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Consumer Attitude Dynamics and Marketing Impact on Sales

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Report Summary

For marketing to justify its funding, marketers must show that marketing actions such as advertising, promotions, pricing, and distribution have a positive effect on business performance, both in magnitude (i.e., the effects are sizable) and duration (i.e., the effects last). CFOs are satisfied with measures such as advertising elasticity and return on sales, but CMOs need more detailed information. They want to know how marketing actions affect consumers' attitudes toward the brand and then how those attitudes affect the brand's performance.

Dominique Hanssens, Koen Pauwels, Shuba Srinivasan, and Marc Vanhuele propose four criteria for evaluating how well attitudinal metrics correspond to changes in purchasing behavior. The criteria are sales conversion (the metric generates actual sales), potential (there is a margin for improvement), staying power (the changes in consumer behavior last), and responsiveness (the metric responds to marketing efforts). The research team investigates how well three metrics—advertising awareness, consideration (that is, inclusion in the set of items consumers are considering for purchase), and brand liking—scored for those four criteria when the brands being marketed fall in two consumer goods categories: bottled water and shampoo.

Bottled water is a low-involvement good (people's purchase decision is made without much thought or emotional involvement), whereas shampoo is a high-involvement good (people tend to have established opinions and preferences, which may require persuasion to change). By studying both low- and high-involvement goods, the authors can test attitudinal metrics both for products that are likely to be swayed by attitude-focused marketing and for products that are not.

Examining survey data collected from January 1999 through May 2006 from 8,000 households in France, the team discovered that awareness and consideration scored better for staying power, whereas liking scored poorly for staying power, especially for bottled water (the low-involvement category), although liking for higher-priced brands in both the low- and high-involvement categories had more staying power than liking for lower-priced brands.

The team also found that for both higher-priced and lower-priced bottled water and shampoo, advertising positively affects awareness. Sales promotion has a positive effect on consideration for higher-priced bottled water and shampoo, while price had a negative effect on both consideration of and liking for higher-priced bottled water.

Analyzing the findings, the researchers concluded that of the three attitude metrics, liking has the highest elasticity, and of the marketing actions, price has the highest elasticity. In the context of the brands of bottled water and shampoo under investigation, all three attitudinal metrics influence shampoo sales, but only awareness and liking influence bottled-water sales. This suggests that marketing campaigns designed to improve brand health by increasing the likelihood that consumers consider the brand for purchase will be effective for shampoo, but not for bottled water.

Using the insights gained from this investigation, the researchers use a holdout sample from the dataset to see how well the metrics work predictively: how accurately can they predict the financial outcomes of marketing decisions? The results are impressive: estimation using the researchers' models results in an average improvement in prediction of more than 28% over the

benchmark model. Understandably, the results are higher for high-involvement products whose sales are more affected by marketing actions that target long-term attitudes and lower for low-involvement products.

The researchers note that one drawback of attitudinal metrics is the cost of gathering the data: customer surveys are more expensive to administer and process than sales data. However, they point out that preliminary evidence has suggested that it may be possible to replace survey data with customer opinions gleaned from their comments on the Internet (in blogs, on social networking sites, in customer reviews), which would reduce those costs.

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Introduction

Brand managers are urged to compete for the 'hearts and minds' of consumers and often collect *brand health* indicators to this end. But how actionable is it to know that, for example, brand awareness stands at 70% while brand liking stands at 40%? Conventional wisdom suggests investing in the 'weakest link', i.e. the metric with the most remaining potential. However, brand liking may have hit its glass ceiling at 40%, while momentum in awareness may still be possible. In addition, awareness could be more responsive to marketing actions than brand liking, and any gains in brand liking may be short-lived due to fickle consumers or tough competitors, while gains in awareness could be longer-lasting. Finally, awareness gains may convert into sales at a higher or lower rate than liking gains do. In sum, it is no small task for brand managers to use consumer attitude information to guide their marketing strategies and actions.

To date, these important issues of marketing strategy effectiveness have not received thorough quantitative answers, mainly because the data sources have been lacking. While we can – especially for fast moving consumer goods – readily observe weekly or monthly sales, price, advertising and distribution movements, we only rarely witness the accompanying readings in consumer attitude metrics such as awareness and consideration. As a result, ex-post marketing effectiveness is typically assessed at the observable transaction level, with measures such as "advertising elasticity" and "return on sales." That practice may satisfy the bottom-line oriented CFO, but leaves the deeper reasons for marketing success or failure unexplored. In particular, the CMO needs to know if movements in the brand's business performance are associated with movements in consumer attitudes toward the brand.

This paper incorporates the evolution of brand health, as assessed by key attitudinal metrics for understanding and predicting marketing impact, using newly available data sources that match consumer attitudes and purchasing behavior. We postulate that using such data as *intermediate performance metrics* allows us to explain and quantify the observed differences in marketing effectiveness across brands and over time. Some of these differences,such as declining advertising elasticities over the product life cycle (e.g. Parsons 1975) and category differences in consumer involvement (e.g. Berger and Mitchell 1989), have long been documented. More recently, Srinivasan, Vanhuele & Pauwels (2010) analyzed over 60 brands in 4 consumer packaged goods categories and reported that changes in attitudinal metrics accounted for about one third of the explained variance in the sales of these brands. However, current literature lacks actionable advice based on closed-loop learning of the intermediate metrics (e.g. "if one observes metrics with the following values/characteristics, then this marketing action will be most effective"). Such understanding permits the formulation of strategies that are more likely to succeed. Indeed, we will demonstrate, using a hold-out sample, that understanding customer attitude dynamics greatly improves our ability to predict future marketing effectiveness and explain why it will differ across conditions.

We start by proposing four criteria for diagnosing each attitude metric. Next, we use consumer behavior foundations to formulate hypotheses on how these criteria differ across brands and over time. We test our hypotheses on a rich dataset comprising relevant consumer attitude metrics as well as full marketing-mix information, and we make predictions about future marketing effectiveness across brands. Finally, we formulate conclusions and an agenda for future research.

Relevance Criteria for Customer Attitude Metrics

There is ample evidence that marketing actions vary widely in their impact on business performance, both in magnitude (e.g. response elasticity) and in duration (e.g. carryover effects). For example, the magnitude of sales call elasticities averages .35, while advertising elasticities average .10 (Hanssens 2009). In terms of duration, most marketing efforts have only a temporary impact, and thus repeated or sustained marketing spending is needed to achieve persistent or permanent results, which is costly (Dekimpe and Hanssens 1999). Furthermore, within the majority class of temporary-impact marketing, there is wide variation in impact duration (i.e. time to mean reversion in sales). For example, advertising is known to have longer-lasting effects than sales promotions. The combination of impact magnitude and duration generates the long-term effect of marketing that should determine its role in the firm's overall resource allocation.

With only transaction data, we can only statistically infer the dynamics of observable sales response to marketing. We do not know if, over the course of the time sample, consumers' attitudes toward the brands have changed, and/or if their reasons for purchasing have changed. By contrast, intermediate attitudinal metrics with sufficient over-time variation allow us to track such changes and assess the extent to which they relate to long-term marketing impact. For example, in some categories consumers may alternate their purchases over time among four acceptable brands, in function of their price promotions, while keeping their relative preferences the same. In other categories they may change their preference after a single trial of brand B, and change their evoked set from there on forward. Our central premise is that tracking and modeling of *relevant* attitudinal metrics will reveal such changes and help explain the nature of marketing impact.

Relevant attitudinal metrics. In the context of marketing resource allocation, a *relevant* attitudinal metric is one that has a long-term association with sales performance, meaning there is *sales conversion*. For example, it must be true that, all else equal, higher brand awareness is associated with higher sales performance. The equilibrium sales conversion of an attitudinal metric is empirically testable, as we will demonstrate below.

Sales conversion is a necessary but not sufficient condition for an attitude metric to contribute to marketing's long-term impact on sales. For any given brand situation, the metric must also have *potential* and *staying power*, and must *respond* to marketing actions. For example, if the relevant metric "brand awareness" is low, is responsive to brand advertising, and stays at higher levels after advertising stimulation, then a firm's advertising campaign that is aimed at increasing this particular attitudinal metric is likely to have a sizeable and long-lasting sales impact. Conversely, if brand awareness is high, unresponsive to advertising, and quick to decay, the same advertising campaign will likely have a much smaller and shorter-lived sales effect. We now examine these three criteria in turn.

Potential as a driver of marketing impact has long been appreciated and used, especially in the context of *market* potential (e.g. Fourt and Woodlock 1960). The central premise is that of diminishing returns, i.e. the larger the remaining distance to the maximum, the higher the impact potential. Fourt and Woodlock applied this principle to new-product penetration forecasting and found that penetration evolves as a constant fraction of the remaining distance to the maximum. Thus if awareness impacts new-product trial, then, all else equal, marketing spending aimed at awareness building will have more impact potential if the beginning awareness is 20% as opposed to 70%.

Stickiness or *inertia* refers to the *staying power* of a change in the attitudinal metric, in the absence of further marketing effort. For example, if consumer memory for the brands in a category is long-lasting, it will take little or no reminder advertising for a brand to sustain a recently gained increase in brand awareness. Similarly, if consumers in a category exhibit strong *habits* and routinely choose among a subset of the same four brands (i.e. the evoked set), then the consideration metric for any of these four brands may be sticky. Overall, if a marketing effort increases a brand's score on a sticky attitudinal metric, then all else equal, that effort is more likely to have a long-run impact on business performance.

Responsiveness or *lift* refers to marketing's ability to "move the needle" on the attitude metric. In this context, different marketing actions will likely have different responsiveness. For example, advertising is known to be better at inducing trial purchases than repeat purchases (Deighton, Henderson and Neslin 1994), so an awareness metric may be more responsive to it than a preference metric. Responsiveness is also related to environmental conditions, especially when the market space is cluttered (Danaher, Bonfrer and Dhar 2008). For example, with limited retailer shelf space, an abundance of offerings in a category limits the power of trade incentives to gain shelf space.

Our goal is to demonstrate the value of these principles in diagnosing a brand's health and in making predictions about the long-term sales impact of its marketing efforts. We will use brand-centric response models on cross-sectional time-series data for that purpose. Our empirical verification starts with testing the relevance of the attitudinal metrics (i.e. are the metrics related to the long-term performance of the brand?). Among the metrics that pass the test, we then formulate measures for their *potential, stickiness and responsiveness*. We also establish predictive capability by demonstrating that the use of attitudinal metrics significantly improves the accuracy of sales outcome predictions in function of planned marketing expenditures. Our study makes new contributions over previous research (e.g., Srinivasan, Pauwels and Vanhuele 2010) in specifying the four criteria – potential, responsiveness, stickiness and sales conversion – that connect marketing actions, attitudinal metrics and sales outcomes, and in establishing predictive capability to help formulate marketing strategies that are more likely to succeed.

Our conceptual framework, displayed in Figure 1, contrasts marketing effects that occur through *changes* in attitudinal metrics with those that occur without such changes. We denote the former as the 'mindset effect' and the latter as the 'transaction effect' in Figure 1. We do not propose that purchases occur without the customers' minds or hearts being involved (e.g., one needs to be aware of a brand at least right before buying it), but instead that customers may simply react to a marketing stimulus without changing their mind or heart (e.g. the brand was in the consideration set before, and remains in the consideration set after a stimulus-induced purchase). Our framework therefore accounts for both generally accepted channels of marketing influence: through building the consumer attitudes that constitute the brand's health and/or through leveraging the brand's existing health. We start by using consumer behavior theory to identify conditions under which marketing actions impact sales performance via movements in attitudinal metrics. (Figures and Tables appear following References.)

Consumer behavior and sales conversion

A fundamental question in consumer behavior is to what extent attitudes translate into purchase behavior (Berger and Mitchell, 1989), i.e. there is sales conversion. The Elaboration Likelihood Model (ELM) holds that a critical factor driving enduring persuasion is whether an individual is motivated to elaborate on, or think about, a potentially persuasive message (Petty and Cacioppo, 1979). One of the most important determinants of elaboration motivation is involvement (Petty et al., 1983). Product involvement is generally understood as referring to the personal relevance of the object based on inherent needs, values and interests (Zaichkowsky, 1985).

How is product involvement relevant for the conversion of attitudes to behavior? Nelson (1970) developed an economic perspective classifying a brand purchase decision as either low involvement, where trial experience is sufficient, or high involvement, where information search and conviction is required prior to purchase. Thus, when product involvement is high, a product or brand needs to change consumers' hearts and minds in order to change their purchase behavior. The perceived risk of changing (purchase) behavior needs to be overcome in the consumer's mind (Bauer, 1967; Peter and Tarpy, 1975). In contrast, when product involvement is low, consumers may buy a product simply because it is available or promoted, without having fundamentally changed their opinion about it. This low-involvement path is compatible with Ehrenberg's awareness-trial-reinforcement model (1974).

In the context of our research, we distinguish two involvement scenarios:

1) High involvement implies that attitudes and product buying decisions are driven by stable, deeper meanings associated with consuming these products (e.g. Fournier 1994). In these conditions, we expect movements in attitudinal metrics to be strongly associated with sales, i.e. there is sales conversion.
2) In low-involvement categories, consumers do not give much thought to their purchase decisions in the category. As a result, we expect low sales conversion. Marketing actions may have a direct impact on sales without affecting the attitudinal metrics, called the

“transaction effect” in Figure 1. Many frequently purchased consumer packaged goods fall within this category, and several studies have demonstrated this type of choice behavior (e.g. Hawkins and Hoch, 1992).

Metrics and Models

Modeling the dynamics of attitudinal metrics requires an operationalization of potential, stickiness and responsiveness as well as their conversion into sales. We review these in sequence.

Potential (POT_t) is the remaining distance to the maximum, preferably expressed as a ratio in light of the multiplicative nature of market response. For example, if maximum awareness (MAX) is 100% and current awareness Y_t is 30%, then

$$POT_t = [\, MAX - Y_t \,] / MAX = .7. \qquad (1)$$

Most consumer attitude metrics are expressed in percent (MAX=100%) or in Likert scales (e.g. 1 to 7, MAX=7), both of which readily accommodate our proposed definition of potential.

Stickiness (ST_t) or *inertia* is the degree to which a change in the level of a metric is upheld over time, absent any new stimuli. This can be modeled by a simple univariate AR(p) process on the attitude metric, where stickiness is quantified as the sum of the AR coefficients (e.g. Andrews and Chen 1994). For example, if the simple AR(1) model represents the over-time behavior of the attitude metric Y, i.e.

$$Y_t = c + \varphi\, Y_{t-1} + \varepsilon_t \quad \text{, where } \varepsilon_t \text{ is white noise,} \qquad (2)$$

with parameter φ=.6, then stickiness = .6. This means that 60% of any shock in Y_t is carried over to the next period. Similarly, if the univariate model is AR (2) with parameters φ_1 = .6 and φ_2 = .15, then stickiness = .75. A priori, we expect consumer attitudinal metrics to be stationary (the sum of the AR parameters is less than 1) because of memory decay effects that are well-documented in psychology (Baddeley, Eysenck and Anderson, 2009).

Stickiness is important because it identifies the long-run impact of a movement in an attitude metric. For example, with φ=.8, if the metric increases from 10% to 15% due to a marketing initiative, the 5% gain in one period will result in total gains over time of 5%/(1-.8) = 25%. If stickiness were 0, the gain would only be the one-time lift of 5%.

Responsiveness or *lift* is the short-term response of the attitude metric with respect to a marketing stimulus. We propose to use well-established, robust response functions to estimate responsiveness. For example, the standard multiplicative response model produces elasticities as responsiveness metrics:

$$Y_t = c\, Y_{t-1}^{\gamma} X_{1t}^{\beta_1}\ X_{2t}^{\beta_2}\ X_{3t}^{\beta_3}\ e^{u_t} \qquad (3)$$

where Y is an attitude metric and X_i (i=1,2,3) are marketing instruments. Not only do such response models provide readily interpretable results, they have also been shown to outperform more complex specifications in forecasting product trial for consumer packaged goods (e.g. Hardie, Fader and Wisniewski 1998).

Note that responsiveness may be related to potential as follows: the closer the attitude metric is to its ceiling value, the more difficult it will be to register further increases through marketing. That phenomenon is readily incorporated in (3) by expressing the dependent variable as an odds ratio (e.g. Johansson 1979):

$$Y'_t = Y_t\ /\ (MAX-Y_t) = c\, Y'^{\gamma}_{t-1}\ X_{1t}^{\beta_1}\ X_{2t}^{\beta_2}\ X_{3t}^{\beta_3}\ e^{u_t} \qquad (4)$$

where the response parameters β_i now indicate either a concave ($\beta_i < 1$) or an S-shaped ($\beta_i > 1$) response curve. The resulting response elasticity η_i is now contingent on the attitude metric's potential as follows:

$$\eta_i = \beta_i * POT_t \quad (5)$$

For example, in an awareness-to-advertising relationship with a response elasticity .2 at zero initial awareness, the response elasticity will decline to .2*.6 = .12 when awareness reaches 40%.

Marketing investment appeal. The product of potential, stickiness and responsiveness is an ex-ante measure of the appeal of the attitudinal metric for marketing investments. For example, all else equal, the higher the potential and stickiness of brand awareness, and the more responsive it is to advertising campaigns, the more the brand manager can justify investing in advertising. However, the desirable level of investment is also determined by the degree to which the intermediate performance metric awareness is related to financial performance, i.e. sales revenue. We have previously referred to this as the *conversion* factor.

Conversion is the degree to which movements in the attitudinal metric convert to sales, similar to a conversion rate of leads into customer orders in B2B. Conversion rates are typically well below unity; for example Jamieson and Bass (1989) reported ratios of stated vs. actual consumer trial in ten product categories ranging from .009 to .896, averaging around .5. When historical data are available, conversion metrics may be estimated from a "funnel" model, with upper-funnel metrics such as awareness and lower-funnel metrics such as preference or liking. However, we do not want to impose a hierarchy-of-effects, because there is little support for such hierarchies (e.g. Batra and Vanhonacker 1988). Instead, we allow for a multiplicative funnel model that can be applied across conditions. For example with intermediate attitudinal metrics awareness (A_t), consideration (C_t) and liking (L_t), a multiplicative funnel model for sales revenue (S_t) would be

$$S_t = c\ S_{t-1}^{\lambda}\ A_t^{\beta_1}\ C_t^{\beta_2}\ L_t^{\beta_3}\ e^{u}_t \qquad (6)$$

Conversion models such as (6) can be tested either with longitudinal or with mixed cross-sectional time-series data.

For different product categories, we expect different estimated values of the conversion parameters. In particular, the higher the consumer involvement with the category, the stronger we expect the conversion parameters to be. In the other direction, a set of near-zero conversion parameters would imply that consumer purchase decisions are made virtually regardless of movements in brand attitudes. This could occur when consumers buy on impulse or in function of in-store display and promotion factors. The conversion equation may also include external factors such as distribution when these are known to vary across purchase occasions.

In addition to category-level differences in conversion parameters, there may be within-category brand differences as well. For example, the liking-to-sales conversion parameter may be higher for a higher-quality, higher-priced brand. We will test for such differences by conducting pooling tests for the presence of brand-level heterogeneity in the conversion equations.

Overall, the conversion model is estimated at the category level, with data that are pooled across brands. It is important to guard against possibly spurious results due to reverse causality, for example the scenario whereby a brand scores high in awareness because its sales are high. In other words, we must verify that attitudinal metrics are *leading,* not *lagging*, indicators of business performance. We employ a Granger causality test for that purpose, i.e. the attitudinal metric M Granger causes S if the model

$$S_t = f\,[\,M_{t-k},\ S_{t-m}\,]\ \text{, where } k > 0 \text{ and } m > 0, \qquad (7)$$

outperforms the univariate model

$$S_t = f [S_{t-m}] \qquad (8).$$

The lag lengths *k* and *m* in these models are derived empirically using the Schwarz information criterion (see e.g. Hanssens, Parsons and Schultz 2001). Model performance is established on a forecast sample using a standard metric such as root mean squared error (RMSE).

System's estimation. Taken together, the attitudinal metrics, sales outcomes and marketing actions form a system with feedforward and possibly feedback loops. Several econometric methods are available to estimate the relevant parameters, ranging from single-equation models to systems models. In what follows we will tailor the estimation method to the objective at hand and conduct specification and robustness tests as needed.

Illustrative example

A few scenarios will illustrate these principles. Consider two brands, A and B, in a product category. We would like to compare marketing investments in price promotion versus advertising with respect to the attitudinal metrics awareness and consideration. Existing statistical models such as (4) reveal that awareness is more responsive to advertising, and consideration is more responsive to price promotion. The brands' starting conditions are as follows:

	Awareness		Consideration		Source
	Brand A	Brand B	Brand A	Brand B	
Beginning level	.8	.3	.4	.5	Data
Potential	.2	.7	.6	.5	Equation (1)
Stickiness	.9	.9	.5	.5	Equation (2)
Response to promotion	.01	.035	.18	.15	Equations (4)(5)
Response to advertising	.04	.175	.06	.1	Equations (4)(5)
Sales Conversion	.15	.2	.4	.5	Equation (6)
Marketing Investment Appeal					
promotion	.015	.07	.14	.15	Equations
advertising	.06	.35	.048	.10	(5)(2)(6)

These scenarios imply different marketing resource allocation prescriptions for the two brands. For example, both brands should favor advertising to increase awareness (higher response). However, because of differences in their potential, brand B stands to gain more from such investments. Furthermore, when considering the sales conversion factors, we can compare the long-term sales impact potential of each marketing investment for each brand. For example, sales promotion investments are more appealing for Brand B, and advertising is more appealing for Brand A. Of course determining the most suitable investment levels will require information on profit margins and other considerations as well.

Empirical Study

Our empirical investigation will contrast a low-involvement consumer product category (bottled water) with a higher-involvement category (shampoo). The data come from a brand performance tracker developed by Kantar Worldpanel, which reports the marketing mix, mindset (based on 8 000 households) and performance metrics across brands in each category on a four-weekly basis. The details on these data sources are described in Srinivasan, Pauwels and Vanhuele[1] (2010).

For the period between January 1999 and May 2006, we analyze data for the leading brands of bottled water (4 brands) and shampoo (6 brands). The focal brand performance measure is sales volume aggregated across all product forms of each brand (in milliliters). The marketing mix data include average price paid, value-weighted distribution coverage, promotion, and total spending on advertising media.

After discussion with the data provider, we selected the following three measures from the available attitudinal metrics: advertising awareness, inclusion in the consideration set and brand liking. This selection aimed at covering the three main stages of the purchase funnel. Two other available measures could not be included due to lack of variation (aided brand awareness) or collinearity ("intention to purchase" correlated highly with consideration, and the data provider considered the latter to be more useful to managers).

For advertising awareness, survey respondents indicated, in a list of all brands present on the market, those for which they "remember having seen or heard advertising in the past two months." Our measure gives the percentage of respondents who were aware. Liking is measured on a five-point scale ("like enormously," "a lot," "a little," "not really," "not at all"), and the measure we use is the average rating. For the consideration set, respondents were asked to indicate "the brands that you would consider buying" from a list of all brands in the market. We use the percentage of respondents who consider buying as measure.

With a time sample of seven years, the presence of different players with different strategies in different product categories, and wide coverage of the marketing mix as well as

[1] That study focused on generalizable response patterns, obtained from over 60 brands in 4 categories. Our study will focus on a more detailed analysis of a subset of these brands.

consumer attitudinal metrics, these data are uniquely suited to address our research questions. The country of investigation is France, which is more homogenous than large multi-cultural markets such as the US in terms of consumer behavior and retail industry structure. Figure 2 illustrates the temporal variation in attitude metrics, marketing mix and business performance for a shampoo brand.

Brand diagnostics

The collection of the relevant brand diagnostics requires several steps, including data averages (for base levels), univariate time series models (for stickiness) and market response models (attitude response models, sales response models, conversion equations). Due to the large number of empirical results, we report on two major water brands (WA and WB) and two major shampoo brands (SA and SB). In each category, brand A is a premium (lower volume share) brand and brand B is a low-priced (higher volume share) brand. Note that an important marketing variable, distribution, is omitted because all leading brands in this dataset had near-perfect levels of retail availability throughout the sample period.

Empirical Results

Table 1 shows the univariate time-series models on the attitudinal metrics. The univariate models include no more than 3 autoregressive parameters and the model residuals are white noise as indicated by the Ljung-Box Q statistic).

Overall, the stickiness measures for upper-funnel metrics awareness and consideration, as computed by the sum of the AR parameters, are high and fluctuate in a narrow range from .6 to .8. By contrast, the lower-funnel metric liking is generally less sticky, especially in the low-involvement category (bottled water). For brands WB and SB, there is no noticeable stickiness for liking. Instead, this attitudinal metric behaves as a zero-order process around its mean. Interestingly, the results suggest that changes in liking are stickier for higher-priced brands (WA and SA) than for lower-priced brands (WB and SB).

Table 2 shows the attitudinal response models. Awareness is positively influenced by advertising for all four brands, WA, WB, SA, and SB. Consideration is positively influenced by sales promotion for both SA and WA and negatively influenced by price for WA. Liking is negatively influenced by price for WA. Interestingly, the water brand WA, with lower levels of customer involvement in the category, is influenced by pricing across all attitudinal metrics.

Turning to sales response, if the brand manager has access only to transactional data on sales and the marketing mix, he or she would be able to estimate the standard marketing-mix model shown in Table 3.

We will use this model as a benchmark for comparison against the more comprehensive funnel models in Table 2.

Overall, the results demonstrate the important role of attitudinal metrics in explaining marketing effectiveness. They also illustrate differences in response structure between high-involvement and low-involvement categories, as predicted by consumer behavior theory. We discuss the specifics by brand.

Brand-level strategic implications

What are the implications of these results for our focal brands? Our focal **shampoo** brand SA has ample room for mind-set expansion across the board (awareness 27%, consideration 17%, liking 5 out of 7). All three attitudinal metrics have comparable stickiness levels (around

70%), and as a result, the brand's potential in attitudinal space is high. Not surprisingly, the highest sales conversion elasticities (around .5) are obtained for consumer liking, about twice as high as for the upper-funnel metrics.

Tables 2 and 3 also summarize marketing responsiveness across attitudinal and transactional (sales) measures. On the sales side (see Table 3), the results are fairly typical, i.e. the highest elasticity (in absolute value) for price, followed by promotion and advertising. Attitudinal response to marketing is typically lower in magnitude than sales response to marketing (see Table 2), reflecting our argument that some marketing actions may affect sales without a corresponding change in specific attitude metrics.

The attitude-to-sales conversion parameters are estimated from a pooled model, combining data from brands in a category, which provide more efficient parameter estimates relative to a brand-level model. A conceptual argument for pooling is that, while mindset responsiveness to marketing may differ across brands (as shown in Table 2), mindset-to-sales conversion depends mostly on category characteristics (e.g. liking may convert to sales more in hedonic versus utilitarian categories). Moreover, if pooling is appropriate, it not only provides more degrees of freedom but also can reduce the level of collinearity in the data (Kumar and Leone 1988). Our empirical tests indicated that brand data could be pooled within each of the two categories.

Table 4 summarizes the results of the conversion equations. All three attitudinal metrics of awareness, consideration and liking significantly influence sales for the shampoo category. In the bottled water category, only changes in awareness and liking influence sales.[2] Thus in one

[2] Granger causality tests revealed that the causality direction was from attitudinal metrics to brand performance for the four brands studied.

category, marketing efforts that improve brand health in terms of consideration set will have a positive impact on sales, but in the other category they will not.

We illustrate the implications of these diagnostics in Tables 5a and 5b for the shampoo and bottled water categories. The tables contrast a marketing campaign that quintuples advertising spending (panels A and B) with a campaign that doubles promotional effort (in panels C and D).

As expected, the promotional campaign would have the highest sales impact (16.8% increase), but that increase is associated with very little mindset movement (only 2.3%) as shown in Table 5a. In contrast, the 2.2% sales increase coming from the advertising campaign is predominantly due to mindset movement (1.7%) and as such is more likely to have an enduring impact.

The results for our focal **bottled water** brand WA are different, and in the proposed directions. Stickiness for awareness and consideration are comparable to shampoo, but stickiness for liking is much lower, suggesting that consumer' purchase decisions are closer to a zero-order process (see Table 1). On the other hand, liking is the only attitudinal metric that converts significantly into sales (elasticity .517 reported in Table 4). Thus, any marketing effort that stimulates attitude metrics other than liking is likely to have only negligible demand effects. On the marketing-mix side, we find, as expected, that advertising works best in the upper funnel (Table 2). Overall, price is the only variable that has substantial investment appeal.

The scenario simulation results support these findings (Table 5b). For both advertising and promotion, long-term sales gains occur predominantly from transactions increases. The difference with shampoo is especially striking for advertising: its sales impact for shampoo comes primarily from mindset movements; of the total sales impact of 2.2% due to increase in advertising, mindset movements account for 1.7%. By contrast, for bottled water the pattern is reversed and the sales impact comes primarily from transaction effects.

Overall, the empirical results illustrate the central premises in our paper: the four criteria of attitude metrics establish they are important intermediate performance measures between marketing and sales, as their relative response differs substantially across the product categories and brands. As a result, different brands find themselves in different quadrants of the strategic scenarios shown in Table 6.

For example, brands that invest substantially in awareness-generating advertising may enjoy lifts in awareness that do not translate into sales improvements. We label this a "wrong focus" scenario; it applies to water brand WA with respect to advertising and awareness. Conversely, if the attitudinal metric has high sales conversion but does not respond well to increased marketing spending that would result in a "wrong marketing instrument" scenario. This is the situation that shampoo brand SA finds itself in with regard to consideration and sales promotion.

Predicting Marketing Impact in a Holdout Sample

The estimates reported in Tables 1-4, based on 84 initial observations (year 1 through 7), are consistent with our arguments on the role of attitudinal metrics in establishing marketing impact. However, in order to gain managerial relevance, the models need to have predictive validity, i.e. collecting and using information on a brand's attitudinal metrics should allow managers to make better predictions of business performance in function of planned increases, cuts or reallocations in marketing spending in year 8 (observations 85-96).

Comparing years 1-7 to year 8, several brands implemented strategic shifts in their marketing allocations. For example, shampoo brand A increased its advertising spending by 50%, tripled its promotional spending and kept its prices the same. In contrast, water brand A cut its advertising spend by 42% and increased its promotion spending by 35%, while also keeping prices the same. Whereas both brands are comparable by virtue of their premium positioning, we observe from Tables 1-5 that shampoo brand A has a higher potential and sales conversion for awareness and consideration and a higher stickiness in all 3 metrics. Because awareness is responsive to advertising, and consideration and liking to promotions, increased spending on these marketing activities should have a strong and lasting impact on sales. In contrast, water brand A's increased use of promotions is unlikely to have these benefits: promotions only marginally translate into consideration increases (Table 2), which in turn do not significantly raise sales (Table 4).

We compare conditional forecast results for year 8, where the brand's resource allocations in year 8 are known (i.e. planned) at the end of year 7. The benchmark forecasts are drawn from the marketing mix models (without attitudinal metrics) reported in Table 3. The comparison forecasts are obtained from models with both marketing-mix and attitudinal metrics. These models thus allow marketing actions to have both 'transactions' and 'mind-set' effects. The comparisons are based on one-step (static) and multi-step (dynamic) forecasts, i.e. projections up to twelve periods ahead. While the one-step forecasts are expected to be more accurate, the multi-step predictions are more realistic in a twelve-month marketing planning scenario.

Table 7 shows the comparative results, with a focus on prediction accuracy, as measured by MAPE. Importantly, the sales predictions made by the "marketing mix and mind-set" models outperform the benchmark forecasts in 17 out of 20 cases. As expected, the sales predictions improvements for one-step (static) forecasts are lower since these are more accurate across the board. The average prediction improvement is sizeable, about 28.2%. The sales response model with attitudinal metrics offers superior prediction improvements for the shampoo category as compared to the water category: 27.8% vs. 15.4% for static forecasts and 34.6% vs. 30.7% for dynamic forecasts. Overall, the degree to which a model with attitudinal metrics and marketing mix outperforms a straight marketing mix model is greater for the higher- involvement categories, as predicted from consumer-behavior theory.

These findings demonstrate that incorporating the role and the responsiveness of 'customer's mind and heart' metrics improves our understanding and predictability of marketing impact on sales. As such, this practice can improve the quality of marketing resource allocation decisions for the analyzed brands.

Conclusions

We argued in our introduction that the CFO's needs for financial accountability of marketing may well be met by traditional marketing-mix models on transactions data. However, the CMO also needs to understand the *consumer behavior reasons* why marketing does or does not impact business performance. Our paper has demonstrated that the objectives of both stakeholders can be met by recognizing the unique properties of attitudinal metrics and their relationship to sales performance. In particular, these measures have potential, stickiness and responsiveness to marketing that can be assessed from the data. Furthermore, the *relevance* of these metrics may be assessed by their conversion into sales performance, which provides the critical accountability link with the CFOs needs. Different product categories and brands within them vary significantly in the magnitude of these diagnostics, and these differences form the basis for formulating marketing resource allocation strategies that are more likely to succeed.

Future research should explore category comparisons with even higher levels of consumer involvement, such as durables and high-value services, possibly using data at different time intervals (e.g. weekly, monthly, quarterly). If individual-level attitude metrics are available, these could be used in more granular response-model specifications. Moreover, data on the profits gained from better decisions would enable managers to weigh them against the cost of collecting attitudinal metrics, thus providing an ROI measure for such data. Indeed, the need for attitudinal metrics that match the transactional records is a limitation of our approach. Such attitudinal tracking data are typically survey based, which is costly and subject to sampling error. However, the digital age offers new opportunities in this regard. Instead of surveying consumers, one can observe how they express themselves on the internet, via searches, chat rooms, social network sites, blogs, product reviews and the like. Some preliminary evidence suggests that "internet derived consumer opinions" are predictive of subsequent behavior (e.g. Shin, Hanssens and Gajula 2010). Future research should examine which internet-derived attitudinal metrics are the most relevant. These metrics could then be substituted for the survey based measures that were used in this paper.

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Figure 1: Conceptual Framework

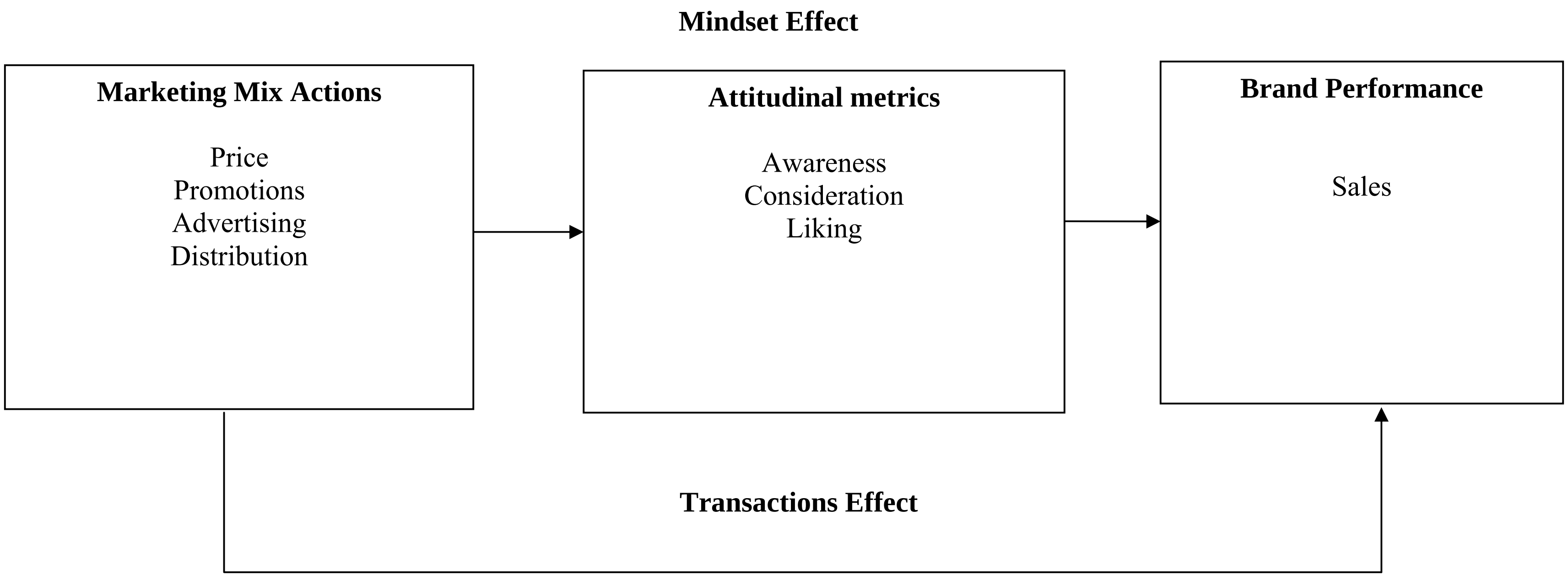

Figure 2: Temporal Variation in Attitude and Business Performance

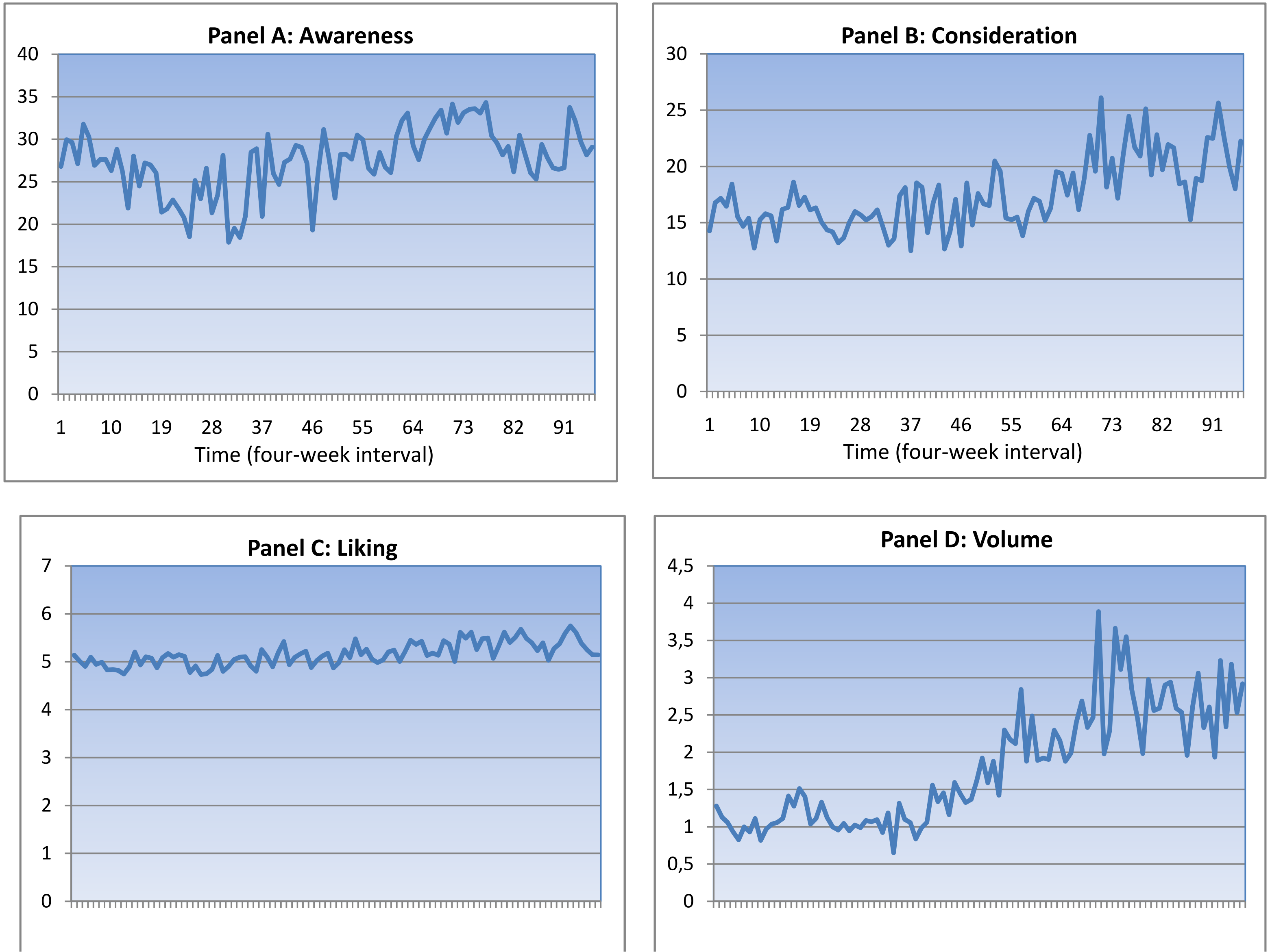

Table 1 – Univariate Models: Estimation of Stickiness

	Shampoo Brand SA				*Shampoo Brand SB*			
	Awareness	Consideration	Liking	Volume	Awareness	Consideration	Liking	Volume
Constant	.378***	.217***	2.957***	2.706	.381***	.453***	7.681***	4.271***
AR(1)	.435***	.218**	.318***	.321***	.048	.019	-.109	.326***
AR(2)	.073	.355***	.153	.292***	.279***	-.017	-.154	.149
AR(3)	.287***	.257***	.355***	.345***	.320***	.027*	-.187	-.037
R-square	.480	.451	.443	.758	.245	.020	.060	.156
Q(12) Statistic	7.198	11.640	10.814	7.479	9.787	13.022	6.513	14.953
Stickiness	.722	.830	.673	.958	.599	.027	.000	.326

	Bottled Water Brand WA				*Bottled Water Brand WB*			
	Awareness	Consideration	Liking	Volume	Awareness	Consideration	Liking	Volume
Constant	.600***	.470***	4.052***	131.183***	.215***	.834***	21.746***	351.486***
AR(1)	.333***	.225***	.363***	.610***	.331***	.303***	.090	.905***
AR(2)	.238**	.347***	.119	.161	.081	.366***	-.064	.135
AR(3)	-.039	.163	.113	.048	.329***	.081	-.025	-.121
R-square	.225	.346	.249	.586	.393	.440	.104	.863
Q(12) Statistic	11.344	9.504	8.443	.819	9.867	17.940	10.970	10.310
Stickiness	.571	.572	.363	.610	.660	.669	.000	.905

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 2 – Attitude Response Models

	Shampoo Brand SA			*Shampoo Brand SB*		
	Awareness	Consideration	Liking	Awareness	Consideration	Liking
Constant	-.701	-1.378**	.014	-.643***	-.651***	2.344***
Price	-.024	.178	.319	-.502***	-.128	-.389
Promotion	.023	.052***	.053***	.054	.006	.083
Advertising	.023***	.006	.003	.007***	-.001	-.001
Carryover	.436***	.400***	.386***	.029	.030	-.106
R-square	.533	.363	.410	.200	.011	.040
Q(12) Statistic	17.939	17.550	14.140	19.782	11.031	14.128

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

	Bottled Water Brand WA			*Bottled Water Brand WB*		
	Awareness	Consideration	Liking	Awareness	Consideration	Liking
Constant	-1.174***	-2.827***	-0.789*	-0.322	-0.116***	2.948***
Price	-0.598*	-1.915***	-1.643***	0.037	0.006	0.069
Promotion	0.047	0.033*	0.045	0.028	0.044	-0.023
Advertising	0.014***	0.003	0.000	0.019***	0.003	0.007
Carryover	0.362***	0.082	0.226**	0.593***	0.622***	0.230**
R-square	0.410	0.433	0.347	0.559	0.440	0.073
Q(12) Statistic	23.383	10.442	7.644	23.699	24.741	11.880

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 3 – Sales Response Models

	Shampoo Brand SA	*Shampoo Brand SB*
Constant	.012	1.193***
Price	-.080	-.466***
Promotion	.083***	.076
Advertising	.005	.001
Carryover	.733***	.310***
R-square	.752	.218
Q(12) Statistic	17.252	17.814

	Bottled Water Brand WA	*Bottled Water Brand WB*
Constant	1.083***	5.680***
Price	-.937***	-.084
Promotion	.055***	.008
Advertising	.005***	-.002
Carryover	.538***	.922***
R-square	.696	.862
Q(12) Statistic	6.388	7.223

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 4 – Sales Conversion Models

	Shampoo	*Bottled Water*
Constant	-1.665***	.181
Awareness	.251***	.050*
Consideration	.169***	-.065
Liking	.462**	.517**
Carryover	.552*	.786***
R-square	.820	.975

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 5a

Advertising and Promotion Scenarios – Shampoo Brand

Panel A: Aggressive Advertising Scenario

	Start	New	Gain	LT Gain	Conversion			
Advertising	100	500	400					
Promotion	100	100	0					
Awareness	.270	.278	3%	5%	1.2%	Long-term Sales Gain=		2.2%
Consideration	.170	.172	1%	2%	.4%	Due to Mindset=		1.7%
Liking	5	5	0%	0%	.1%	Due to Transactions=		.6%
Sales	1.800	1.819	1%	2.2%				

*Read: initial awareness is 27%. Quintupling advertising spending (from index 100 to index 500), while keeping promotion the same, raises awareness to 27.8%, for a 3% gain. This gain translates into a 5% long-term gain, which converts to a 1.2% sales gain. Total sales gain is 2.2%, of which 1.7% (=1.2+.4+.1) is due to movements in attitudinal metrics.

Panel B: Aggressive Sales Promotion Scenario

	Start	New	Gain	LT Gain	Conversion			
Advertising	100	100	0					
Promotion	100	200	100					
Awareness	.270	.273	1%	2%	.4%	Long-term Sales Gain=		16.8%
Consideration	.170	.176	3%	6%	1.2%	Due to Mindset=		2.3%
Liking	5	5.1	1%	1%	.7%	Due to Transactions=		14.4%
Sales	1.800	1.942	8%	16.8%				

Table 5b

Advertising and Promotion Scenarios – Water Brand

Panel C: Aggressive Advertising Scenario

	Start	**New**	**Gain**	**LT Gain**	**Conversion**			
Advertising	100	500	400					
Promotion	100	100	0					
Awareness	.360	.366	2%	3%	.3%	Long-term Sales Gain=		2.1%
Consideration	.320	.321	0%	0%	.0%	Due to Mindset=		.3%
Liking	6	6	0%	0%	.0%	Due to Transactions=		1.8%
Sales	13.000	131.050	1%	2.1%				

Panel D: Aggressive Promotion Scenario

	Start	**New**	**Gain**	**LT Gain**	**Conversion**			
Advertising	100	100	0					
Promotion	100	200	100					
Awareness	.360	.368	2%	4%	.3%	Long-term Sales Gain=		7.3%
Consideration	.320	.324	1%	2%	.0%	Due to Mindset=		1.1%
Liking	6	6.1	1%	1%	.8%	Due to Transactions=		6.1%
Sales	130.000	133.655	3%	7.3%				

Table 6: Strategic Importance of Attitudinal Metrics

Impact Potential	Sales Conversion	
	Low	**High**
Low	Transactions effect at best	Wrong marketing instrument
High	Wrong focus	Long-term effect potential

Table 7: Predictive Performance for
Marketing Mix Model vs. Consumer Attitude and Marketing Mix Model

Holdout sample: periods 85 through 96

Forecast Solution	**Category**	**Brands**	**Marketing Mix**	**Consumer Attitude + Marketing Mix**	**Improvement**
			MAPE	MAPE	
Static	Water	WA	6.2%	3.7%	40%
		WB	.9%	.5%	41%
		WC	9.4%	12.6%	-33%
		WD	7.0%	6.0%	14%
	Shampoo	SA	5.5%	2.1%	61%
		SB	1.0%	.6%	39%
		SC	5.3%	.4%	93%
		SD	2.4%	3.5%	-50%
		SE	.9%	.7%	22%
		SF	8.5%	8.5%	1%
Dynamic	Water	WA	12.0%	6.2%	48%
		WB	7.2%	4.4%	39%
		WC	24.6%	22.2%	10%
		WD	14.5%	10.7%	26%
	Shampoo	SA	8.6%	2.1%	76%
		SB	1.6%	1.0%	36%
		SC	6.8%	.4%	94%
		SD	5.4%	7.4%	-37%
		SE	1.2%	.8%	37%
		SF	12.2%	12.0%	2%

Note: MAPE denotes the Mean Absolute Percent Error over the 12-month forecast period. The static forecasts are consecutive one-period-ahead predictions with updating. The dynamic forecasts are one to twelve-periods-ahead predictions without updating.