		
It is likeable		
The advert leaves its mark and creates 'buzz'		
It sticks in the mind	}	Average correlation with brand impact: 0.31
It advert is impressive to watch		
It will get people talking		
I would talk about it		
The advert evokes the brand		
It makes me more interested in the brand	}	Average correlation with brand impact: 0.36
It tells me something new about the Brand		
The advert evokes <i>relevant personal experience</i>		
It brings to mind things I really care about	}	Average correlation with brand impact: 0.42
It brings to mind things I really enjoy		

According to InterBrand, Coca-Cola is still the most valuable brand in the world. One of the essential elements of its communications strategy for over 100 years has been the relentless repetition of imagery which embeds the brand in desirable contexts. Two examples are the association of Coke with food and with Christmas. We know from knowledge of how the mind works that repetition creates associations. My point here is that what matters are not associations which speak to the characteristics of the brand, but *associations which embed the brand in relevant personal experiences*. This is what creates emotional engagement.

How do we measure this 'fourth' dimension? Here's the question we use: 'To what extent, if at all, does the advert bring to mind things you really care about?' This is followed by an open-ended question as to what the advert evoked and which aspects of the advert did the evoking. The first part of the question gives us our measure of emotional engagement. The second gives us our diagnostics.

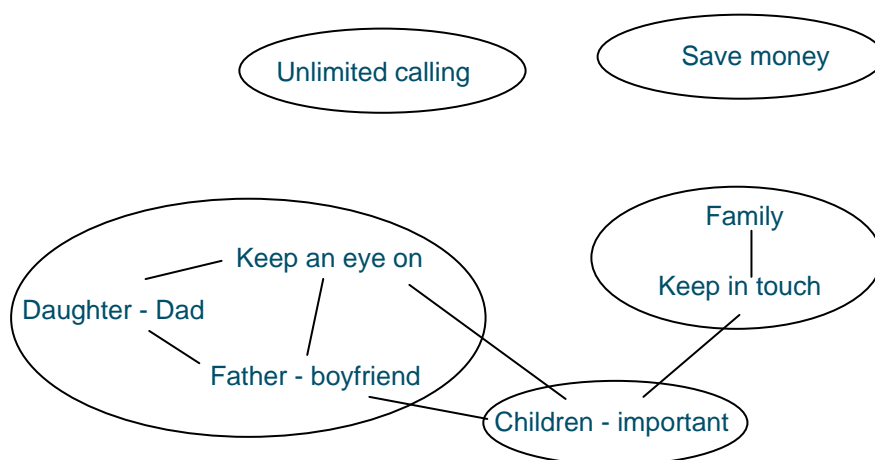
*ii). Understanding the 'why' of an advert's emotional impact: Brand Nets*

I've questioned the value of conventional attribute association when measuring the motivational aspect of brand image. I've pointed out that we make decisions heuristically; and that the fundamental drivers of our responses to brands are processed holistically and may be few in number. We also know that the brain stores information around goals, not objects; which means that the conventional 'associative network' model of how we store brand information - i.e., as a spider-web of associations with the brand at the centre - is wrong. An example may help to make this clearer: Coca-Cola (yet again)!

Coca-Cola is evoked in many ways and in many contexts. Examples include Disney and McDonald's. It may also be evoked by its association with social events; or, at work, with coffee (actually, Coke) breaks. Each evocation brings to mind different aspects of the brand - Disney (pleasure, entertainment), McDonald's (fast food, kids, messy fingers), social events (friends), and so on. The model we need, if we're to build an accurate picture of this mental network, is a web of loosely linked associations with numerous 'centres of gravity' created by different brand-use contexts. This is what I mean by a 'brand net'. Its an associative network in which contexts need not be explicitly linked.

Given that we're heuristic in nature, building a brand net is not best done through lists of attributes. It's best done using qualitative techniques: open-ended questions and text mining technology. In figure 3 I show the network of associations that was created by an advert for T-Mobile (the cell-phone service provider) - evoked when we asked the open-ended question about important things the advert had evoked. The web is built using simple correlations. Technically, it's an undirected graphical model. From our point of view, what was most important is that it was possible to cluster respondents in terms of where their 'centre of gravity' in the net, lay.

**Figure 3:** A 'brand net' for responses to what's important in the T-Mobile advert



In other words, we were able to quantify how many people were emotionally engaged by the advert; link the level of engagement to changes in brand ratings; and then to identify which aspects of the ad evoked that engagement and why.

Consider the following list of verbatims obtained by asking the conventional question: What was the main message of the advert? 'That you can have five favourite people that you can contact anytime', 'you can put anyone you want into your five favourite people', 'unlimited calls to five selected people', and so on...

Now compare that with the kinds of response we got when asking about what mattered to people: 'The ad reminded me of my daughter who is the age of the daughter in the ad, and of situations she might get into', 'this ad reminded me of my Dad who was just like that when my sisters and I were dating', 'being able to keep in touch with your kids when they're out at night', 'a parent's relationship with their children.' And so on...

The emotional power of the second set is clearly greater than that of the first.

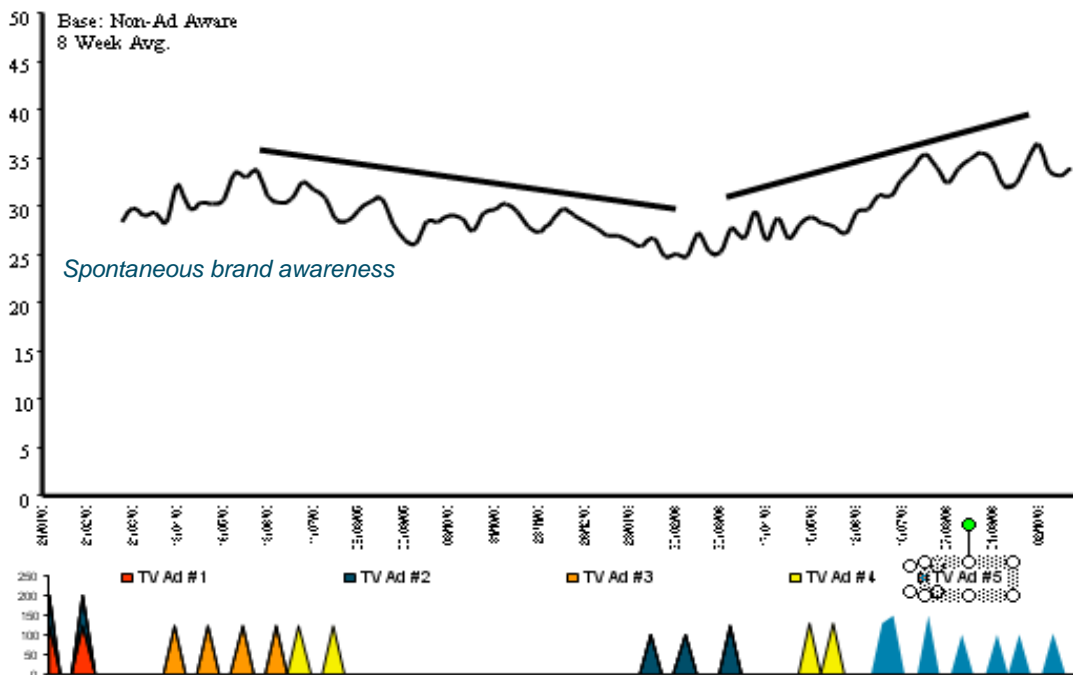
*iii). Ad-tracking: picking up unconscious/unremembered ad-impacts*

The last aspect of advertising testing and tracking on which I want to touch, is the vexed question of the fact that people do not need to remember having been exposed to an advert, for the ad to have had an impact. In the literature this will usually be referred to as the unconscious impact of the advert. I prefer the less mystical phrase 'unremembered exposure'. Given the extent of daily exposure to commercial communications, it's almost certainly true that most of what people are exposed to, is unremembered. How do we pick-up whether or not it is having an impact?

The answer is to turn conventional ad-efficiency modelling on its head: instead of analysing people who claim to have 'seen an advert recently', focus on people who cannot remember seeing anything.

Figure 4 shows the outcome of an analysis of 'spontaneous brand awareness' among people who claimed not to have seen any advertising for the brand 'recently'. Yet there is a strong relationship between GRP's and spontaneous brand awareness. After controlling for other potential causes, we were able to say with confidence that communications were having an impact without being remembered. It made a big difference to the evaluation of ad performance.

**Figure 4:** First mention brand awareness decreases with a decrease in advertising but increases when advertising is increased - among people who claim to be unaware of the advertising



*iv). Summary: improved ad testing and tracking*

A brief summary is in order:

- Responses to adverts would do better to measure the extent to which the advert successfully connects the brand to things that people care about, than to focus narrowly on aspect of the advert.
- Given what we now know about how the way the mind works, the 'associative network' view of how brand beliefs are stored, needs to be replaced with a fuzzier model which we call 'brand nets'. Open-ended questions and text mining tools are one method one can use to build such nets.
- The unconscious effects of advertising can be measured - by focusing on respondents who claim not to have seen any advertising recently, rather than on those who do.

## Better Measurement of Attitudinal Brand Equity

*i). What we see in panel behaviour*

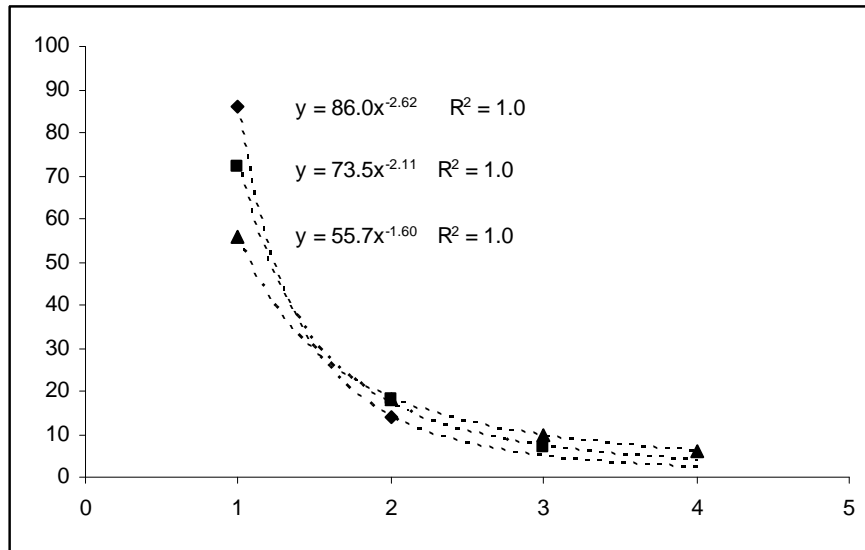
I begin with an analysis of how people actually behave over time, using the Synovate Aztec consumer panel in Australia. We'll look at two product categories, namely, instant coffee and toilet paper. Details of the sample are shown in table 3.

**Table 3**  
Household Panel Sample Statistics  
(Period: October, 2005 – March 2007 i.e. 76 weeks)

	Total Sample		Details for first ten purchases	
	Instant Coffee	Toilet Tissue	Instant Coffee	Toilet Tissue
Sample size	536	629	158	427
Number of brands	46	53	43	51
Mean repertoire size	2.4	4.3	2.9	3.6
Percent 100% loyal	40	13	22	12
Mean purchase events	7.9	16.8	10	10
Mean spend per purchase	\$8.29	\$4.97	\$7.97	\$4.94

Since our interest is in developing measures and models that predict what people actually do; and since share of wallet ought to be our focus, a useful starting point is to look at how panellists distributed their category spending across brands. I show this in figure 5.

**Figure 5:** Mean Share of Wallet (vertical axis) as a function of Brand Rank (horizontal axis)  
Organised according to brand rank and repertoire size



Three aspects of these data stand out: first, panellists distribute their spending in a category according to a power law; second, the share of wallet that each brand gets is a function of its rank in the spending 'pecking order'; and third, the exponent which best captures the equation in the relationship, varies as a function of the number of brands a person uses. When we used this information to model share of wallet among panellists in a hold out sample we got respondent level correlations of  $R = 0.96$ ; and brand level correlations of  $R = 0.98$ .

My thinking is this: *attitudinal measures of brand strength ought to produce estimates of individual propensities to spend across brands that reflect what we see in actual behaviour.*

Let's turn therefore, to the development of a new measure of respondent level attitudinal equity.

*ii). Putting these findings to use to develop valid attitudinal metrics*

The appropriate form of the power law when modelling behaviour in markets is:

$$Attitudinal\ equity_i = \frac{1}{Rank_i^s \left[ \sum_{i=1}^m \left( \frac{1}{Rank_i^s} \right) \right]}$$

**Eq. 2**

where  $i$  is the brand being scored and  $m$  is the number of brands that are relevant to the respondent. The algorithm is simplicity itself. It involves a measurement step and a calculation step.

To *measure* attitudinal equity

- Establish which brands in a product category are relevant to a respondent. Use some combination of used and considered brands for this purpose.

- Ask a brand performance and involvement question for all relevant brands. Use a minimum of a 7-point scale. We use one 10-point scale for performance and one 7-point scale for involvement.

To *calculate* attitudinal equity

- Non-considered brands get a zero.
- Use a respondent's brand performance ratings to create respondent level brand ranking as per table 4.
- Run the ranking through the power law (Eq. 2), using the mean 's' values established in the analysis of the panel data (figure 5)

**Table 4**  
Illustration of Ranking Method

	Brand <sub>1</sub>	Brand <sub>2</sub>	Brand <sub>3</sub>	Brand <sub>4</sub>	Brand <sub>5</sub>
Ratings	17	16	15	14	13
Ranking	1	2	3	4	5
Ratings	17	16	16	15	14
Ranking	1	2.5	2.5	4	5
Ratings	17	13	13	13	8
Ranking	1	3	3	3	5
Ratings	15	15	14	13	12
Ranking	1.5	1.5	3	4	5

Note: The algorithm incorporates 'brand involvement' into the base brand score. Ranking turns the ratings into a set of comparative measures. Allowing ties captures ambivalence.

Note that the algorithm incorporates the principle of brand involvement in the measurement, and that it incorporates the principle of comparative ratings through the ranking mechanism. Finally, note that it recognises the presence of ambivalence by allowing ties. It is therefore true to what we know from cognitive psychology; and replicates what we see in panel data.

The result is a set of estimated purchase propensities for every brand for every respondent (See table 5). It is a method of predicting how likely a person will be to buy a brand in a product category - and it predicts the purchase likelihood, not just for one brand, but for all of them, no matter how many, by identifying those that are in each respondent's choice set.

**Table 5**  
An illustration of a hypothetical data-set

		Brand <sub>1</sub>	Brand <sub>2</sub>	Brand <sub>3</sub>	Brand <sub>4</sub>	...	Brand <sub>i</sub>
Respondent <sub>1</sub>	Attitudinal equity	0.83	0.17	0.00	0.00	...	
	Claimed share	70	30	0	0	...	0
Respondent <sub>2</sub>	Attitudinal equity	0.11	0.68	0.21	0.00	...	0.00
	Claimed share	20	50	30	0	...	0
Respondent <sub>3</sub>	Attitudinal equity	0.00	0.83	0.00	0.17	...	0.00
	Claimed share	0	80	0	20	...	0
Respondent <sub>4</sub>	Attitudinal equity			0.14	0.14	...	0.68
	Claimed share	0	0	30	30	...	40
...	...	...	...	...	...	...	...
Respondent <sub>i</sub>	Attitudinal equity	0.11	0.00	0.11	0.22	...	0.56
	Claimed share	10	0	10	20	...	60

In table 6 we show how strongly the results correlate with claimed share of wallet across numerous product categories and countries. These results for what I call 'within survey' validation are significantly better than anything reported by Szymanski and Henard (2001) (Compare their correlations: R = 0.52, R = 0.57; with ours: Respondent level = 0.77; brand level = 0.72).

**Table 6**  
'Within survey' correlations between attitudinal equity and share of wallet

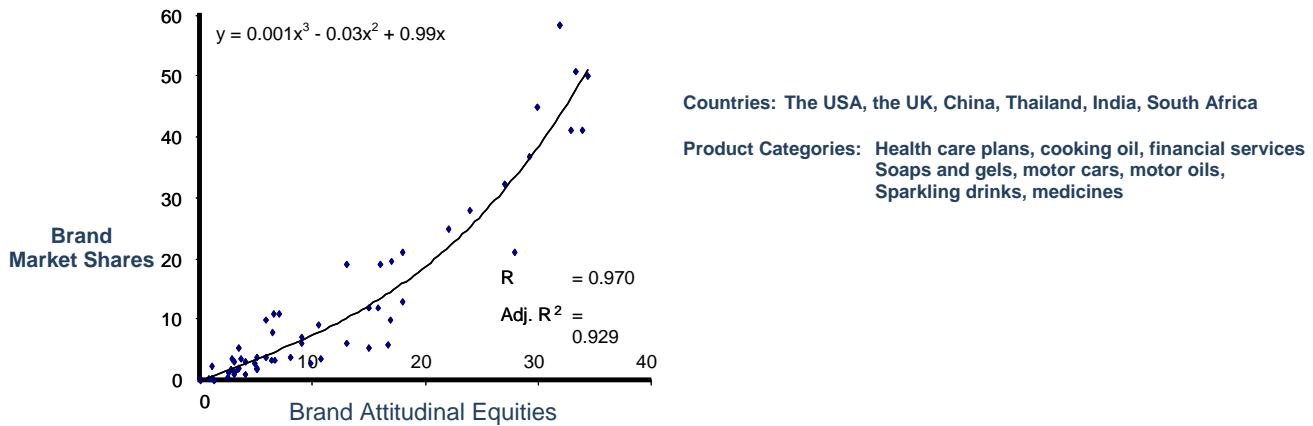
	Test Surveys							Ttls/Mns
	Beverages		Banks		T'paste	Laundry	QSR's	
	USA	UK	UK	Aus	USA	UK	Greece	
Sample	815	880	538	3004	871	898	773	9 583
Total brands	163	83	25	14	10	9	60	321
Brand rated	9.0	10.2	3.1	2.8	2.7	3.5	4.2	5.1
Respondent 'R'	0.68	0.71	0.74	0.79	0.87	0.85	0.75	0.77
Brand 'R'	0.67	0.66	0.66	0.74	0.82	0.77	0.72	0.72

- Notes:
- Respondent 'R': Imagine two rows. The top row is respondent attitudinal equities laid end to end. The bottom row is respondent share of wallet. 'R' is the correlation between the two.
  - Brand 'R': Imagine a column of the attitudinal equities a brand gets from each respondent. The second column is the share of wallet the brand gets. Brand 'R' is the correlation between the two, averaged over all brands in the study. The correlation is the average for all brands in each study, except for USA beverages where it is limited to the top sixty brands.
  - 'Ttls/Mns' refers to 'totals' or 'means', depending on which is appropriate

iii). Validation: performance against real-world market shares and diary panel data

Although what I've called 'within survey validation' is common, we need external validation to make a stronger claim. I show two such validations. The first (See figure 6) looks at the relationship between attitudinal equity as established in surveys and market share as established independently using industry sources or panel data.

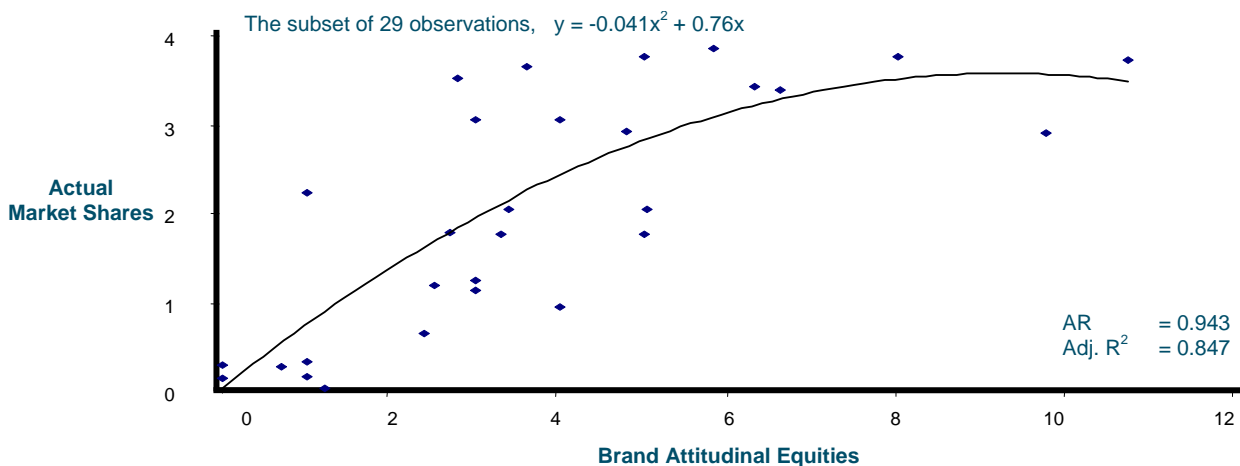
**Figure 6:** The relationship between attitudinal equity and market share (All brands - 99 observations)



The relationship has a cubic shape. This means that brands go through an initial phase during which increases in attitudinal equity are not rewarded by similar gains in market share. Eventually, however, a kind of 'tipping point' is reached where market share gains accrue faster than attitudinal equity. The results are consistent with the idea of 'double jeopardy' (Ehrenburg and Uncles, 1995); i.e., that bigger brands score better on all brand health metrics. What drives the upward slope of the curve is the way increasing brand demand leads marketers to devote increased channel resources to a brand; and customers and consumers to accept default use of dominant brands. Eventually, the most desired brands (attitudinal equity) crowd out those that are less desired because of the way marketers direct marketing resources to them.

Because the strength of the correlation is driven by the big brands, I also show the shape of the relationship among small brands (See figure 7).

**Figure 7:** The relationship between attitudinal equity and market share (Smaller brands - market share < 5%)



The correlation is remarkable considering the normal variability one would expect to see in sample data. Note that these correlations include multiple product categories and countries; e.g., motor manufacturers. A universal cubic equation fits all.

The second validation comes from a study of medical prescriptions using diary panel data. Synovate Healthcare (UK) has created a panel of medical practitioners who record their prescriptions in a diary. We fielded a brand equity study among the panel in May 2007. There are two ways of looking at the data; i.e., in terms of individual propensities to distribute prescriptions across brands (respondent level); and in terms of the resulting share of prescriptions that each brand gets (brand level). The results are in table 7.

**Table 7**  
Correlations between attitudinal equity and diary panel share of prescriptions

	Respondent 'R'	Brand 'R'
Sample	70	70
Observations	350	350
Diary Panel Correlations		
Mean 'R'	0.69	0.47
Mean 'R <sup>2</sup> '	0.48	0.22
Correlation: Barrier Effects		
Mean 'R'	0.82	0.54
Mean 'R <sup>2</sup> '	0.67	0.29
Claimed Share Correlations		
Mean 'R'	0.75	0.70
Mean 'R <sup>2</sup> '	0.56	0.49

Notes: 1. Respondent 'R' and Brand 'R' refer to the same kind of correlation as for the surveys reported in table 6.

I report on three sets of panel results:

- Correlation of attitudinal equity with diary panel data: the most appropriate comparison for these results is with the data in tables 1 and 2. Our simple measure of attitudinal equity easily outperforms purchase intention and satisfaction.
- Correlation when what I call 'barrier effects' are included: we included a survey measure of the extent to which practitioners were unable to prescribe what they wanted to, because, for example, medical insurance may force the use of certain brands. When this measure is included, the correlations rise very substantially.
- Correlation of attitudinal equity with claimed share: the most appropriate comparison for these results is with those reported by Szymanski and Henard. Attitudinal equity easily outperforms conventional approaches.

*iv). Predicting 'sliding', not just defection/recruitment*

I've noted above that simple retention-defection models are no longer adequate. In a past working life, I developed such a model (the Conversion Model). Many of its reported validations show that estimated levels of brand commitment correlate with the likelihood of brand users defecting; and the likelihood of non-users starting to use a brand. But what is not shown, is its ability to predict the likelihood that users may increase use in the future; or that they may decrease use but not defect.

The measure of attitudinal equity I've presented in this paper takes, as its purpose, to provide an attitudinal, survey based measure of brand strength which links strongly to real purchase propensities and share of wallet. The correlations I've shown demonstrate that it does. But there is another challenge - and that's the challenge of providing a metric that's forward looking, in other words, that predicts what I've

referred to above as 'sliding'. While I have seen many retention models - some good, some not so good - I have not yet seen a strong model of the likelihood that someone will increase or decrease their use of a brand in the future *no matter what its current level*. This is a much more challenging task.

A simple method is to create what I call an *attitudinal equity gap*. This is the gap between what a person wants to do - measured by attitudinal equity; and what they claim currently to be doing - measured, for example, by a 'last 10 brands' question. In the case of single-brand purchases (e.g., motor cars), simply assign a value of 100 to current share of wallet.

The algorithm is:

$$\text{Attitudinal Equity Gap} = \text{Attitudinal Equity} - \text{Claimed Share of Wallet} \quad \text{Eq. 3}$$

In table 8 I report the results of two longitudinal projects, namely, laundry detergents in Spain and toothpaste in the United States. Respondents were surveyed in September 2006 using Synovate's ViewsNet internet panel. Six months later they were re-contacted and surveyed again. To measure brand share of wallet we asked respondents to answer a question about 'the last 10 brands bought' in both surveys. We then regressed the attitudinal equity gap established for each respondent for each brand in the first survey, against changes in each brand's share of wallet across the two surveys.

**Table 8**  
Correlations between attitudinal equity gap and changes in share of wallet

	Toothpaste	Detergent	Totals/Means
Sample	158	290	448
Observations	1783	4004	5787
Correlations: R	0.78	0.60	0.69
Adjusted R <sup>2</sup>	0.59	0.32	0.46

The average correlation is R = 0.60, Adjusted R<sup>2</sup> = 0.32 for laundry detergent in Spain; and R = 0.78, Adjusted R<sup>2</sup> = 0.59 for toothpaste in the USA. To my knowledge, there is no other attitudinal measure in our industry which successfully predicts 'sliding' - i.e., changes in share of wallet - going forward.

v). *Summary: improved brand strength measurement*

A brief summary is in order:

- I've shown that a measure of attitudinal equity based on two questions (brand performance, brand involvement) and asked only for the subset of brands that are relevant to a respondent, outperforms most reported loyalty metrics
- The algorithm is based on a power law (Zipf distribution) and produces predictions about how a respondent will distribute their category spending across brands. I have shown multiple validations:
  - 'Within survey' share of wallet: the measure achieves very high respondent level correlations with claimed share of wallet in surveys.
  - Diary panel data: the measure improves on other reported loyalty measures when correlated with the diary record of medical prescriptions.
  - Changes in share of wallet: it is the only measure of which we're aware that successfully predicts likely changes in share of wallet over time

## The Conservatism of our Industry

Ours is a knowledge-based industry. We call ourselves 'researchers'. It is a characteristic of researchers that we should be subjecting our theories and methods to constant improvement. In many respects we are. Yet there can be few knowledge-based industries which are as afraid of change as ours. I've benefited from this conservatism. I summarise it as follows: it is the fear of changing dashboard metrics used in tracking - whether that tracking be punctuated or continuous.

Put another way: it is the fear of changing squiggly lines on a chart

I have both benefited and been frustrated by this conservatism: benefited in that we've maintained business relationships long after we could have lost them; and frustrated in that I've struggled to get my own colleagues to accept improved metrics. What are the reasons? Let me suggest the following short list.

- The switch causes a temporary disjunction in market information, particularly when it involves a change of supplier and the new supplier cannot provide transition metrics which run the 'old' and 'new' in parallel.
- People prefer to stick with known metrics that perform poorly, particularly if they understand the weaknesses of those metrics. To quote a colleague: 'I know purchase intention is poor, but at least I know how poor.'
- Marketing researchers don't want to have to make the effort of understanding or of explaining the change to their internal clients. Internal clients (e.g., corporate CEO's) can't be bothered to understand new charts
- A tendency in our own companies to put *revenue* before *truth*. It takes time, in companies, to get new ideas accepted, particularly when they challenge currently successful lines of business. Often, better ideas will not even be given a hearing.

I am sympathetic to the first reason, somewhat sympathetic to the second; and wholly unsympathetic to the third and fourth. If I thought that the burden of explanation fell on the first reason, I might be sympathetic overall. But I've too often been confronted by a refusal to change *even when a valid transition process can be mapped out*.

The first company in the world to appoint a director of marketing research was General Motors in the 1930's. That appointment was deemed so significant that that person appeared on the front cover of Time magazine. Given the current standing of our practice, it is hard to imagine that a marketing researcher would make the front cover of Time again. Put simply: we have allowed ourselves to settle into conventional theories and practices which have led to a slow and inexorable decline in the value our clients assign to our numbers. As corroboration, I note the extent to which many of the interesting and significant contributions to our practice are made by outsiders; e.g., at the moment, neuroscientists and mathematical modellers running large-scale computer experiments.

I don't think we will ever become a true, knowledge based industry without a change of culture. Three changes, in particular, are needed:

- An understanding among both clients and suppliers that knowledge 'marches on'; and a willingness to accept that key numbers may be subject to constant change.
- At a corporate level: a commitment to the development of corporate processes which allow for the smooth transition of old lines of business to the new.
- At an individual level: a willingness to make the effort to understand difficult metric systems; and a desire to be at the forefront of knowledge development.

I have lost count of the number of times I've been told by both colleagues and clients that 'that chart is too difficult'. Engineers never say 'that drawing is impossible to understand.' Accountants never complain about how difficult it is to read balance sheets (except when genuine deception is involved). Lawyers don't complain about having to work through decades of case history. Let's have a little more courage and a lot more commitment to truth.

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