A new measure of brand attitudinal equity based on the Zipf distribution

Jan Hofmeyr, Victoria Goodall and **Martin Bongers**
Synovate's Brand and Communications Practice
Paul Holtzman
Synovate's Statistical and Modeling Services

In this paper the authors present a parsimonious measure of attitudinal equity for all brands in a survey at respondent level. Their purpose is to provide marketing researchers with a survey-based measure of brand strength that is attitudinally pure and can therefore be used with confidence for modelling purposes. The authors validate the measure against typical 'within survey' metrics, but also against individual behaviour as established in diary and scanner panels. In both cases, they show that the measure correlates strongly with the way that each person in the survey distributes her/his share of wallet across brands in a category. The measure outperforms other attitudinal indicators of brand strength both in terms of 'within survey' validation and in terms of ex-survey panel data.

Introduction

The logic of much brand loyalty research can be described quite simply:

- Define a survey measure of brand strength that can be used as a dependent variable against which to model.
- Define further measures representing factors such as marketing initiatives, touchpoint experiences or brand characteristics that may impact on brand strength.
- Explore models to quantify the link between brand strength (as defined) and its potential causal factors.
- Derive strategic implications for brand management.

Received (in revised form): 17 September 2007

Our purpose in this paper is to offer a new measure of *attitudinal brand strength* for use as a dependent variable in survey questionnaires. Based on the Zipf distribution, it takes little space in a questionnaire, but predicts share-of-wallet behaviour at respondent level for all brands in a survey. We validate the measure at respondent level against both survey and panel data across multiple product categories and countries.

Our approach insists on respondent-level prediction because aggregate models of brand share may correlate strongly with real-world market share but be wrong about individual respondents (when respondent-level errors offset each other). From the marketer's point of view, this is problematic – particularly if respondents need to be profiled.

Preliminary conceptual issues

Brand loyalty, share of wallet, purchase probability

In the classic definition of brand loyalty (Jacoby & Kyner 1973), a person is defined as loyal if they use a brand repeatedly because they are strongly attached to it. In other words, true brand loyalty is 'high share of wallet' underpinned by attitudinal preference.

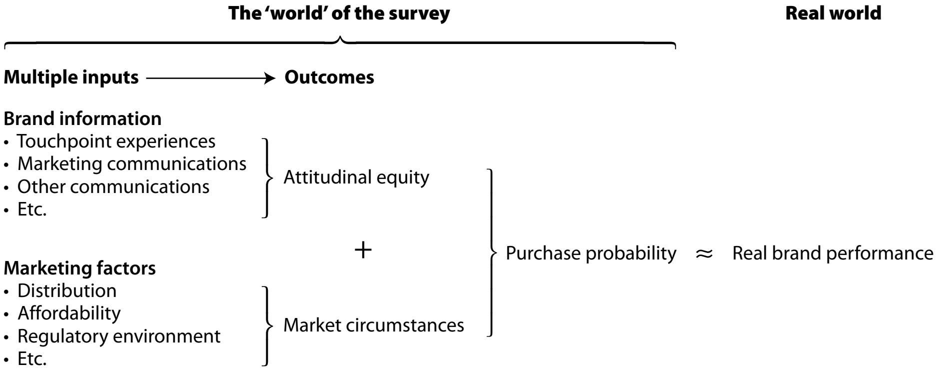
The classic definition recognises that market circumstances may interfere with what people use or buy. It therefore recognises that loyalty requires a combination of preferences that drive it, with circumstances that permit it. What people actually use or buy is the outcome of these two factors.

Scanner panel data show that few consumers are habitual brand switchers (McQueen *et al.* 1993), but they also show that sustained loyal behaviour is rare (DuWors & Haines 1990). A summary would be that people appear to drift through states of relative behavioural loyalty, shifting over time from brand to brand. For this to be the case, what we see in transactional data must be the outcome of a series of underlying and fluctuating purchase probabilities. In any particular time period, therefore, the share of wallet that a brand gets is the average of the underlying purchase probabilities, and the probability associated with buying a brand at the beginning of the period may be substantially different from its probability at the end. For this reason we make a conceptual distinction between over-time share of wallet and point-in-time purchase probabilities. If loyalty is about maintaining a high share of wallet, then it is about maintaining point-in-time purchase probabilities at a high level.

From the attitudinal point of view, the challenge to marketers can be formulated in the following question: 'What must be done to create attitudinal preferences for a brand that drive a sustained, high purchase probability?'

The challenge to marketing researchers therefore, is twofold:

1. to provide a measure of attitudinal equity that correlates strongly with individual purchase behaviour
2. to embed the measure within a schema that enables marketers to work out how to achieve the required level of attitudinal equity (see Figure 1).



Note: Our purpose in this paper is to provide a valid, parsimonious measure of attitudinal equity, which nevertheless links to real-world brand performance.

Figure 1 A summary schema of our framework

An important aspect of the schema is the separation of the dependent variables for modelling, into attitudinal and behavioural components. This is because marketers can only know what's driving the strength of the desire to use or buy their brands if they have an attitudinally pure outcome against which to model. The measure of attitudinal equity aims to provide such an outcome and is the focus of this paper.

Why 'loyalty' isn't about retention or acquisition

Although household panel data allow us to see the results of potentially fluctuating probabilities in individual transaction streams, we're seldom in a position at each transaction to measure the probabilities or the attitudes behind them. Marketers therefore field attitudinal surveys through which they attempt to identify the factors that underpin visible sales. A great many models of attitudinal loyalty have been proposed to serve this purpose. Most tend to be validated within the system of survey measurement because of the difficulty of collecting attitudinal and behaviour data from a single source. When real behaviour is available (e.g. in databases or through longitudinal surveys), loyalty analysis tends to focus on retention or acquisition. The logic runs: establish which brand(s) a person is using at time, t_0; measure the strength of that person's attachment to all services or brands at that time; follow the person up at t_1 (i.e. after a lapse of time); establish which service(s)/brand(s) they are using and derive defection/recruitment rates. If defections/acquisitions are higher, the lower/higher the levels of attachment at t_0, then we appear to have a valid and predictive model. But the question is: predictive of what?

The answer is: predictive of just one kind of change – namely, a 'user/non-user' change. This is very limited in scope. It ignores, for instance, poorly committed, low-share users who improve their relationship instead of defecting, or highly committed users whose commitment, and therefore use, slips. In fact, database analysis has shown that business gains or losses have more to do with the extent to which people increase or decrease their use/buying of a brand than it has to do with outright defection or recruitment (Coyles & Gokey 2002). 'Retention/acquisition' approaches therefore ignore the kinds of share change that are responsible for most of a brand's underlying gains and losses.

In common with others (e.g. Perkins-Munn *et al.* 2005), we take the view that what matters is share of wallet, not retention/acquisition. As Perkins-Munn *et al.* note, while the standard 'chain of effects' model runs as follows: attribute performance → satisfaction → *retention* → profits; research suggests it should run: attribute performance → satisfaction → *share of wallet* → profits. As per Figure 1, therefore, our purpose in this paper is to present a survey-based measure that we call 'attitudinal equity', which can be used instead of the 'satisfaction' (or any other) term. As we will show, it easily outperforms reported 'chain of effects' models, no matter what the attitudinal term.

A brief review of recent share-of-wallet literature

Overview: characteristics of share-of-wallet research

In Table 1 we summarise recent share-of-wallet literature according to the following characteristics.

Table 1 A summary: the prediction of share of wallet

Author(s)	Product categories	Dependent variable	Brand(s)	Best attitude	Items	Results
De Wulf *et al.* (2001)	Retailers (food and apparel): multi-country	Current SoW: claimed in survey (within-survey)	One per respondent	Relationship quality	9	Modelled SoW bands. Best-performing attitude: $R = 0.36$
Verhoef & Franses (2003)	Financial services: one category, one country	Change in SoW: database and claimed at t_0 and t_1	Target brand only	Stated preference t_0	10+	Attitude correlations not reported. Attitudinal prediction very poor
Verhoef (2003)	Financial services: one category, one country	Change in SoW: database and claimed at t_0 and t_1	Target brand only	Affective commitment t_0	3	Total model: $R = 0.36$. Attitude correlations not reported
Keiningham *et al.* (2003)	B-to-B banking: one product category	Mean SoW (12 months): database for all brands (concurrent)	Target brand only	Overall satisfaction	1	Cubic regression model using 'overall satisfaction': $R = 0.33$
Bowman & Narayandas (2004)	B-to-B processed metal supplier: one category	Current SoW: claimed in survey (within-survey)	Target brand only	Competitor satisfaction	1	Total model: size of effects only; no R Attributes: size of effects only; no R
Baumann *et al.* (2005)	Retail banking: four categories, one country	Current SoW: claimed in survey (within-survey)	Target brand only	Varies for each model	2–5	Models for 'dissatisfied' only: Mn R = 0.50. Attitudes marginally significant.
Perkins-Munn *et al.* (2005)	Class 8 trucks: one category, two countries	Current SoW: 3rd party database aggregator, post-survey	One per respondent	Repurchase likelihood	1	No total model. Best-performing attitude: $R = 0.47$
Perkins-Munn *et al.* (2005)	Prescriptions: one category, one country	Current SoW: claimed in survey (within-survey)	One per respondent	Overall efficacy	5	No total model. Best-performing attitude: $R = 0.46$
Gustaffson *et al.* (2005)	Swedish telecoms: one category, one country	Months not a customer: database (behaviour post-survey)	Target brand only	Calculative commitment	3	Total model: $R = 0.76$. Best-performing attitude: $R = 0.15$
Cooil *et al.* (2007)	Retail banking: one category, one country	Change in SoW: claimed in survey at t_{1-1} and t_1	Up to three brands	Customer satisfaction t_{-1}	3	Contribution of attitudinal measure significant, but 'modest'
Wirtz *et al.* (2007)	Credit cards	Current SoW: claimed in survey (within-survey)	Target brand only	Attitudinal loyalty	3	No total model. Best-performing attitude: $R = 0.61$

- Categories: what product categories and how many data sets are involved?
- Dependent variable: how is share of wallet measured?
- Brands: does the model predict for one brand or for multiple brands?
- Attitude: which attitudinal measure performs best?
- Items: how many items are used to measure the best-performing attitude?
- Results: how well do both the total model and the relevant attitude perform?

Note that the two Verhoef studies (Verhoef 2003; Verhoef & Frances 2003) are based on the same data, but report different analytic approaches. In some respects, therefore (e.g. when summarising measures of share of wallet), we treat them as one. By contrast, the Perkins-Munn *et al.* study (2005) incorporates two data sets with different measurement methods, but identical modelling procedures. We therefore count it as two instances of share-of-wallet measurement.

- *Product categories:* as is typical of most contemporary loyalty studies, all the product categories involve services. Packaged goods models aren't reported.
- *Share-of-wallet measurement:* six of ten studies measure share of wallet as claimed in a survey. The two Verhoef studies report only one instance of share-of-wallet measurement, in which stated share of wallet is combined with what's found in a database. Three use behaviour as seen in databases supplied by database aggregators. Eight of eleven models attempt to predict share of wallet (including all three of the database studies). Three attempt models of change in share of wallet. The largest number (five) attempt models of 'within survey' share of wallet.
- *Attitudes and items:* there is no consistency with respect to the best-performing attitudes although most (eight of the eleven) find that some form of classical loyalty measure (commitment, satisfaction, purchase intention) performs best. Most studies measure the best-performing attitude with multi-item scales.
- *Brands:* ten of the eleven studies present a model of share of wallet *for just one brand per respondent*. The only exception is Cooil *et al.* (2007), who model for up to three brands per respondent. One of the reasons for the failure to model all brands for all respondents is probably the fact that most are based on multi-item measures of

attitude. Consider, for example, Verhoef and Franses (2003): their measure of stated brand preference requires in excess of ten items. In practice it would not be feasible to implement this measure if one wanted to model multiple brands at respondent level.

- *In summary:* almost all studies model for one brand per respondent, and the majority use within-survey measures of share. Most model from a mixture of behavioural and attitudinal variables, and most use multi-item measures of attitude. Most model average share of wallet, either as claimed or as in a database. Only one attempts validation across multiple data sets (De Wulf *et al*. 2001).

Results: measure and model performance

The studies referenced in Table 1 use various modelling procedures. Most, however, involve some form of regression (linear, multiple, logistic or latent class). De Wulf *et al*. (2001) use structural equation modelling, but report item correlations. The performance of attitudinal measures is generally poor. In some instances (e.g. Baumann *et al*. 2005), they fail completely.

The average correlation between an attitudinal measure and *within-survey share of wallet* is: $R = 0.40$ (four studies, eight data sets). The best-performing measure across all these studies is 'attitudinal loyalty' ($R = 0.61$), as measured by Wirtz *et al*. (2007) using three items per brand and modelling for only one brand per respondent.

The average correlation between an attitudinal indicator and *share of wallet as measured in databases* is: $R = 0.32$ (three studies). The best-performing indicator is 'repurchase intention' ($R = 0.47$), as measured by Perkins-Munn *et al*. (2005).

In all cases where the independent variables include a mix of behavioural and attitudinal variables, the behavioural variables easily outperform the attitudinal variables (e.g. Verhoef 2003; Baumann *et al*. 2005; Gustaffson *et al*. 2005). Still, even the performance of the combined models tends to be quite poor.

The development of a new measure of attitudinal equity

What is the Zipf distribution?

The Zipf distribution (or power law) specifies a mathematical relationship between the rank of a phenomenon and its frequency or size. In Zipf's original example, the relationship was found for the frequency of English words in a text as a function of their rank. The most frequently occurring word was 'the'. It occurred just about twice as often as the next most frequently occurring word, 'of', which, in turn, occurred about twice as often as the fourth-ranking word; and so on. Mathematically:

$$f(k;s,N) = \frac{1/k^s}{\sum_{n=1}^{N} 1/n^s} \tag{1}$$

where N is the number of ranks, k is each observation's rank, and s is the exponent characterising the distribution. The ranking criterion is usually the frequency or size of each observation.

Approximations to power laws were noted some time before Zipf, the first being a note on the frequency with which digits occur in natural numbers (Newcomb 1881). The first note on city sizes appeared in German (Auerbach 1913), while the first note on word distributions appeared in French (Estoup 1916). In the 1990s, the pace quickened with the increasing interest in non-linear approaches to describing natural phenomena (see www.nslij-genetics.org/wli/zipf).

We have found two papers about power laws in markets (Riemer *et al.* 2002; Kohli & Sah 2004). Kohli and Sah show that brand market shares conform to a power law, with market shares as the ranking criterion. They also show that the relationship between a brand's rank and its market share is robust under varying definitions of what constitutes the market. Finally, they show that a power law fits the data better than an exponential distribution and that it is consistent with Ehrenberg's work, using the Dirichlet distribution (see Ehrenberg & Uncles 1995).

There appear to be no papers that apply power laws to attitudinal survey data – whether modelled at respondent level or in aggregate.

When applied to survey data in order to specify the likelihood that a person will use or buy a brand, the appropriate form of the law is:

$$\text{Attitudinal equity}_j = \frac{1}{\text{Rank}_i^s \left[\sum_{j=1}^{m} \left(\frac{1}{\text{Rank}_j^s} \right) \right]} \tag{2}$$

where j is the brand being scored and m is the number of brands that are relevant to that person. The output is a set of estimates of that person's point-in-time attitudinal equities, one for each brand. The estimates sum to 1 at respondent level. Although these are point-in-time estimates, they should correlate with share-of-wallet behaviour as estimated during or at the same time.

We turn now to the development of the measure.

Method: questionnaire and surveys

To develop the measure, we fielded two development surveys. To validate and test its universality, we fielded seven further surveys in multiple countries and product categories, using Synovate's ViewsNet access panels (see Table 2 for survey statistics).

To establish the set *m* of relevant brands for each respondent, we ask two questions: first, which brands are currently used and, second, which brands would be considered if all of the currently used brands were unavailable. To measure attitudinal equity we ask just one question (i.e. an *overall brand performance* question for each brand that is relevant to a respondent). For modelling and development purposes, we ask respondents to estimate the share of wallet that they give to each brand, using a constant sum question (see Appendix 1 for questionnaire details).

An important aim is for the measurement of attitudinal equity to be as parsimonious as possible. Apart from the fact that this is in line with good practice (Occam's razor), it has also become imperative in the world of the practitioner. Marketing researchers face a pressure to combine comprehensive measurement (i.e. measurement that includes all

Table 2 Details of all surveys conducted for this research

	Development		Testing							
	Toothpaste	Laundry	Beverages		Banks		Toothpaste	Laundry	QSRs	Total/
	UK	Spain	US	UK	UK	Australia	US	UK	Greece	mean
Sample	901	903	815	880	538	3004	871	898	773	9,583
Total brands	17	11	163	83	25	14	10	9	60	321
Mean repertoire size	2.0	2.0	8.0	9.2	1.8	1.7	1.5	2.0	3.0	3.5
Mean brands rated	3.7	3.7	9.0	10.2	3.1	2.8	2.7	3.5	4.2	5.1

Note: Each respondent rated brands they claimed to use regularly or would consider using if their current brands were unavailable; note that, with the exception of the beverages studies, respondents rated 60%+ more brands than they claimed to use.
QSR stands for Quick Service Restaurants.

potentially relevant factors) with the need to keep questionnaires short. The latter need is driven by both decreasing respondent cooperation and the need to lower survey costs. Although there is an academic tendency to insist on multi-item scales, we take advantage of the recently published work of Bergkvist and Rossiter (2007), which suggests that single-item scales are as good as multi-item scales.

It can be seen from Table 2 that each respondent rated 5.1 brands on average. Our measurement system therefore involves an average of about seven measurement items per respondent (i.e. brand use, brands considered, performance rating for all relevant brands). This gives us the ability to model share of wallet for *all brands* in a survey *at respondent level* in contrast to the approaches we've reviewed that are restricted to modelling a *target brand only*, and mostly require a minimum of three measurement items.

Developing the algorithm

There are two steps to developing the algorithm. First, we need to turn the brand ratings into respondent-level brand rankings; second, we need to estimate values for the parameter s in equation (2). Table 3 illustrates the ranking method. By ranking and allowing ties, we preserve two important principles of attitudinal brand commitment – namely, that people may be ambivalent about which brands they prefer (Hofmeyr & Rice 2000); and, second, that the performance of a brand relative to its competitors counts for more than its absolute rating (e.g. Bowman & Narayandas 2004).

To optimise s we plug brand rankings into equation (2) and use the 'solver' function in Excel. Since there should be an association between a brand's attitudinal equity and the likelihood that a person will use or buy

Table 3 Illustration of ranking method

	Brand$_1$	**Brand$_2$**	**Brand$_3$**	**Brand$_4$**	**Brand$_5$**
Ratings	10	9	8	7	6
Ranking	1	2	3	4	5
Ratings	10	9	9	7	6
Ranking	1	2.5	2.5	4	5
Ratings	10	6	6	6	3
Ranking	1	3	3	3	5
Ratings	8	8	7	6	5
Ranking	1.5	1.5	3	4	5

a brand, we use claimed share of wallet as the dependent variable. We show the results in Table 4.

Table 4 Optimising the exponent *s* using the development studies

	Observations		Optimal *s*		Correlation		
Brands rated	UK	Spain	UK	Spain	UK	Spain	Mean *s*
One	26	21	n/a	n/a	1.00	1.00	n/a
Two	129	109	2.60	2.06	0.87	0.87	2.33
Three	115	104	1.79	1.59	0.84	0.86	1.69
Four	67	90	1.33	1.30	0.78	0.80	1.32
Five +	124	116	1.15	0.61	0.73	0.63	0.88

Notes:
(1) We estimate the optimal value for the exponent *s* as a function of number of brands rated (i.e. as a function of the number of brands in the consideration set).
(2) There is a consistent pattern of declining *s*; this means that the size of the attitudinal equity gap between brands decreases as the number of brands rated increases; put another way, the more brands in a consideration set, the less likely it becomes that 'the winner takes all'.
(3) The mean *s* is the universal values we carry forward when testing the algorithm in other countries and product categories.

Notice that optimal values for *s* follow a neatly declining trend as the number of brands rated by a respondent increases. This allows us to calculate a mean value for *s* to be used in all further studies. The resulting universal algorithm for 'attitudinal equity' then has two steps: a measurement step and a calculation step.

1. 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 an overall brand performance rating question for all relevant brands; use a minimum of a 7-point scale (we use a 10-point scale).

2. To *calculate* attitudinal equity:
   - Non-considered brands get a zero.
   - Use a respondent's brand performance ratings to create a respondent-level brand ranking as per Table 3.
   - Run the ranking through the power law (equation (2)), using the mean *s* values established in the development studies as per Table 4.

The result is an estimate of the attitudinal equity that each brand has for each respondent, across all brands. In other words, it's a measure of the strength of the purely attitudinal desire of each respondent to use or buy each brand. We illustrate a typical set of outputs in Table 5. It is this measure that we advocate as a substitute for 'satisfaction' (and other loyalty metrics such as 'purchase intention') in chain-of-effects models.

Table 5 An illustration of a hypothetical data set

		$Brand_1$	$Brand_2$	$Brand_3$	$Brand_4$		$Brand_j$
$Respondent_1$	Attitudinal equity	0.83	0.17	0.00	0.00	…	
	Claimed share	70	30	0	0	…	0
$Respondent_2$	Attitudinal equity	0.11	0.68	0.21	0.00	…	0.00
	Claimed share	20	50	30	0	…	0
$Respondent_3$	Attitudinal equity	0.00	0.83	0.00	0.17	…	0.00
	Claimed share	0	80	0	20	…	0
$Respondent_4$	Attitudinal equity			0.14	0.14	…	0.68
	Claimed share	0	0	30	30	…	40
	…	…	…	…	…	…	…
$Respondent_i$	Attitudinal equity	0.11	0.00	0.11	0.22	…	0.56
	Claimed share	10	0	10	20	…	60

Predicting each respondent's share of wallet as a function of attitudinal equity

Predicting brand share at respondent and market level as a function of attitudinal equity

Validation against both claimed share and real-world brand metrics

Within-survey validation against claimed share

To test the algorithm, we turn to the seven validation studies. Two kinds of validation are relevant: first, the algorithm should produce a prediction about how each respondent is likely to distribute their share of wallet across all the brands in a study. Second, the algorithm should produce predictions about the share of wallet each brand can expect to get from each respondent. In other words, with reference to Table 5, we need to validate across rows (for respondents) and down columns (for brands). We report the results of such validation in Table 6.

The average correlation across respondents is $R = 0.77$, $R^2 = 0.59$; and, within brands, $R = 0.72$, $R^2 = 0.52$. This is for 218 brands and more than 9,000 respondents in four countries and five product categories. It is markedly better than what is typically found for 'within-survey' measures

Table 6 Validation: correlations between attitudinal equity and claimed share of wallet

	Validation surveys							
	Beverages		Banks		Toothpaste	Laundry	QSRs	Total/ mean
	USA	UK	UK	Australia	US	UK	Greece	
Sample	815	880	538	3,004	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:
(1) 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
(2) 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 US beverages, where it is limited to the top 60 brands.
QSR stands for Quick Service Restaurants.

of attitudinal brand strength – for example, the American Customer Satisfaction Index (Fornell *et al.* 1996, $R^2 = 0.36$) – or either the average or best-performing attitudinal measures as reported in Table 1 (average: $R = 0.40$, $R^2 = 0.16$; Best: $R = 0.61$, $R^2 = 0.36$).

Validation against behaviour measured in panels

Although, as we've shown, it's common in marketing research to validate against 'within-survey' metrics, it's important to validate against real-world behaviour if possible. Table 7 shows the results for two such validations.

Table 7 Validation: correlations between attitudinal equity and panel behaviour

	Pharmaceutical	Retail	Total/mean
Nature of panel	Diary	Scanner	n/a
Share over …	6 months	12 months	n/a
Timing	Spans survey	Spans survey	n/a
Sample	67	3,712	3,779
Total brands	5	16	21
Brand prescribed/used	2.6	3.2	3.6
Brands rated	3.6	10.8	6.5
Respondent *R*	0.61	0.51	0.55
Brand *R*	0.38	0.49	0.435

Note: Correlations as for Table 6; as before, the 'Respondent' correlations are one correlation across all respondents and brands; 'Brand' correlations are separate correlations run on each brand.

The first data set comes from a diary panel run by Synovate (Healthcare) among medical practitioners in the United Kingdom. It is for a particular class of drugs called 'Proton Pump Inhibitors' prescribed by 67 members of the panel. The diary panel data are for the period December 2006 to May 2007 and record the number of 'new' prescriptions of each drug written by each practitioner in that period. Practitioners wrote an average of 15 'new' prescriptions during that period. By 'new' is meant 'prescriptions for new patients, or when switching patients from one drug to another'. The practitioner survey data were collected in March 2007.

The second data set comes from a commercial retail scanner panel in Italy. Panellists were surveyed in March 2007. The results were then combined with data about each panellist's share of spend at any of the 16 retailers being tracked. Panel share was for the 12-month period August 2006 to July 2007.

The average correlation between attitudinal equity and share of wallet is: R = 0.55, R^2 = 0.30. This is considerably better than the average of R = 0.32 (R^2 = 0.10) and the best of R = 0.47 (R^2 = 0.22) reported in the literature (Table 1).

When looking at individual correlations for each of the 21 brands in our studies, the best-performing correlation reported in the literature – i.e. R = 0.47 (Perkins-Munn *et al.* 2005) – should be left out because it is not based on a separate correlation for each brand. That makes the average in the literature R = 0.24 in comparison with our average of R = 0.44.

The fact that our results are for two very different product/service categories lends support to the potential universality of the approach. Further, when one considers that what medical practitioners can prescribe is constrained by the regulatory environment, then the results, at both respondent level and across multiple brands, are encouraging.

Summary

Using just one question and a simple algorithm with universal parameters, we produce estimates of the psychological propensity that a person has to use or buy each of a set of relevant brands. Unlike many brand strength measures, it is attitudinally pure. It is more ambitious in scope than most measures, in that it assigns an attitudinal purchase propensity to every brand a respondent can buy, not just a target brand. Even so, when correlated with share of wallet, it outperforms other attempts to estimate individual purchase propensities for a brand.

Other forms of validation: correlation with real market share

Although we have argued that aggregate models of brand share are inadequate when marketers need to profile their users, a good respondent-level model should result in good predictions when aggregated up to market level. In Figure 2 we show a scatter-plot of the relationship between aggregate attitudinal equity as established in nine separate surveys (on the one hand) and brand market shares as *independently established* using industry sources and purchase panels (on the other). There are 88 observations in all. The data come from five developed and emerging markets (i.e. the United States, the United Kingdom, China, South Africa and Thailand) and eight product categories (i.e. motor manufacturers, health plans, carbonated beverages, cooking oil, financial institutions, personal cleansing brands, motor oil and pharmaceutical prescriptions). It is important to note that in fitting this relationship we did not need to calibrate the data to market shares. Nor did we adjust the scales or the algorithm for different markets. In other words, this appears to be a 'one size fits all' metric.

Table of models and correlations

Linear model:	$y = 1.13x$;	Adj $R^2 = 0.89$
Quadratic model:	$y = 0.025x^2 + 0.51x$;	Adj $R^2 = 0.92$
Cubic model:	$y = 0.001x^3 - 0.04x^2 + 1.08x$;	Adj $R^2 = 0.93$

Table of p-values for cubic model terms

x^3 $p = 0.0000$; x^2 $p = 0.0405$; x $p = 0.0008$

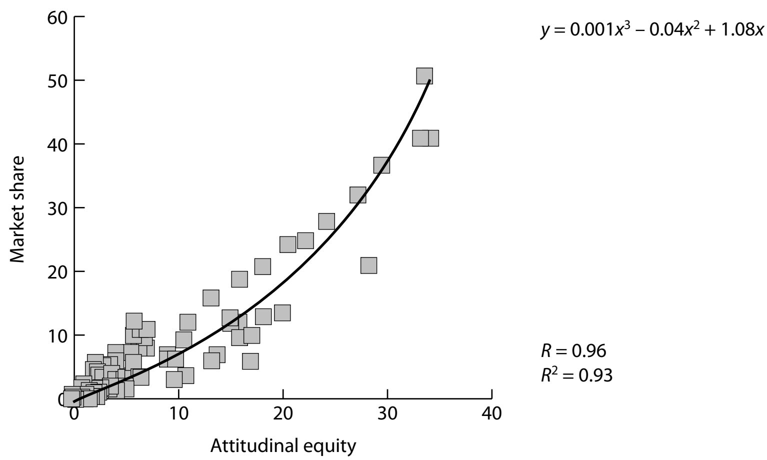


Figure 2 The relationship between aggregate attitudinal equity and market share

The best-fitting function is cubic with R = 0.97 and adjusted R^2 = 0.93. All three terms are significant. This means that the algorithm produces *an attitudinal survey measure of brand strength* that can be used with confidence to model *real-world market share*. Put simply: identify what needs to be done to change surveyed attitudinal equity, and market share changes can be predicted, all else being equal.

Consumer behaviour in a scanner panel

As a final observation we note the consistency between application of a power law to the development of our attitudinal measure of brand strength, and the appearance of a Zipf distribution in individual behaviour in two consumer panels. While such consistency does not constitute validation, it adds evidence for the application of power laws to models of individual behaviour in markets. The data come from two product categories: instant coffee and toilet tissue (Synovate household scanner panel, Australia). We show descriptive statistics of the samples in Table 8.

Table 8 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
Percentage 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

From the practitioner point of view, we see an interesting result in the toilet tissue data: although loyalty levels are low, the average panellist uses only 3.6 brands in an 18-month period. Now consider how we tend to crowd our attitudinal surveys with brand ratings. These results suggest that typical attitudinal surveys ask respondents about *more brands than is necessary*. They suggest that we can cut attitudinal measurement.

The procedure we use to test for the power law is as follows.

1. Establish the share of wallet that each brand gets from each household or medical practitioner, and use the share to rank each brand at individual level.

2. Plug the brand rank into equation (2). Use Excel 'solver' to obtain a best fit for every repertoire size.
3. Compare the predicted distribution of share of wallet at respondent level, with the actual share given to each brand by each respondent.

In Table 9 we show the optimal values obtained for the exponent *s*. Note the consistency between the optimal *s* values obtained for the panel data on the one hand, and the optimal values obtained for the survey studies on the other. These results come from five completely different data sets. They therefore suggest that a parsimonious approach that fixes the parameter estimates for *s*, and applies them without variation, may be reasonable.

Table 9 Optimising the exponent *s* on panel data

Number of brands bought	Observations		Optimal *s*		Correlation		Mean optimal *s*	
	Coffee	Tissue	Coffee	Tissue	Coffee	Tissue	Panel *s*	Survey *s*
One	35	50	n/a	n/a	1.00	1.00	n/a	n/a
Two	42	75	2.39	2.35	0.95	0.94	2.37	2.33
Three	28	91	1.73	1.66	0.93	0.92	1.70	1.69
Four	26	80	1.19	1.40	0.90	0.91	1.29	1.32
Five +	27	60	1.04	0.93	0.91	0.89	0.99	0.88

We show the results in Table 10. As with our survey results, the correlation is very strong across both respondents and brands. This suggests that individual behaviour in markets can be modelled using a power law.

Table 10 Correlations between panel share of wallet and predicted share based on ranking

	Instant coffee	Toilet tissue	Total/mean
Sample	158	356	514
Total brands	43	51	94
Mean brands bought	2.9	3.6	3.2
Respondent *R*	0.96	0.95	0.96
Brand *R*	0.98	0.97	0.98

Note: Respondent *R* and Brand *R* refer to the same kind of correlation as for the surveys reported in Table 6; brand correlations (Brand *R*) are calculated for the ten biggest brands in the data – ranging from market shares of 27% down to market shares of 3%.

Summary and conclusions

If the purpose of marketing research is to help marketers develop strategies that improve brand profits; and if profitability tends to be linked to brand share of wallet (at individual level) and market share (at aggregate level); then marketers need measures of attitudinal brand strength against which they can model with confidence. The approach we present in this paper achieves that. Changes in respondent-level attitudinal equity are associated with changes in real behaviour, circumstances allowing.

In contrast with many current commercial methods, it has the following virtues.

- It is not a 'black box' (i.e. anyone can implement the method).
- It is an individual-level measure that covers all brands that are available to a person in a product category, no matter how many brands there are.
- It is highly correlated with share of wallet as measured in surveys and in panels; and with market share as established independently of the survey.
- It is consistent with what we've seen in panel data.

Two features of the approach stand out. The first is its parsimony with respect to both survey length and algorithm. The second is its apparent universality with respect to countries and product categories. In comparison with what we find in the literature:

- it correlates strongly at respondent level with share of wallet for *all brands* (up to 163 in one study), not just a target brand
- it has been validated across *multiple* countries and product categories, including both packaged goods and services
- it *outperforms* existing attitudinal measures, whether single or multi-item, and whether validated within-survey or in databases.

Our brand measure isn't new. We use a typical overall brand performance measure on a 10-point scale. What's new is our insistence on multi-brand measurement (rather than multi-item measurement) and the application of a transformation based on ranking and a power law. To summarise, we suggest that the main reasons for the measure's success are:

- that it recognises that a brand's attitudinal strength cannot be established without comparing how it performs relative to other brands

- that the 'scoring' distances between the attitudinal strength of one brand and another at respondent level are, in reality, probably non-linear.

It is important to note that we're not arguing that 'overall brand performance' is a constituent of attitudinal brand equity. We're arguing that it *is* attitudinal brand equity – but that it needs to be transformed according to a power law in the context of multiple brand ratings.

In taking our approach 'out of' a black box, we recognise that we're exposing our algorithm to further checking and improvement. But that is as it should be. We welcome the possibility that the approach should be stress tested and refined by others.

Appendix 1: Questions to measure attitudinal equity

Outline of the questionnaire

- Key demographics: gender, age
- Spontaneous awareness
- Aided awareness

(i) Questions used to identify brands for rating purposes (the consideration set)

Q: Which of the following brands do you buy/use regularly?

Q: Suppose none of the brands you've just selected were available, which of the remaining brands would you buy/use instead?

(ii) Typical question to establish brand performance for ranking purposes

Q: How would you rate each brand you regularly buy/use or would consider buying/using?

Please use this scale for your answer where 10 means it is excellent and 1 means it is extremely poor

- Attribute association battery
- Barrier association battery

(iii) Question used to measure share of wallet

Q: Please think about the last ten times you bought <product category>. Selecting from the brands you regularly buy or would consider buying, how often did you buy each one?

- Recall of exposure to brand advertising through various media

References

Auerbach, F. (1913) Das gesetz der bevolkerungskonzentration. *Petermanns Geographische Mitteilungen*, **LIX**, pp. 73–76.

Baumann, C., Burton, S. & Elliot, G. (2005) Determinants of customer loyalty and share of wallet in retail banking. *Journal of Financial Services Marketing*, **9**, 3, pp. 231–248.

Bergkvist, L. & Rossiter, J.R. (2007) The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, **44**, 2 (May), pp. 175–184.

Bowman, D. & Narayandas, D. (2004) Linking customer management effort to customer profitability in business markets. *Journal of Marketing Research*, **41**, 4 (November), pp. 433–447.

Cooil, B., Keiningham, T.L., Aksoy, L. & Hsu, M. (2007) A longitudinal analysis of customer satisfaction and share of wallet: investigating the moderating effect of customer characteristics. *Journal of Marketing*, **71**, 1 (January), pp. 67–83.

Coyles, S. & Gokey, T.C. (2002) Customer retention is not enough. *The McKinsey Quarterly*, **2**, pp. 81–89.

De Wulf, K., Odekerken-Schroder, G. & Iacobucci, D. (2001) Investments in consumer relationships: a cross-country and cross-industry exploration. *Journal of Marketing*, **65**, 4 (October), pp. 33–50.

DuWors, R.E. & Haines, G.H. (1990) Event history analysis measures of brand loyalty. *Journal of Marketing Research*, **27**, 4 (November), pp. 485–493.

Ehrenberg, A.S.C. & Uncles, M.D. (1995) Dirichlet markets: a review. Working Paper, South Bank Business School and Bradford Management Centre.

Estoup, J.B. (1916) *Les Gammes Stenographiques*. Paris: Institut Stenographique de France.

Fornell, C., Johnson, M.D., Anderson, E.W., Cha, J. & Bryant, B. (1996) The American Customer Satisfaction Index: description, findings, and implications. *Journal of Marketing*, **60**, 4 (October), pp. 7–18.

Gustaffson, A., Johnson, M.D. & Roos, I. (2005) The effects of customer satisfaction, relationship commitment dimensions, and triggers on customer retention. *Journal of Marketing*, **69**, 4 (October), pp. 210–218.

Hofmeyr, J. & Rice, B. (2000) *Commitment-led Marketing*. Chichester: Wiley & Sons.

Jacoby, J. & Kyner, D.B. (1973) Brand loyalty vs repeat purchasing behavior. *Journal of Marketing Research*, **10**, 1 (February), pp. 1–9.

Keiningham, T.L., Perkins-Munn, T. & Evans, H. (2003) The impact of customer satisfaction on share-of-wallet in a business-to-business environment. *Journal of Service Research*, **6**, 1 (August), pp. 37–50.

Kohli, R. & Sah, R. (2004) Market shares: some power law results and observations. Unpublished manuscript, Columbia University and University of Chicago.

McQueen, J., Foley, C. & Deighton, J. (1993) Decomposing a brand's consumer franchise into buyer types. In: D.A. Aaker & A.L. Biel (eds) *Brand Equity and Advertising*. Hillsdale, NJ: Lawrence Erlbaum and Associates.

Newcomb, S. (1881) Note on the frequency of use of different digits in a number. *American Journal of Mathematics*, **4**, 1, pp. 39–40.

Perkins-Munn, T., Aksoy, L., Keiningham, T.L. & Estrin, D. (2005) Actual purchase as a proxy for share of wallet. *Journal of Service Research*, **7**, 3 (February), pp. 245–256.
Riemer, H., Mallik, S. & Sudharshan, D. (2002) Market shares follow the Zipf distribution. Unpublished manuscript, Department of Business Administration, University of Illinois (Urbana-Champaign).
Verhoef, P.C. (2003) Understanding the effect of customer relationship management efforts on customer retention and customer share development. *Journal of Marketing*, **67**, 4 (October), pp. 30–45.
Verhoef, P.C. & Franses, P.H. (2003) Combining revealed and stated preferences to forecast customer behaviour: three case studies. *International Journal of Market Research*, **45**, 4, pp. 467–474.
Wirtz, J., Mattila, A.S. & Lwin, M.O. (2007) How effective are loyalty reward programs in driving share of wallet? *Journal of Service Research*, **9**, 4, pp. 327–334.

About the authors

Jan Hofmeyr is International Director of Innovation, Synovate's Brand and Communications Practice, Cape Town. Jan Hofmeyr serves as an Honorary Professor in the Dept of Business Administration at the University of Stellenbosch (Stellenbosch, South Africa), and as an Adjunct Professor in the Department of Commerce at the University of Cape Town (Cape Town, South Africa).

Paul Holtzman heads up the methological and research division of Synovate's Product Design and Development practice. Paul has worked for Synovate and its predecessor, Market Facts, for more than 25 years. In this time he has served as a statistician and quantitative consultant; and for many years as the International Director of Synovate's Decision Systems group. Decision Systems is the statistical consulting arm of Synovate.

Victoria Goodall is a Research Analyst and Statistician in Synovate's Brand and Communications Practice in Cape Town. Victoria graduated from Rhodes University in 2003 with a BSc (Hons) majoring in mathematics and statistics. Before joining Synovate, she worked for a major motor manufacturer as a Data Analyst for customer relationship management. Victoria joined Synovate in 2006. She has a Master's degree in Statistics.

Martin Bongers is a Research Analyst and Statistician in Synovate's Brand and Communications Practice in Cape Town. Martin graduated from the University of Kwa-Zulu Natal in 2004 with a BSc (Hons) majoring in statistics. In 2005, Martin's statistical dissertation on extreme value theory was judged the best dissertation by a postgraduate student in South Africa for that year. Martin joined Synovate in 2007.

Address correspondence to: Jan Hofmeyr, 10 Gilquin Crescent, Hout Bay, Western Cape, South Africa 7806.
Email: Jn.Hofmeyr@iafrica.com